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Pan-tropical modelling of the effects of tree cover growth on water quantity and regulation services

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Pan-tropical modelling of the effects of tree cover growth on water quantity and regulation services

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Abstract

Forest restoration and reforestation projects are multiplying in the tropics and globally, but most of them are designed for climate change mitigation and often neglect to critically examine the hydrological services provided by forests. Furthermore, the impact of large-scale afforestation on water quantity and regulation in the tropics is not fully known. Lacking specifically, is the knowledge of where and when forest increase can lead to more positive or more negative hydrological outcomes, which is at the centre of the "infiltration-evapotranspiration trade-off" debate. Equally, there are no hydrological models suitable to address this gap on large spatial scales and with publicly available datasets that have good coverage in the tropics.

The aim of this study was to address these gaps in several ways. A new spatially distributed hydrological model, DTRIE, was developed to adequately represent the effects of tree cover on surface and subsurface flows on large spatial scales. DTRIE operates on a monthly time step to model long-term changes to annual and seasonal water availability. Second, the study produced a novel, realistic scenario for tree cover growth in the tropics which is constrained by environmental and socio-economic data. Third, a data-driven incremental growth model to estimate fractional tree cover at multiple management-relevant time steps was developed.

The key findings from this study are as follows: DTRIE performed acceptably when compared with estimates from other published models and datasets, such as evapotranspiration data from MODIS or GLEAM, or monthly stream discharge from the Global Runoff Data Centre (GRDC).

Across the tropics, 812 million hectares of area of opportunity for tree cover growth were identified, most of which is located in Central and South America, followed by Africa, and Asia and Oceania. The tree cover growth model projected an increase in tropical tree cover from 25.8 per cent (current/ in 2018) to 31.3 per cent (in 2118). Because of low tree cover in 2018, tropical Africa saw the highest relative increase.

When applied to the scenario tree cover conditions, DTRIE results supported the consensus that annual water quantity declines with more tree cover, except

where cloud forests are present. A new finding was that the sensitivity of water balance to tree cover change, i.e., the change in water balance per change in unit tree cover, averaged over larger tropical basins, was generally low. The maximum change in water balance per unit change in tree cover was 0.6 mm, but 90 per cent of the values were below 0.25 mm. The sensitivities of AET (actual evapotranspiration) and infiltration to forest increase were compared. Areas where increased infiltration exceeded increased AET after tree growth were found to have a higher baseline tree cover and a higher aridity index (meaning they were more humid). These areas have the potential to see increased dry season flows because less water leaves the system as AET.

The intra-annual variability of streamflows in several tropical dam watersheds increased more steeply with tree cover growth when watersheds were more humid and more area was under restoration. In some watersheds dry season flows increased despite an overall more uneven distribution throughout the year.

These findings are relevant in the seasonally dry tropics, and especially where streamflow regulation is important. For example, in regions with high dependency on irrigated agriculture but low-capacity dam infrastructure upstream forestation may be beneficial. Here, increases in dry season flows may outweigh the expected decreases in annual water quantity through forestation. Conversely, since the reduction of water quantity is almost a given, areas where regulation is not an issue but overall quantity is important may not want to sacrifice water quantity for an increase in tree cover.

COVID-19 impact statement

The COVID pandemic and the associated restrictions had a profound impact on the scope and methodology of this research project. In mitigation, this project transformed from a field-based to a desk-based study using remote sensing data, which could no longer integrate an entire year's worth of work that took place pre-pandemic in support of the then field-based project.

This PhD research was begun in March 2019 with a focus on the catchment-scale hydrological effects of land abandonment at field sites in Colombia and Nepal. To this end, an entirely-field based project was designed, using low-cost environmental sensors to collect soil moisture, river stage and weather data in the study catchments. In Colombia, soil moisture and weather stations could be installed, but vital measurements to complete stream discharge calculations that were to take place at a later visit could not be done as a result of travel restrictions associated with the pandemic. Early results from Colombia featured in this thesis' upgrade report from February 2020. Stations were in the process of being set up in Nepal in February and March of 2020, which meant I was actually doing field work when the early pandemic restrictions were coming into force and had to return home at short notice.

Having to end field work in Nepal early and not being able to complete the setup in Colombia made it impossible to use the field data that was collected in this thesis. While local collaborators were and are involved in Colombia, they could not conduct the stream related measurements necessary. Conversely, the Nepal field work was conducted with local NGO that does not have the required capacity (or staffing) to continue setting up and maintaining monitoring stations. Most importantly, however, local teams were living through a pandemic and its restrictions as well. By the time most restrictions were lifted in both the UK and Nepal (mid to late 2021), a resumption of field work was unviable because the temporal coverage of the monitoring data starting then would have been too short to capture the necessary period including seasonal variability.

The COVID pandemic therefore required a complete overhaul of this project in terms of spatial and temporal scale, methodology and research question. As catchment scale field data was no longer an option, I moved from field-based to

desk-based research. This meant using freely available remote sensing data, thus moving from catchment point data to, at best, 250 m raster data.

The entire methodology therefore had to be reworked. With a shift in scale, more than half of the previously completed literature review was no longer applicable.

While both my funding body and the university were able to grant extensions on my submission deadline of five months in total, I essentially lost an entire year's worth of work through the pandemic and the necessary mitigation measures. It also meant that the modelling aspects of the thesis had to rely entirely on secondary data instead of - as expected - the novel aspects, particularly infiltration trade-offs being supported by an extensive field data programme.

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First and foremost, I would like to thank my supervisor, Mark Mulligan, without whom this project would never have been possible. I started this journey with a hot glue gun and bending aluminium panels for a what now seems like a distant dream of PhD project. But with Mark's steady guidance and clear vision of how I could pivot from field- to desk-based work during the pandemic, I was able to finish this new version of my PhD. I would also like to thank my two other supervisors, Jane Catford and Sampurno Bruijnzeel, who provided invaluable inputs, both in the early incarnations of this project and later.

Indeed, in an earlier life, this project was a field-based one with field sites in Colombia and Nepal. For the initial field work in Colombia, I have to thank Jorge Rubio and his family for providing excellent technical support and a welcome that could not have been better. Kris Chan and Heather Needham, whose support and muscle was essential to this first field visit will probably never forget how hard it is to dig 60 cm deep holes in a former coffee plantation, and neither will I. Sophia Burke should also not go unacknowledged. Many freestations were built together for the Por el Parámo project in Colombia in 2019.

Before the pandemic stopped all field work, I was also lucky enough to conduct two visits to Nepal, where I cannot overstate the support and care I received from Forest Action Nepal, especially Naya Sharma Paudel, Madan Bashyal, Anukram Adhikary, and the community of Chaubas in Kabhrepalanchok District.

I would also like to acknowledge the Rstats community, especially R spatial, in helping to develop my coding skills. A desk-based modelling project was not my initial idea PhD, but it did open many windows into the rather exciting world of data science for me.

To my friends and proof-readers, Aoife Bennett, Gino Brignoli, Kelly Gunnell, Sabrina Johnson and Paul Young I extend the deepest thanks for great inputs and even greater turnarounds.

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Abbreviations

ACRONYM	Description
ABG	Aboveground biomass
ABG _{WOOD}	aboveground woody biomass
AET	Actual evapotranspiration
AGC	aboveground carbon
AI	Aridity index
AW & UAW STORE	Available & unavailable water store
C _{ACCUM}	Accumulated carbon
CHELSEA	Climatologies at High resolution for the Earth Land Surface Areas
CV	Coefficient of variation
D _{ROOT}	root depth
DTRIE	<i>Distributed TRade-off in Infiltration and Evapotranspiration</i>
E _I	Interception loss
ESA CCI	European Space Agency Climate Change Initiative
E _{WB}	Water balance elasticity
FAO	United Nations Food and Agricultural Organization
FLR	Forest landscape restoration
GLEAM	Global Land Evaporation Amsterdam Model
grc	Carbon growth rate
ha	hectares
HB4	HydroBASINS level 4 basins
H _s	Hydrological sensitivity, water balance sensitivity
LAI	Leaf area index
LC	Land cover
MAT	Mean annual temperature
MODIS	Moderate Resolution Imaging Spectroradiometer
MRB	Major river basins of the world
NASA	US National Aeronautics and Space Administration
NDC	Nationally determined contributions
NGO	Non-governmental organization
NPP	Net primary productivity
NPP _{AB}	Aboveground mean NPP

NPP_{TOTAL}	Total above- and belowground NPP
P	Precipitation
PBIAS	Percentage bias
PET	Potential evapotranspiration
POI	Point of interest
R_1 - R_3	Surface runoff 1-3
r_{CB}	carbon-to-biomass ratio
RMSE	Root mean square error
r_{RS}	Root-shoot-ratio
r_{WC}	woody-to-canopy ratio
r_{WT}	woody-to-total ratio
SET	Soil evaporation and plant transpiration
SF	Surface flows
SSF	Subsurface flows
UN	United Nations
UNFCCC	UN Framework Convention on Climate Change
USDA	United States Department of Agriculture
VOD	Vegetation optical depth
v_T	Throughflow velocity
WB	Water balance
WC_{FC}	Water content at field capacity
WC_{WP}	Water content at wilting point
WS	Watershed

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Chapter 1 Introduction

1.1 Context and research problem

Over the past three years, the COVID-19 pandemic has touched upon all aspects of our lives. To many, the crisis of the pandemic did not happen in a vacuum but in a climate of – and in – crisis. In industrialised, or “Western” countries, there is now a perception that these are “times of continuous crises”, where climate change, biodiversity loss, economic struggles, social unrest, armed conflict and other global issues collide (Stanturf, 2021; UN Secretary General, 2019).

For many people, the pandemic triggered a change in their perceptions of nature and how it contributes to quality of life or livelihood. Consequently, the COVID pandemic has given rise to widespread interest in so-called *build-back-better* (Stanturf, 2021), *green recovery* (Mita and Singer, 2020) or *Green Deal* (European Commission, 2019) programmes, many of which rely on large scale forest restoration and reforestation for various purposes, but principally, carbon sequestration for climate change mitigation (Busch et al., 2019).

While the field of reforestation and forest restoration is by no means new, it has undergone a significant transformation in recent years. Additional financial support streaming in from corporations and private investment alongside the more traditional governmental and multilateral actors, all aiming to contribute to climate change mitigation (Holl and Brancalion, 2020; Löfqvist and Ghazoul, 2019; Stanturf and Mansourian, 2020).

However, the dominant focus on carbon sequestration has meant that the hydrological effects of these reforestation endeavours regarding water provisioning and regulation services have been relatively overshadowed and overlooked. In many policy briefs, for example, references to it are opaque (such as “watershed protection” Mita and Singer, 2020) and often lumped with the similarly vague catch-all term of *co-benefits*. Worse still, the misperception that forests are inherently good for water supply persists, even though researchers have been pointing it out for two decades (Calder, 2002, 2007; Filoso et al., 2017). A case in point is the business case document of one of the newest and most prominent forest restoration initiatives, the “One Trillion Trees Platform”, launched by the World Economic Forum in 2021. Within a year

of forming it has received private sector commitments of 1.2 billion USD, but its documentation exclusively refers to positive effects of tree cover on water ecosystem services (It.org Secretariat, 2022; World Economic Forum, 2021).

Many of these tree planting and forest restoration programmes are or will take place in the tropics (Martin et al., 2021), a region still under-represented in the scientific literature on the hydrological effects of reforestation (Filoso et al., 2017). Hence, there exists a need for evidence-based research that can inform the expanding array of reforestation and forest restoration projects, ensuring that the potential for adverse outcomes in water-related services is given due consideration.

1.2 Research aim

The aim of this research project is to advance the understanding of the relationships between tree cover growth and water provisioning and regulation ecosystem services by examining the trade-offs between increased evapotranspiration and increased infiltration under tree cover change in the tropics. Ultimately, the research project aims to identify areas where net positive outcomes for water can and cannot be attained to provide recommendations in support of impact analyses for reforestation, forest restoration, related initiatives and policies.

1.3 Objectives

To achieve the research aim set out above, I have defined the following objectives:

Objective 1

Develop a spatially distributed model of evapotranspiration and infiltration to model water provisioning and regulation services in response to tree cover increase that is driven by remote sensing data products and can be applied to large spatial scales.

Objective 2

Produce an up-to-date map of the potential for tree cover growth in the tropics as well as maps of potential fractional vegetation cover over multiple decades of incremental tree cover growth.

Objective 3

Examine, through the application of the DTRIE model, the effect of tree cover growth on annual water quantity, monthly runoff and dry season flows and their relationships with the given environmental conditions.

Objective 4

Examine, through the application of the DTRIE model, where the trade-off between increased evapotranspiration and improved infiltration can deliver net positive outcomes for water quantity and regulation services.

Objective 5

Translate the findings from the trade-off experiment into recommendations for reforestation and restoration policy and planning.

1.4 Overview of the thesis

Chapter 2 introduces the literature and research on the effects of tree cover change on hydrological variables as well as the debate that shapes a large part of this thesis, the “evapotranspiration - infiltration trade-off hypothesis”.

Chapter 3 presents a new hydrological model for the monthly estimation of gains and losses under tree cover increase (DTRIE). DTRIE builds on the existing plethora of hydrological and landscape models, which is briefly introduced in this chapter. The chapter therefore addresses **objective 1**.

Chapter 4 describes a new tree cover expansion model to investigate the hydrological effects of tree cover growth, thereby acting as a “scenario generator” for the following chapters. Drawing on published maps of potential forest cover and a range of other determinants, the chapter delineates areas with potential for tree cover growth based on up-to-date inputs. Subsequently, it proceeds with “growing” tree cover in a stepwise manner in these areas to produce potential fractional tree cover maps, and therefore addresses **objective 2**.

These maps of potential fractional tree cover are then used as inputs in the hydrological model, DTRIE, in **Chapter 5**. This chapter first outlines the hydrological effects of the tree cover growth model when applied to the tropics as a whole and selected major river basins. Then, it explores the general sensitivity of hydrological variables to tree cover change and how these sensitivities respond to a variety of environmental factors such as annual total rainfall and others. Effects on the annual water

quantity, as well as on the timing thereof will be analysed, using larger basins and a small set of dam watersheds (as a subset of economically and socially important locations where water is abstracted) from across the tropics. This chapter therefore attempts to achieve **objective 3** and **objective 4**.

Finally, **Chapter 6** summarises the conclusions of the preceding chapters and integrates their findings into recommendations for reforestation and restoration policy and planning, thus addressing the final **objective 5**. The chapter then concludes by assessing the extent to which the defined objectives have been achieved and outlines opportunities for future research.

Chapter 2 Literature review

The present chapter will first examine the literature surrounding tree cover and its areal expansion in the tropics with a view to the political and financial drivers that facilitate the changes in tree cover, followed by a review of the effects of changes in the extent of tree cover on water quantity and water regulation.

2.1 Tree cover growth in the tropics

Section 2.1 first investigates the political and funding landscape that shapes reforestation, forest restoration and other change in the extent of forest cover in the tropics to illustrate the relevance and timeliness of the proposed research. Following that, the section outlines the technical terminology used to describe these various changes to situate the proposed research in the wider literature.

2.1.1 International political and financial commitments to reforestation

Rates of deforestation and forest degradation remain high despite overwhelming evidence for the negative impacts on the environment and local livelihoods (da Silva et al., 2023; FAO, 2020; Lambin and Meyfroidt, 2011; Popp et al., 2014; Powers and Jetz, 2019; Winkler et al., 2021). The resulting threats to biodiversity, food security and globally significant carbon sinks, especially affecting the tropics, have inspired a host of international political and funding commitments to address this crisis. A growing number of multilateral agreements link financial support from typically industrialised countries, and more recently, the private sector, to area commitments for forest restoration: for example, the global scale *Bonn Challenge*, the *Initiative 20x20* in Latin America and the Caribbean, the African Forest Landscape Restoration Initiative *AFR100*, the 1t.org initiative to plant 1 trillion trees by the World Economic Forum, the Glasgow Leaders' declaration on forests and land use (UN, 2021), and others under the umbrella of the United Nations Decade of Ecosystem Restoration 2021 – 2030 (2019 UN Resolution 73/284) (see Löfqvist and Ghazoul, 2019 for a topology of private investment in FLR; and Mansourian et al., 2021 for a general chronology of these initiatives; Stanturf and Mansourian, 2020 for an overview of country commitments). It is not difficult to see why some have called this a “widespread obsession over planting trees” (Holl and Brancalion, 2020, p. 580).

Many of these programmes, especially the relatively new corporate and private investment commitments, focus predominantly on mitigating climate change and promote reforestation and forest restoration as a tool to improve carbon sequestration (Busch et al., 2019; Seymour, 2020). In addition, increasing tree cover is also a fix-

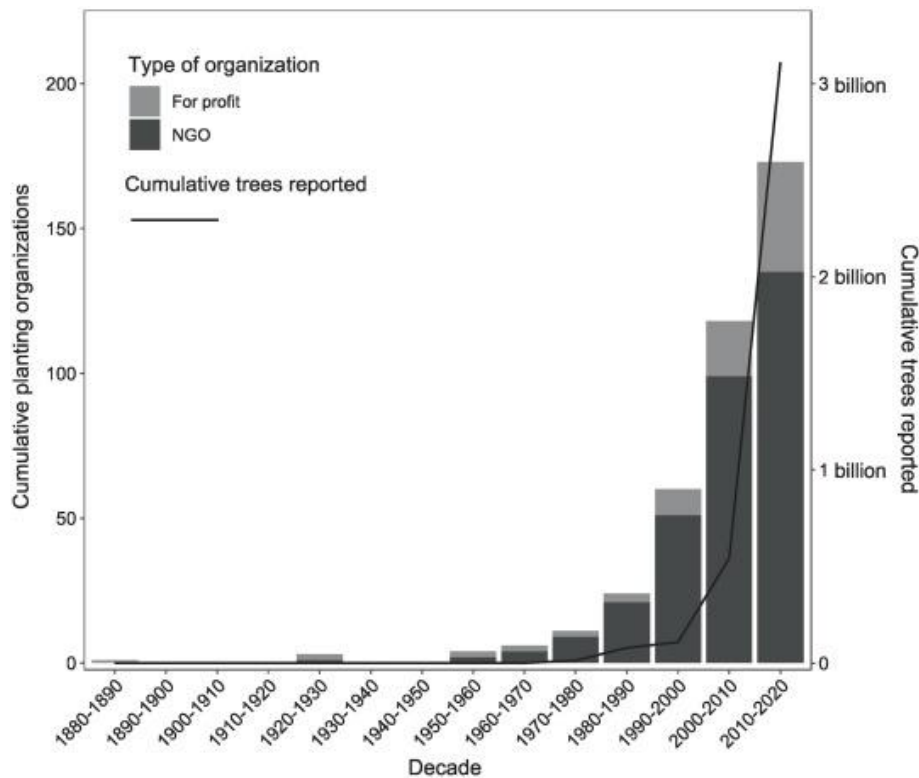


Figure 2.1 Timeline new reforestation/tree planting organisations, showing the cumulative number of organisations operating in each decade, as well as the cumulative number of trees reported planted. Dark grey bars = non-profit NGOs; light grey bars = for-profit organisations. Decadal estimates of trees planted are based on annual mean trees reported planted and are shown on a second y-axis due to the difference in scale between organisations and trees. Source: Martin et al. 2021

ture in many countries' Nationally Determined Contributions to the Paris Agreement (NDCs), whose express purpose, under the United Nations Framework Convention on Climate Change (UNFCCC), is climate mitigation (IUCN, 2020). The plethora of initiatives means that money will be available for forestation projects and thus likely lead to at least some increase in tropical forest cover (Melo et al., 2021). It should also be noted, that the tropics have seen spontaneous, or unassisted, natural forest regrowth in recent decades, for example, following agricultural land abandonment (Aide et al., 1995; Bennett et al., 2023; Chazdon and Guariguata, 2016; Grau and Aide, 2008; Schneibel et al., 2017).

Halting deforestation in the tropics, or even fostering a net increase in tree cover has thus established itself on the global political agenda and is met with an eager base of

NGOs, practitioners, and development organisations on the ground, illustrated by Figure 2.1 (Martin et al., 2021).

As a consequence of the dominance of climate change in these programmes, however, many of the other effects of forest regrowth and reforestation are frequently given short shrift, if not entirely ignored. While additional benefits (often called co-benefits, see Sarira et al., 2022), for example those relating to alternative livelihoods, are readily included in project documents, many of the less clear-cut effects, such as the impacts on water supply and regulation services, are not fully represented (Erbaugh et al., 2020; Filoso et al., 2017). Many articles aimed at policy- and decision-maker audiences neglect, or mention only cursorily, the various effects that an increase in tree cover can have on water quantity and regulation despite a long tradition of research on the matter (Ellison et al., 2017; Griscom et al., 2017; Marshall et al., 2023; Sheil et al., 2019). There are, of course, exceptions and a notable one from the policy sphere is for example, India's NDC commitments to the UNFCCC, which aim to increase the nationwide forest and tree cover to 33 per cent, while also explicitly stating the improvement of hydrological services as a goal (Clark et al., 2021). In the face of such an extremely ambitious target, the highlighted role of hydrological services stands out positively.

2.1.2 Short overview of forest-related terminology

First, it is important to define what counts as a forest, and most of the terminology listed below follows the definition of the UN Food and Agricultural Organization (FAO) which requires an area of at minimum 0.5 hectares to have a minimum canopy cover of 10 per cent. Furthermore, the minimum height of the tree cover is 5 metres and agricultural use or human settlements are excluded (FAO, 2012a).

Second, the increase in forest cover can take many forms and there are therefore a great number of terms for it. The broadest term in this short glossary is probably *forestation*, which is commonly used when the long-term history of the land cover is not important, and it is defined by Bentley and Coomes (2020) as “a change in land cover from a stable, non-forested state to a forested one, independent of the long-term history of forest cover”.

When the long-term history *is* of interest to the research question, one arrives next at the terms *reforestation* and *afforestation*; these are defined as “[p]lanting of forests

on lands that have previously contained forests but that have been converted to some other use” (for reforestation), and “[p]lanting of new forests on lands that historically have not contained forests” (for afforestation) (McCarthy et al., 2001). These two terms imply an active role of the project or practitioner, but where such interventions are limited or absent, research will typically refer to, for example, *assisted*, *passive* or *natural forest regeneration*, *forest regrowth*, or *natural expansion of forest* (FAO, 2012a; Holl and Brancalion, 2020; Lamb, 2018). For example, Cook-Patton et al. (2020) define *natural forest regrowth* as “the recovery of forest cover on cleared lands through spontaneous regrowth after cessation of previous disturbance or land use”. Lastly, when the focus lies on ecological functioning of the forest, more appropriate terms are *forest restoration* or *forest landscape restoration*, which Chazdon and Guariguata (2016) define as “holistic process that aims to regain ecological integrity and enhance human well-being in deforested, human-impacted, or degraded forest landscapes”.

The term used in this study is *tree cover growth*, defined as the increase in tree cover that can take place on already forested land (thus purely *increasing* tree cover) or on land with the natural potential for tree cover (thus *establishing* or *re-establishing* tree cover). As such, it is perhaps most aligned with the terms *reforestation* and *afforestation*, except in this research no distinction is made between active approaches, such as planting (as embedded in the definitions of *re-/afforestation*) or more passive ones (as in *natural forest regeneration*). The choice of *tree* as opposed to *forest* cover growth stems from the fact that the tree growth model developed in Chapter 4 could result in tree cover below the FAO minimum cover thresholds for *forests*, which is 10 per cent.

When it comes to the projects implemented or funded under the initiatives outlined in section 2.1.1, a large share of commitments under NDCs is for reforestation and afforestation, i.e. planted forests (IUCN, 2020, p. 8) while pledges under the Bonn Challenge and its regional counterparts are more inclusive of natural, or passive forest regeneration (see for example, the progress update on Brazil’s Bonn Challenge pledge in Dave et al., 2019). The wider scope of *tree cover growth* is therefore best suited to exploring the hydrological effects of this panoply of projects.

This term also captures best the literature on the hydrological effects of tree cover change, in which the simpler distinction of afforestation and deforestation is

prevalent, although there are mentions of the more ecologically focused forest landscape restoration (Filoso et al., 2017). The following section reviews the effects of these as well as the effects of deforestation, which are often discussed and reviewed in tandem under the umbrella of *tree cover change*. For the remainder of the thesis, deforestation will not be considered, and the term *tree cover growth* will be used.

2.2 Review of the effects of tree cover change on water quantity and regulation

The following section reviews the effects of tree cover change on water quantity and regulation by at first outlining empirical research and synthetic reviews on the issues, followed by an introduction to the evapotranspiration-infiltration trade-off hypothesis as well as the empirical research examining the hypothesis. The section concludes with an overview of the main uncertainties in the debate and opportunities for further research.

2.2.1 Empirical research and systematic reviews thereof

There are now many studies investigating the changes in water quantity induced by forest cover change. Streamflow, which is surface runoff occurring in channels, is the most commonly studied outcome variable, but many studies also examine total runoff (defined as surface plus subsurface runoff) or water yield, which is the aggregate amount of water flowing from a watershed into a stream. A generally well replicated finding in this area of research is that deforestation increases streamflow (Bosch and Hewlett, 1982; Jackson et al., 2005; Zhang et al., 2017) and that an increase in tree cover reduces streamflow (Bentley and Coomes, 2020; Farley et al., 2005; Filoso et al., 2017; Li et al., 2017; Ochoa-Tocachi et al., 2016).

These conclusions are largely based on research at small spatial scales of less than 1000 km² in catchment area because the most common approach is to use paired catchments-based field studies (Filoso et al., 2017; Zhang et al., 2017). Paired catchments are a so-called “space-for-time” approach, where water yield or streamflow from catchments with, in this case, different tree cover, but otherwise similar environmental characteristics, are compared. This method imposes an upper limit on the size of the study area as with size increasing, the internal heterogeneity (for example climatological or geological) of the catchments can diminish their comparability, and instrumentation costs can become prohibitive (Cuo, 2016). It is worth mentioning, however, that the alternative to the space-for-time approach, long-term or

longitudinal studies, are also fraught with problems. While these may not suffer from the same spatial heterogeneity issue, the problem with these studies is that they may be too short to detect an increase in streamflow, which has also been explored in the Filoso et al. (2017) review. As most of the included studies report water yield for less than ten years, they likely do not capture positive effects of tree cover change on soil infiltration capacity that may materialise only after decades (Brown et al., 2013, 2005). Furthermore, they are prone to confounding changes from tree cover with those from other factors, such as interannual rainfall variability.

The effect of spatial scale has been investigated by Zhang et al. (2017) who demonstrated that the aforementioned consensus (deforestation leads to increase in streamflow yield; afforestation leads to decrease in streamflow) get weaker when large watersheds are included. Their review found that while the relationship between forest loss and runoff gain is still significant at large scales, the inverse relationship, that is that forest cover gain leads to runoff decreases, is not.

Furthermore, this question of streamflow changes remains unresolved for the tropics because there is a distinct lack of studies from the region (Bentley and Coomes, 2020; Filoso et al., 2017). While the aforementioned Filoso et al. (2017) review reported that 80 per cent of the investigated case studies support the negative impacts of afforestation, they caution that the tropics are vastly under-represented in their study sample. In fact, the few cases from humid tropics more commonly exhibited an increase in water yield with afforestation, but this result is based on five case studies. This particular finding, however, is likely to apply to the specific case of cloud forests, a montane ecosystem where a large input into the system comes from cloud water interception and subsequent stemflow and throughfall (Bruijnzeel, 1990; Bruijnzeel and Proctor, 1995; Gomez-Peralta et al., 2008). Here, afforestation is also likely to increase water yield because increased canopy cover raises the potential for interception and offsets the increases evapotranspiration of the tree cover, compared to previous land cover. In addition, cloud forests are located in cooler climates which, in combination with the reduced radiation through frequent cloud cover, likely causes smaller additions on the evapotranspiration side of the equation (Jarvis and Mulligan, 2011; Letts and Mulligan, 2005).

The extent to which climate variables such as annual total rainfall or mean annual temperature influence the relationship between forest change and water yield was

explored by Li et al. (2017) in their synthetic assessment of large watersheds. However, as in other reviews, the number of tropical case studies is low. Only 11 out of the 67 watersheds used for the detailed analysis are located in the tropics, based on an assessment of the article's database (see Li et al., 2017, Table S1 & S2).

Lastly, the hydrological consequences of increasing forest cover are also more affected by land use and land cover history than those of deforestation (Lozano-Baez et al., 2018). For example, runoff reductions differ between afforestation of grasslands versus shrublands; and between increasing tree cover in a mix of shifting cultivation and plantation as opposed to natural regrowth (Farley et al., 2005; Lacombe et al., 2016). Such research considering previous land use or degradation status has gradually led to an awareness that infiltration may regulate water yield changes through tree cover change as much as evapotranspiration does. This is due to the governance of infiltration by soil properties, which may have been altered by previous land use and degradation. This line of reasoning is explored in the following section.

2.2.2 Shifting the focus towards infiltration: the trade-off hypothesis

Emphasising the aforementioned variation in streamflow response attributed to land use and cover history, the *infiltration trade-off* hypothesis has gained traction in recent years. While actual evapotranspiration (AET) has been at the centre of most of the aforementioned studies, changes in infiltration, it is argued, may contribute in meaningful ways to the change in streamflow.

The evapotranspiration-infiltration trade-off hypothesis (*trade-off hypothesis*, for short) concerns the trade-off between changes in evapotranspiration and changes in infiltration after forest cover change (Bruijnzeel, 2004, 1989). It expands the earlier conceptualisation of forests as *pumps*, according to which forests lose more water through evapotranspiration and evaporation of intercepted rainfall, by the idea that forests can also be *sponges* (Hamilton and King, 1983; Peña-Arancibia et al., 2019). Thinking of forests as sponges emphasises their infiltration and soil moisture storage capacity, acknowledging that forests can also regulate water input into the system compared to other land cover types. Such regulation can become relevant in seasonally dry areas when precipitation is low during dry seasons. Then, streamflow draws on rainfall stored in the soil (throughflow) or groundwater (baseflow) in the

previous wet season, the amount of which can be greater if infiltration is improved (Dralle et al., 2016).

Specifically regarding increasing tree cover, the trade-off question asks whether, given the increased evapotranspiration of the tree cover, infiltration is also improved sufficiently to compensate for it. In short, with higher tree cover, there will be higher water losses, but will there also be high enough (or even higher) redistribution from wet to dry season?

2.2.3 Empirical research into the trade-off question

Research reviewed in section 2.2.1 gives valuable indications but because it predominantly uses streamflow or water yield as an outcome variable, it is not adequate to test the infiltration trade-off hypothesis as such. This stems from the fact that these variables integrate both AET and infiltration over a catchment and cannot be separated after the fact to examine the two components individually for their relative contributions to the trade-off. In this section, the focus lies on works that explore both the potential losses (AET) as well as the potential regulation (infiltration) from tree cover change, although the reported outcome variable may also be water yield or streamflow.

Such research is still scarce and limited to small spatial scales, because data collection for both aspects is laborious, especially for soil water infiltration (Bonnesoeur et al., 2019; Litt et al., 2020; van Meerveld et al., 2021), but a number of studies on the catchment scale have been published since the early 2010s. These support the notion that infiltration does affect streamflow in a significant way, in addition to the typically discussion-dominating evapotranspiration. There is some support for higher baseflows or dry season flows under tree cover in the tropics (Bonell et al., 2010; Krishnaswamy et al., 2018, 2013; Ribolzi et al., 2018; Roa-García et al., 2011; Zhou et al., 2010), and more so outside the tropical region (Filoso et al., 2017), which was explicitly linked to enhanced infiltration under tree cover. Other results are more neutral: Ghimire et al. (2014b) found that reforesting a degraded pasture likely does not increase dry season flows, because the trade-off between increased infiltration and increased evapotranspiration is more balanced. Beck et al. (2013) also found no changes in streamflow caused by forest cover change, but their results do suggest a higher water loss through AET. Bentley and Coomes (2020) reviewed the recovery

of river flow after forestation and also found evidence for the greater losses in the initial decline of river flows, but at the same time concluded that river flows did not recover within at least 50 years after the initial decline.

Reviewing the issue for the Andes, Bonnesoeur et al. (2019) found that infiltration did increase within the first two decades, but again, total water supply dropped due to higher water use. Interestingly, on the matter of exotic tree plantations, this review finds a consensus in the reduction in low flows, except for on degraded land, contrasting the aforementioned increases in low flows with general tree cover increase. Support for the importance of infiltration capacity and thus the relevance of the trade-off hypothesis also comes from the following studies, which, although they do not examine both losses and gains from tree cover change, deliver vital justifications for the continued interest in infiltration.

Zimmermann, Papritz and Elsenbeer (2010) studied the changes from forest to pasture and back to forest cover from a soil infiltration perspective and found that within the seven years their study covered, infiltration (as measured by saturated hydraulic conductivity, K_{sat}) did improve, but not significantly. Their study again highlights the slow recovery of soil infiltration properties and that it typically extends beyond the timeframe of empirical studies. Similar conclusions were also drawn by Lozano-Baez et al. (2021, 2019), who additionally stressed the relevance of previous land use history for the trajectory of infiltration restoration.

2.2.4 Main uncertainties in the debate and opportunities for further research

Summarising the previous section, the current state of trade-off research has several gaps: 1) It is typically small-scale and uses a space-for-time approach, or 2) longitudinal, but with too short a temporal coverage, and 3) the tropics are poorly represented.

The issue of spatial scale presents a challenge because the variability of watershed characteristics will be small on a catchment scale and thus generalising results from small to larger spatial scales may be problematic. Insufficiently long study periods cause two issues: first, the under-detection of changes in infiltration through tree cover change, because soil recovery may take much longer than the average study period; soil recovery may also progress even more slowly depending on the history of land use or degradation. The second issue relates to the over-estimation of AET

losses (i.e. 'increased water losses through AET'). If the study period targets early stages of tree cover growth, AET reflects the higher values of early tree growth and will not observe the decreased transpiration rates of older forest stands (Asbjornsen et al., 2011; Vertessy et al., 2001). Conversely, the longer the study period, the more difficult it is to separate the effect of tree cover changes from that of climatic changes (Krishnaswamy et al., 2018).

Modelling the trade-off on the basis of remotely sensed data can complement catchment-based research in meaningful ways. For example, it may be better at capturing landscape heterogeneity in a watershed than isolated point measurements collected in field studies and it may also enable research in remote or field data-poor areas such as the tropics (Marshall et al., 2023). Models on the basis of remote sensing products can be especially useful there because observational data from the tropics, for example from weather stations, is in decline (Wohl et al., 2012). To date, however, the infiltration trade-off hypothesis has been tested only a few times with modelling approaches.

Statistical modelling has been done with different types of regression models (Hall et al., 2022; Krishnaswamy et al., 2018). Krishnaswamy, Kelkar and Birkel (2018) applied Bayesian regression in several watersheds in Costa Rica and found strong support for the *sponge* effect, that is an improvement of infiltration through tree cover increase which equals or exceeds the increase in AET. Their study period covered both deforestation and forest regrowth from 1962 to 1992 and used rainfall and streamflow data from 22 rain gauges and 8 streamflow gauges stations. Both the long-term data record and the large watershed size (up to 4,774 km²) are rare in this field.

In the realm of physically-based and remote-sensing models, Peña-Arancibia and colleagues (2019) applied a gridded landscape model to explore the trade-off hypothesis for the tropics after *deforestation*. In this case, the question is, does infiltration *decline* as much as AET does after tree cover is gone. For the tropics as a whole they found an *increase* in annual streamflow by 18 per cent, going up to 26 per cent when soil surface degradation was included in the model. The study integrated this via the Hydrological Soil Condition used in the Curve Number Method (USDA-SCS, 1985). They also identified a *decrease* in dry season flow in almost a fifth of the pixels when infiltration was constrained; these pixels commonly had very

seasonal streamflow and rainfall, rainfall exceeded PET for some months, and infiltration and water retention was high.

Similarly, Clark et al. (2021) used a gridded hydrological model to assess the effect of India's national reforestation goals on groundwater recharge in the Central India Highlands. They concluded that reaching the national goal of 33 per cent forest cover in the Central Highlands would result in a 3 per cent increase in recharge if non-paddy agriculture is converted to forest, and a 1 per cent decrease on conversion of paddy agriculture. This difference comes from the large infiltration from depression storage associated with paddy rice which would be lost under forest increase.

Among the different types of models, the distributed, physically-based approach may be the way forward, to improve the representation of watershed heterogeneity and assess the effect of tree cover change over suitably long timeframes. Furthermore, if driven by remote sensing products, it can give a first estimate of the trade-off of enhanced evapotranspiration and enhanced infiltration in data scarce regions such as the tropics.

2.3 Summary of the literature review

Reforestation, forest landscape restoration and other approaches have been gaining popularity and funding commitments on an international scale for several years, and an area of particular growth has been the tropics. While hydrological research on the effects of tree cover and changes thereof has been taking place for much longer, with some seminal work published dating back to the 1980s, there is still a lack of certainty on the direction of effects of reforestation, deforestation and other changes on the availability of water throughout the year.

In an attempt at explaining incongruous and sometimes opposing results the infiltration trade-off hypothesis emerged. This hypothesis further examines the contributions of land use and cover history via changes in infiltration to changes in water availability. While there is empirical research on this hypothesis, it has several gaps: 1) It is typically small-scale and uses a space-for-time approach, or 2) it is longitudinal, but with too short a temporal coverage; and 3) the tropics are poorly represented in the field. To overcome these shortcomings, modelling approaches with remotely sensed data have been applied, for example to improve the representation of

landscape heterogeneity, or the applicability in data-poor areas such as the tropics. Some studies have already contributed to this field, but with either a regional focus, or a focus on deforestation processes. What still remains a research gap, is the study of the trade-off hypothesis on both a tropical scale, and with a focus on re-growth of forest cover, which constitutes a highly relevant process in the tropical region. This gap is addressed by the research conducted in this thesis.

Chapter 3 Development of a new hydrological model to test the infiltration-evapotranspiration trade-off using satellite-derived data products

3.1 Introduction

This chapter introduces a new spatially explicit physically-based hydrological two-source model called DTRIE (*D*istributed *T*Rade-off in *I*nfiltration and *E*vapotranspiration) to determine the trade-off between increased infiltration and increased evapotranspiration under different stages of tree cover growth. DTRIE was developed in this PhD project to use freely available remote sensing products and to operate on a monthly timestep to model seasonal water availability and annual totals. This chapter therefore aims to achieve **objective 1**.

The DTRIE model will then be used to calculate AET, water balance and effective infiltration for the reference year 2018. This year was chosen because of good data availability and processing status across all DTRIE input datasets at the time of writing. For example, in comparison to 2018 data, the 2019 Copernicus Global Land Cover Service dataset was still in the “near-real time” processing stage at which product value is still subject to change (Buchhorn et al., 2020a). Furthermore, the years 2017 to 2020 were not classified as *el niño* or *la niña* phases of the El Niño Southern-Oscillation (NOAA, n.d.) which means that the long-term climatological input datasets used in the DTRIE model can be assumed to reflect climate and seasonal conditions in the tropics. In contrast, during *el niño* or *la niña* events, spatial and seasonal pattern in temperature and precipitation can differ greatly from the norm in the equatorial Pacific, but also outside of tropical latitudes (Earth Observatory, 2017), which would render the year 2018 less suitable as a baseline year.

AET estimates will be used to verify the DTRIE outputs by comparing them to other remote-sensing derived AET datasets and values from literature. Lastly, the spatial and temporal patterns of AET, water balance and effective infiltration estimates are examined, as well as their relationships to environmental conditions such as temperature and rainfall.

3.1.1 A short recap of the trade-off debate

As outlined in section 2.2.2, the infiltration trade-off hypothesis concerns the trade-off between changes in evapotranspiration and changes in infiltration following forest cover change. This trade-off determines how overall water quantity and seasonal timing of water yield change with reforestation as it describes the partitioning of rainfall into effective infiltration and actual evapotranspiration. For the purpose of this analysis, *effective infiltration* is defined as the infiltrated water volume that does not leave the soil as return flow in the same month it fell as rainfall. Such immediate return flows are considered surface runoff (or *overland flow* at the hillslope scale) and is typically not considered part of infiltration in the trade-off debate.

Effective infiltration also provides the soil water for soil evaporation and plant transpiration (SET), which in addition to interception loss (E_i), makes up total actual evapotranspiration (AET). After enabling SET, the remaining soil water becomes *subsurface runoff (throughflow and baseflow)*, which enters a slow hydrological pathway and contributes to total runoff with a delay. Thus, the annual trade-off of effective infiltration and evapotranspiration can give an indication of the magnitude of slower subsurface flow contributions to downstream runoff versus those of faster surface flows. As these subsurface flows may experience a lag in joining a stream as return flow, the trade-off question becomes relevant to examine dry season flow and the effects of tree cover growth on it.

3.1.2 Existing model landscape to address the trade-off debate

In addition to the lack of larger scale research on the trade-off, there is also no suitable model among the existing evapotranspiration and hydrological models, with which to jointly estimate evapotranspiration and infiltration changes with vegetation cover, as required by this study's research aim (van Meerveld et al., 2021). Especially as hydrological models commonly operate on an event-based timescale in order to model the effects of vegetation change on stormflow, rather than baseflow.

While AET models can represent the effects of vegetation cover change in various degrees of detail, they are not built to simulate subsurface processes such as soil moisture fluxes, and thus incapable of addressing the infiltration related questions. A vast majority of hydrological models are data-intense, need calibration and are therefore unsuitable for global or tropical scale, for example the models SWAT (Arnold et

al., 1998; Arnold and Fohrer, 2005), HBV (Bergström, 1992) or TOPMODEL, (Beven et al., 1984). In addition to their data requirements, these models are also spatially semi-distributed. This means they operate on spatial units with similar combinations of environmental conditions, for example the *hydrologic response unit* in the SWAT model, rather than on a raster grid cell. However, the large extent of the research area covered in this thesis increases the spatial heterogeneity in environmental data inputs such as climate, soil and topography and others, which heightens the need for a spatially-disaggregated model (Peña-Arancibia et al., 2012; Zhou et al., 2015). Furthermore, it is anticipated that the change in tree cover generated by the scenario described in Chapter 4 may only affect a few pixels in some areas (see Figure 4.2), a grid-based model should better capture the hydrological effects of such small changes. Some gridded models are, for example, global hydrological models (GHMs). However, while these are better suited to large scales, this comes at the cost of coarse spatial resolutions. For example the PCR-GLOBWB model (Bierkens and Beek, 2009; van Beek et al., 2011), the LPJmL model (Bondeau et al., 2007; Schaphoff et al., 2018) and LISFLOOD Van Der Knijff et al. (2010) run at a 0.5° and 0.1° resolution. Many other hydrological, or “rainfall-runoff” models require weather station data as well as remote sensing data, for example for calibration. This reduces their applicability in large areas and data-scarce regions, such as in the Congo River basin in tropical Africa where there are very few weather stations (Menne et al., 2012). Two example models are the HBV model and LISFLOOD (Joint Research Centre et al., 2013; Van Der Knijff et al., 2010). A comparison of a range of hydrological models and their suitability to address the trade-off research questions is presented found in Table 3-1.

3.1.3 Development of a hydrological model to examine trade-offs on large scales

3.1.3.1 Framework requirements for the model design

To address this research gap, this chapter describes a new grid-based model to simulate the trade-off in infiltration and evapotranspiration on large spatial scales and a monthly timestep. Building on existing robust and well-evaluated evapotranspiration (ET) models, this chapter identifies a physically-based and remote sensing data driven ET model then expands it by adding a subsurface component to explicitly model belowground water fluxes for the trade-off related research questions.

Table 3-1 Comparison of existing models producing evapotranspiration and hydrological variables using remote sensing and field data.

Model	Description	Spatial resolution	Temporal resolution	Data inputs	Suitability	References
GLEAM (Global Land Evaporation Amsterdam Model) V3	Global evaporation model, calculating transpiration, bare-soil evaporation, interception loss, open-water evaporation and sublimation. Additionally, surface and root-zone soil moisture, potential evaporation and evaporative stress conditions	0.25°	Daily	Net radiation, air temperature, precipitation, vegetation optical depth (VOD), soil moisture, soil properties, lightning frequency, vegetation cover, snow-water equivalent	Mismatch of temporal scale (too fine) and spatial scale (too coarse)	Miralles et al. (2011), Martens et al. (2017)
HBV (Hydrologiska Byråns Vattenbalansavdelning)	Semi-distributed conceptual model for catchment runoff simulation	Semi-distributed	Daily, hourly	Precipitation, Temperature, PET, discharge	Unsuitable for large scale studies due to its use of meteorological observations instead of remote sensing data; semi-distributed models do not capture variability in fractional vegetation cover	Bergström and Forsman (1973)
Hydro JULES (Joint UK Land Environment Simulator)	Land surface model (LSM) used to calculate the impacts of environmental change on evaporation, transpiration, and soil moisture, amongst other purposes	25 km (global scale)		Radiation, Precipitation (rainfall and snowfall), Temperature, Surface pressure, Specific humidity, Wind speed	Spatial resolution too coarse;	Cox et al. (1998); Best et al. (2011); Clark et al. (2011)
LISFLOOD	Grid-based hydrological rainfall-runoff model; Simulation of the combined effects of weather and	0.1° at global scale	Daily, monthly	Several inputs from topography, land use, soil, meteorological variables	Unsuitable for tropical extents due to data input	Van Der Knijff et al. (2010); JRC

Model	Description	Spatial resolution	Temporal resolution	Data inputs	Suitability	References
	climate changes, land use, socio-economic changes on water demand in surface and subsurface				& calibration requirements, coarse resolution	(2013)
LPJmL (Lund-Potsdam-Jena managed Land)	Distributed dynamic global vegetation model with a hydrology component; it simulates vegetation composition and distribution and processes such as processes such as photosynthesis, plant growth, maintenance and regeneration losses, soil moisture, runoff, evapotranspiration and others	0.5°	Daily, monthly, annual	Gridded data of climate, human land use, soil properties, and river flow directions	Spatial resolution too coarse; high model complexity & number of outputs that are not of interest in this study	Bondeau et al. (2007), Schaphoff et al. (2018)
MIKE-SHE	Physically-based distributed model of catchment surface and subsurface hydrology			Meteorological observation (temperature, solar radiation, precipitation) and gridded data (topography, soil and land use)	Not fully remote sensing data driven & unsuitable for large scales due to calibration needs; source code not in public domain; not UNIX compatible;	Refsgaard et al. (2010)
PCR-GLOBWB (PCRaster Global Water Balance)	Large scale grid-based hydrological model for global and regional studies; models water exchange between soil and atmosphere, within soil layers and groundwater reservoir	0.5° (5' for version 2)	Daily	Precipitation, temperature, reference PET, land cover (4 types), soil properties, topography, additional parameters for phenology, groundwater	Spatial resolution too coarse	van Beek and Bierkens, (2009); van Beek et al., (2011), Sutanudjaja et al. (2018) Hoch et al. (2023)
PCR-GLOBWB <i>ctd.</i>		1km				

Model	Description	Spatial resolution	Temporal resolution	Data inputs	Suitability	References
PCR-GLOBWB <i>ctd.</i>		ctd.	ctd.	ctd.	Not assessed as version released only in April 2023	ctd.
SWAT (Soil and Water Assessment Tool)	Semi-distributed semi-physically-based model developed to quantify the impact of land management practices on water quantity and quality	Small watershed to river basin	daily	Meteorological data, Topography, land use and soil maps	Unsuitable for tropical extent modelling due to data input requirements & calibration	Arnold et al. (1998); Arnold and Fohrer (2005) Gassman et al. (2007)
TOPMODEL	Semi-distributed conceptual rainfall-runoff model based on the topographic wetness index	Small catchment scale		Topographic index, topography	Unsuitable for tropical extents, better suited to small catchments	Beven and Kirkby (1979)
VIC Variable Infiltration Capacity Model	Semi-distributed grid-based global hydrological model	2°	Hourly	Precipitation, daily temperature, wind speed from meteorological stations, topography, soil properties, land cover type & fraction	Unsuitable due to very coarse resolution & use of meteorological point data	Nijssen et al. (2001)
SPHY (Spatial Processes in Hydrology model) V2.0	Gridded hydrological model, calculating ET, interception, surface runoff, lateral flow, baseflow	250 m	Daily or monthly	DEM, land use type, soil characteristics, glacier cover, lands/reservoirs, precipitation, temperature, reference evapotranspiration	Not fully remote sensing driven, needs calibration with daily discharge data	Terink et al. (2015)

Although many of the well-established ET-models operate on a daily timestep, such high temporal resolution is not required to achieve this study's research aim. For one, the research questions relating to water quantity are examined with *annual* total water balance; and the questions regarding water regulation and the trade-off in infiltration and evapotranspiration are examined via *monthly* streamflows. This streamflow, to recapitulate **research objective 3**, is investigated specifically to assess the effect of increasing tree cover on dry season flows, rather than, for example, flooding, which would indeed benefit from a daily or event-based resolution.

For such dry season flows, which consist mostly of baseflow, a monthly timestep is considered preferable and more efficient with regards to the need for input data and computing resources, while conducting the analysis on a spatial resolution of 1 km (equivalent to $\approx 0.008^\circ$ at the equator).

Based on the objective of the chapter to develop a coupled AET and subsurface model to calculate both AET and infiltration, the following requirements for the selection of an appropriate model framework for this study were defined:

1. Remote sensing data driven – due to the large spatial extent (the tropics) and presence of data-scarce regions, field measurements and point data should be avoided.
2. Components of the model need to consider the soil system and vegetation characteristics and be adaptable to the conditions of the tree regrowth scenario.
3. The model should be applicable and accurate in the tropical region and in high tree cover areas.

3.1.3.2 Selection of an appropriate evapotranspiration model framework

In this short review the wealth of physically-based ET models using remote-sensing data is broadly classified as surface energy balance methods, water balance, or radiation models (Fisher et al., 2011; Zhang et al., 2016). Each class is briefly described and their applicability to the proposed research evaluated.

In surface energy-based models evapotranspiration, or latent heat, is considered a residual of the surface energy budget. These methods are some of the first, dating back to the 1980s and include for example the Surface Energy Balance Algorithm for Land (SEBAL) (Bastiaanssen et al., 1998) or the Atmosphere-Land Exchange

Inverse model (ALEXI) (Anderson et al., 2007, 1997). Surface energy balance methods do not meet requirement 2 (above) due to their lack of vegetation-related inputs.

Water balance models calculate evapotranspiration as a residual of the water balance, for example the difference between precipitation (input), runoff (output) and a change in water storage, if applicable. These models will struggle with requirement 1 (above) with respect to their runoff component. The calculation of AET with the simplest water balance approach requires precipitation and runoff data. However, remote sensing of runoff, or stream discharge, is still a developing field with the first global coverage satellite mission (NASA SWOT) only launched at the end of 2022. Therefore, the use of gauge station data for stream discharge is currently predominant in water balance analyses, which limits its applicability to no larger than the basin scale (Zhang et al., 2016).

Lastly, in the tropics, where radiation is the dominant driver of evapotranspiration, radiation-based models are often recommended (Fisher et al., 2009; Li et al., 2022). These meet the remote sensing data and accuracy requirements (1 and 3, above) and have the potential to meet requirement 2 (above) as well.

Two of the most commonly used radiation-based algorithms are the Penman-Monteith (henceforth called “PM”) and Priestley-Taylor (“PT”) equations (Monteith, 1965; Priestley and Taylor, 1972). Some of the most widely used AET products applying the PM equation are the MODIS MOD16 product (Mu et al., 2011, 2007) and the Penman-Monteith-Leuning (PML) product (Leuning et al., 2008). The Priestley-Taylor equation on the other hand is at the core of the Jet Propulsion Lab PT-JPL ECOSTRESS product (Fisher et al., 2008) and the Global land Surface Evaporation: Amsterdam Method (GLEAM) product (Martens et al., 2017; Miralles et al., 2011).

Out of these two model families, a PT-based model was chosen for two reasons: First, most Penman-Monteith (PM) models do not include soil moisture constraints (Fisher et al., 2008; Miralles et al., 2011; Zhang et al., 2016), while several PT models do; this integration is one of the key requirements of this study, and overall is regarded as a major constraint on actual evapotranspiration and therefore model accuracy (Michel et al., 2016; Yang et al., 2017). Second, PT models are easier to parameterise on a global scale, yet they are still considered theoretically robust and accurate (Fisher et al., 2008; Yao et al., 2015). The easier parameterisation is due to

the simplification of the PM equation that requires fewer meteorological inputs by eliminating the need to calculate aerodynamic or stomatal resistance, which cannot be observed from remote sensing data and are difficult to model on a global scale (Fisher et al., 2008; Miralles et al., 2011; Mu et al., 2011). Even the widely used PM-based MOD16 product only approximates these resistances via a look-up table relying on broad land cover classes, which has been criticised before for inadequately representing the variability in tropical forest biomes (Fisher et al., 2009). Instead, the PT equation approximates these resistances via the dimensionless resistance parameter α (see (Eq. 3-4) and this implementation has been found suitable for a range of different biomes, including (Ershadi et al., 2014; Fisher et al., 2011).

Two of the most widely published and utilised PT models, PT-JPL and GLEAM, fulfil all three requirements, to 1) work with only remotely sensed inputs, 2) be adaptable to use the scenario-adjusted input variables of the tree regrowth model of this study, and 3) as a radiation-based PT model are well-suited to the use in the tropics.

Although the PT-JPL model includes plant and soil moisture, and temperature constraints, neither its interception nor soil moisture model parts leave any water for runoff. This is because the model does not use a precipitation input. Instead of using a precipitation input, interception evaporation and soil moisture are both derived from relative air humidity, the latter in combination with the vapour pressure deficit. This approximation is based on the assumed link of surface moisture and evaporative demand (Bouchet, 1963; Fisher et al., 2008) but this link provides no insight into other soil water components that could become, for example, subsurface flow. This renders the model unsuitable to compute effective infiltration which is required for the trade-off related research questions, and surface and subsurface runoff, which are of interest for the water regulation research questions of this study.

The GLEAM model, on the other hand, includes precipitation in a data-driven representation of canopy interception by expanding a widely used interception model by Gash (see Miralles et al., 2011 for a description) with an improved representation of storm intensity, and in soil moisture constraints, which are rainfall-driven and constrained by remotely sensed microwave surface soil moisture. Therefore, because of its more detailed and explicit representation of interception and soil moisture, GLEAM was selected for this study.

GLEAM is widely used in the tropics for ET and hydrological studies (Chagas et al., 2022; Hiernaux et al., 2022; Hu and Mo, 2022; Pham-Duc et al., 2022). It has been evaluated for the tropics extensively and been found to perform well overall, or better when compared to other remotely sensed ET products such as MODIS MOD16, water balance derived ET or in site measurements of ET from eddy covariance flux towers (Chao et al., 2021; Khan et al., 2018; Liu et al., 2023; Melo et al., 2021; Pan et al., 2020; Ruhoff et al., 2022; Salazar-Martínez et al., 2022). The GLEAM model itself (as opposed to the ET product) has also been evaluated and found to outperform most other commonly used ET models (McCabe et al., 2016; Michel et al., 2016).

For example, Ruhoff et al. (2022) compared the ET results from global models such as the GLEAM algorithm and those of MOD16, PML (Penman-Monteith Leuning), SSEBOP and four land surface model results to water balance derived ET (“ET_{WB}”) for South America. Over 50 basins and on a monthly timestep, they found that although GLEAM and other global models generally slightly overestimate ET compared to ET_{WB}, estimates were within the deviation range of ET_{WB}. For the major basins examined by this study (excluding all that are outside of the tropical boundaries defined for this study, 24 S to 24 N), GLEAM ET correlation coefficients (Pearson’s r) were moderate to high ranging from $r = 0.56$ to 0.81 , while coefficients for the other two remote-sensing based ET datasets were lower at $r = 0.36$ to 0.76 for MOD16 and $r = 0.23$ to 0.65 for PML. The root square mean error (RSME) ranged from 27.53 to 42.23 mm/month in basin averages for GLEAM, which is slightly lower than the values for PML (RSME 31.96 to 46.23 mm/month) and MOD16 (33.60 to 46.60 mm/month).

In another example, Salazar-Martinez et al. (2022) evaluated GLEAM and MOD16 against flux tower measurements in low latitudes (between 30° S and 30°N) and for different land cover types. Overall, GLEAM agreed better with flux tower reference values than MOD16 and other ET products in the tropics and in forest land cover types: GLEAM showed the strongest correlations, lowest error and smallest bias. For example, they found strong to moderate correlations between GLEAM and reference values in deciduous broadleaf (DBF $R^2 = 0.81$) and evergreen needleleaf forest (ENF $R^2 = 0.5$) compared to the lower correlations of MOD16 (DBF $R^2 = 0.65$, ENF $R^2 = 0.47$). Both GLEAM and MOD16 correlated weakly ($R^2 = 0.32$ for GLEAM) or

very weakly ($R^2 = 0.04$ for MOD16) for evergreen broadleaf forests. Furthermore, while, both GLEAM and MOD16 overestimate ET for forest and underestimate ET for non-forest vegetation, biases in GLEAM were smaller.

The GLEAM is therefore deemed the best possible ET model framework for this study because it has low error and bias in the tropics, and has at least lower error and bias in densely forested areas than other ET models such as those underlying the ET projects of MODIS MOD16.

3.2 Methods

The following three sections describe first the general components of the proposed hydrological model DTRIE and changes from the “parent” model GLEAM, second, the model equations used in DTRIE and third, the model’s assumptions and associated limitations.

3.2.1 Components of the proposed DTRIE model

3.2.1.1 Aboveground fluxes: *Evapotranspiration, interception loss and surface runoff*

The Global Land Evaporation Amsterdam Model (GLEAM) version 3 product, on which the proposed model is based, has four components: 1) a potential evaporation module using the Priestley-Taylor equation and observed surface meteorology, 2) a rainfall interception model, based on Gash’s analytical model and precipitation, 3) a multi-layer soil module driven by precipitation and satellite surface soil moisture, and 4) a stress module which is built on a semi-empirical relationship between root-zone soil moisture and vegetation optical depth (VOD). Note that the authors use the term evaporation (E) instead of the more commonly used evapotranspiration, the preference for which they explain in Miralles et al. (2020). For consistency with the wider literature, however, this thesis will use the term evapotranspiration (ET).

GLEAM operates on a daily timestep. The high temporal resolution of a sub-daily or daily timestep is necessary for GLEAM’s calculations of interception loss, which is event-based. However, to achieve the overarching goal of this research, to investigate the effect of tree cover change on the output variables, a monthly timestep is the most appropriate temporal resolution. In order to distil tree cover effects rather than those of weather conditions that may have high interannual variation, long-term climatological inputs are used. The use of climatologies means that a monthly

timestep is the finest and most reasonable resolution possible. Similarly, for the scope of this project, to examine spatial patterns using annual outputs or seasonal patterns with monthly outputs, a monthly timestep is sufficient because the increase in tree cover is modelled on an annual timestep.

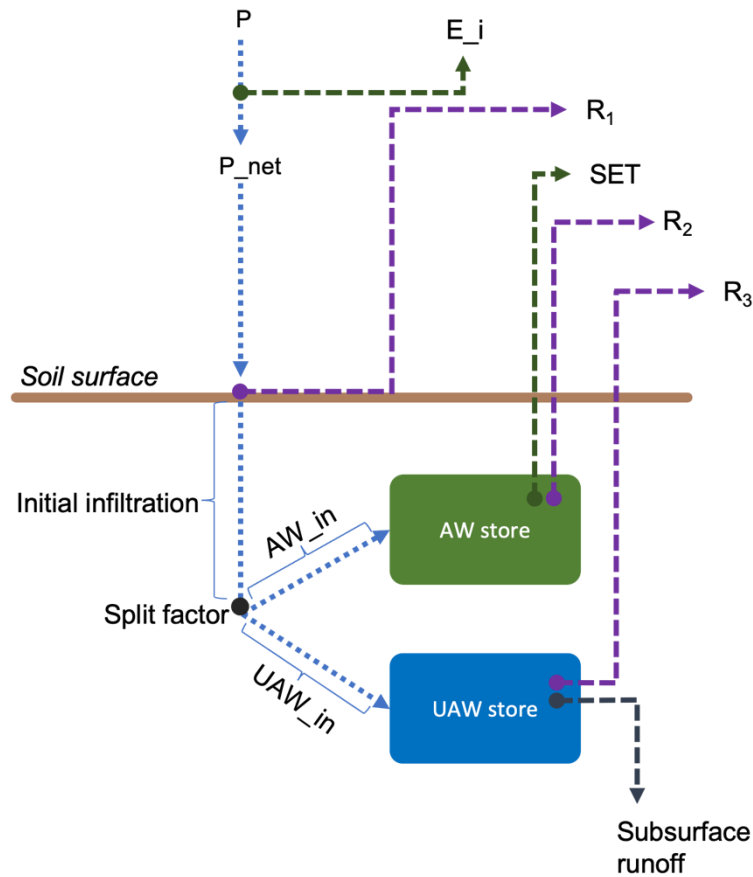


Figure 3.1 Process diagram for the infiltration-evapotranspiration model, with dotted lines representing inputs and dashed lines outputs; P = total rainfall, P_{net} = effective rainfall after interception loss, E_i = interception loss, R_1 , R_2 , R_3 = overland flow, AW_{in} = available water store input, UAW_{in} = unavailable water store input, SET = soil evaporation or plant transpiration. Split factor is set to 0.5.

Several modifications to the input datasets were therefore made to adjust the model to the monthly timestep. The input datasets are described in brief in Table 3-2 (p. 40).

First, daily and hourly observational input data for rainfall, temperature, net radiation and VOD were substituted for monthly climatologies (in the case of VOD, an LAI climatology is used because a VOD climatology is not available). Second, the soil module and interception loss module were adjusted to work with monthly input data as described in the following section. Third, the GLEAM model was expanded by an

infiltration and subsurface flow component as required by the research question focusing on the infiltration to evapotranspiration trade-off.

Actual evapotranspiration

Actual evapotranspiration is calculated for each land cover fraction (tree (tall), herbaceous (low) vegetation) and bare soil separately as

$$AET = PET * S + E_i$$

(Eq. 3-1)

where AET is the actual evapotranspiration (mm), PET is the potential evapotranspiration (mm), S is the soil stress factor (dimensionless), E_i is the interception loss (mm, with $E_i = 0$ for bare soil). PET is calculated with the Priestley-Taylor equation. The product of PET and S is also called SET, or *soil evaporation or plant transpiration*.

The total pixel AET is the weighted mean of each land cover type's AET, where the cover type fraction are the weights. Two further changes from the original GLEAM model are that snow sublimation is not calculated, because the study focuses on the tropics; and that open water evaporation from streams or other water bodies is excluded because the research examines the effect of tree cover change, which cannot take place on open water pixels such as lakes or streams and the area of open water is assumed not to change in our tree cover change scenarios. The evaporation of intercepted rainfall as a form of open water evaporation or evaporation from freely evaporating surfaces is, however, included in the model and described below.

Interception loss

The model presented here runs on a monthly timestep, therefore the GLEAM approach using storm events and lightning strike data is not feasible. Instead, a mean ratio of rainfall interception loss to total rainfall per month was calculated from the GLEAM model results for the reference year 2018 (see further description in section 3.2.2 and (Eq. 3-9).

Stress factor

The stress factor is calculated with LAI seasonality instead of VOD (vegetation optical depth) seasonality in this study.

Due to the long modelling periods and the emphasis on seasonal patterns rather than short-term monitoring, the use of climatological data is preferable to the daily resolution of VOD datasets, for which no climatology datasets exist at the time of writing. The creation of such a monthly long-term climatology of VOD data is beyond the scope of this thesis because of the processing time, computing resources and need for quality control following from the high temporal resolution of VOD data. For example, the 0.25° resolution X-band and C-band VOD archives from Moesinger et al. (2020), which correspond to the VOD bands used in GLEAM v3, consist of daily global files spanning 1997 to 2002. Each archive has a total unzipped size of 140 to 180 GB, which is unfeasible to process with the computing resources available to this study.

Long-term monthly climatologies of LAI, such as the climatology produced by Mao and Yan (2019a), however, are easily accessible, of a comparable spatial resolution to VOD data, and the positive spatial and temporal correlation between LAI and several VOD bands is well documented (Grant et al., 2016; Li et al., 2021; Moesinger et al., 2020). Thus, the use of the existing LAI climatology is preferable to the time-intensive processing of VOD data.

3.2.1.2 Belowground flux outputs: Infiltration and subsurface flow

Soil volume and plant available water volume

Further modifications relate to the soil module. Where GLEAM considers one to three soil layers of fixed depths for the respective land cover types of a pixel, the model presented here derives soil depth from a global map of root depth, or in the case of bare soil, depth to bedrock. Root depth is used to reflect the depth to which vegetation can access water in the soil column and thus drive the evaporation and transpiration process. As bare pixels do not have vegetation depth to bedrock is used, with an upper threshold depth of 10 cm. This upper threshold reflects the assumption that only topmost soil depths deliver water to the process of bare soil evaporation. Where new tree cover is established in the scenario, the values are averaged over regions defined by forest type (ESA and Hengl Land cover classifications) and water table depth (see Appendix A1.3 for details) and then this value is used. This results in one soil layer as opposed to GLEAM's up to three layers. A single layer but data-driven soil layer was preferred to the three layer model of the original

GLEAM model because it contributes to a better representation of spatial variability of soil and the soil water store and thus ET & flow model. In the original GLEAM model, the layers depths are constant and spatial heterogeneity in soil depth is only approximated via the vegetation cover and is therefore much coarser. The soil volume is then partitioned into plant available (AW) and unavailable water stores (UAW store) using soil volumetric water contents at field capacity and wilting point. The AW store limits plant transpiration amounts and the UAW store limits subsurface flow amounts.

Generally, GLEAM v3.5 assimilates ESA CCI v5.3 surface soil moisture into the topmost of its three soil layers to improve the stress factor that adjusts potential to actual evapotranspiration. However, this assimilation does not occur where tall canopy cover is higher than 70 per cent, i.e. in most tropical forests (Miralles et al., 2011). This is sensible because remote sensing soil moisture datasets do not perform well over dense vegetation (Beck et al., 2021; Dorigo et al., 2017). As the tropical dense forests are an integral part of this study it was decided that soil moisture should not be assimilated. With a look to future improvements of the DTRIE model, a new 1 km dataset derived from satellite data and using machine learning from 2000 to 2020 has become available during writing which could in the future be used to constrain modelled soil moisture, if they perform well in densely forested areas.

Effective Infiltration

As this study examines the trade-off between increased infiltration and increased evapotranspiration through tree cover growth, the model also has to calculate monthly infiltration, return flows and subsurface flows, which are not outputs of the original GLEAM model.

The term *effective infiltration* is used for the volume of infiltrated water that does not return to the surface within the same month as return flow R_2 or R_3 . Such return flows can be triggered if soil storage capacities (AW or UAW store) are exceeded.

$$\text{Effective infiltration} = \text{initial infiltration} - R_2 - R_3$$

(Eq. 3-2)

Initial infiltration (mm) is calculated from the monthly effective rainfall, P_{net} (mm), defined as the rainfall minus interception loss E_i , and limited by an infiltration capacity threshold based on hydraulic conductivity, K_{sat} , of the topmost 5 cm of soil; where

$P_{\text{net}} > K_{\text{sat}}$, R_1 is created (see Figure 3.2 for a detailed description of how return flows R_2 and R_3 are created).

Subsurface flow

Subsurface flow (hereafter SSF) is used to calculate the grid cell contribution to dry season flows and is defined as water volume that reaches the nearest stream grid cell via a “slow hydrological pathway” as throughflow. The subsurface movement of water to the stream occurs at the *velocity* of saturated hydraulic conductivity (K_{sat} of lower soil layers, 0.3 – 2 m below surface), adjusted to simulate the presence of macropore flow under tree cover. Macropores are large soil pores shaped by biotic activity from plant roots or soil fauna and are thus associated with greater vegetation cover (Clothier, 2008; Gao et al., 2018; Muñoz-Villers et al., 2012; Yu et al., 2015). These pores can conduct much larger volumes of water than the smaller pores of the soil matrix, which conduct the so-called “matrix flow”. Furthermore, macropore flow velocities are also higher than those of matrix flow because the latter is governed by gravitational and capillary forces (Beven and Germann, 2013, 1982). For these reasons, their presence is included in DTRIE. In the tree cover growth scenario considered in Chapter 4, throughflow velocity is then adjusted to scenario vegetation cover conditions with the help of a macropore factor as identified by Gao et al. (2018). This factor increases the velocity, based on the assumption that vegetation cover promotes the creation of macropores which have higher flow velocities than matrix flow. For example, in a hypothetical pixel with 100 per cent tree cover, throughflow velocity is multiplied with a macropore factor of 10^3 , for herbaceous cover with 10^2 . No adjustment is made for the bare cover fraction, which is assumed to have no macropores.

The time *lag* between creation of subsurface flow and when it reaches the nearest downstream stream cell is calculated as aforementioned *throughflow velocity* divided by distance to the nearest downslope stream grid cell. A grid cell’s subsurface flow volume at month i is therefore added to the water balance of month $i + \text{lag}$. A detailed description of the calculation of SSF is given in section 5.2.2.2.

3.2.2 DTRIE model equations

1. Actual evapotranspiration (AET)

For each vegetation cover type of a pixel, actual evapotranspiration (AET) is calculated as

$$AET = PET * S + E_i \quad (Eq. 3-1)$$

AET is limited by the amount of water in the available water store, AW_{act_start} , and therefore

$$\begin{aligned} AET &= PET * S + E_i & \text{if } PET * S < AW_{act_start} \\ AET &= AW_{act_start} + E_i & \text{if } PET * S \geq AW_{act_start} \end{aligned} \quad (Eq. 3-3)$$

where AET is the Actual Evapotranspiration (mm), PET is the Potential evapotranspiration (mm), S is the soil stress factor (dimensionless), E_i is the interception loss (mm, with $E_i = 0$ for bare soil) and AW_{act_start} is the actual water content in the available water store at the start of month. $PET * S$ is also called SET, for *soil evaporation or plant transpiration*, depending on the vegetation cover.

2. Potential Evapotranspiration (PET)

Potential evapotranspiration (PET, W/m^2) is calculated with the Priestley-Taylor equation (1972) as follows

$$PET = \alpha * \frac{\delta}{\delta + \gamma} * Rn_{ai} - G \quad (Eq. 3-4)$$

Where α is the dimensionless resistance coefficient, δ is the slope of the saturation-to-vapour pressure curve, γ is the psychrometric constant (kPa/C), Rn_{ai} is the net radiation after interception loss (W/m^2 , with $Rn_{ai} = Rn$ for bare soil) and G is the ground heat flux.

For α a default value of 1.26 is used (as previously done by Fisher et al. (2009) and others), and for γ , a default value of 0.066 is used, and G is considered negligible on a monthly timestep (Fisher et al., 2009; as commonly done, see Ma et al., 2021).

The slope of the saturation-to-vapour pressure curve (δ) is calculated as

$$\delta = \frac{4098 * e_{sat}}{(T_a + 237.3)^2} \quad (Eq. 3-5)$$

Where e_{sat} is the saturation vapour pressure and T_a is the air temperature in degree Celsius:

$$e_{sat} = 0.611 * e^{(17.27 * T_a) / (237.3 + T_a)} \quad (Eq. 3-6)$$

PET is converted from its energy to its water volume equivalent as follows:

$$PET [mm/day] = PET [W/m^2 * day] * \left(\frac{0.0864}{2.45} \right) \quad (Eq. 3-7)$$

To calculate monthly total PET, the daily PET is multiplied by 30:

$$PET[mm/month] = 30 * PET[mm/day] \quad (Eq. 3-8)$$

3. Interception rainfall fraction & volume

First, the mean monthly fraction of total rainfall that becomes interception loss, f_{E_i} , is calculated from GLEAM monthly interception loss data and the monthly rainfall input dataset (observations) used in its calculation for the years 2003 to 2020.

$$f_{E_i} = \frac{E_{i_gleam}}{P_{gleam}} \quad (Eq. 3-9)$$

where E_{i_gleam} is the mean interception loss value calculated from GLEAM data and P_{gleam} is the mean rainfall input used in GLEAM. f_{E_i} is considered 0 for bare soil.

The intercepted rainfall loss E_i (mm) is then calculated by multiplying the interception fraction with the monthly rainfall climatology used in this study:

$$E_i = f_{E_i} * P \quad (Eq. 3-10)$$

4. Net radiation after interception loss

In order to avoid the double use of radiation energy by both interception loss evaporation and canopy evapotranspiration, the net radiation input R_n is reduced by the amount of energy needed to vaporize the intercepted rain volume E_i .

$$Rn_{ai} = Rn - \left(\frac{E_i}{30} * 1000 * \frac{2.45}{0.0864} \right) \quad (\text{Eq. 3-11})$$

Where Rn_{ai} is the net radiation after interception loss (W/m^2), Rn is the input net radiation (W/m^2) and E_i is the monthly interception loss (mm).

5. Stress factor (S)

The dimensionless stress factor S is used to reduce PET to AET and ranges from 0 to 1, with 0 reflecting maximum water stress. The factor depends on leaf area index (LAI_{seas}) seasonality, the potential plant available water volume (AW_{pot}), and the actual water volume in the AW store at the beginning of the month. LAI seasonality for a pixel is the LAI of month i divided by the annual maximum LAI of that pixel.

$$S = \sqrt{LAI_{seas}} * \left(\frac{AW_{actstart}}{AW_{pot}} \right)^2 \quad (\text{Eq. 3-12})$$

where $AW_{actstart}$ is the actual water volume in the AW store at the beginning of month i (mm) and AW_{pot} is the potential plant available water volume (mm). LAI_{seas} is dimensionless and ranges from 0 to 1, with $LAI_{seas} = 1$ for bare soil.

6. Potential plant available water (AW_{pot})

Potential, or maximum, plant available water volume AW_{pot} is a measure for how much of the soil volume can be accessed by the plants for water and is therefore one of the delimiters of actual evapotranspiration. All evapotranspiration except interception loss E_i therefore come from the available water store AW_{pot} .

For tree and herbaceous cover fractions, AW_{pot} is calculated from the plant rooting depth (d_{ROOT} , m), standard area (m^2), the volumetric water contents at field capacity (WC_{FC}) and at wilting point (WC_{WP}) (see Rushton (2003) p.76).

$$f_{AW} = \frac{WC_{FC} - WC_{WP}}{100} \quad (\text{Eq. 3-13})$$

$$AW_{pot} = f_{AW} * d_{ROOT} * 1 \text{ m}^2 \quad (\text{Eq. 3-14})$$

where f_{AW} is the fraction of plant available water, or the pore space available for water (see Figure 3.2), and AW_{pot} is the potential available water store (m^3/m^2). Note

that the unit m^3/m^2 is easily converted to mm by multiplying with 1000.

For bare soil areas, rooting depth is substituted with depth to bedrock, with an upper threshold of 0.1 metres because it is assumed that soil evaporation does not draw on soil water from layers below that. Field capacity is defined as the water content at -33 kPa, the wilting point is defined as the water content at -1500 kPa.

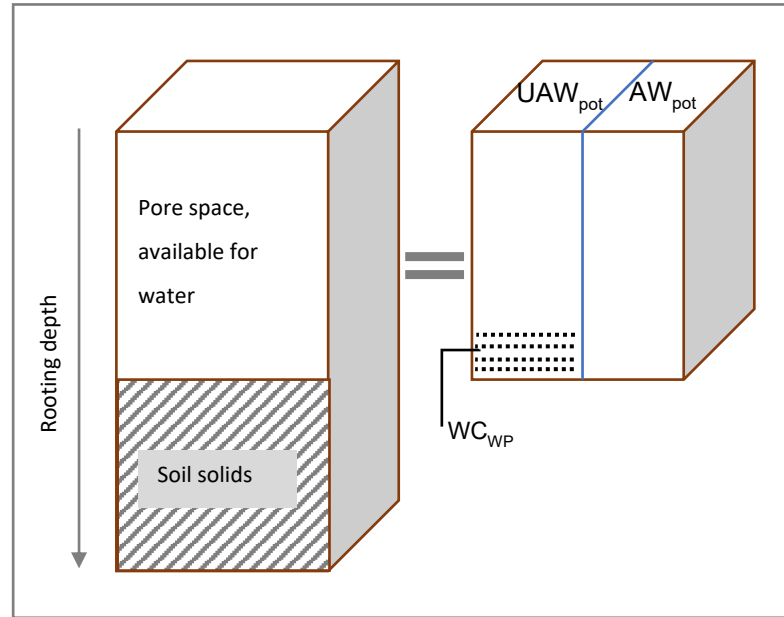


Figure 3.2 Schematics of rooting depth d_{ROOT} , available and unavailable soil water stores AW_{pot} and UAW_{pot} . WC_{WP} is part of the UAW store as indicated by the dotted section.

7. Potential unavailable water store (UAW_{pot})

The unavailable water store (UAW_{pot} , m^3/m^2) is the remainder of the soil pore space. It is inaccessible to plant roots and plant water extraction and can produce subsurface flow.

$$UAW_{\text{pot}} = (1 - f_{\text{AW}}) * d_{\text{ROOT}} * 1 \text{ m}^2$$

(Eq. 3-15)

8. Monthly input into plant available water store (AW_{in})

The monthly input into the available water store, AW_{in} , is calculated from the monthly effective rainfall, P_{net} (mm), which is the rainfall after interception loss E_i is subtracted, and limited by an infiltration capacity threshold based on hydraulic conductivity, K_{sat} , of the topmost 5 cm of soil. The water volume thus infiltrating the soil is called *initial infiltration* (mm).

Lastly, the input is scaled down by a constant split factor. This is done to represent a simplified synchronous infiltration into available water to unavailable water store.

$$\begin{aligned} \text{Initial infiltration} &= P_{\text{net}}, & \text{if } P_{\text{net}} < K_{\text{sat}} \\ \text{Initial infiltration} &= K_{\text{sat}}, & \text{if } P_{\text{net}} \geq K_{\text{sat}} \end{aligned} \quad (\text{Eq. 3-16})$$

$$AW_{\text{in}} = \text{split_factor} * \text{Initial infiltration} \quad (\text{Eq. 3-17})$$

$$UAW_{\text{in}} = \text{split_factor} * \text{Initial infiltration} \quad (\text{Eq. 3-18})$$

where the AW_{in} is the monthly input into the available water store (mm), and UAW_{in} is the monthly input into the unavailable water store (mm). The split_factor is set to 0.5 (see section 3.2.3, p. 41 for a discussion on the choice).

The infiltration capacity threshold is derived from the saturated hydraulic conductivity (K_{sat}) maps by Montzka et al. (2017) by converting it to cm/day to mm/month.

9. Monthly actual water volume in the AW store

Over the course of a month, the volume of water in the available water store changes: after infiltration of the monthly input (AW_{in}) it is called $AW_{\text{act_start}}$ and after evapotranspiration it is called $AW_{\text{act_end}}$.

In the first step, the actual water content after infiltration is calculated as follows:

If the available water store is empty (e.g. during spin-up), for month i

$$\begin{aligned} AW_{\text{act_start}}(i) &= AW_{\text{in}}(i), & \text{if } AW_{\text{in}}(i) < AW_{\text{pot}} \\ AW_{\text{act_start}}(i) &= AW_{\text{pot}}, & \text{if } AW_{\text{in}}(i) \geq AW_{\text{pot}} \end{aligned} \quad (\text{Eq. 3-19})$$

If the available water store contains water from previous months, then, for month i

$$\begin{aligned} AW_{\text{act_start}}(i) &= AW_{\text{in}}(i) + AW_{\text{act_end}}(i-1), & \text{if } AW_{\text{in}}(i) + AW_{\text{act_end}}(i-1) < AW_{\text{pot}} \\ AW_{\text{act_start}}(i) &= AW_{\text{pot}}, & \text{if } AW_{\text{in}}(i) + AW_{\text{act_end}}(i-1) \geq AW_{\text{pot}} \end{aligned} \quad (\text{Eq. 3-20})$$

In the second step, the available water volume is reduced by the volume of water used for evapotranspiration to create $AW_{\text{act_end}}$ for month i , which carries over into the following month:

$$\begin{aligned}
AW_{act_{end}}(i) &= AW_{act_{start}}(i) - (PET * S), & \text{if } AW_{act_{start}}(i) - (PET * S) > 0 \\
AW_{act_{end}}(i) &= 0, & \text{if } AW_{act_{start}}(i) - (PET * S) \leq 0
\end{aligned}$$

(Eq. 3-21)

10. Overland flows, or surface runoffs

Runoff, i.e. a positive water balance, can originate from both available and unavailable water stores and is created under three circumstances in the model (see Figure 3.1 and Figure 3.3):

- 1) if the effective rainfall, P_{net} , reaching the soil surface exceeds the infiltration capacity proxy, K_{sat} , called R_1
- 2) if initially infiltrated water is allocated to the available water store but exceeds the store's capacity AW_{pot} , called R_2 and
- 3) if the water allocated to the unavailable water store exceeds its capacity, UAW_{pot} , called R_3 .

11. Throughflow, or subsurface flow volume

Subsurface flow (SSF) originates in the unavailable water store (UAW store). It is created at a monthly timestep from the water content of the UAW store minus the water content at the wilting point (WC_{WP}), which is assumed to always remain in the soil. Except for the latter (WC_{WP}), no water is carried over to the following month and thus $UAW_{act_{end}} = WC_{WP}$. SSF is an essential variable for the model applications in Chapter 5.

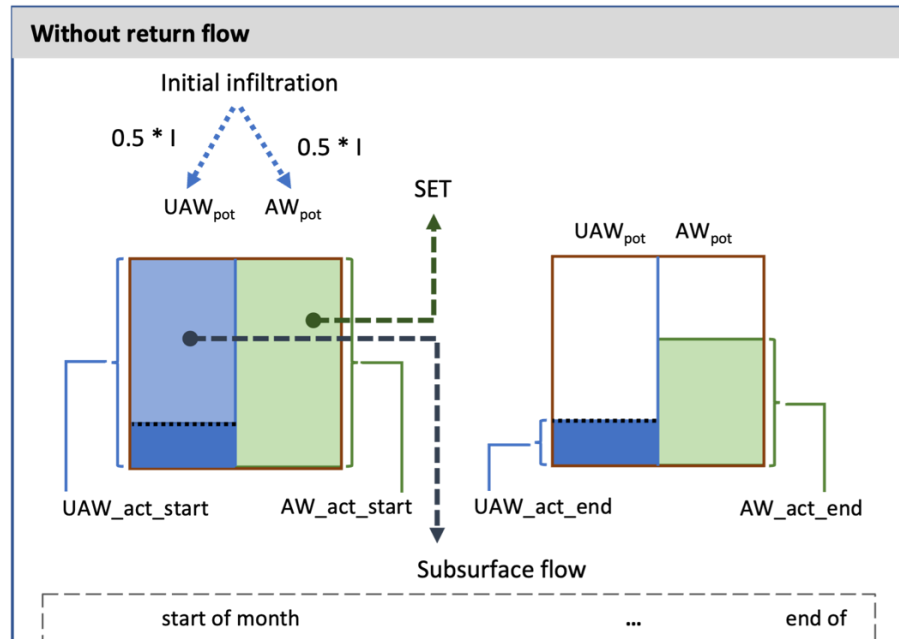
12. Effective Infiltration

The model defines *effective infiltration* as all water that infiltrates (*initial infiltration*) the soil minus the fluxes that leave the soil within the same month, R_2 and R_3 :

$$\text{Effective infiltration} = \text{initial infiltration} - R_2 - R_3$$

(Eq. 3-2)

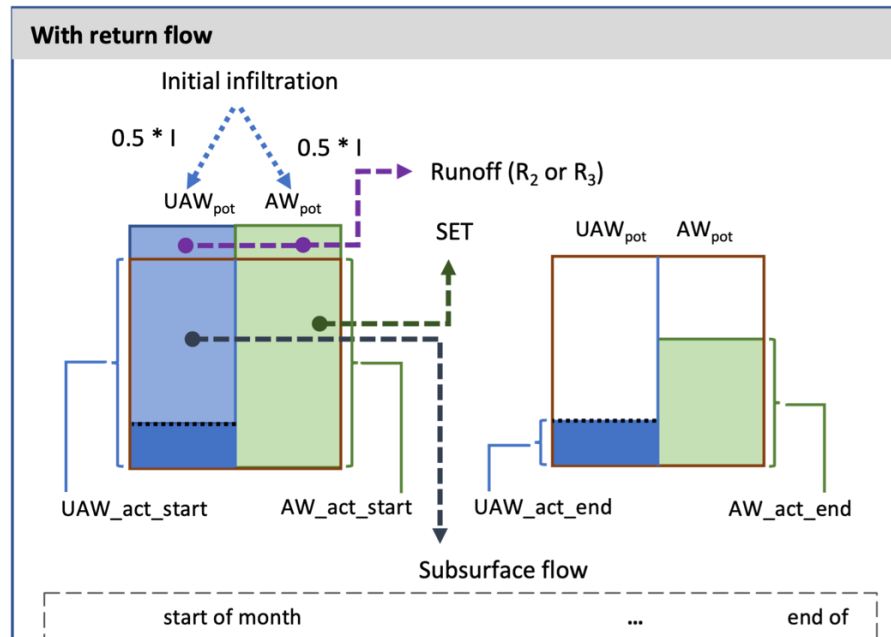
Like AET, the initial infiltration, R_2 and R_3 values are the results combined from the different preliminary outputs for each vegetation type.



At the start of month, I is split according to split factor, creating AW_{act_start} and UAW_{act_start} . Here, AW_{act_start} and UAW_{act_start} do not exceed AW_{pot} and UAW_{pot} , respectively.

Now $UAW_{act} > WC_{WP}$ & recharge removes water in excess of WC_{WP} ; SET removes water from AW_{act_start}

At the end of the month, UAW store is emptied down to WC_{WP} and thus $UAW_{act_end} = UAW_{pot} - WC_{WP}$ and thus $AW_{act_end} = AW_{act_start} - SET$



At the start of month, I is split according to split factor, creating AW_{act_start} and UAW_{act_start} . Here, AW_{act_start} and UAW_{act_start} exceed AW_{pot} and UAW_{pot} , respectively, and therefore leave the soil as surface runoff (R_2 or R_3).

Now $UAW_{act} > WC_{WP}$ and recharge removes water in excess of WC_{WP} ; SET removes water from AW_{act_start}

At the end of the month, UAW store is emptied down to WC_{WP} and thus $UAW_{act_end} = UAW_{pot} - WC_{WP}$ and thus $AW_{act_end} = AW_{act_start} - SET$

Figure 3.3 Schematics of the creation of return flows R_2 and R_3 .

Table 3-2 Inputs datasets for the DTRIE hydrological model

Variable name	Dataset name	Version	Temporal coverage	Resolution	Reference
Rooting depth	Maximum rooting depth	NA	NA	1000 m	Fan et al. (2017)
Depth to bedrock	SoilGrids Absolute depth to bedrock (cm)	1	NA	1000 m	SOILGRIDS v. 2017, Hengl et al. (2017)
Water content at field capacity & wilting point	SoilGrids Volumetric water content at - 33 and -1500 kPa	2	NA	1000 m	Poggio et al. (2021)
Saturated hydraulic conductivity, Ks, mean at different depths	A global data set of soil hydraulic properties and sub-grid variability of soil water retention and hydraulic conductivity curves	NA	NA	0.25°	Montzka et al. (2017)
Net radiation climatology	CERES EBAF Ed. 4.1 Surface Net Total Flux, Clear-sky	4.1 Level 3B	2005-2015	0.25°	Loeb et al.(2018), Kato et al. (2018)
Monthly LAI climatology	Global Monthly Mean Leaf Area Index Climatology, 1981-2015	NA	1981 - 2015	0.25°	Mao and Yan (2019b)
Monthly temperature climatology	CHELSA Mean daily air temperature	2.1	1981 - 2010	1000 m	Karger et al. (2021, 2017)
Monthly rainfall climatology	CHELSA Monthly precipitation amount	2.1	1981 - 2010	1000 m	Karger et al. (2021, 2017)
Monthly rainfall amount	TRMM (TMPA/3B43) Rainfall Estimate L3 1 month	7	1998 - 2019	0.25°	TRMM (2011)
Interception loss amount	GLEAM interception loss	3.5b	2003 - 2020	0.25°	Miralles et al. (2011), Martens et al. (2017)

3.2.3 Assumptions and limitations of the model and its data inputs

Key assumptions of the model relate to belowground components. The first key assumption regarding belowground model components is that the topsoil infiltration capacity is unchanged by tree cover increase. This may seem counter-intuitive at first because some literature supports the opposite relationship (Bonnesoeur et al., 2019; Ghimire et al., 2014a; Ilstedt et al., 2007). Such research into infiltration under vegetation cover change typically examines rainfall events, thus focuses on an event scale of minutes to hours. However, in this model a monthly measure of infiltration capacity is needed. As there is no global gridded infiltration capacity data, the model approximates this input via topsoil saturated hydraulic conductivity (K_{sat}), which is then aggregated to mm/month from its original mm/s unit. The result is an infiltration capacity that is very rarely exceeded by monthly effective rainfall and thus hardly any runoff R_1 is produced across the tropics (see section 3.5.1.3 and Figure 3.13). If this infiltration capacity were to be increased even further through tree cover, as supported by the aforementioned studies, the changes to the amount of R_1 would be negligible as R_1 can practically not shrink further. Additionally, evidence of the pace at which infiltration capacity increases with tree cover growth is still inconclusive (Pereira et al., 2020; Zimmermann et al., 2010). Lastly, the pace and magnitude of improvement of infiltration capacity through tree cover is greatly affected by the land cover and use history (Lozano-Baez et al., 2018). This history varies at fine spatial scales which make the integration into DTRIE unfeasible within the timeframe of this research project. It was therefore decided to not adjust infiltration capacity to scenario vegetation covers.

Soil variables that are adjusted to scenario conditions are 1) soil depth, which increases AW and UAW stores (thus increasing the potential for SET and subsurface flows); and 2) K_{sat} of lower soil layers, which is used in the calculation of subsurface flow throughflow velocities v_T . The former mimics the combination of soil generation (for example through litter decomposition) and the greater rooting depth of trees as opposed to short vegetation or bare soil. The K_{sat} adjustment on the other hand, approximates the increase in macropores and macropore flow under tree cover (Gao et al., 2018).

The second key assumption is, as Figure 3.1 illustrates, that “initial infiltration” (which equals effective rainfall minus interception loss and less than the monthly infiltration capacity) is distributed to available and unavailable water stores (AW_{pot} and UAW_{pot}) in equal parts, i.e. that the “split factor” is 0.5, or equal (see (Eq. 3-17 and (Eq. 3-18). For example, half of “initial infiltration” becomes AW_{in} and the other UAW_{in} (see Figure 3.1), or put differently, both stores fill in parallel and at the same rate. An alternative representation to the “equal split factor” would be a random distribution of soil pores available (AW) and unavailable for water storage (UAW) throughout the soil column. In this case, a split of infiltrating water into AW_{in} and UAW_{in} according to the ratio of the two volumes (AW_{pot} to UAW_{pot}) would be sensible. However, I argue that the equal split captures reality better. This is because although most grid cells have more pores that accommodate plant unavailable water (i.e. $UAW_{pot} > AW_{pot}$), these pores are usually less common in upper soil layers due to overall lower bulk densities and the presence of macropores. Splitting effective initial infiltration between both stores equally is thus a simple solution to reflect the increased likelihood of rainfall to encounter a pore of the AW store as it moves downwards in the soil column. Furthermore, the consequence of overestimating the amount of water received by the AW store (i.e. if the split factor of 0.5 were indeed too high) would be an inflated volume of SET (soil evaporation or plant transpiration) and return flow R_2 . As section 3.4.1 will demonstrate, however, the volumes of actual evapotranspiration from DTRIE are generally already lower than those from other remote sensing product based models. An overestimation of the amount of AW_{in} is therefore unlikely.

3.3 Results: model estimates for the reference year

3.3.1 Estimates of actual evapotranspiration, infiltration and water balance

The DTRIE model was applied to the baseline year of 2018 to calculate actual evapotranspiration, effective infiltration, water balance and the ratio of infiltration to AET on an annual and monthly scale. Here, the annual estimates across the tropics are presented for comparison with published literature and to investigate the geographic and spatial patterns in the results. In addition to estimates on a grid cell basis, variables are also averaged over HydroBASINS level 4 basins

(hereafter *HB4*) as well as several of the major river basins of the world (hereafter *MRB*) (GRDC, 2020; Lehner and Grill, 2013).

3.3.1.1 Actual evapotranspiration (AET)

On the pixel scale, the median and 95th percentile AET are 511 millimetre per year (mm/yr) and 1,581 mm/yr. Modelled AET in the tropics ranged from virtually no AET in the Sahel region to a maximum of 2,600 mm/yr in Indonesia (New Guinea), exceeding the 95th percentile. Very high AET values were also found in the Amazon rainforest and central Borneo with around 2,100 to 2,200 mm/yr. The rainforest belt in Africa, on the other hand, only reaches between 1,000 to 1,200 mm/yr in AET, with some exceptions in Cameroon and Equatorial Guinea (1,500-

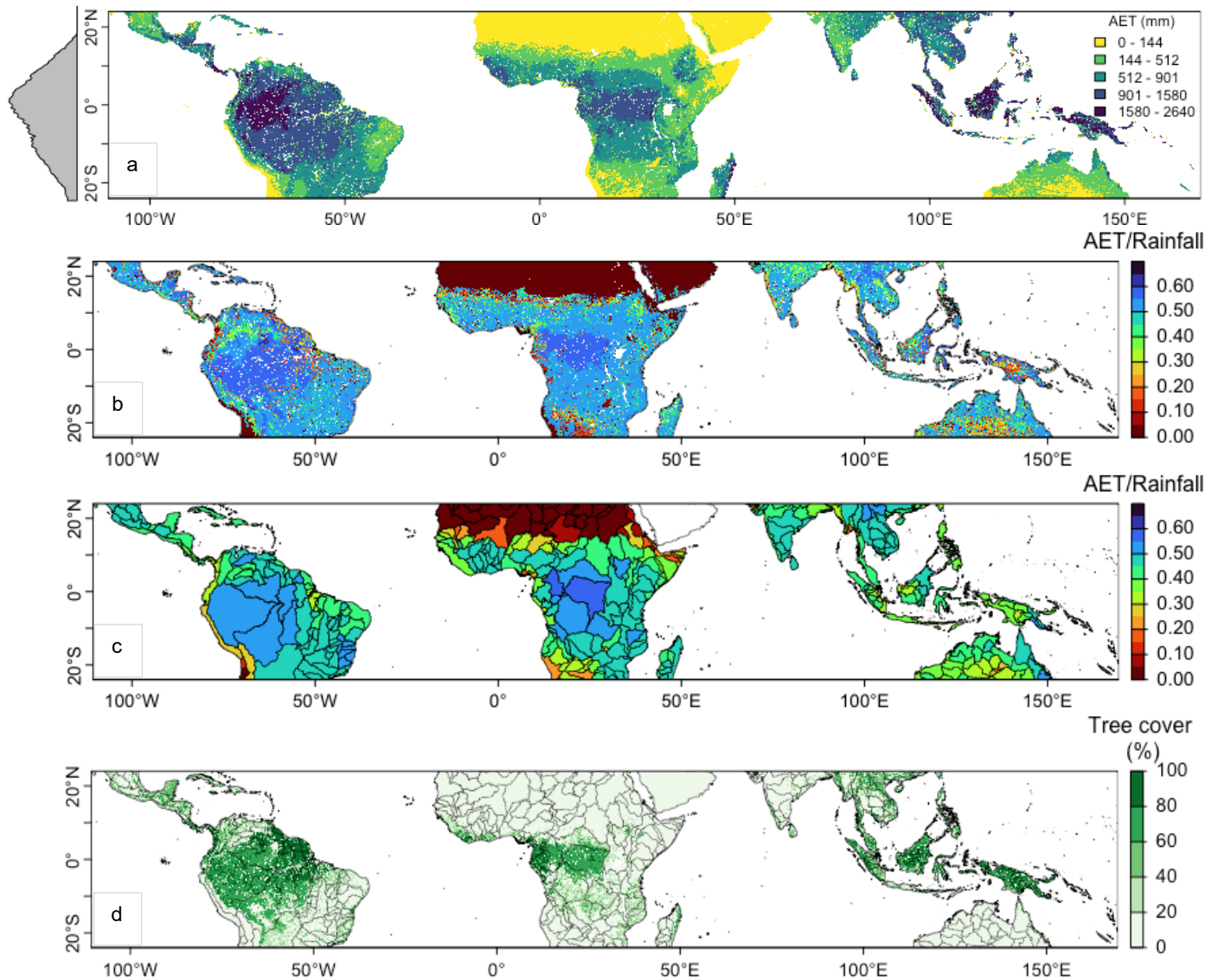


Figure 3.4 a) Annual actual evapotranspiration (mm/yr). The marginal plot presents AET along the latitudinal gradient. Grid cells with NA values are white; this includes all inland and ocean water pixels as well as urban area pixels. b) Annual AET divided by Annual rainfall (“evaporative index” on pixel scale, c) Annual AET/ Rainfall averaged over tropical basins; e) MODIS MOD44B tree cover in 2018 (%)

1,600 mm/yr) and at the border between Democratic Republic of the Congo (DRC), Burundi, and Rwanda (up to 2,000 mm/yr) (see Figure 3.4a).

As Figure 3.4a and its marginal plot show, the relationship between AET and latitude is negative. On the basin scale, the highest annual AET is modelled for the Rajang basin in Malaysia with 1,850 mm/yr, followed by the neighbouring Mahakam basin (Indonesia) with 1,536 mm/yr, and the Purari basin (Papua New Guinea) with 1,514 mm/yr (see Appendix A1.4).

For some of the MRB, the estimates are as follows: the Amazon River produces 1,205 mm of AET per year, the Orinoco and Magdalena River basins produce 1,183 and 1,090 mm/yr. In Africa, the Congo basin achieves an AET of 852 mm/yr and the Niger basin reaches a mere 275 mm/yr. In South and Southeast Asia, 584 mm/yr is estimated for the Godavari basin (India), 660 mm/yr for Chao Phraya (Thailand), and 1,389 mm/yr for the Malaysian Kapuas basin. For these eight basins, values were averaged over major river basins of the world as opposed to HB4 basins to preserve their boundaries.

Because rainfall is the most dominant driver for AET (see section 3.3.2 and Figure 6a-d) Figure 3.4b-c also show the “evaporative index” calculated as AET divided by rainfall (Arciniega-Esparza et al. 2022) which illustrates where AET is highest per unit rainfall. The maximum evaporative index across the tropics is 0.67, the mean and median are 0.38 and 0.5. The highest evaporative indices are modelled for dense lowland rainforests (see Figure 3.4b). This is in keeping with the spatial pattern from Figure 3.4a, except for parts of Southeast Asia such as the islands of New Guinea and Borneo and the Pacific coast of Colombia. Here, the evaporative index is below 0.1, indicating less than 10 per cent of rainfall become evapotranspiration. The HB4s with the highest indices are found in the northern and north-western subbasins of the Congo River basin, followed by its remaining subbasins, as well as the sub-basins of the Amazon River.

3.3.1.2 Water balance

The annual water balance (WB) is calculated as follows:

$$WB = P - AET$$

(Eq. 3-22)

Where P is annual rainfall and AET is actual evapotranspiration. Changes in water storage are typically discounted at annual timesteps (Bari et al., 2005; Zhang et al., 2001).

Consequently, water balance is the amount of water that becomes runoff (surface or subsurface) at some point.

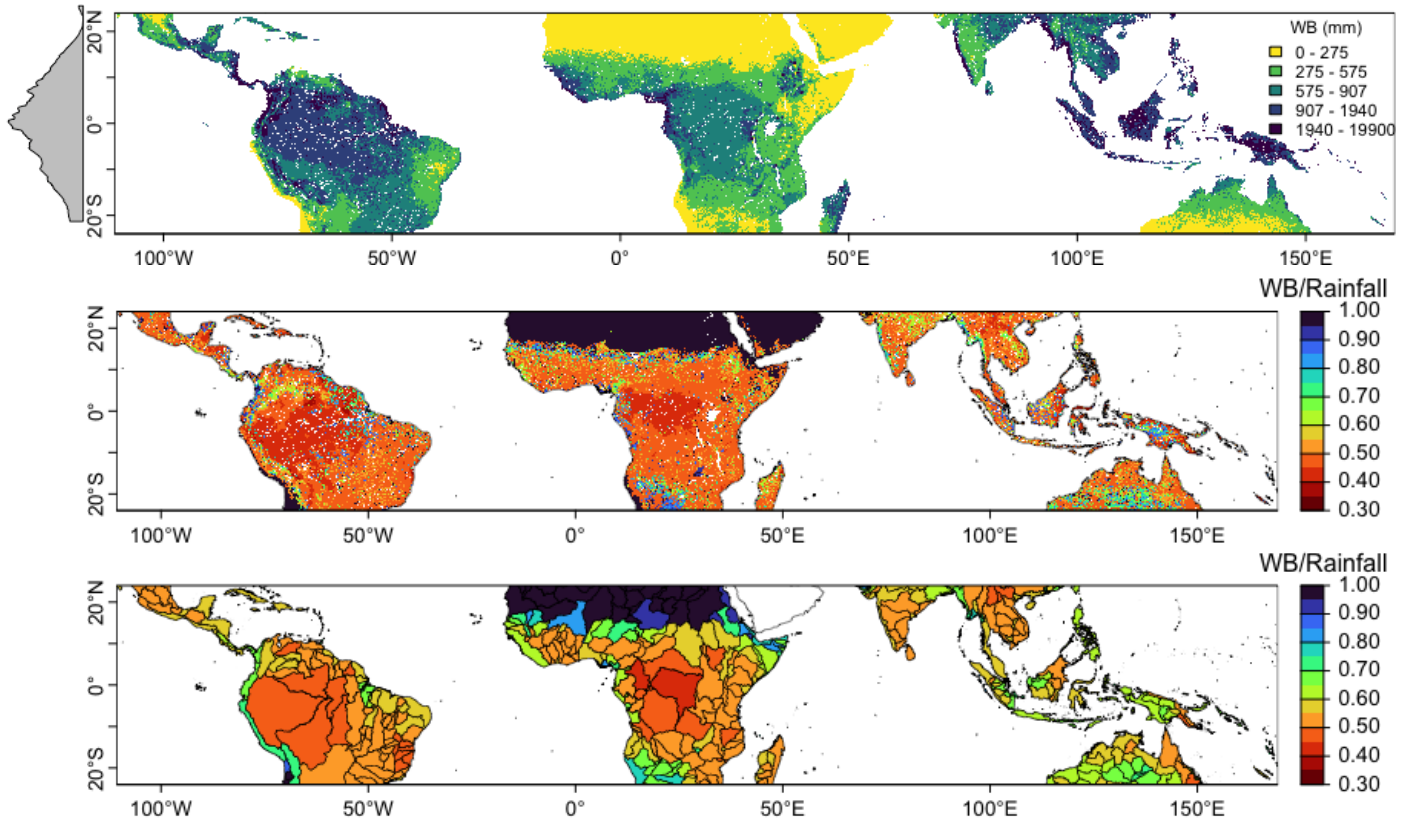


Figure 3.5 a) Annual water balance (mm/yr); the marginal plot presents water balance along the latitudinal gradient. Grid cells with NA values are white; this includes all inland and ocean water pixels as well as urban area pixels; b) annual water balance divided by annual rainfall on pixel scale, c) b, averaged over tropical basins (HB4).

Figure 3.5a shows the annual water balance for the tropics on a grid cell basis. The median and 95th percentile annual water balance are 575 mm/yr and 1,937 mm/yr, respectively. Only few areas produce a water balance in excess of the 95th percentile on a grid cell basis: coastal fringes in West Africa (Cameroon, Nigeria and, Guinea, Sierra Leone and Liberia) and large parts of Borneo are in the range of 2,000 to 6,000 mm/yr, while the south-western coast of India, western coast of Myanmar as well as parts of the islands Sumatra and Java register between 4,000 and 6,000 mm/yr. In Southeast Asia, central areas in New Guinea have the highest water balance values with around 9,000 mm/yr. In Central and South America, the highest overall values are found on the western coast of Colombia with 16,000 mm/yr and in Costa Rica and Nicaragua, where water

balance ranges from 4,000 to 7,000 mm/yr. As can be seen in Figure 3.5a and its marginal plot, the relationship between water balance and latitude is negative, similar to AET. Averaged over HB4 basins, the Sungai Fly (Fly River) basin in Papua New Guinea has the highest water balance with 3,118 mm/yr, followed by the Rajang basin in Malaysia (2,986 mm/yr), the Atrato basin in Colombia (2,913 mm/yr), the Kapuas basin in Indonesia (2800 mm/yr) and the Karnaphuli basin in Bangladesh (2441 mm/yr) (see Appendix A1.6). Looking at some of the MRB, the South American basins Magdalena, Orinoco and Amazon basins achieve 1,446, 1,437 and 11,08 mm/yr respectively. In Africa, the Congo and the Niger basins average 740 and 379 mm/yr and in Asia, the Godavari basin has an annual water balance of 702 mm/yr while the Chao Phraya basin estimate is 665 mm/year.

Per unit rainfall, the spatial pattern of water balance changes somewhat. Figure 3.5b, c show where water balance is highest, that is where total runoff is highest, per unit rainfall. As expected, drier areas, such as Northern Africa, have the highest water balance on account of their low AET and rainfalls. This ratio declines towards the equator, with the lowest water balance per rainfall values in sub basins of the Congo basin. Southeast Asian HB4 basins on the islands of Borneo and New Guinea, however, do not follow this pattern, as they have higher water balance values per unit rainfall.

3.3.1.3 Effective Infiltration

Figure 3.6a shows the annual effective infiltration per grid cell. Effective infiltration was calculated as the amount of infiltrated rainfall that does not exit the soil as return flow again within the same month, and thus is available for both evapotranspiration (SET) and subsurface flow. The median and 95th percentile of effective infiltration are 1,110 mm/yr and 2,486 mm/yr.

The highest pixel values are modelled for the western coastline of Colombia (8450 mm/yr), on the islands of New Guinea and Borneo (up to 5,700 mm/yr). The western coastlines of India and Myanmar, as well as parts of Venezuela also reach up to 4,000 mm/yr. The relationship between infiltration and latitude is also negative.

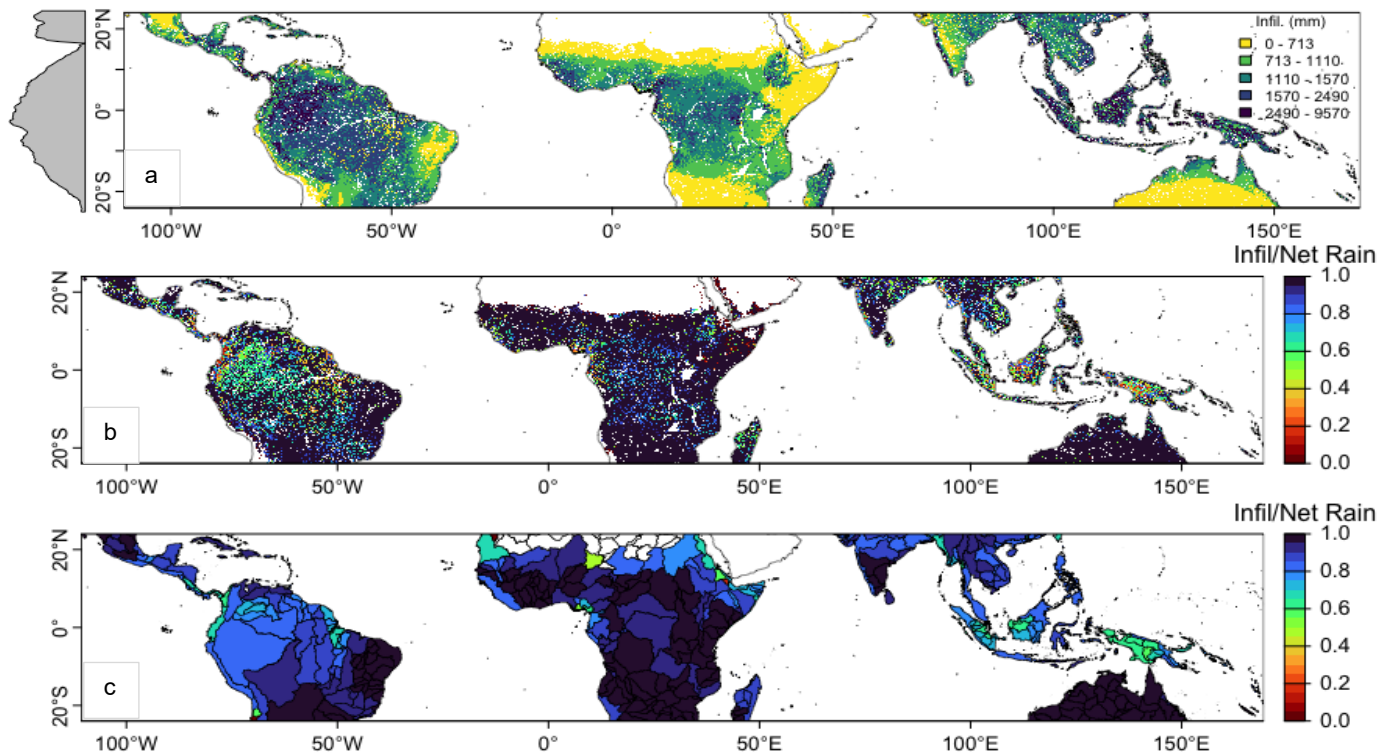


Figure 3.6 a) Effective infiltration (mm/yr); the marginal plot presents infiltration along the latitudinal gradient. Grid cells with NA values are white; this includes all inland and ocean water pixels as well as urban area pixels; b) annual effective infiltration divided by annual effective rainfall on pixel scale (here called “Net Rain”); c) Annual effective infiltration/ effective rainfall averaged over tropical basins. Effective rainfall is total annual rainfall minus total annual interception loss.

Among the HB4 basins, the Southeast Asian Rajang basin has the highest effective infiltration with 2,941 mm/yr, followed by 2,501 mm/yr on west Sulawesi and 2,491 mm/yr in the Kapuas basin. Averaged over MRB, in the South American Amazon, Orinoco and Magdalena basins, effective infiltration reaches 1,704, 1,873 and 1,853 mm/yr, respectively. In Africa, the means for the Niger and Congo basins mean are 869 mm/yr and 1,362 mm/yr. The Chao Phraya basin mean is 1,177 mm and the mean for the Godavari basin is 1,108 mm/yr.

Similar to AET, rainfall is the most dominant driver for effective infiltration (see section 3.3.2 and Figure 3.8q-t). Therefore, Figure 3.6b-c present the effective infiltration per unit effective rainfall by pixel and HB4 basin. The median of this ratio is 1, which means that in half of the grid cells the entire volume of effective rainfall becomes effective infiltration. The majority of grid cells with extremely high effective infiltration per unit rainfall (> 0.9) are found in Africa, Australia, India, the south-eastern parts of tropical South America. Lowland rainforest areas in the Amazon and Orinoco subbasins have a lower ratio, ranging between 0.5 and 0.7. Among the HB4 basins with lowland rainforests, those in the Congo basin have

the highest ratio, above 0.9, followed by the Amazonian sub-basins, the Orinoco subbasins and lastly, the Southeast Asian HB4 basins on Borneo and New Guinea (see Appendix A1.4).

Although, as expected for this model, little overland flow is produced due to high effective infiltration, subsurface flows are very well produced, as shown in Figure 3.7.

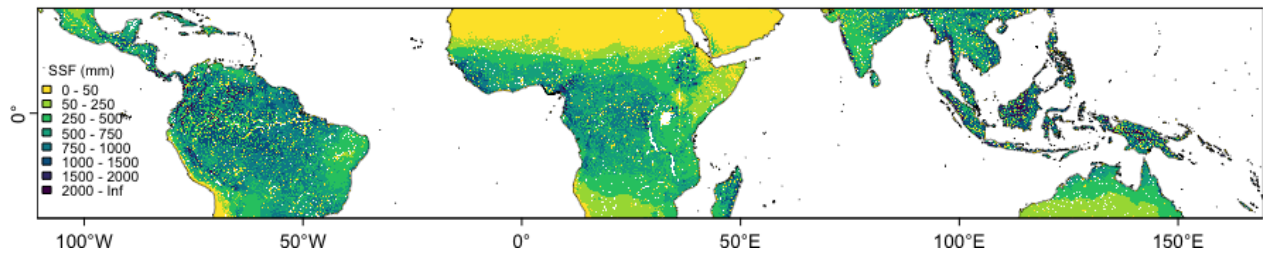


Figure 3.7 Subsurface flows (SSF, mm) in the baseline year. Apart from arid environments such as the Sahara and Atacama deserts, subsurface flow is produced to some extent everywhere in the tropics.

3.3.2 Spatial patterns and influences of environmental covariates on hydrological variables

Scatter plots in Figure 3.8 show the relationships between AET, water balance, SET, E_i and effective infiltration, as well as the main input variables annual rainfall, net radiation, tree cover and mean annual temperature for a random sample of 293 points. The Spearman correlation coefficient is presented because all four main input variables are non-normally distributed (Shapiro-Wilk test normality test with $p < 0.05$ for all four variables). Rainfall is the dominant forcing for all outcome variables and the correlation coefficient (Spearman's ρ) ranges from 0.72 to 0.93, when rainfall values above 6,000 mm/yr are excluded (see Figure 3.8a, e, i, m & q).

All output variables show a mostly weak to moderate positive correlation with tree cover which saturates at around 80 per cent tree cover because of the saturation in the tree cover input. The highest correlation coefficient occurs between tree cover and interception loss E_i ($\rho = 0.7$), and the linear model can explain 43 per cent of the variation in E_i ($R^2_{adj} = 0.43$). AET and SET show moderate correlations ($\rho = 0.59$ and $\rho = 0.42$), water balance and tree cover have the weakest positive correlation ($\rho = 0.23$). Mean annual temperature on its own did not show any significant correlations (Figure 3.8c, g, k, o & s).

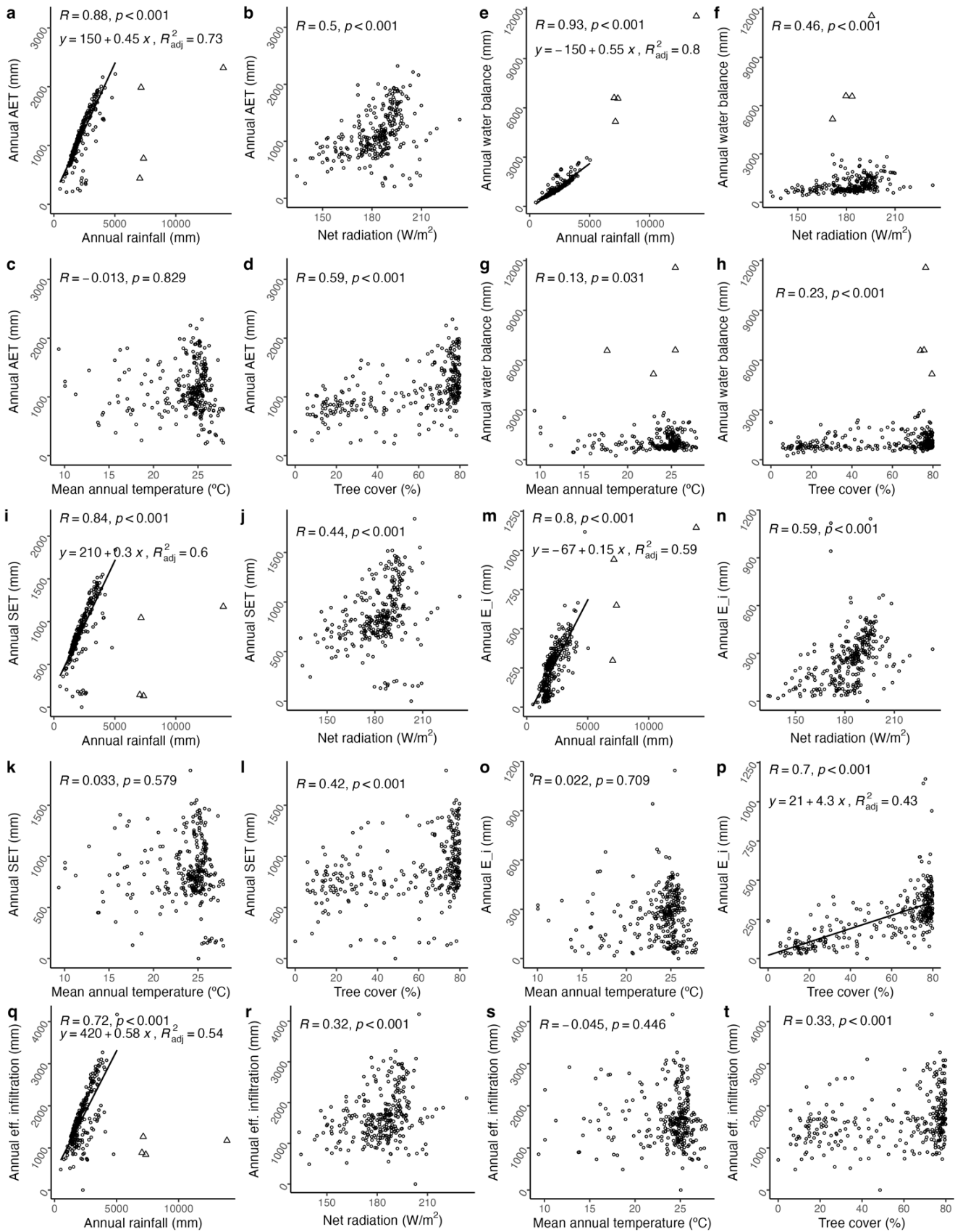


Figure 3.8 Scatter plots of annual estimates of main model outcome variables against forcings. A-d) AET, e-h) water balance; i-l) SET; m-p) E_i (interception loss); q-t) effective infiltration. Spearman's ρ ("R") is given with p-value; where $p > 0.7$ a regression line is plotted with its equation and R^2 . Plots with rainfall or aridity index on the x-axis and plots e-h) show values above 6000 mm as triangles; these are excluded from the regression and correlation computation. Annual rainfall is the sum of monthly rainfall inputs, while all other variables are annual means.

3.4 Verification of evapotranspiration estimates with MOD16 and GLEAM estimates

In the following, basin averages of the modelled estimates for actual evapotranspiration are compared to MOD16 and GLEAM estimates. For MODIS, the MOD16A2GF 8-day ET product (hereafter “MODIS”) for 2018 was aggregated to a monthly timestep. Estimates for GLEAM come from the v.3.5b dataset and are composed of variables E_i , E_b and E_t , which were aggregated from a daily to a monthly timestep. This amounts to the same components as DTRIE AET, because it specifically excludes open water evaporation (E_w) and snow sublimation, which are not modelled in DTRIE. Note that the variables AET and MODIS ET also comprise the same components and are therefore comparable; as such AET is used in the following section for all three datasets for ease of reading.

The comparison was conducted on pixel level for a random sample of pixels from the Amazon, Magdalena, Congo, Kapuas, Chao Phraya and Xe Bang Hieng basins on annual scale (see Figure 3.9) (sample size: 100 pixels per basin). The comparison of monthly estimates used basin level averages for the aforementioned six basins (see Figure 3.11 and Table 3-4).

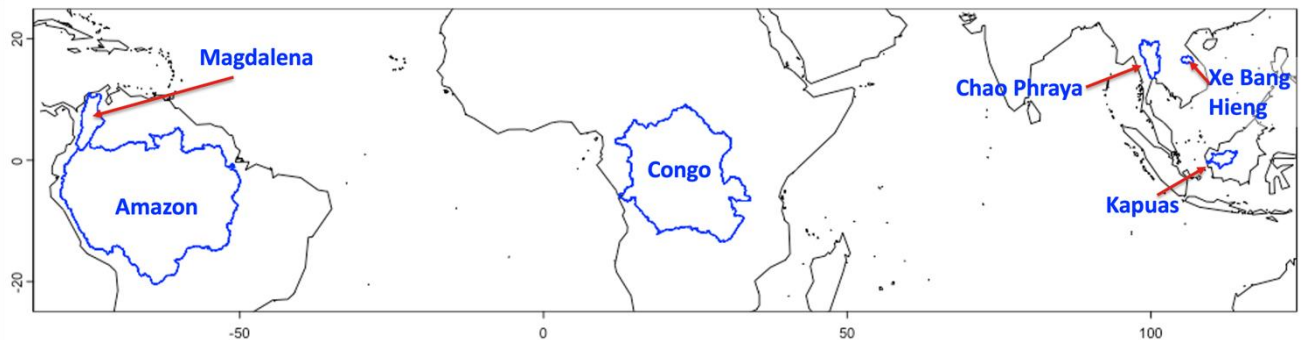


Figure 3.9 Location of the six basins chosen for the verification analysis.

3.4.1 Comparison of annual total AET between DTRIE, GLEAM and MODIS in selected basins

The best agreement in basin means of annual total AET between models is found in the Magdalena River basin where the annual AET totals are 1,075 mm/yr (DTRIE), 1,139 mm/yr (MODIS) and 1,113 mm/yr (GLEAM), and in the Xe

Bang Hieng basin, with 1,010 mm/yr (DTRIE), 1,067 mm/yr (GLEAM) and 1,071 mm/yr (MODIS).

In the Congo basin and Chao Phraya basins, the disagreements in basin means are greatest. For the Congo basin, the DTRIE estimates a total of 847 mm/yr, compared to GLEAM with 1,117 mm/yr and MODIS 1,152 mm/yr. The values for Chao Phraya are 693 mm/yr (DTRIE), 1,083 mm/yr (MODIS) and 953 mm/yr (GLEAM). In the remaining two basins, Amazon and Kapuas, the differences are in-between. The estimates are 1,197 mm/yr (DTRIE), 1,341 mm/yr (GLEAM) and 1,315 mm/yr (MODIS) in the Amazon basin, and 1,386 mm/yr (DTRIE), 1,479 mm/yr (GLEAM) and 1,284 mm/yr (MODIS) in the Kapuas basin.

Overall, the absolute differences in annual total AET between GLEAM and DTRIE range from 38 mm/yr to 271 mm/yr, while the absolute differences between MODIS and GLEAM range from -102 mm/yr to 390 mm/yr. The percentage difference between DTRIE and other models was also calculated (as $100 \times [\text{GLEAM value} - \text{DTRIE value}] / \text{DTRIE value}$). The percentage difference between GLEAM and DTRIE ranged from 3.5 per cent in the Magdalena basin to 37.5 per cent in the Congo basin; the percentage differences between DTRIE and MODIS range from -7.4 per cent (Kapuas) to 56.2 per cent (Congo). In the comparison between MODIS and GLEAM, the percentage differences (calculated as a share of the GLEAM value) range from -13.2 per cent (Kapuas) to 13.6 per cent (Congo).

Table 3-3 Mean and standard deviation (SD) of annual (total) AET for the selected large basins for the base-line year 2018 for DTRIE, MODIS MOD16 and GLEAM. The two measures reflect spatial variation across the basin in the annual sum of AET: mean is the basin mean of the annual sum of AET, SD is the standard deviation across the basin of the annual sum of AET.

Basin	DTRIE		MODIS		GLEAM	
	Mean	SD	Mean	SD	Mean	SD
Amazon	1197	351	1315	198	1341	258
Xe Bang Hieng	1010	175	1171	256	1067	163
Congo	693	143	1083	230	953	84
Kapuas	1386	502	1284	140	1479	89
Magdalena	1075	310	1139	229	1113	148
Chao Phraya	846	205	1152	191	1117	209

The spatial variation in total annual AET across the basin is given by the standard deviation (SD) presented in Table 3-3 for each basin and model. Overall, DTRIE values have a higher SD in absolute terms except in Chao Phraya, where GLEAM SD exceeds them, and in the Congo and Xe Bang Hieng basins, where MODIS SD exceeds them.

The overall patterns on an annual scale are: 1) in most cases the annual AET total of the DTRIE model is lower than that of MODIS or GLEAM, except for the Kapuas basin in Borneo, where MODIS is actually smaller; 2) there are typically larger differences between MODIS and the DTRIE model, than between GLEAM and DTRIE; 3) the lowest percentage differences are found in the Magdalena River basin for both MODIS and GLEAM comparison; 4) the largest percentage differences exist in the Congo basin, ranging from 37.5 (compared to GLEAM) to 56 per cent (compared to MODIS); the Congo basin also shows the highest percentage differences in the GLEAM -MODIS comparison, although much lower at 13 per cent.

3.4.2 Comparison of monthly estimates and seasonality between models

Figure 3.10 presents the alignment of monthly AET estimates between models, with each point representing a pixel in the basin, across all months of the year. Table 3-4 shows the corresponding statistical metrics of the goodness of fit: root mean square error (RMSE) as a measure of both random and systematic error, percentage bias (PBIAS) as a measure of systematic error as percentage of the average of observations, Pearson's correlation coefficient (r) and the coefficient of determination (R^2). For these calculations, the DTRIE estimates were treated as observed, and the MODIS and GLEAM values were considered simulated values; where MODIS and GLEAM are compared, GLEAM estimates are considered as the observed. Thus, a positive percentage bias (PBIAS see (Eq. 3-25) in the DTRIE – GLEAM comparison, for example, means that GLEAM values exceed DTRIE values. Statistics were calculated with the R package *hydroGOF*, function *ggof()*, which calculates goodness-of-fit measures for timeseries. Figure 3.11 shows monthly basin means for AET for an easy visual comparison of seasonal patterns between the models.

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (X_{obs,i} - X_{model,i})^2}{N}}$$

(Eq. 3-23)

$$BIAS = \frac{\sum_{i=1}^n (X_{obs,i} - X_{model,i})}{N}$$

(Eq. 3-24)

$$PBIAS = 100 * \frac{BIAS}{\sum_{i=1}^n X_{obs,i}}$$

(Eq. 3-25)

with X_{obs} = observed data (in the comparison between DTRIE and other models, DTRIE values are considered observed, for the comparison between GLEAM and MODIS, GLEAM is considered observed); X_{model} = GLEAM or MODIS data; N = number of data points.

In the Amazon basin, agreement between the models is generally good (Figure 3.10a-c). When seasonal patterns are compared, the overall amplitude of both GLEAM and MODIS estimates are lower than DTRIE's, but GLEAM and DTRIE agree well with each other. There is a positive and high correlation (Pearson's $r = 0.91$) between DTRIE and GLEAM results, and a high coefficient of determination ($R^2 = 0.84$) further underscores the overall linear relationship. The RMSE of the DTRIE – GLEAM comparison is 17.56 mm, and the percentage bias is relatively low at 12 per cent (see Table 3-4). Figure 3.11a shows that the seasonality of GLEAM values is similar to that of DTRIE, although the amplitude of DTRIE estimates is larger over the year; for example, from June to September, both GLEAM and DTRIE show periods of decreased AET, but the DTRIE estimates dip considerably lower. MODIS and DTRIE show opposing seasonality, the former estimating lowest values in February and April, while the DTRIE are lowest in August, when MODIS estimates peak (see Figure 3.11a). Therefore, the correlation coefficient is negative between model and MODIS (Pearson's $r = -0.78$), and also between MODIS and GLEAM ($r = -0.6$). This is also visible in Figure 3.10b, where the spread around the 1:1 line (dotted line) for MODIS and DTRIE is large.

Due to the seasonality mismatch, the percentage bias is relatively low (9 per cent): when PBIAS is calculated for each month, it keeps the sign of the

differences between MODIS and DTRIE intact; this means that when summed up over the year, negative and positive bias values from different months can cancel or smooth each other out. Where bias values are negative in some months and positive in others, there is a seasonality mismatch.

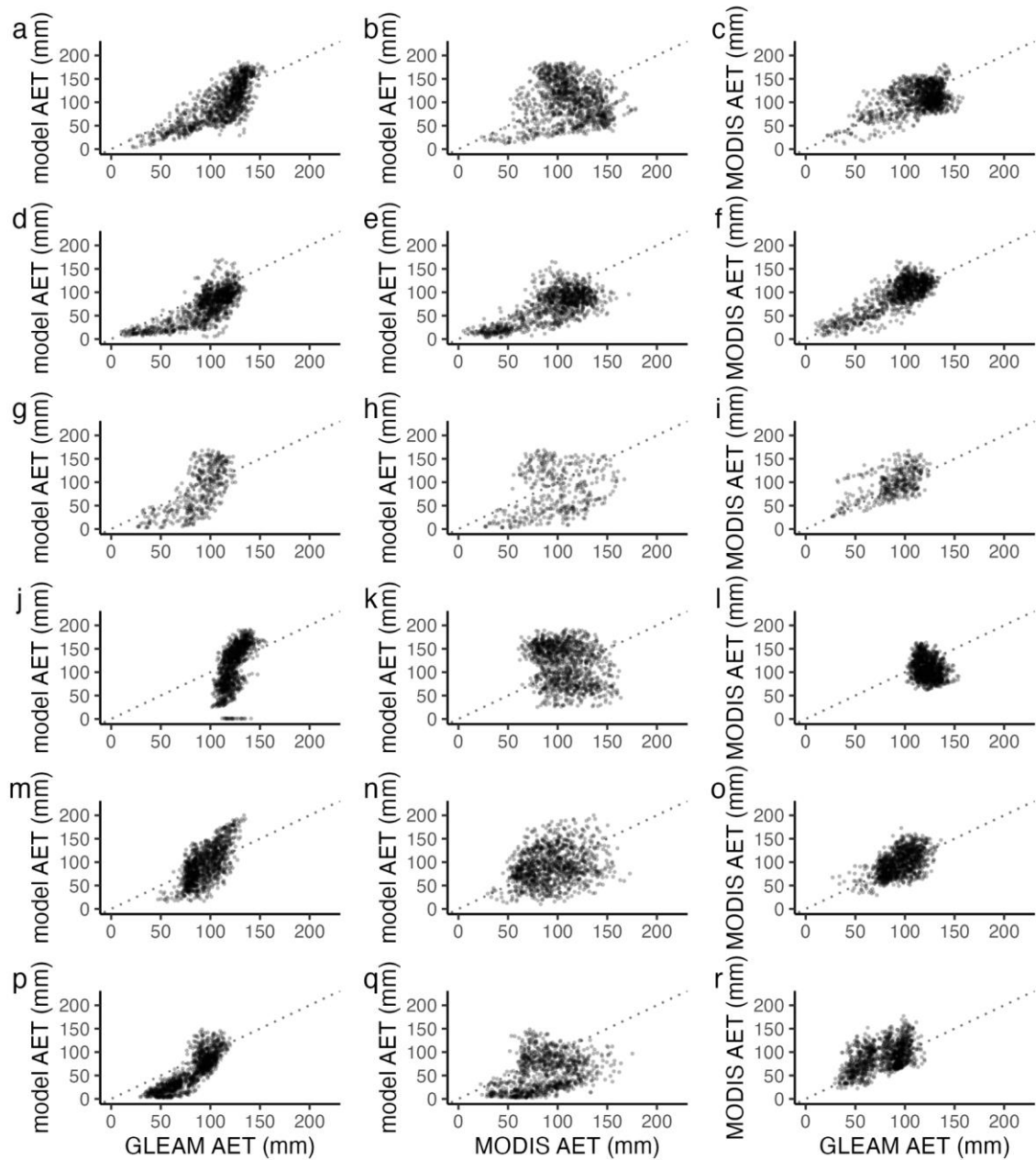


Figure 3.10 Scatter plot of ET estimates for 2018 across all months by DTRIE versus MODIS AET or GLEAM AET, and MODIS AET versus GLEAM AET for the Amazon River basin (a-c), Congo River basin (d-f), Xe Bang Hieng (Mekong) basin (g-i), Kapuas basin (j-l), Magdalena basin (m-o), Chao Phraya basin (p-r). Each plot point is a land pixel in the respective basins. Data was resampled to match the coarsest resolution of 0.25 degrees. Sample size is 100 pixels per basin. Note that the GLEAM product is called AET here, but “E” (for evaporation) in the relevant documentation and reference articles. However, the components reflect a general comparability to other AET products and Miralles et al. 2016, Melo et al. 2021 and others in fact make that comparison in their validation of the GLEAM product. Therefore, it was decided to use the acronym AET for ease of understanding in this figure. For reference, the authors explain their preference for the term evaporation (E) over AET in Miralles et al. 2020.

Table 3-4 Similarity metrics for monthly AET estimates between DTRIE, GLEAM and MODIS (MOD16), and between GLEAM and MODIS. RMSE = root mean square error (mm), PBIAS = percentage bias (%), r = Pearson correlation coefficient, R^2 = coefficient of determination

Basin	Metric	RMSE	PBIAS	r	R^2
	Dataset				
Amazon	GLEAM	17.56	12	0.91	0.84
	MODIS	29.63	9.8	-0.78	0.61
	MODIS-GLEAM	15.97	-1.9	-0.6	0.36
Congo	GLEAM	24.41	32	0.76	0.57
	MODIS	28.55	36.1	0.53	0.28
	MODIS-GLEAM	5.86	3.1	0.91	0.82
Xe Bang Hieng	GLEAM	28.95	5.7	0.87	0.76
	MODIS	41.91	16	0.26	0.07
	MODIS-GLEAM	16.61	9.7	0.59	0.35
Kapuas	GLEAM	9.26	6.7	0.82	0.67
	MODIS	23.08	-7.4	-0.63	0.39
	MODIS-GLEAM	23.57	-13.2	-0.23	0.05
Magdalena	GLEAM	13.74	3.5	0.75	0.56
	MODIS	20.93	5.9	-0.1	0.01
	MODIS-GLEAM	8.42	2.3	0.5	0.25
Chao Phraya	GLEAM	27.04	37.5	0.93	0.87
	MODIS	42.41	56.2	0.53	0.28
	MODIS-GLEAM	17.25	13.6	0.7	0.49

The scatter plots of Figure 3.10d for the Congo basin show an agreement between DTRIE and GLEAM comparable to that in the Amazon, although the spread around the 1:1 line in the MODIS comparison is smaller. Seasonal patterns agree very well with each other in all models, even MODIS (see Figure 3.11b), the main difference being that DTRIE seasonality is pulled forward in the year by one to two months. Again, MODIS and GLEAM estimates are higher than DTRIE values, with RMSE values of 24.41 mm and 28.55 mm and some of highest relative biases of all basins (PBIAS = 32 and 36.1% for GLEAM and MODIS, respectively). These are likely due to the large absolute differences in estimates in the first half of the year, and also results in an overall less linear relationship (lower correlation coefficient r and coefficient of determination R^2).

In the Xe Bang Hieng basin, MODIS estimates show a more bimodal seasonality, with peaks in May and October, while GLEAM and DTRIE are more unimodal.

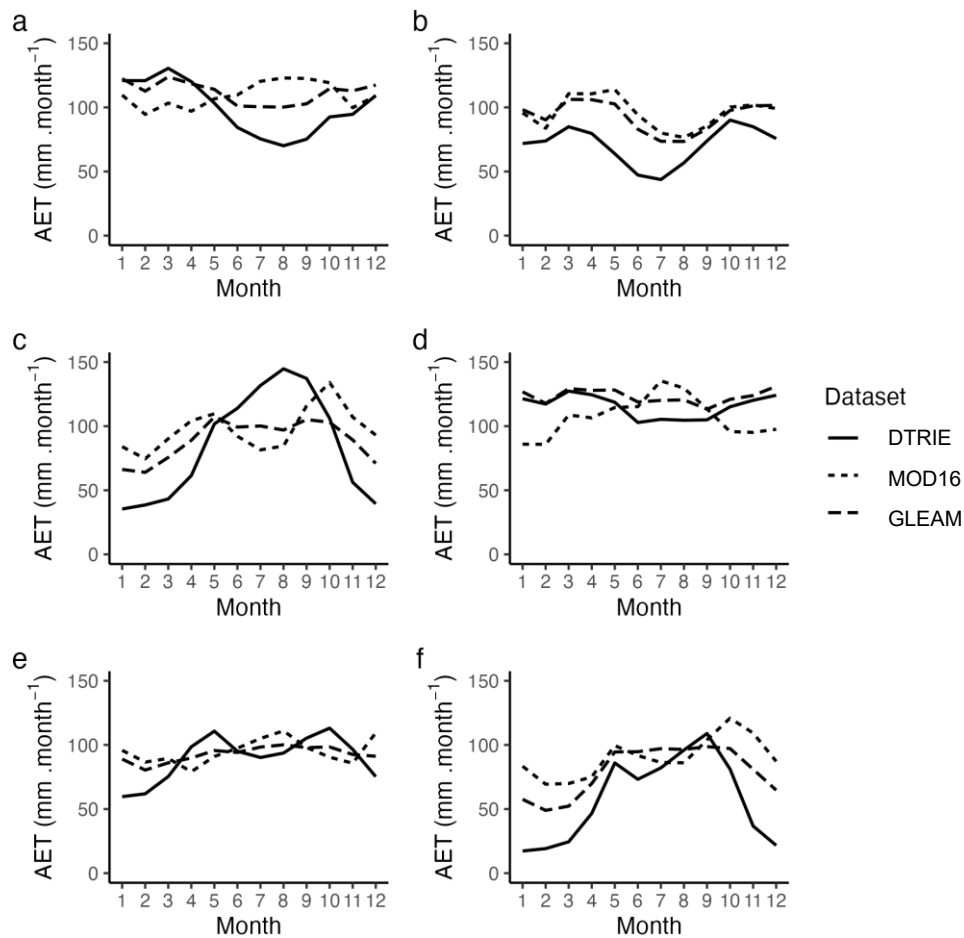


Figure 3.11 Comparison of basin mean monthly AET between DTRIE estimates (solid line), MODIS (MOD16) (dotted) and GLEAM (dashed). From top left to bottom right: a) Amazon basin, b) Congo basin, c) Xe Bang Hieng basin, d) Kapuas basin, e) Magdalena basin, f) Chao Phraya basin. Monthly AET for MODIS was calculated for each basin on the basis of the 8-day MOD16A2GF v6 data for 2018; for GLEAM E (AET), version 3.5b was used.

This is supported by very high r and high R^2 values for the DTRIE – GLEAM comparison (see Table 3-4). Whereas GLEAM estimates are higher than DTRIE between November and May, DTRIE exceeds GLEAM in the remaining months and reaches a much higher peak value (see Figure 3.11c).

The Kapuas basin scatter plots show a large amount of spatial variation within the basin for DTRIE estimates which does not appear in GLEAM (see Figure 3.10j). However, when averaged over the basin, the relationship between DTRIE and GLEAM data is very good (see Figure 3.11e). This is supported by a very high correlation coefficient (r) and moderately high coefficient of determination (R^2), indicating an overall linear relationship. The MODIS seasonal pattern is

opposite that of DTRIE and GLEAM ($r = -0.63$ and -0.23) and for most of the year, MODIS values are smaller (PBIAS = -7.4% and -13.2%).

Scatter plots of the Magdalena River basin show similar patterns to those of the Kapuas basin; more spatial variation within the basin is found in DTRIE than in GLEAM and MODIS (see Figure 3.10m-n). The line graphs in Figure 3.11e show the bimodal seasonality of DTRIE, but this is not matched by either of the other models. As the amplitudes of either model curve are small, the overall differences are also small (RMSE = 13.74 mm for GLEAM and RMSE = 20.93 mm for MODIS). The comparison with GLEAM yielded the lowest relative bias (PBIAS = 3.5%) of all basins in comparisons with DTRIE and because GLEAM seemingly has no seasonal pattern, it also correlates fairly well, but only moderately linearly with DTRIE ($r = 0.75$, but $R^2 = 0.56$).

The scatter plots for the Chao Phraya basin show a widespread underestimation by DTRIE as compared to GLEAM and MODIS, and by GLEAM when compared to MODIS (see Figure 3.10p-r). The spatial variation of AET values within the basin differs less between GLEAM and DTRIE than in other basins. The seasonal pattern of DTRIE has a larger amplitude than the other two models, but it still aligns very well in terms of peaks and troughs with GLEAM. This is underscored by very high coefficients of correlation and determination for the GLEAM comparison ($r = 0.93$ and $R^2 = 0.87$). The RMSE is 27.04 mm and the percentage bias is one of the highest (PBIAS = 37.5%) due to the different amplitudes. The correlation with MODIS estimates is moderate and positive ($r = 0.53$), but not very linear because of a slight shift in seasonality ($R^2 = 0.28$). The RMSE and percentage bias are high (RMSE = 42.41 mm, PBIAS = 56.2%).

3.5 Discussion

This section will first discuss the general spatial patterns of AET, water balance and infiltration, surface and subsurface flows and how they relate to the model structure, and then proceed to put the results into the context of published literature.

3.5.1 Spatial patterns and relationships illustrated by the baseline estimates

3.5.1.1 Actual evapotranspiration and its components

As section 3.3.1.1 illustrated, DTRIE produces high AET where rainfall input is high. This is supported by a very high correlation coefficient between AET and rainfall, as well as very high coefficient of determination of the corresponding regression line. This relationship is the strongest out of all the input variables tested for AET, followed by a moderately strong correlation with tree cover. When the evaporative index is used (calculated as $AET / \text{rainfall}$), AET maxima are more closely associated with densely forested areas at low latitudes, as shown in Figure 3.4c-e. In these areas, AET is highest per unit rainfall further underscoring the effect of tree cover.

The relationships with rainfall and tree cover affect AET first and foremost via the interception loss component, E_i . In DTRIE, E_i takes precedence over SET as it happens before water infiltrates the soil. As highlighted in Figure 3.8m & p, the correlation between rainfall and tree cover and E_i is high; this is because E_i is calculated as a fraction of rainfall. This fraction is a long-term average based on GLEAM data and thus takes into account prevailing land cover, which is reflected by the E_i relationship with tree cover. This proportionality is expected because interception requires a plant surface on which to take place and thus a pixel with higher canopy cover or leaf area index has the potential to intercept more rainfall. If the rainfall is also very high, this potential can be realised.

As E_i regulates the amount of effective rainfall its strong connection with rainfall and tree cover is carried forward into the second AET component, soil evaporation or plant transpiration (SET) (see Figure 3.8i & l). However, the strong positive correlation between E_i and tree cover weakens the effect of tree cover on SET. Whereas greater tree cover should result in greater plant transpiration, its interception potential lessens the water volume available for transpiration.

The scatter plot with net radiation shows a moderate correlation and a less linear relationship that saturates at roughly 180 W/m^2 (see Figure 3.8b). Below this threshold the variables seem more linearly related, which is in line with the general expectations given the role of net radiation in the Priestley-Taylor equation for AET (see (Eq. 3-4)). However, in the study region, net radiation is not limiting

in most pixels. This is again a consequence of using a monthly timestep because interception is event-based and in reality, would occasionally exceed radiation input. In this case, net radiation available for SET would be limited. As interception loss in DTRIE is evenly spread out over the month, net radiation is not limiting in the model. The same argument can explain the lack of correlation with mean annual temperature, which is generally very high and thus not limiting.

3.5.1.2 Water balance

Water balance has the same strong relationship with rainfall as AET, rainfall being the other of the two components of water balance. For example, Southeast Asian basins (and grid cells) show a water balance of roughly 3,000 mm/yr despite a very high AET (~1,800 mm/yr), which is due to the high rainfall input. Once water balance is divided by rainfall, the spatial pattern is, as expected, the opposite of that exhibited by the evaporative index (which is calculated as AET/P). The magnitude of water balance reflects the amount of water in a grid cell that becomes runoff at some point (that is, after some period in surface storage); it comprises both surface and subsurface runoff. The spatial pattern of water balance over rainfall then shows where the highest amount of runoff is produced per unit rainfall. The greatest ratio of water balance to rainfall is modelled for sparsely vegetated and dry areas in the Sahel zone, where little evapotranspiration takes place.

Moving towards the equator this changes as less runoff per unit rainfall is created in basins (and grid cells) of densely forested areas, which also receive large rainfall volumes. Southeast Asia is however, an exception to this because there is more runoff per unit rainfall in comparably dense forest areas. This is due to the even higher rainfall amounts in that region, most of which cannot be evaporated.

A separate issue to discuss are the extremely high values for water balance along the western coastline of Colombia and on the island of New Guinea. Here, annual water balance reaches up to 19,000 mm/yr, which is higher than gauge station recorded rainfall. The Pacific coast of Colombia has one of the highest annual rainfall totals on earth, with averages above 12,500 mm/yr.

Higher totals have been recorded at gauge stations for individual years (Poveda et al., 2014 and references therein; Poveda and Mesa, 2000). These already

extreme values are exceeded by the DTRIE water balance estimates. However, a closer look shows the annual water balance estimates do not exceed the annual sum of monthly rainfall inputs (CHELSA v.2.1 monthly rainfall climatology) used by DTRIE. For example, in Colombia the maximum water balance is 19,000 mm/yr compared to the annual total rainfall of 22,000 mm/yr (see Figure 3.12c). In New Guinea, maximum water balance estimates for isolated clusters reach up to 12,000 mm/yr (see Figure 3.5a), while the rainfall input is just above that (see Figure 3.12a). This also results in the Sungai Fly River basin having the highest overall major river basin (MRB) average of water balance at 3,118 mm/yr.

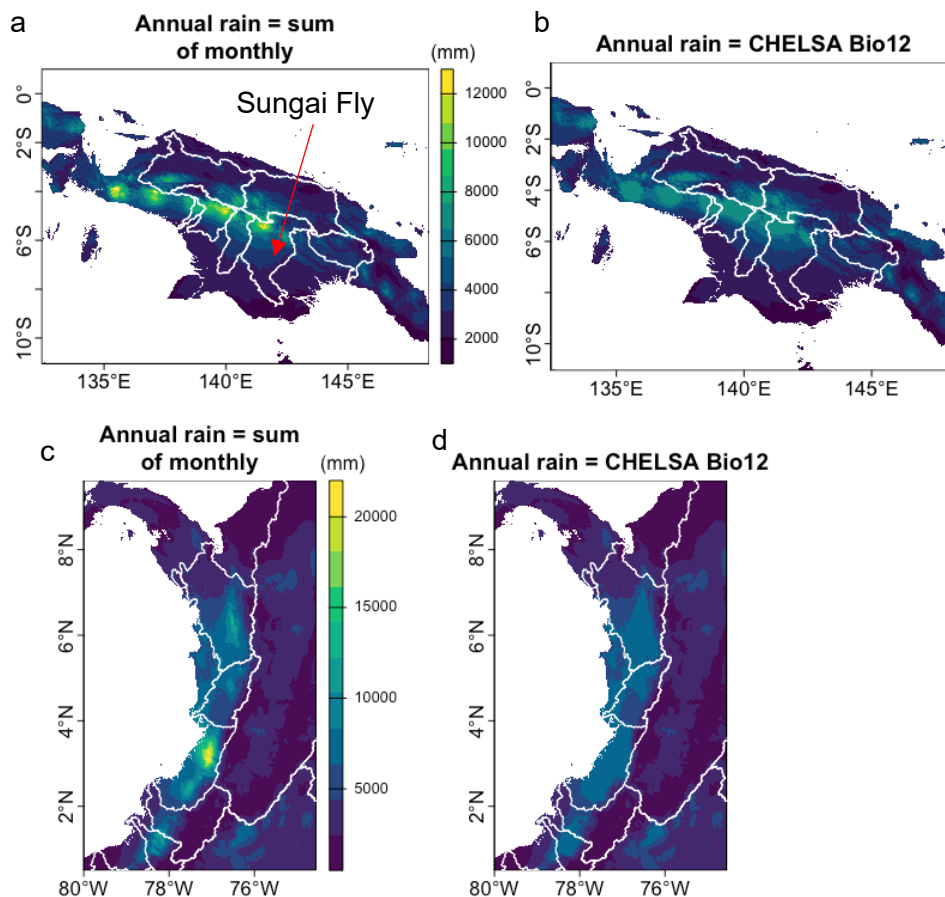


Figure 3.12 Illustration of the discrepancy between annual total rainfall summed up from monthly CHELSA variable (a, c) as opposed to CHELSA bioclimatic variable 12 (b,d). a, b: New Guinea, c, d: West coast of Colombia. Outlines in white are major river basins (GRDC MRB).

The annual total rainfall summed up from monthly rainfall amounts are likely exaggerated and also exceed the annual total rainfall from CHELSA bioclimatic variable 12 (“accumulated precipitation amount over one year”). However, while summarising the monthly rainfall to annual total clearly creates unrealistically high values, the bioclimatic variable 12 from CHELSA does not recognise the

extremely rainy regions that are documented by rain gauge records. A comparison of other precipitation climatologies and the reasoning behind choosing CHELSA is described in Appendix A.1.3.

3.5.1.3 Effective infiltration, overland and subsurface flows

Effective infiltration is defined as the effective rainfall (P_{net}) that infiltrates the soil, and which does not leave the soil again as return flows R_2 or R_3 in the same month; it is thus the part of effective rainfall that is *not* overland flow (see section 3.2.1.2, (Eq. 3-2). Effective infiltration can become SET or subsurface flow (SSF).

Across the tropics, effective infiltration is highest in the north-western Amazon region and Southeast Asia, mirroring the pattern of water balance. The strongest environmental driver is again annual rainfall, with which it has a linear relationship. Effective infiltration does correlate somewhat with tree cover, but this is due to the effect of tree cover on interception loss. Where tree cover increases, so does interception loss (see Figure 3.8p), which reduces the amount of effective rainfall P_{net} . When the ratio of effective infiltration to effective rainfall is tested for correlation with tree cover it is no longer significant, because the distribution of this ratio is highly left-skewed.

For more than half of the grid cells this ratio is 1, dipping below in some areas, such as the Amazon basin and in Southeast Asia. In these areas, where the ratio of effective infiltration to effective rainfall is high, overland flow (R_1 , R_2 & R_3) must be low as most of the rainfall reaching the ground infiltrates, and *vice versa*. Therefore, this means that in more than half of the grid cells across the tropics there is practically no overland flow according to DTRIE. Runoff takes place as lateral subsurface flow (SSF) (see Figure 3.7). As will be shown in Chapter 5 section 5.3.2.2 DTRIE estimates of streamflow, which sums up lagged SSF and overland flows, are comparable to reference values (see chapter 5, Figure 5.12), which means the DTRIE representation of runoff amounts is realistic.

The causes of very low or negligible overland flows are:

- 1) R_1 is 0 because monthly effective rainfall never exceeds the monthly infiltration capacity. The conceptualisation of the monthly infiltration capacity in DTRIE, which is not an event-based model, is already described in section 3.2.3. In brief

the effects are the following: The monthly infiltration capacity is given by K_{sat} , converted from its usual timestep (mm/s) to a monthly one (mm/month). For event-based models, where K_{sat} is typically used, rainfall could exceed the K_{sat} infiltration capacity and thus create infiltration excess overland flow. However, aggregating K_{sat} to a monthly timestep results in very high infiltration capacities; likewise monthly rainfall totals do not reflect the event-based nature of rainfall but rather a more evenly distributed one. This means that R_1 is rarely produced. This is expected behaviour since the focus of DTRIE is not storm scale infiltration dynamics but longer-term water balance and subsurface flow lags. While the lags will be overestimated by the absence of quickflow in many areas, the computational power required to develop an event-based pantropical model precludes overcoming this limitation.

2) R_2 occurs when the soil moisture storage capacity of the AW store (*plant available water store*, AW_{pot}) is exceeded. This happens when the input into the AW store (called AW_{in}) for a month is greater than the AW store capacity (AW_{pot}), either on its own, or in combination with soil moisture carried over from the previous month (see section 3.2.2, p.38 and Figure 3.3). Hence, where soils are deep or rainfall is lower, R_2 is not likely to be produced.

3) The creation of R_3 follows the same process as R_2 , except that the model does not carry over moisture in the UAW store between months. Where overland flow is produced, for example in the Amazon basin and in Southeast Asia (as highlighted in Figure 3.13) the causes of these overland flows, consisting of R_2 and R_3 , are a combination of shallower soils and higher rainfall amounts (see Figure 3.13 bottom two panels). This indicates that overland flow here is akin to the event-scale process of saturation-excess runoff.

3.5.2 Comparison of DTRIE AET to estimates from GLEAM, MODIS and published literature

3.5.2.1 Magnitude of annual AET totals

The comparison between DTRIE, GLEAM and MODIS AET values showed that on an annual scale, DTRIE AET estimates are *lower* than that of MODIS or GLEAM in most cases, and the difference is greater between MODIS and DTRIE, compared to the difference from GLEAM.

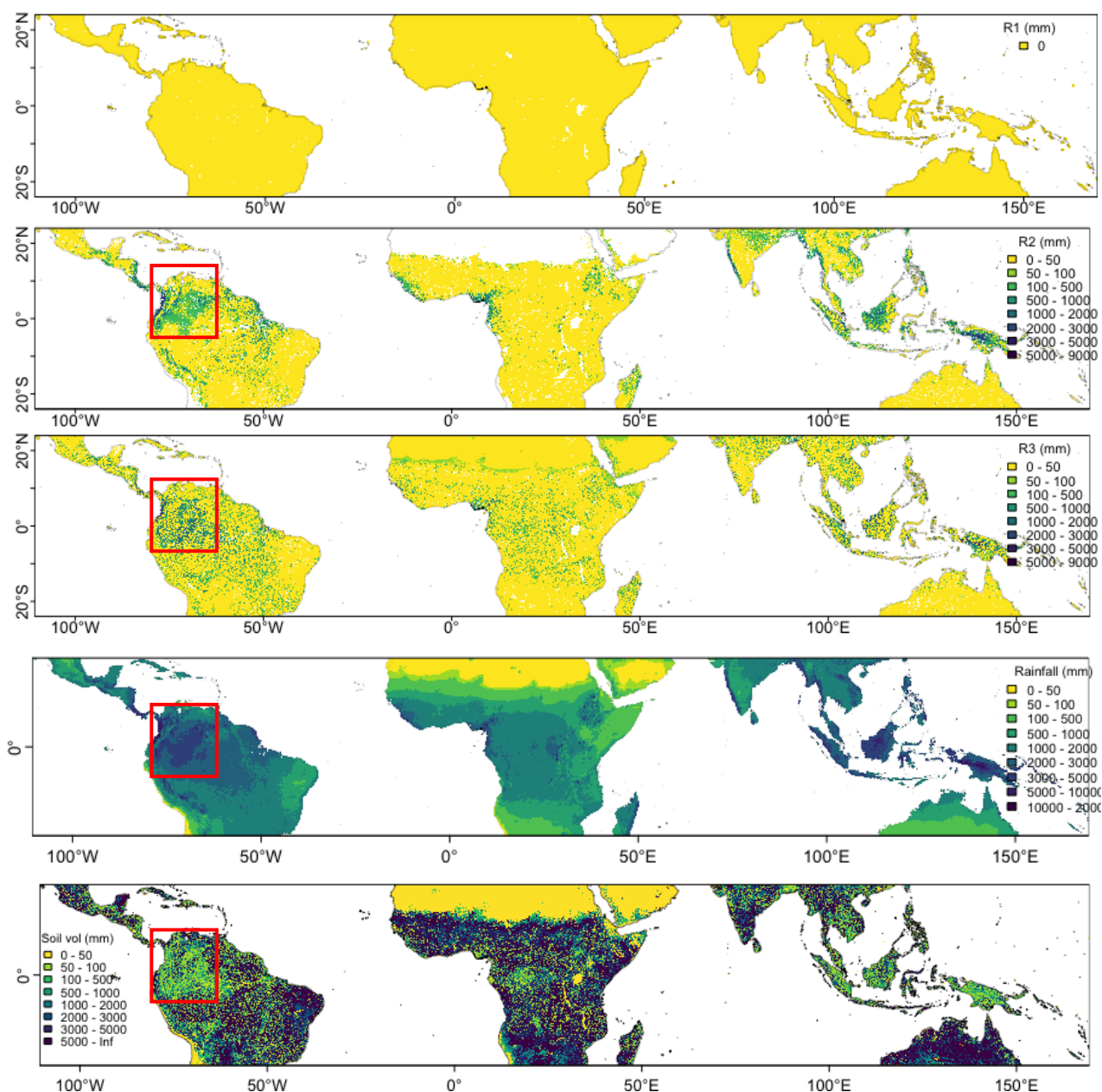


Figure 3.13 Annual total overland flows and annual rainfall input (mm). From top to bottom: R1, R2, R3, Annual total rainfall and total soil volume (mm). There is no R1, patchy R2 and slightly more randomly scattered R3. The spatial pattern in R2 corresponds with very high annual rainfall amounts of over 3,000 mm per year and low soil volumes in the range of 50 to 100 mm. One such area is highlighted with a red box.

Previous work validating the GLEAM product by the model developers (Miralles et al., 2011) indicated a strong correlation of annual AET with *in situ* eddy covariance flux tower measurements ($R = 0.80$), with a root mean square error (RMSE) value of 110 mm/yr and a bias of -5 per cent, meaning that GLEAM underestimates AET on average. They also did not detect any systematic bias for rainfall or broad vegetation type. Except for the rather high RMSE these statistics indicate very good agreement between GLEAM and *in situ* ET measurements, and the fact that DTRIE AET is lower than GLEAM would mean DTRIE is even further

from flux tower measurements. However, this GLEAM validation was conducted using flux towers outside of the tropics, which may reduce the meaningfulness of comparing DTRIE values to GLEAM in the tropics. Furthermore, validation against flux towers measurements may suffer from issues inherent with the flux tower measurements themselves. Because at the point measurement scale the energy balance may not be closed, the results from flux towers may also be biased (Masseroni, 2014; Miralles et al., 2011). A similar validation was conducted for the MOD16 AET product by Mu et al. (2011), who found a correlation between the MOD16 product and flux tower measured AET of 0.58 (note that this validation was conducted for daily estimates). This reflects only a moderate agreement with the in situ measurements (and therefore lower than between GLEAM and in situ measurements). Again, the validity of the flux tower measurements can be questioned along the same lines as for GLEAM, and therefore the disagreements between DTRIE and MOD16 may not necessarily indicate poor performance by DTRIE.

Instead, and to investigate the performance of DTRIE further, the following section outlines that annual AET estimates are generally comparable to those in published literature.

Among the six chosen for the verification analysis (Amazon, Chao Phraya, Congo, Kapuas, Magdalena, Xe Bang Hieng), the best agreements between published values and DTRIE estimates were found in the Magdalena and Xe Bang Hieng basins while the largest disagreements were in the Congo and Chao Phraya basins, while the Amazon and Kapuas basins lie in-between. For two of the basins of the Amazon and Congo Rivers, a more detailed comparison was possible due to the availability of more published literature.

In the Amazon basin, for example, the DTRIE calculated an annual total AET of 1197 mm, which is well within the range of published AET values: Across a variety of studies, annual AET totals for the Amazon basin have been estimated to be in the range of 872 to 1,905 mm/yr (Baker et al., 2021; Beighley et al., 2009; Costa and Foley, 1997; Getirana et al., 2014; Marengo, 2006). Estimates by Getirana et al. (2014), for example range from 872 to 1,190 mm/yr when they compared AET from difference land surface models, which is only slightly smaller than DTRIE AET (1197 mm). In the Congo basin, DTRIE estimates amount to

849 mm/yr, which is lower than previous estimates from water balance based approaches of $1,172 \pm 3.5$ mm/yr (Burnett et al., 2020) as well as the estimates derived from GLEAM and MODIS data (GLEAM: 1117 mm/yr, MODIS: 1152 mm/yr). In short, DTRIE AET is slightly to moderately lower than those of other global models.

As a complement to the above comparison of AET estimates, the ratio of AET to rainfall input is compared in the following section between the model and published values for 14 basins where such values were published (see Table 3-5). These are derived either from published runoff coefficients (also called *runoff ratio* or *water yield coefficient*), or *evaporative index* data and are listed in Table 3-5 (Arciniega-Esparza et al., 2022; Xiong et al., 2022; Yang et al., 2016). The runoff coefficient, RC, is the ratio of Runoff / Rainfall, while the evaporative index is the ratio of AET / Rainfall (or put differently $1 - RC$).

Table 3-5 Comparison of the ratio of annual total AET to annual total Rainfall (AET/Rainfall) for several MRBs and other basins between DTRIE and published literature ("other study"). The latter is either the ratio itself (for source 2), or calculated from the runoff coefficient, $RC = \text{Runoff} / \text{Rainfall}$, $AET / \text{Rainfall} = 1 - RC$ (for sources A & C). For Source B, column Basin gives the streamflow gauge station name. Sources: A = Xiong et al. 2022, B = Arciniega-Esparza et al. 2022, C = Yang et al. 2016.

Basin	DTRIE	Other study	Source	Basin	DTRIE	Other study	Source
Amazon	0.52	0.5-0.6	A	Guardia	0.47	0.6	B
Congo	0.53	0.7-0.8	A	Oriente	0.36	0.24	B
Fly River	0.34	0.3-0.4	A	Dos Montañas	0.39	0.31	B
Kapuas	0.33	0.3-0.4	A	Palmar	0.31	0.39	B
Magdalena	0.45	0.5-0.6	A	Terron Colorado	0.32	0.35	B
Mekong	0.48	0.6-0.7	A	Kinabatangan	0.5	0.53	C
Orinoco	0.46	0.5-0.6	A	Pahang	0.52	0.5	C

In the Congo basin, the ratio of AET to rainfall is 0.53 (i.e. 53 per cent of rainfall become AET), while Xiong et al. (2022) find a much higher one of 70 - 80 per cent (see Table 3-5). This is in accordance with the previous comparison of overall AET values. Three other basins where DTRIE derived ratios differ for more than 10 per cent were: in the Mekong, Guardia 12 to 17 per cent *less* of the rainfall becomes AET in DTRIE; and in the Oriente basin where 12 per cent *more*

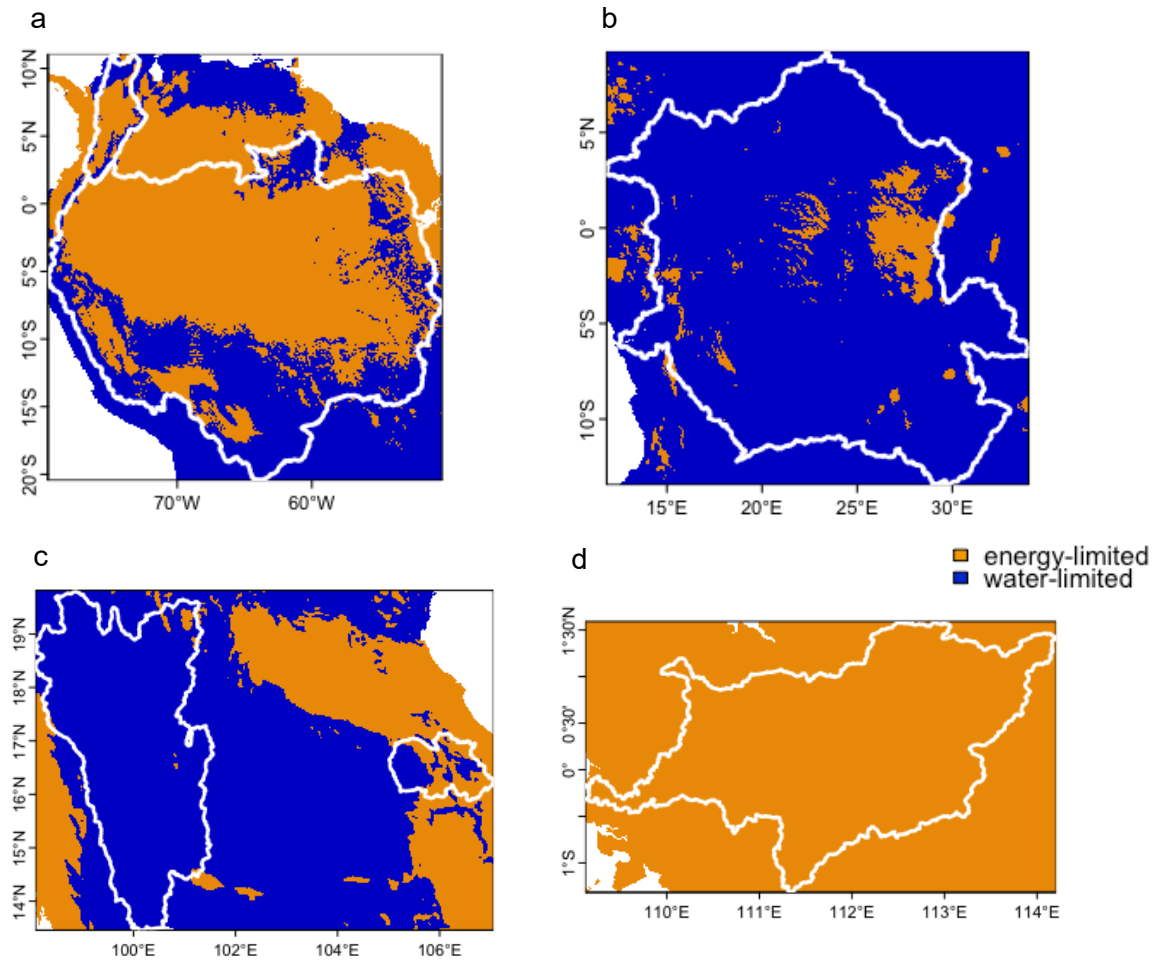


Figure 3.14 Water- and energy limitations in the six basin a) Magdalena (top) and Amazon (bottom), b) Congo, c) Chao Phraya (left) and Xe Bang Hieng (right), and d) Kapuas. Water- and energy-limited basins are defined by their annual total rainfall: below 2,000 mm = water-limited, above 2,000 mm = energy-limited following Ahlströhm et al. 2017 and Guan et al. 2015.

rainfall becomes AET. Apart from the Oriente basin, these basins are either predominantly or somewhat water-limited, i.e. have annual rainfall totals of less than 2,000 mm, which means a relatively small increase in AET can result in a large increase in AET/rainfall ratio. The separation into water- and energy-limited follows Ahlströhm et al. (2017) and Guan et al. (2015), defining basins by their annual total rainfall below 2,000 mm as *water-limited*, and *energy-limited* basins as those above this threshold (Note that in section 5.4.3.2 a different definition will be used to examine hydrological sensitivity).

Very good agreements between ratios of AET to rainfall were found in the remaining 10 of 14 examined basins. In the Amazon, DTRIE AET makes up 52 per cent of rainfall inputs, compared to shares presented by Getirana et al. (2014), which range from 45 to 49 per cent, or by Xiong et al. (2022), which range from

50-60 per cent (see Table 3-5). The remaining nine basins are Fly River (or Sungai Fly), Kapuas, Magdalena, Orinoco, Pahang, Kinabatangan, Palmar, Teron Colorado and Dos Montañas basins. These basins are all either predominantly or entirely energy-limited basins (see Figure 3.14 for a map of water- and energy-limitations in a subset of the basins), with high to very high annual rainfall totals, and evaporative indices (AET/Rainfall) are therefore less sensitive to smaller changes in AET.

3.5.2.2 Spatial patterns of AET

As demonstrated in the previous section, the basin AET estimates by DTRIE are mostly in moderate to strong agreement with AET estimates and evaporative indices from published literature. While the agreement shows some spatial variability this seems to be linked to water- and energy limitation as: in predominantly energy-limited basins, i.e. where rainfall is higher than 2000 mm/yr, DTRIE corresponds published and reference GLEAM and MODIS values better, while in more water-limited ones, there is less agreement.

Salazar-Martínez et al. (2022) have previously examined the dependence of AET products on latitude, climate zone and vegetation cover. However, they employed broader climate classes (e.g. “wet tropical climate” or “humid”, but without quantitative definitions of these terms) rather than the annual rainfall cut-off proposed by Guan et al. 2015 which is used here. Their findings show that other AET products (GLEAM among them) also vary in performance across climates. However, products showed weakest agreements with reference values in wet tropical climates, and best agreements in drier climates, which was echoed by Ruhoff et al. (2022) who investigated the question for 50 basins in South America.

These results are contrasting the results of this study, where better agreement with literature and reference values is reached in wetter, more energy-limited areas. Potential explanations for this discrepancy could be that Salazar-Martínez et al. (2022) and Ruhoff et al. 2022 group site along broader Köppen-style climate classes, which are delineated on the basis of more criteria than annual rainfall, thus including more covarying factors. More likely, however, is it a consequence of the verification method: Here, DTRIE AET is compared to AET values from a range of studies, which each cover only one to a few basins, but never a full

range of conditions spanning water- and energy-limited environments. The limited number of studies on the selected basins did furthermore not allow for an investigation into whether the broad AET methodology of the comparison study (e.g. water balance approach, modelling or in situ measurements) affects the model agreement in addition to the water limitation criterion.

3.5.2.3 Seasonal patterns of AET

Monthly DTRIE AET estimates are typically lower than those of other models. Monthly AET estimates agreed reasonably well with reference values from GLEAM v. 3.5b. Seasonality, when averaged over basins, aligns very well in Amazon with that of GLEAM, but also other reference values from other AET models such as P-LSH, and CMIP5 & CMIP 6 (see Baker et al. (2021). Furthermore, seasonality comparison with GLEAM was similarly good for the Kapuas, Chao Phraya and Magdalena basins in terms of timing of seasonal peaks and troughs as well as their magnitude. Seasonality is similar to GLEAM in the Congo basin, but here, DTRIE estimates are lower by almost a third. However, in addition to the GLEAM reference results, the bimodal seasonality of AET in the Congo basin is also supported by other studies, such as Crowhurst et al. (2021) and Burnett et al. (2020) (see the authors' Figures 1b for the former and Figure 3 for the latter in the respective publications).

The comparison with MODIS (MOD16A2GF, v.6, or MOD16 for short) data yields a different result. While in the Congo and Chao Phraya basins, seasonality agrees between MODIS and DTRIE, MODIS showed an opposing seasonal pattern to DTRIE in the Amazon, Kapuas and Magdalena and the Xe Bang Hieng basins. In the Magdalena and Xe Bang Hieng basins, seasonality differs in modality as well, that is, it is bimodal in MODIS as opposed to unimodal in DTRIE in the Xe Bang Hieng, and unimodal in MODIS while bimodal in DTRIE in the Magdalena basin. These differences in seasonality are also found in general between MODIS and GLEAM both in this study, but also wider literature, where the MODIS-GLEAM seasonality discrepancy is also well documented (Hu and Mo, 2022; Sheffield et al., 2018).

Sheffield et al.'s (2018) work highlights the large differences in timing and amplitude of AET seasonality between the various published and commonly used AET

models and datasets. Therefore, it is perhaps sufficient to compare the range of monthly AET values estimated by DTRIE to that of other studies.

For the Amazon basin, for example, they compare GLEAM AET (called *E* in by Miralles et al. 2011, but equivalent to AET here) to estimates from a range of other models, both PM and PT-algorithm based. In their study, the seasonal pattern of GLEAM AET corresponds well with that of DTRIE (and the GLEAM verification data used in Sheffield et al. itself), as does the DTRIE minimum and maximum monthly AET, which are 70 and 130 mm, compared to Sheffield et al.'s (2018) largest range for AET of 90 to 140 mm/month. This also compares well to other published results, e.g. from Baker et al. (2021), whose estimates range from 60 to 120 mm/month, derived using a catchment water balance approach. While this range is slightly lower than that modelled by DTRIE, Ruhoff et al. (2022) can be consulted for support of why water balance approaches yield lower estimates. Their study compared AET from global models (GLEAM, MODIS MOD16 and others) to a water balance derived AET for several South American basins, including sub-basins of the Amazon. They found that the evaluated AET model outputs slightly overestimate AET compared to water balance derived AET in more humid regions such as the Amazon basin, while agreement between model and water balance outputs was found in drier areas. Overall, the range of values for monthly AET modelled for the Amazon basin fits well into the published literature.

In the Congo basin, the range of monthly AET is similar to published literature, but overall minimum and maximum monthly AET are slightly lower. DTRIE minimum and maximum monthly AET are 50 and 100 mm/month, while Crowhurst et al. (2021) find a range of 66 to 120mm/month (ERA5-Land) and 81 to 132 mm/month (MERRA-2), depending on the model used. Burnett et al. (2020) estimate a low of 60 mm and high of 160 mm/month, using a water balance approach with a triple collocated rainfall input. Although the referenced minima and maxima are overall higher than those of DTRIE, the ranges are comparable in absolute terms.

In the Chao Phraya basin, DTRIE monthly AET ranges from 25 to 100 mm/month while Abishek et al. (2022) presented results of 50 to 110 mm/month for GLEAM and MERRA.

All in all, while monthly DTRIE AET estimates are typically lower than those of GLEAM, MODIS and other literature, the seasonality of the majority of basins agrees well, either in both timing and magnitude of highs and lows (especially for the comparison with GLEAM), or well in terms of magnitude and acceptably regarding the timing.

3.5.2.4 *Differences explained by model input data*

Differences between DTRIE and the MODIS product (MOD16A2GF v.6) can be explained largely by the model equations and components, as the MODIS algorithm does not use precipitation data and calculates wet canopy evaporation via relative humidity rather than explicitly via interception. MOD16 has previously been found to underestimate AET in wet seasons (Salazar-Martínez et al., 2022), which further points toward the importance of a rainfall input.

While in the Amazon, Xe Bang Hieng and Kapuas basin examples, peak and trough are reversed between DTRIE / GLEAM as compared to MODIS (see Figure 3.11), this can be explained as an effect of including rainfall and is visualised in Figure 3.15. The dip in DTRIE AET, for example in the month of August in the Amazon basin (Figure 3.11) matches a decrease in monthly rainfall (Figure 3.15a); the AET peak in August in the Xe Bang Hieng basin coincides with a clear rainfall peak, while MODIS AET does not follow the rainfall pattern at all and exhibits two AET peaks; lastly, the slightly bimodal seasonality in AET in the Kapuas basin with peaks around March and December is visible in the rainfall input as well, while MODIS AET has a single high point around July.

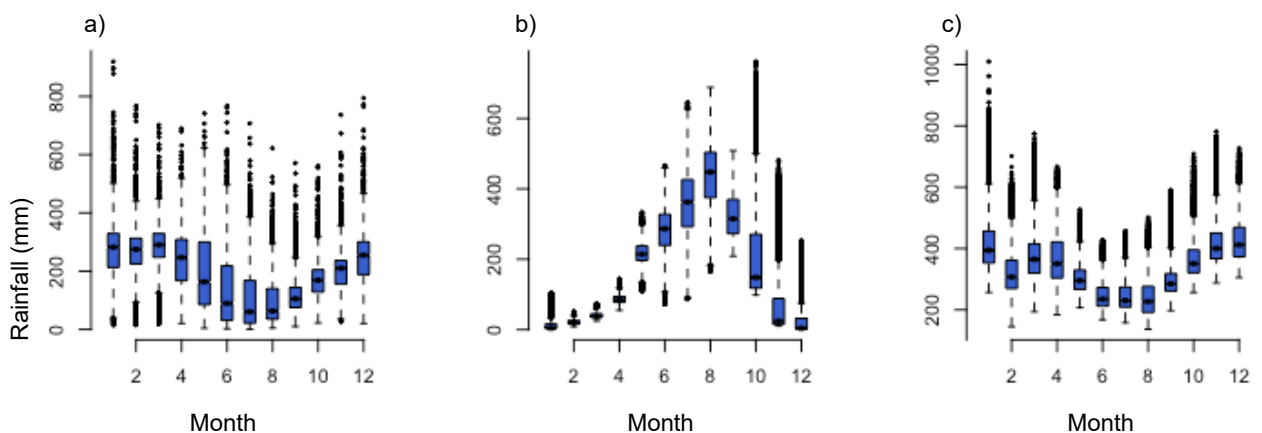


Figure 3.15 Monthly rainfall climatology (mm) from CHELSA v.2.1 for a) Amazon, b) Xe Bang Hieng and c) Kapuas basins.

Differences between DTRIE and models using a rainfall input, such as GLEAM, are in large parts based on differences between these rainfall inputs. GLEAM is created on a daily timestep and uses real time data, however, DTRIE runs with climatological average data (since the focus of the research is the effect of land cover, not meteorological inputs). Therefore, instead of the original high temporal resolution inputs for rainfall that GLEAM uses (MSWEP v2.8), DTRIE uses a rainfall climatology from the Climatologies at High resolution for the Earth Land Surface Areas (CHELSA) database which spans 34 years. The comparison with GLEAM was done with a climatological mean or the respective GLEAM components of AET in order to reduce the effect of specific meteorological patterns or events. However, even the comparison with reference values based on climatological inputs can be underwhelming because the globally available climatologies vary greatly in their spatial resolution and range of values.

Climatological averaging was not possible for comparisons with reference values from other studies, which mostly present minimum and maximum monthly AET for specific time periods. These reference values are thus likely to capture specific meteorological patterns or events which have been smoothed out in DTRIE through the use of climatologies. Both discrepancies can propagate easily through the DTRIE model as the relationship between AET and rainfall is highly linear (see Figure 3.8a).

3.6 Conclusion

This chapter introduced a new spatially explicit physically-based hydrological model, DTRIE (*Distributed TRade-off in Infiltration and Evapotranspiration*), to determine the effects of gradual tree cover extent growth on water quantity and regulation, using freely available remote sensing products.

Model estimates for actual evapotranspiration (AET) aligned well with reference values from published literature as well as other remote sensing based datasets such as GLEAM, but DTRIE values are typically lower. MODIS MOD16 data frequently had a different seasonality to DTRIE. This discrepancy is due to the integration of rainfall data in DTRIE, which is not a part of the MOD16 algorithm. This has also been documented for the comparison of MOD16 and the GLEAM algorithms, from which DTRIE is derived.

Key conclusions from this chapter regarding the spatial patterns and environmental drivers of output variables are:

- 1) Among the meteorological inputs in the model, the dominant driver for AET and thus water balance is rainfall. Mean annual temperature is not significantly correlated with any of the output variables. The relationship with net radiation is not linear; below 180 W/m^2 , an increase in net radiation does lead to a higher AET, but above, the relationship saturates: AET (and water balance) show a much higher variability when mean annual net radiation is above 180 W/m^2 .
- 2) Interception loss (E_i) is most strongly correlated to annual rainfall, and secondly to tree cover and both of these relationships are fairly linear. Net radiation and mean annual temperature do not have a linear relationship with interception loss. While SET correlates highly with rainfall as well, the correlation between tree cover and SET is only moderate. This follows from the two opposing effects of tree cover: Tree cover is obviously what conducts transpiration, but at the same time, it reduces the amount of effective rainfall through interception loss, thus reducing the input of water available for plant transpiration.
- 3) After the effect of rainfall is accounted for, the relationship between AET and tree cover showed better that AET is high where tree cover is high; this pattern is mostly due to the increase interception loss (E_i) rather than plant transpiration (SET).
- 4) The share of effective infiltration (infiltration that does not immediately become runoff again) per unit of effective rainfall was close to 100 per cent across the tropics, leading to very low overland flow modelled by DTRIE. Areas where overland flow occurred have high rainfall and shallow soils, and it was shown that these overland flows are conceptually akin to saturation-excess runoff. Infiltration excess, as expected, does not occur in DTRIE since it is a monthly model. As such it focuses on monthly water balance and lags in water balance rather than infiltration/ runoff dynamics at the storm scale.
- 5) Subsurface flows, or throughflows, are the dominant runoff component in the model results across the tropics, except for the arid desert landscapes of the Sahara and Atacama deserts, where there is neither surface nor subsurface flow.

Chapter 4 Development and application of a tree cover growth scenario and spatially explicit growth model

4.1 Introduction

The model presented in this chapter first identifies potential areas of opportunity for tree cover growth under a realistic biophysical and socio-economic scenario. It then calculates tree cover over multiple decades in an effort to better represent the decades-long process of tree growth and the implications thereof on environmental services and decision-making. This chapter will therefore address **re-search objective 2**.

In the first part of this chapter, biophysical limitations to tree growth are combined with socio-economic constraints to determine “*areas of opportunity*” for tree cover increase in the tropical forest ecosystems. In the second part of the chapter, the model uses a growth rate derived from remotely sensed net primary productivity (NPP) to increase tree cover in these areas over 25 to 150 years starting from the reference year 2018. The result of this process is a set of scenario tree cover fractions. Lastly, scenario herbaceous and bare cover fractions are calculated by splitting the remaining non-tree cover fraction at each timestep according to the reference year ratio of herbaceous to bare cover.

4.1.1 Definition of the term tree cover growth

This study examines the effects of tree cover growth and is thus situated in the wider research landscape of reforestation, forest regeneration and forest re-growth, which is described in detail in Chapter 2 section 2.1.2. The term used here, *tree cover growth*, was defined as the increase in tree cover area that can take place on already forested land or on land with the natural potential for tree cover, whether through active or passive approaches.

4.1.2 Revisiting published forest growth scenarios

Two of the most widely used maps of reforestation and afforestation opportunities were produced by Zomer et al., and the World Resources Institute (henceforth *WRI map*) (Laestadius et al., 2011; Potapov et al., 2011; Zomer et al., 2008). Both maps use environmental and socio-economic criteria to delineate areas for

change, but at their core use forest cover data that makes them unsuitable for this study. Firstly, both maps are built with forest cover data from the early 2000s (the widely used dataset by Hansen et al., 2003), which reflect forest extent well over two decades in the past; secondly, both extrapolate from forest areas in the recent historical record, meaning they exclude areas from their reforestation opportunity maps where forest conversion took place before the remote sensing record began.

A more recent range of publications have modelled the potential extent of forest or tree cover (Bastin et al., 2019; Brancalion et al., 2019; Griscom et al., 2017; Lewis et al., 2019), however, their methodologies make these models similarly unsuitable for this study. Bastin et al.'s map, for example, was criticised for its inclusion of savannas and grasslands as areas suitable for tree restoration (Bond, 2016; Bond et al., 2019). It was argued by Veldman et al. (2019) that not only are savanna and grassland ecosystems valuable systems in their own right, but they are also shaped and maintained by fire and herbivory, rather than only human land use change. In another response to the Bastin paper, Delzeit and colleagues argue that a large proportion of the global grasslands area is used for extensive livestock production, highlighting their socio-economic importance (Delzeit et al., 2019). These processes and land uses compete with the increase in tree cover and have the potential to limit the persistence of tree cover restoration efforts. The increase of tree cover in savanna and grassland areas was therefore deliberately excluded in the scenario presented in this chapter.

The “Global Reforestation Potential Map” produced by Griscom et al. (2017) does exclude grasslands to avoid negative impacts on biodiversity, but as it is a reforestation map it excludes areas where there is potential for tree cover without recent historical records, as well as where tree cover exists but could still be increased. Furthermore, it is based on the WRI map, and thus on restoration potential derived from early 2000s forest cover extents, which are unlikely to still be accurate, and the map generally inherits the limitations of this map.

Lastly, the map of Brancalion and colleagues (2019) of tropical lowland rainforest restoration opportunities is unsuitable because it is limited to lowland forests, and through its forest cover inputs excludes large swathes of important forest areas such as the Amazon and Congo basins. In their map, these areas are excluded

because they are classified as over 90 per cent forested (in 2016) according to the input dataset (Hansen et al., 2013). The same areas, however, have less than 80 per cent tree cover according to the MOD44B tree cover data in the reference year used in this study, 2018 (which was calculated as mean over 2017 to 2019 to eliminate spurious values).

Building on the robust methodologies employed by Zomer et al. (2008), Laestadius et al. (2011) and Zeng et al. (2020), this chapter creates an updated map of *tree cover growth* potential for the year 2018, based on the following datasets: 1) the MODIS tree cover product for 2018, 2) a spatial dataset on compounded human impacts (Kennedy et al., 2019; Theobald et al., 2021), 3) a map of potential natural biome extent (Hengl et al., 2018) and 4) up-to-date land cover information (ESA CCI & Copernicus land cover).

4.1.3 Revisiting published forest regrowth models

Many research articles on regrowth, restoration and regeneration are limited to modelling the extent of potential forest cover, developing a tree cover regeneration or reforestation scenario and essentially populating it with a fully grown, mature forest stand. Such models are typically part of carbon sequestration and storage models (Bastin et al., 2019; Brancalion et al., 2019; Hoek van Dijke et al., 2022; Strassburg et al., 2020; Zeng et al., 2020). These models have no need to calculate tree cover at different time steps over the course of regrowth because their purpose is the estimation of end point carbon stocks.

For water management on the other hand, it is interesting to calculate hydrological outcomes at multiple time steps, i.e. for different tree cover fractions, because the effects on water yield and water regulation are not unidirectional over time. Rather, studies have identified hydrologically relevant tree cover thresholds; Bosch and Hewlett (1982), for example, found that there is minimum threshold for tree cover changes to have any effect on water yield at all, and Ilstedt et al. (2016) identified an optimum, intermediate tree cover threshold for such effects. Additionally, when the water yield outcome is measured as channel runoff, the effects of tree cover change are integrated over all grid cells in a watershed, not just channel cells. Unless tree cover increase is restricted to bare or herbaceous land (as opposed to already, but not fully forested land) the modelled tree cover

varies across the watershed, and grid cells may reach hydrologically relevant tree cover thresholds at different times.

Therefore, this chapter presents a new model which considers tree cover growth as a long-term process and produces raster outputs of fractional vegetation (tree, bare and herbaceous) cover at several time steps from 25 to 150 years. These cover fractions can then be used in the DTRIE hydrological model to investigate the hydrological effects of tree cover growth at the chosen time steps.

4.2 Methodology

4.2.1 A new tree cover growth map for 2018 constrained by up-to-date environmental and socio-economic spatial data

This section outlines the criteria and input data used to create the map of “areas of opportunity” for tree cover growth for the year 2018 in the tropics.

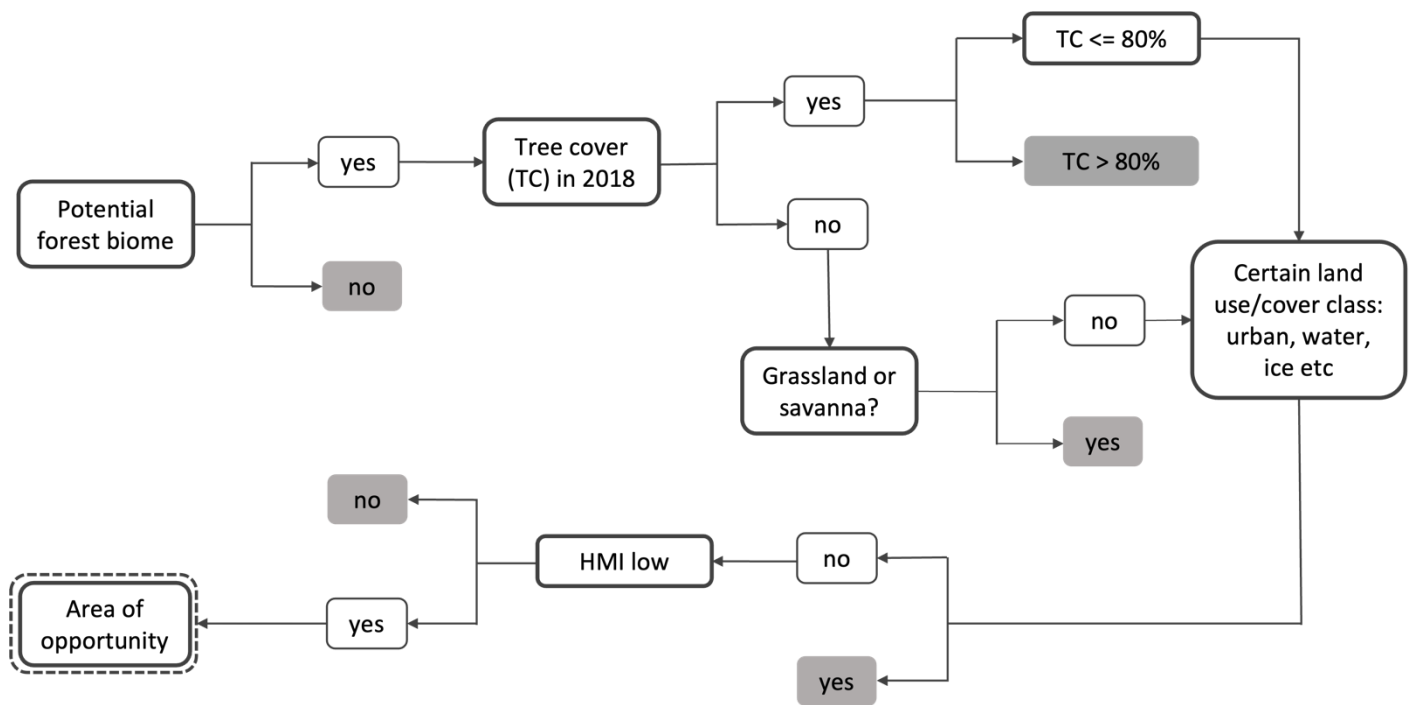


Figure 4.1 Decision tree for the identification of tree growth areas of opportunity on the basis of biophysical and socio-economic constraints; TC = tree cover in 2018 (MOD44B); HMI = human modification index. A solid grey box means the pixel is excluded from the area of opportunity map. For details on the datasets and their references see Table 2.

4.2.1.1 Biophysical constraints of the tree growth scenario

The basis for the tree growth scenario is the map of potential natural extent of different vegetation biomes modelled by Hengl and colleagues (2018) (hereafter

Hengl map) using the pollen record, tree observation data and an extensive set of biophysical drivers describing land, atmospheric, climate, topographical and soil conditions. The forest-type biomes of this map make up the initial pool of areas of opportunity and are listed in Table 4-1.

Additionally, pixels have to fulfil the following requirements: 1) have a tree cover of 80 per cent or less in the reference; 2) not be classified as a grassland or savanna (see section 4.1.2 for the reason to exclude); 3) and not be classified as one of the following land cover classes which are unsuitable to support dense tree cover: lichens and mosses; tree or herbaceous cover that is flooded (fresh, brackish or saline water); permanent snow and ice; ocean or inland water bodies. Flooded vegetation covers are excluded because impacts of tree cover growth in these habitats relate to coastal inundation, which is beyond the scope of this research. These requirements are evaluated on the basis of the MOD44B tree cover product for 2018 (infilled with Copernicus LC100 Tree cover fraction) for the tree cover threshold (1), the World Grassland Types dataset by Dixon et al. (2014) (2) as well as the ESA and Copernicus land cover maps of 2018 and the HydroLAKES and HydroRIVERS datasets for the remaining land cover classes that are excluded (3). Full dataset and variable names, references, version numbers and other metadata can be found in Table 4-2.

Table 4-1 Forest-type biomes in the Hengl et al. map

Forest biome name	Presence in tropics
Tropical evergreen broadleaf forest	yes
Tropical semi-evergreen broadleaf forest	yes
Tropical deciduous broadleaf forest and woodland	yes
Warm-temperate evergreen and mixed forest	yes
Cool evergreen needleleaf forest	yes
Cool mixed forest	yes
Temperate deciduous broadleaf forest	yes
Cold evergreen needleleaf forest	yes
Cold deciduous forest	no
Cool-temperate rainforest	no

Regarding reference year tree cover (requirement 1), two more specifications need to be mentioned. Firstly, the model never decreases tree cover. If a grid cell has tree cover in the reference year but does not have a forest-type biome associated with it in the Hengl map (as listed in Table 4-1), it will simply retain the reference year tree cover. Secondly, because the upper tree cover limit for growth is set to 80 per cent, the regrowth model applies to both currently, but less densely forested areas as well as those with a potential forest biome but currently no tree cover. The threshold of 80 per cent was chosen to include grid cells that have essentially full tree cover, but small gaps exist due to tree fall, rock outcrops or other small disturbances (see Brancalion et al. 2019 for a similar approach). Moreover, such areas may also be able to increase in fractional cover through the CO₂ fertilisation effect, which posits that a rise in atmospheric carbon dioxide will lead to increased carbon accumulation (Solomon and Cramer, 1993) with higher rates of photosynthesis, gap-filling and lower tree longevity (Bugmann and Bigler, 2011).

Conversely, areas with tree covers in excess of 80 per cent, for example in tropical dense forests, may be underestimated to begin with as a consequence of the saturation effect (Sexton et al., 2013). This effect means that MODIS VCF tree cover (and other, for example Landsat-derived products), cannot accurately resolve dense tree cover above 80 per cent due to this effect, which occurs when the reflectance input exceeds the sensor's dynamic range. Therefore, it is possible that a grid cell with a reference year tree cover close to the threshold is eligible for tree cover growth although it is effectively already fully covered.

Because of the contributions of the former type of tree cover growth (i.e. through gap-filling or CO₂ fertilisation), however, the threshold was not reduced below 80 per cent. In support of this decision, the effect of tree cover thresholds 80 and 70 per cent is briefly examined in section 4.3.2.4 and in Chapter 5 section 5.3.3.1 using water balance changes from the baseline to the scenario. A comparison of upper thresholds 60, 70 and 80 per cent for the tree cover criterion is shown in Figure 4.2. The 60 and 70 per cent thresholds show little difference in the number of pixels they would include in the area of opportunity, while 70 compared to 80 per cent would exclude large areas of dense tropical forests, for example in the Congo and Amazon River basins.

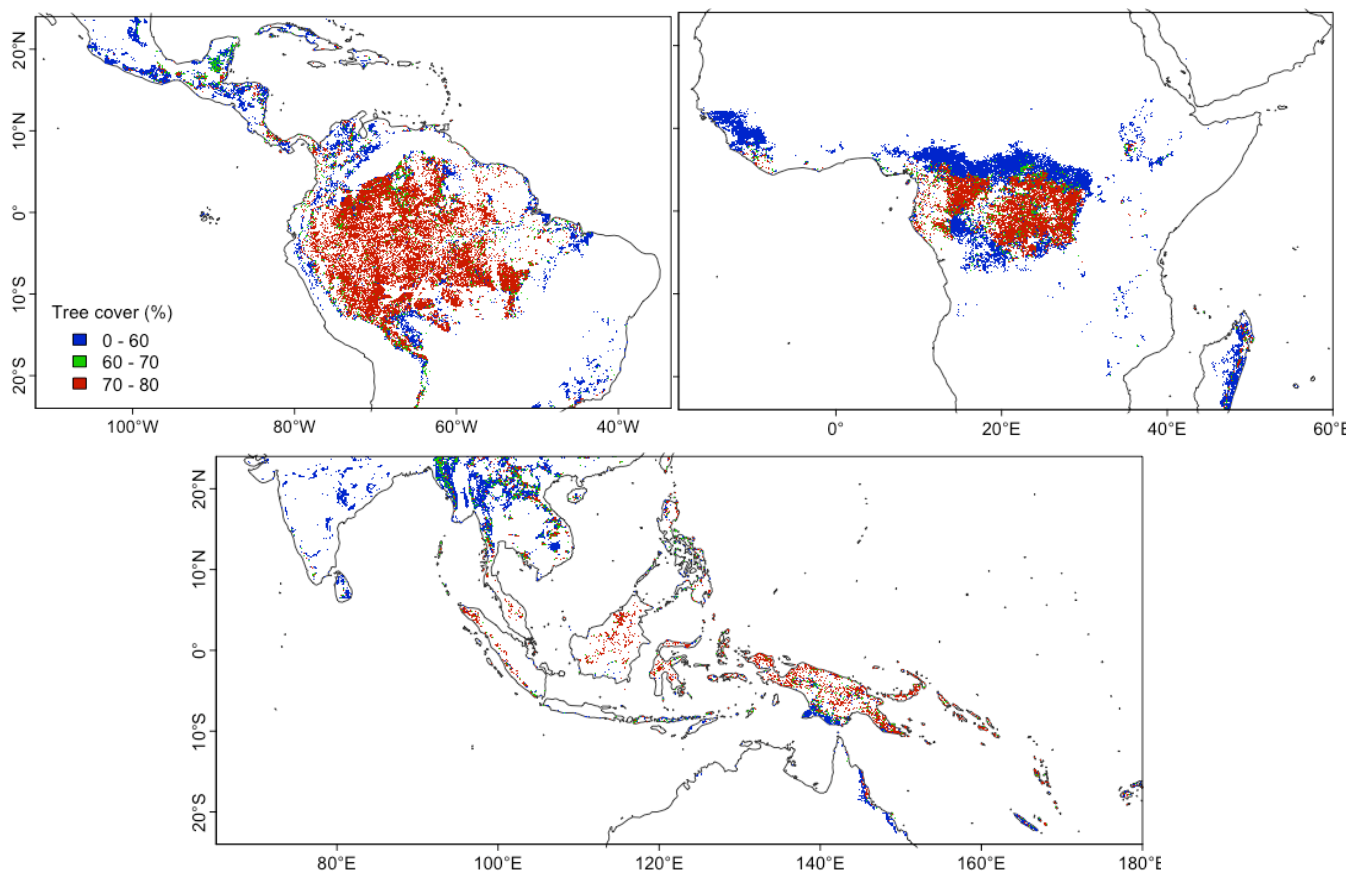


Figure 4.2 Comparison of the three different thresholds for reference year tree cover, 60 (only blue pixels), 70 (blue and green pixels) and 80 per cent (blue, green and red pixels). The 60 and 70 per cent threshold show little difference in the number of pixels, while 70 per cent threshold excludes large areas of dense tropical forests when compared to the 80 per cent threshold. Source: MOD44B fractional tree cover for 2018, gap-filled with Copernicus fractional tree cover for the same year.

4.2.1.2 Socio-economic constraints of the tree growth scenario

The socio-economic constraints to tree regrowth are captured first from the ESA and Copernicus discrete land cover products used to exclude urban areas and irrigated croplands; and second, from the map of human modification (henceforth *HMI*) compiled by Kennedy et al. (2019) and expanded upon by Theobald et al. (2021). Areas with an *HMI* classified by the authors as moderate to very high (i.e. $HMI > 0.1$) in the map for 2015 are excluded from the areas of opportunity.

Irrigated croplands are excluded because irrigation is assumed to reflect some degree of financial investment in the construction and upkeep of infrastructure. It is assumed that any restoration or passive tree cover growth would contrast with local interest, and ultimately not persist in such areas. The same argument applies to areas with a “moderate” or higher *HMI*: the stressors used to calculate the human modification index also represent a degree of financial investment (e.g. population density), or the increased opportunity for competing land uses

(e.g. road networks that can facilitate deforestation). As such, these two criteria represent the opportunity cost of tree cover increase.

The reason to exclude areas with an HMI other than “low” is purposefully restrictive. According to UN demographic data and projections the largest population growth currently does and will continue to take place in tropical regions throughout the remainder of the century (UNDESA, 2021). Even now, 30 per cent of the population in tropical countries are highly depended on natural areas (Fedele et al., 2021). The restrictive HMI criterion is therefore enforced to pre-empt potential conflicting land uses that can arise from such demographic changes. Detailed metadata for the datasets used as socio-economic constraints can be found in Table 4-2.

4.2.1.3 Choice of input datasets

In addition to their more current temporal coverage, the datasets were chosen because the MODIS tree cover product MOD44B is a well-established ready-to-use data product of sufficient spatial resolution and coverage for the reference year 2018. The decision to use MODIS rests on the following arguments: first, MODIS data has a daily revisit time as opposed to Landsat’s 16 days which increases the chance of cloud-free imagery (a common obstacle to forest remote sensing in the tropics) (Filipponi et al., 2018). Second, another product from the MODIS family, net primary productivity (MOD17), is used for the tree cover growth model and thus the choice of MOD44B as tree cover product limits the introduction of additional methodological assumptions and limitations. Thirdly, while the high spatial resolution of Landsat data of 30m is commensurate with the Hansen study’s objective to measure forest *change* (Hansen et al., 2013, 2003), it does not provide any advantages over the 250 m resolution MODIS product, because the product is used as a *static* reference, tree cover is at 1000 m resolution.

The human modification index developed by Kennedy et al. (2019) reflects multiple facets of human impact. It combines spatial information about a set of indications of human presence and modification, such as: human settlements, agriculture, transportation, energy, and mining infrastructure. It was chosen due to its comprehensive list of human stressors.

Table 4-2 Input datasets and variable names, references and other metadata for the datasets used in the tree cover growth scenario and growth model.

Purpose	Variable name	Dataset name	Version	Temporal coverage	Resolution	Reference
Biophysical constraint	Potential natural vegetation	Potential distribution of biomes (Potential Natural Vegetation) at 250m spatial resolution	0.2	NA	250 m	Hengl et al. (2018)
Biophysical constraint	Tree, herbaceous (non-tree vegetation) and bare (non-vegetated) cover fractions	MOD44B MODIS/Terra Vegetation Continuous Fields Yearly L3	6	2017-2019	250 m	DiMiceli et al. (2015)
Biophysical constraint	Inland water bodies and rivers	HydroRIVERS, HydroLAKES	1	NA	NA	Lehner et al. (2013); Messenger et al. (2016)
Biophysical & socio-economic constraint	Land cover classification & tree cover fraction for 2018	Copernicus Global Land Service: Land Cover 100m: collection 3	3.0.1	2018	100 m	Buchhorn et al. (2020b)
Biophysical & socio-economic constraint	Land cover classification for 2018	ESA CCI Land cover time-series - Climate Research Data Package (CRDP)	2.1.1	2018	300 m	ESA Climate Change Initiative (2017)
Socio-economic constraints	Grasslands and savanna systems	World Grassland Types	NA	NA	NA	Dixon et al. (2014)
Socio-economic constraints	Human modification index for 2015	Data for detailed temporal mapping of global human modification from 1990 to 2017	1.3	2015	300 m	Theobald et al. (2021); Kennedy et al. (2019)
Carbon accumulation rate	Net primary productivity	MOD17A3HGF MODIS/Terra Net Primary Productivity Yearly L4	6	2000-2020	500 m	Running and Zhao (2019)
Carbon accumulation rate	Aboveground biomass for 2018	ESA Biomass Climate Change Initiative: Global datasets of forest aboveground biomass for the years 2010, 2017 and 2018	3	2018	100 m	Santoro and Cartus (2021)
Real-term growth rate	Leaf area index (LAI) climatology	Global Monthly Mean Leaf Area Index Climatology	1	1981-2015	0.25 °	Mao and Yan (2019a)

Lastly, instead of the Olson biome map at the core of many of the aforementioned studies (Olson et al., 2001), this study uses the map of potential natural biome map by Hengl and colleagues. This map is a product of machine learning using a range of spatial data on climatic, topographical, soil and other variables together with pollen records. This allows the model to extend the potential extent of biomes beyond what is historically documented (e.g. via the remote sensing imagery record) and potentially makes it easier to adjust it to future climate conditions. For current climates, the difference in which areas qualify as an area of opportunity are negligible. A comparison of these datasets is presented in Appendix A2.3.

4.2.2 Building a data-driven tree growth model

As laid out in section 4.1.3 of this chapter the objective of this study, to investigate the hydrological effects of tree cover growth, requires the creation of a model which considers tree cover growth as a long-term process and produces raster outputs of fractional vegetation (tree, bare and herbaceous) cover at several time steps from 25 to 150 years. In the following, the methodology of the tree cover growth model is described, detailing the five steps essential to the model (see Figure 4.3 for a process diagram), and the relevant input data and associated assumptions (see Table 4-2).



Figure 4.3 Process diagram of the tree growth model

Step 1: Calculation & application of a pixel-based carbon growth rate

An annual carbon accumulation rate is derived from MODIS NPP products (Net primary productivity, MOD17A3HGF) from 2000 to 2020 as follows: using all pixels with a “low” human modification index to focus on “natural” NPP, the 20-year mean annual NPP (NPP_{total}) is calculated, aggregated to 0.00833° (equivalent of ~ 1 km at the equator) resolution and then converted from total above- & below-ground to aboveground only NPP (NPP_{AB}) with a root-shoot-ratio, r_{RS} , as

$$NPP_{AB} = \frac{NPP_{total}}{1 + r_{RS}}$$

(Eq. 4-1)

where NPP_{AB} is the annual mean aboveground net primary productivity in $Mg\ C/km^2$, NPP_{total} is the annual mean above- & belowground net primary productivity and r_{RS} is the root-shoot-ratio ($r_{RS} = 0.6$) (see Table 4-3 for description and references for all conversion factors).

A carbon accumulation rate, gr_C is then defined as 1) $gr_C = NPP_{AB}$ if tree cover growth adds to the reference year cover (i.e. $TC_{2018} > 0$), or else 2) as the mean of NPP_{AB} over the climate classes. The latter process involves excluding all pixels with a tree cover of less than 70 per cent and then averaging NPP_{AB} over a set of climate classes combining spatial information from climatological mean annual temperature and annual total rainfall.

This carbon accumulation rate gr_C is then applied to all pixels in the “area of opportunity” map to “grow” carbon so that for pixel x , over k years of growth the amount C_{ACCUM} is calculated as follows:

$$C_{ACCUM} = k \cdot gr_C$$

(Eq. 4-2)

Step 2: Convert carbon to preliminary cover equivalent

Next, the carbon accumulated in step 1 is converted to a preliminary tree cover equivalent with the help of conversion rate r_{CTC} calculated from reference year MODIS tree cover fraction (MOD44B) and ESA biomass data. Since ESA biomass data is given as aboveground woody biomass (AGB_{WOOD}) it is converted to total aboveground (i.e. woody plus canopy) carbon (AGC) to correspond with the carbon growth rate using ratios of woody-to-total biomass and biomass-to-carbon (Anderson-Teixeira et al., 2016; IPCC, 2006).

$$AGB = \frac{AGB_{WOOD}}{r_{WT}}$$

(Eq. 4-3)

$$AGC = AGB \cdot r_{CB}$$

(Eq. 4-4)

Where AGB is the aboveground biomass, AGB_{WOOD} is the aboveground woody

biomass, AGC is the aboveground carbon, r_{WT} is the woody-to-total ratio ($r_{WT} = 0.96$), and r_{CB} is the carbon-to-biomass ratio ($r_{CB} = 0.47$).

A lower limit for aboveground carbon values of 1 Mg C/km² is applied.

The conversion rate r_{CTC} (“carbon-to-tree cover”) is thus calculated as follows:

$$r_{CTC} = \frac{AGC}{TC_{2018}} \quad (Eq. 4-5)$$

where AGC is the aboveground carbon and TC_{2018} is the percentage tree cover of the reference year (which equals 100 * MODIS tree cover fraction).

Both TC_{2018} and AGC data are filtered to ensure only pixels with “low” human modification index are used to preclude conversion rates that are more typical of less natural vegetation, such as urban green spaces, gardens, or plantations. Values of r_{CTC} above the 95th percentile are excluded to reduce the influence of extreme values.

The accumulated aboveground carbon C_{ACCUM} is then converted to preliminary tree cover equivalent TC_{PE} (in %) as follows:

$$TC_{PE} = \frac{C_{ACCUM} \cdot (1 - r_{WC})}{r_{CTC}} \quad (Eq. 4-6)$$

where r_{WC} is the woody-to-canopy ratio ($r_{WC} = 0.5$).

As with the carbon accumulation rate, a climate class average conversion rate based on “high tree cover” (reference year cover > 70 per cent) pixels is applied in new tree cover pixels, and the actual rate where tree cover already exists.

Step 3) Calculate real-term pixel tree growth rate and tree cover fractions at different time steps

To convert the preliminary tree cover equivalent of step 2 to the final scenario tree cover fraction steps are as follows:

First, TC_{PE} is converted to an LAI equivalent, LAI_E . To this end, the process of tree growth assumes that the biomass of new vegetation is invested in area coverage first, and second, in height gain. Consequently, a pixel TC_{PE} of 100 cannot initially

be considered as full coverage of a fully grown tree stand, but as the equivalent of one unit of leaf area index (see Figure 4.4).

$$TC_{PE} = 100 \approx LAI_E = 1$$

(Eq. 4-7)

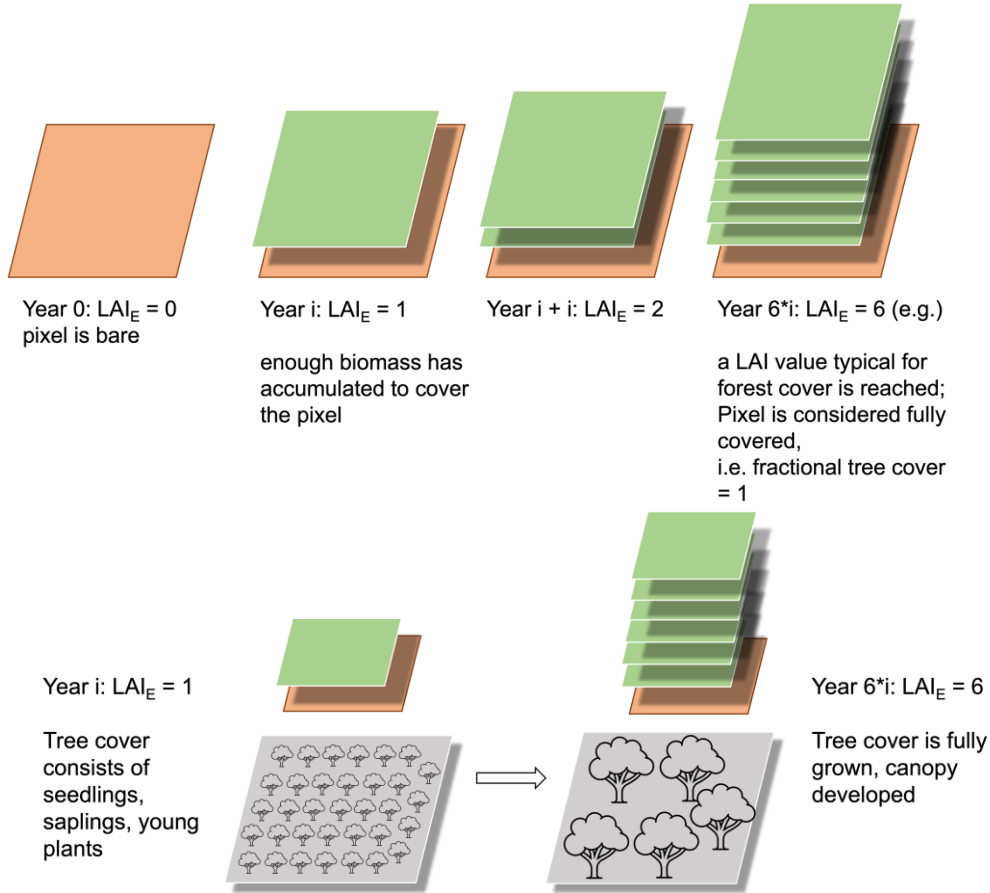


Figure 4.4 Schematic of the conversion process of preliminary to final scenario tree cover .

For example, starting out with a completely bare pixel, once TC_{PE} reaches 100% for the first time, LAI_E equals 1; TC_{PE} is then reset to 0 and once it reaches 100 for the second time, LAI_E equals 2 and so forth.

$$LAI_E = \frac{TC_{PE}}{100}$$

(Eq. 4-8)

This cycle is repeated until a reference climatological maximum LAI for the pixel's climate conditions is reached, at which point tree coverage is considered 100%. The real-term tree cover growth rate gr_{TC} is then calculated as the inverse of the number of years, K , needed for the grid cell to equal or exceed the maximum LAI.

$$gr_{TC} = \frac{1}{K}$$

(Eq. 4-9)

when

$$LAI_E \geq LAI_{climat_{max}}$$

(Eq. 4-10)

where $LAI_{climat_{max}}$ is the climatological maximum LAI.

Lastly, the final scenario tree cover TC at different timesteps is calculated by multiplying this real-term growth rate with the timesteps K_D (here: 25, 50, 75, 100, and 150 years).

$$TC = gr_{TC} \cdot K_D$$

(Eq. 4-11)

Step 4) Add final modelled to existing reference year tree cover

Since many pixels within the regrowth areas of opportunity have pre-existing tree cover, the reference year tree cover TC_{2018} is added to the scenario tree cover TC to create TC_{total}

$$TC_{total} = TC_{2018} + TC$$

(Eq. 4-12)

Step 5) Create scenario herbaceous and bare cover fractions

In the last step of the regrowth model, scenario cover fractions are calculated for herbaceous and bare covers from the pixel non-tree remainder in accordance with the reference year ratios:

$$Fraction_{bare_{new}} = \frac{(1 - Fraction_{tree_{new}})}{1 + \frac{Fraction_{herb_{old}}}{Fraction_{bare_{old}}}}$$

(Eq. 4-13)

$$Fraction_{herb_{new}} = \frac{Fraction_{bare_{new}} \cdot Fraction_{herb_{old}}}{Fraction_{bare_{old}}}$$

(Eq. 4-14)

where $Fraction_{tree_{new}}$ equals the scenario tree cover fraction, $TC_{total}/100$;

$Fraction_{bare_{new}}$ equals the scenario bare cover fraction, $Fraction_{herb_{old}}$ equals the reference year bare cover fraction and so forth.

Table 4-3 Conversion factors used in the tree growth model and applied globally

Name	Description	Value	Reference
Wood-to-canopy NPP ratio, r_{wc}	splits grown carbon between canopy and wood	0.5	Anderson-Teixeira et al. (2016)
Woody-to-total biomass stock, r_{wt}	converts reference biomass stock data from woody only to total biomass	0.96	Anderson-Teixeira et al. (2016)
Carbon-to-biomass ratio, r_{cb}	converts reference biomass stock to carbon equivalent	0.47	IPCC (2006, p. 112 and references therein)
Root-to-shoot ratio, r_{rs}	converts grown biomass data from total to only aboveground NPP	0.6	Anderson-Teixeira et al. (2016)

4.3 Results

The following two sections present the results of the tree growth scenario developed in section 4.2.1, as well as the results of the tree growth model developed in section 4.2.2 by continent, across the entire tropics and for the selected basins Amazon, Congo, Chao Phraya, Kapuas, Magdalena and Xe Bang Hieng.

4.3.1 Areas of opportunity for tree cover growth as identified in the scenario

In the following, areas of opportunity for tree cover growth are presented and classified as either *new* or *increased cover* according to whether tree cover existed in the pixel in the reference year 2018 or not.

4.3.1.1 Areas of opportunity across the tropics

The tree growth scenario identifies around 812 million hectares of land that qualifies as areas of opportunity in the tropics. Figure 4.5 shows the distribution of these areas across the tropics and illustrates that most areas are receiving an

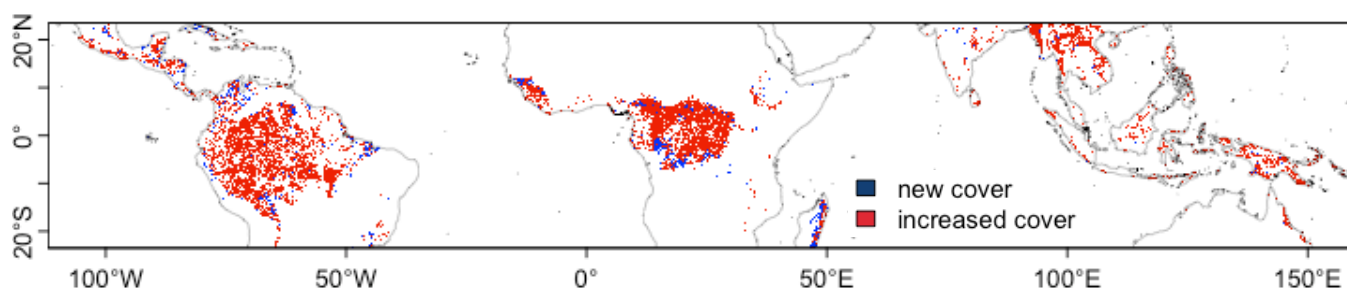


Figure 4.5 Areas of opportunity in the tropics as identified in the tree growth scenario. Blue colour represents grid cells where tree cover of the reference year was 0; red grid cells are those where tree cover existed in reference year, but scenario still allows tree cover growth.

increase tree cover (red grid cells) as opposed to new tree cover (blue grid cells). The tropical Americas have the largest area with potential for tree growth, with 392.77 million ha, of which 11.1 per cent are new growth. Tropical regions in Africa have 270.35 million hectares of which 13.6 per cent area new growth, and tropical Asia and Oceania has the lowest total area of opportunity with 149.11 million hectares of which 5.8 per cent are new growth (see Table 4-4).

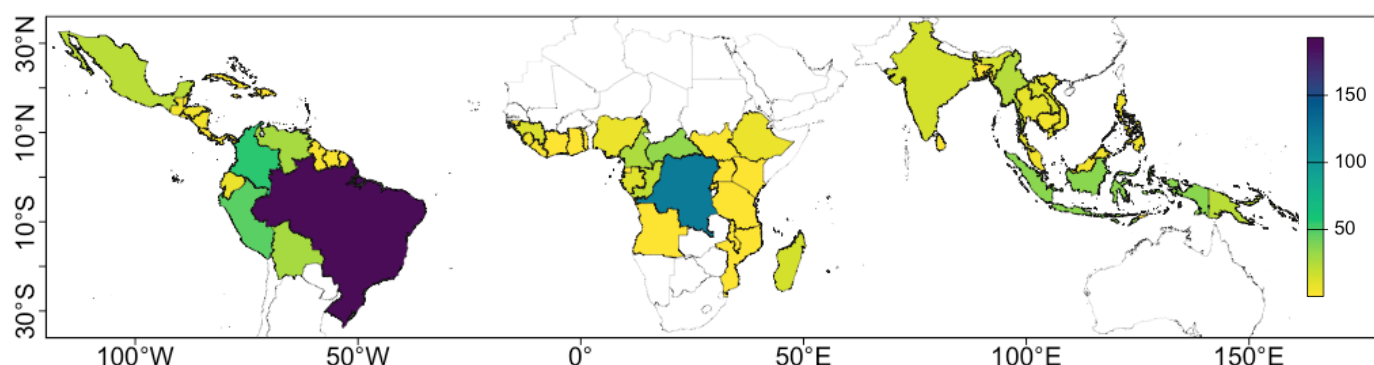


Figure 4.6 Total area of opportunity for tree growth (new & increased cover) by country in million hectares. Countries with a total area of opportunity less than 5,000 ha and where the area of opportunity represents less than 1 % of the country's total area are not shown.

The top five countries by total area of opportunity are Brazil (193 million ha), the Democratic Republic of the Congo (DRC) (123 million ha), Colombia (55 million ha), Peru (48 million ha) and Indonesia (36 million ha) (see Figure 4.6). Most of this area is already forested in the reference year; only approximately ten per cent are new cover in the DRC and Colombia, while for Brazil, Peru and Indonesia that share is even less.

Table 4-4 Total extent of areas of opportunity in million hectares across different continents and selected major basins, divided into "new" and "increase" tree cover.

Region/Basin	New cover	Increased cover	Total area of opportunity	Basin area
Africa	36.64	233.71	270.35	NA
Americas	43.54	349.23	392.77	NA
Asia	8.67	140.44	149.11	NA
Total tropics	88.84	723.39	812.23	NA
Amazon	12.79	252.62	265.41	594.1
Congo	18.13	157.91	176.04	368.92
Xe Bang Hieng	0.022	0.511	0.533	1.99
Kapuas	0.00128	0.775	0.776	8.35
Magdalena	3	6.38	9.38	25.96
Chao Phraya	0.118	3.21	3.33	15.72

The top five countries with respect to how much of the area of opportunity is *new* as opposed to already forested are, in ascending order, Nicaragua, the Bahamas, Cuba, Kenya, and Madagascar. Here, one third to one half of the area identified by the scenario consists of land that did not have tree cover in 2018 or was classified as a forest.

4.3.2 Additional tree cover after multiple decades of growth

4.3.2.1 Projected percentage tree cover and absolute increases

The tree growth model increases the mean tree cover in the tropical region from 25.8 per cent in the reference year 2018 to 31.3 per cent after 100 years of growth. By continent, this means that tropical parts of Africa, Asia and the Americas experience an absolute increase in tree cover of 4, 5.7 and 8.3 per cent respectively (see Table 4-5 & Figure 4.7).

By basin, the model projects a gradual increase in tree cover for all basins, which plateaus sooner (for example, in the Kapuas basin after 100 years) or later (see Table 4-5 and Figure 4.7). Among these basins, the Kapuas basin reaches the highest mean tree cover by the end of the modelling period, and the Chao Phraya basin the lowest (79 and 35.8 per cent, respectively).

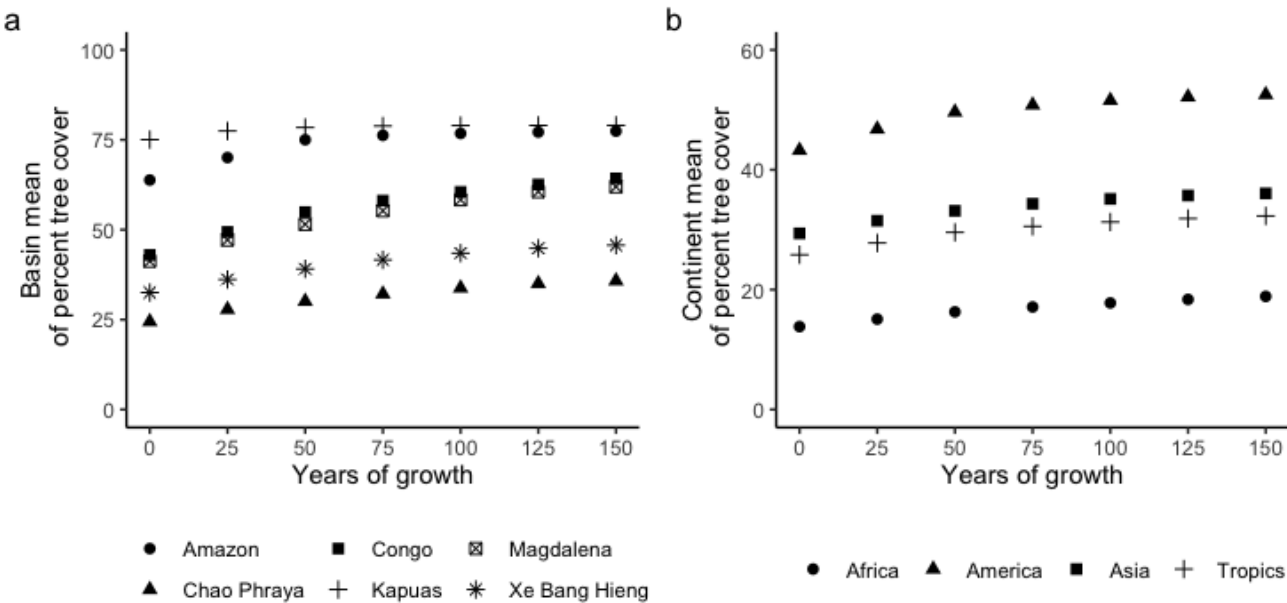


Figure 4.7 Basin and continent means of tree cover (%) for the reference year (year 0) and multiple years of tree growth. a) selected basins, and b) continent and all tropics.

Table 4-5 Mean tree cover in per cent (%) for tropical continents, all tropics and selected major river basins; year 0 is the reference year 2018.

Region/Basin	After 0	25	50	75	100	125	150 years
Africa	13.8	15.1	16.3	17.1	17.8	18.4	18.87
Americas	43.3	46.8	49.6	50.8	51.6	52.2	52.54
Asia	29.4	31.5	33.2	34.3	35.1	35.7	36.34
Total Tropics	25.8	27.8	29.6	30.6	31.3	31.9	32.68
Amazon	63.8	70.0	75.0	76.3	76.8	77.2	77.42
Congo	43.0	49.4	54.9	58.1	60.5	62.6	64.28
Xe Bang Hieng	32.5	36.2	39.1	41.6	43.5	44.8	45.69
Kapuas	75.1	77.4	78.4	78.8	79	79	79
Magdalena	41.2	47.1	51.5	55.3	58.3	60.6	61.9
Chao Phraya	24.4	27.8	30.1	32.1	33.8	35	35.8

4.3.2.2 Projected relative increases in tree cover

The percentage increase of tree cover was calculated as the difference between projected and reference year tree cover divided by the reference year cover and multiplied by 100 for all pixels within the area of opportunity. Tropical Africa has the highest relative increases in tree cover, followed by Asia and Oceania and lastly Central and South America. As most of the area of opportunity grid cells do not qualify as “new”, but only increased tree cover, the distributions of percentage increase values for all continents are right-skewed, meaning small increases are much more common than large ones.

In tropical Africa the median percentage increase for 25 years of tree growth are 22.2 per cent, rising to 90.6 per cent after 125 years. The 75th percentiles for 25, 50 and 75 years of tree growth are 52.8, 105.6 and 158.4 per cent. This means that after 25 years, a quarter of the pixels gain around half of their reference year tree cover, and after 50 or more years, a quarter of pixels have at least double or 1.5 times their reference tree cover. This rapid growth is also illustrated in Figure 4.8b using the Congo basin as an example.

For tropical Asia and Oceania, the median after 25 years is 18.3 per cent, and it increases to 58.4 per cent after 125 years. The 75th percentiles for 50, 75 and 100 years are 55.4, 83.1 and 110.1 per cent, which means that after 50 years, a

quarter of the grid cells gain approximately half their reference year tree cover, and after 75 years, 25 per cent of grid cells almost double in tree cover.

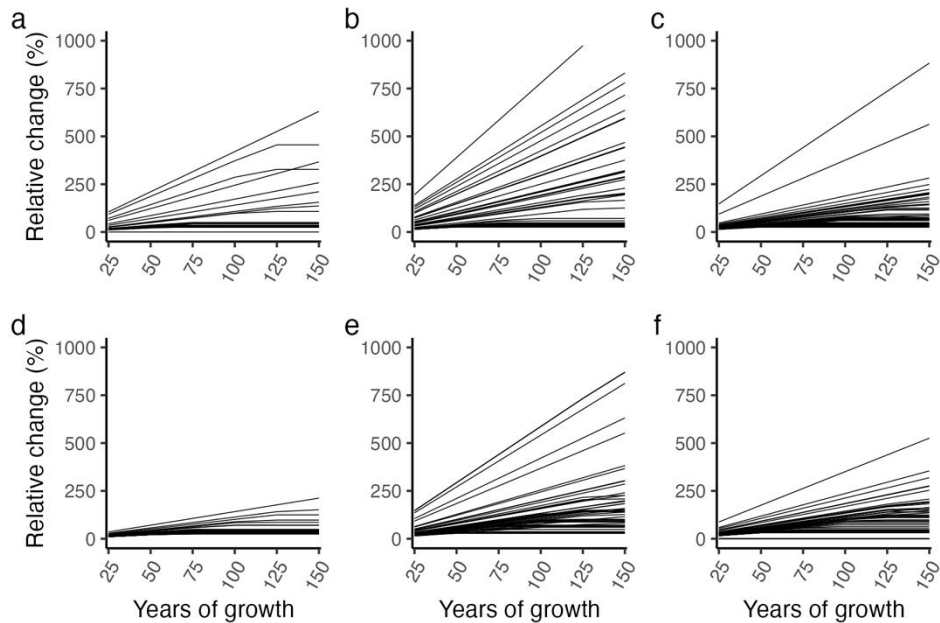


Figure 4.8 Relative change in tree cover from the baseline for different basins. Each line represents a sample point. a) Amazon, b) Congo, c) Xe Bang Hieng, d) Kapuas, e) Magdalena, f) Chao Phraya. Relative change is calculated as $100 \times \frac{\text{tree cover in year } x - \text{baseline tree cover}}{\text{baseline tree cover}}$. Sample size per basin is 50 points, randomly sampled from the basin's area of opportunity.

The lowest values are found in the tropical Americas, where the median percentage increase in tree cover is 15.6 per cent after 25 years of tree growth and increasing to 32 per cent after 125 years. The 75th percentiles for 25, 50 and 75 years of running the model are 19.4, 38.5 and 56.4 per cent indicating that in the Americas more grid cells are slower in increasing their tree cover than in Africa and Asia.

Figure 4.9 shows the spatial pattern of percentage change. While all continents have low values in the first map (25 years of growth), higher percentages cluster around the fringes of established dense forest biomes such as the Congo and Amazon forests in the second map (after 125 years of growth) (see Figure 4.9c, d, f). Percentage increases in South and continental Southeast Asia are rather higher, whereas values are lower further toward the southeast in insular Southeast Asia (for example the Kapuas basin on Borneo, see Figure 4.8d), which is a function of their high reference year tree cover.

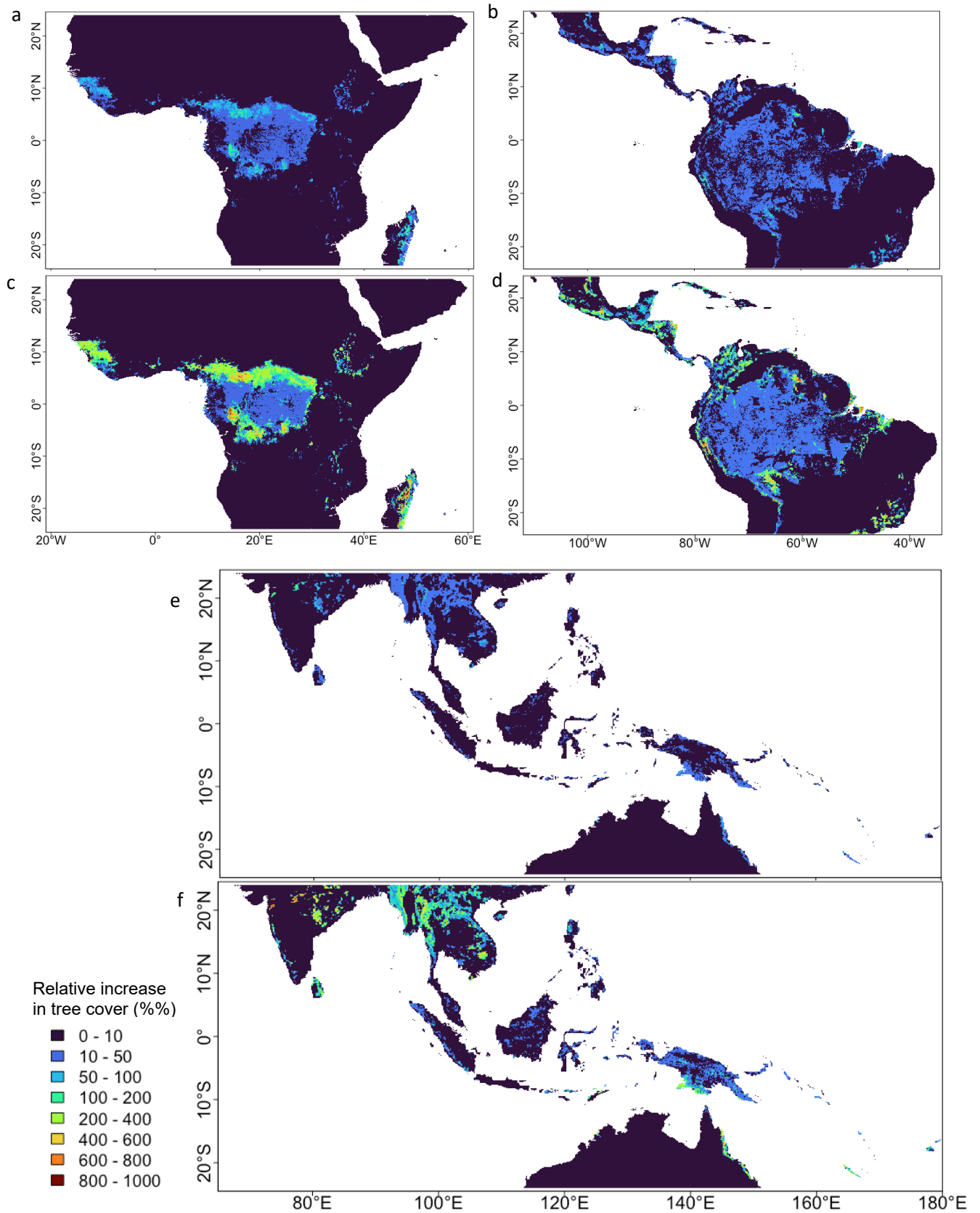


Figure 4.9 Percentage increase in tree cover between reference year 2018 a, b & e) 25 years of tree growth, and c, d & f) 125 years of tree growth for a & c) Africa and b & d) Central and South America and e & f) Tropical Asia & Oceania. Grey lines represent country boundaries.

4.3.2.3 Additional tree covered area

Table 4-6 shows the increase in area under tree cover in millions of hectares, calculated as the absolute increase in tree cover fraction multiplied with the grid cell size, where grid cell size is calculated from projected data. This is the increase in area rather than the increase in fractional tree cover.

The Americas have the largest addition to their tree-covered area with already an additional 44.88 million hectares after 25 years, followed by Africa with 31.24 and Asia with around 16.26 million hectares. The entire tropical region combined gains 292.43 million hectares after 125 years of modelled tree cover increase.

By basin, the Amazon and Congo basins receive 30.8 and 20.3 million hectares of additional tree cover after 25 years and 70.6 and 67.2 million hectares after 125 years. The two basins together therefore receive around 55 and 47 per cent of the total tropical additional cover at 25 and 125 years of growth.

Table 4-6 Additional tree-covered area in millions of hectares across the tropics and for selected basins with the standard threshold for area of opportunity delineation of 80 % tree cover in the reference year 2018.

Region/basin	after 25	50	75	100	125	150 years
Africa	31.24	61.66	82.09	98.86	113.63	126.12
Americas	44.88	86.56	103.63	114.57	122.74	128.37
Asia	16.26	32.07	43.11	50.75	56.06	59.44
Total Tropics	92.38	180.29	228.83	264.18	292.43	313.93
Amazon	30.76	58.69	65.52	68.51	70.6	72.1
Congo	20.34	39.97	51.23	59.87	67.24	73.29
Xe Bang Hieng	0.06	0.12	0.17	0.2	0.23	0.25
Kapuas	0.08	0.16	0.19	0.2	0.21	0.21
Magdalena	1.09	2.14	3.05	3.79	4.33	4.66
Chao Phraya	0.33	0.66	0.96	1.2	1.38	1.49

The next largest additions in major global river basins are expected in the Orinoco, Niger and Sanaga basins (see Figure 4.10 for the top ten of major river basins by additional tree cover area). These basins receive between 3.6 and 1.8 per cent of the tropical additions each.

By country, Brazil and the Democratic Republic of the Congo lead the table due to the Amazon and Congo River basins. The increase in the Congo basin also extends into the Central African Republic, which consequently has the fifth-largest addition to tree cover area (see Table 4-7).

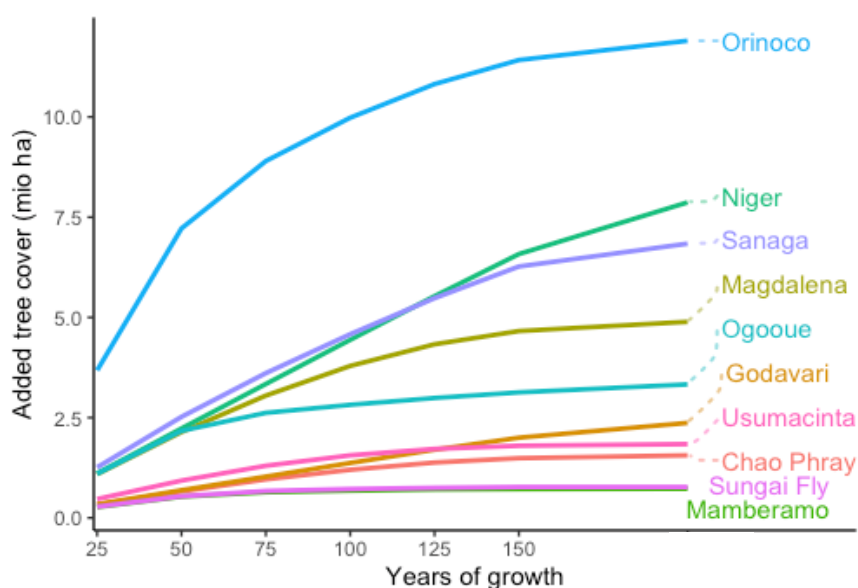


Figure 4.10 Top ten major river basins (MRB) for additional tree cover area in millions of hectares, excluding the Amazon and Congo River basins. Only basins that entirely within the tropical belt are considered. River basin outlines are derived from the Major River Basins of the World dataset compiled by the Global Runoff Data Centre, GRDC, ed. 2, 2020. Standard threshold for area of opportunity delineation of 80 % tree cover in the reference year 2018 is applied. Applying the lower threshold did not change the order of basins, but reduced the magnitude of additions. See Appendix A2.4 for MRB results with both thresholds.

Table 4-7 The top five countries for additional tree-covered area, with area in million hectares with the standard threshold for area of opportunity delineation of 80 % tree cover in the reference year 2018. A full table of tropical countries with area of opportunities can be found in Appendix A2.4

Country	after 25	50	75	100	125	150 years
Brazil	21.59	41.21	46.92	50.21	52.79	54.76
D. R. Congo	13.93	27.26	33.84	38.45	42.17	45.01
Colombia	6.15	11.86	14.29	15.93	17.1	17.82
Peru	5.34	10.19	11.51	12.13	12.54	12.78
Central African Republic	3.93	7.84	11.47	14.88	18.03	20.81

The above results are based on the assumption that tree cover can increase in already densely forested areas due to the CO₂ fertilisation effect and other processes discussed in section 4.2.1.1. When the threshold for the exclusion of a grid cell as area of opportunity is lowered to 70 (from the standard 80 per cent), the Congo and Amazon River basins still receive the largest addition in tree-covered area (Congo: 10.32 million ha after 25 years and 46.75 million ha after 125 years; Amazon: 5.2 million ha after 25 years and 6.4 million ha after 125 years). The top five countries are then the D.R. Congo, Brazil, the Central African Republic and Myanmar. A complete list of tree-covered area increase for MRBs and

countries is presented in Appendix A2.4 for both area of opportunity thresholds, 70 and 80 per cent.

4.3.2.4 Comparison of tree cover increase between two area of opportunity thresholds

As described in section 4.2.1.1, two different thresholds for the tree cover growth scenario were considered, one considers only pixels with < 80 per cent of baseline tree cover as area of opportunity (hereafter also *group 2*), the other uses < 70 per cent as threshold (hereafter also *group 1*). Figure 4.2 mapped where pixels qualifying according to either threshold are located. In this section, the effect on basin mean tree cover changes is briefly outlined. Overall, the choice in threshold has no effect in 90 of the 196 major river basins of the world in the tropics. To illustrate the effect on the remainder when tree cover has been grown, the Congo River basin is used; in this example, after 25 years of growth. Figure 4.11 shows the difference (Δ Tree cover) between tree cover in year 25 and the baseline tree cover for threshold less than 80% (Figure 4.11a) and less than 70% (Figure 4.11b).

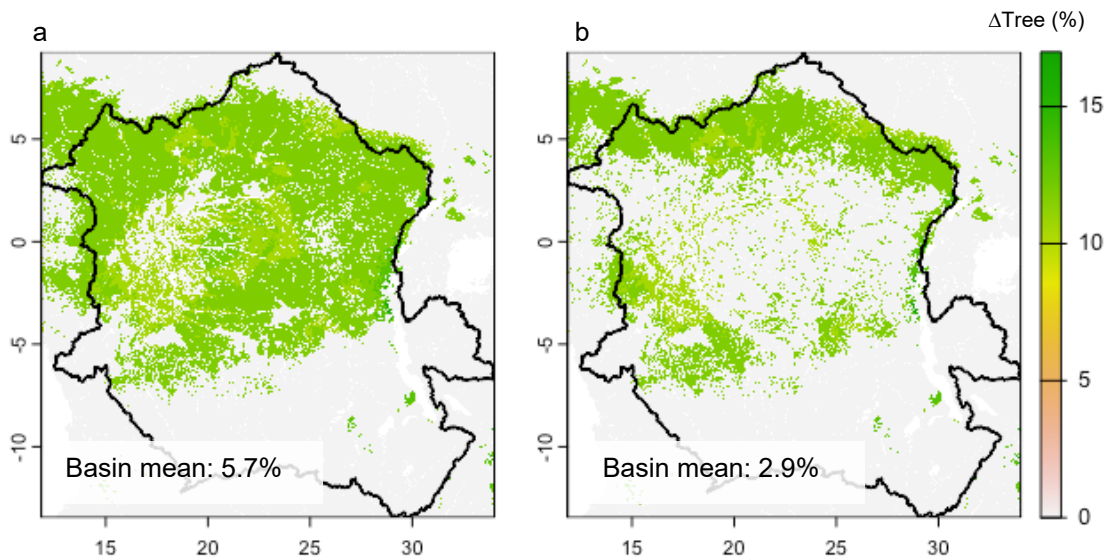


Figure 4.11 Δ Tree cover for year 25 in the Congo River basin for two different thresholds. a) all pixels <80 % baseline tree cover are included in tree growth scenario, b) only pixels <70 % baseline tree cover are included. Mean Δ tree cover over the basin is higher in a). Δ Tree cover = year 25 tree cover – baseline tree cover. Dark indicates the MRB basin boundary.

The basin mean of the Δ Tree cover is greater when all pixels below 80 % baseline tree cover are used in the scenario. This means that on basin level, the Congo River basin experiences a higher growth in tree cover under the 80% (group 2) threshold as compared to the 70% threshold (group 1).

Across all MRBs where the threshold has an effect (106/196), this effect lessens over the years of tree growth, but the basin mean of group 2 (80 % threshold) is always greater than that of group 1 (see Figure 4.12). The greatest absolute difference in basin mean Δ Tree cover between the two groups was 15 percentage points.

The relative change in basin mean Δ tree cover between the two groups shown in Figure 4.12 is calculated as follows:

For each group, and year p

$$\Delta \text{ Tree cover} = \text{tree cover}(\text{year_p}) - \text{baseline tree cover}$$

(Eq. 4-15)

$$\text{Relative change} = \frac{100 * (\Delta \text{Treecover}(\text{group2}) - \Delta \text{Treecover}(\text{group1}))}{\Delta \text{ Tree cover (group 2)}}$$

(Eq. 4-16)

4.4 Discussion

4.4.1 Comparison of the areas of opportunity map with other tree growth scenarios

It is possible to compare the area of opportunity for tree cover growth delineated here to Bastin et al.'s (2019) estimates of global forest restoration potential because both describe where an increase in forest cover could take place. Since Bastin et al. exclude

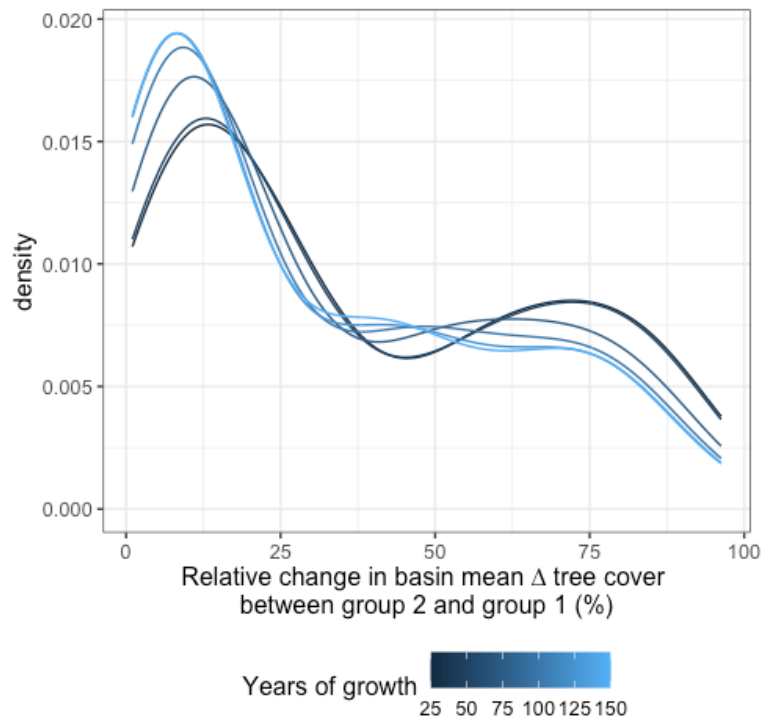


Figure 4.12 Effect of the two thresholds, 80 (group 2) and 70% (group 1) on the mean basin change in tree cover between baseline and scenario ("basin mean Δ tree cover") for MRBs. Line colour indicates scenario year and density (y-axis) reflects the relative frequency of a value on the x-axis. As all values are greater than 0, group 2 always has greater increases in tree cover between baseline and scenario than group 1. A relative change of 100% means that the basin mean Δ tree cover for group 2 is twice that of group 1. The 90 MRBs where the threshold makes no difference are excluded here.

pixels with more than 10 per cent tree cover from their map, however, it can only be compared to the “new” growth area of opportunity.

Although Bastin et al. include grasslands, shrublands and savanna biomes in South America and Africa in their map, these could be excluded in the above estimate because the authors present their result disaggregated by biome in their supplementary material. Thus, it is possible to compare Bastin and colleagues’ estimate of 131.5 to 176.5 million hectares with forest restoration potential in tropical and subtropical forest biomes to the 89 million hectares of “new” growth area of opportunity identified in this chapter. Since the estimates for grasslands, shrublands or savanna were excluded in this comparison, the difference between the two set of estimates is likely due to the difference in study region. In this study, *tropical* pixels, i.e. between 23.5° S and 23.5° N, are considered, while Bastin et al.’s estimate uses WWF ecoregions, which combine both *tropical* and *subtropical* ecoregions and thus include a larger area (Dinerstein et al., 2017).

Brancalion and colleagues (2019) estimated a “global restorable area in tropical rainforests” covering 863 million hectares, which is close to the 812 million hectares identified as area of opportunity for tree cover increase identified in this chapter. However, the two maps differ substantially in the location of these pixels (see Figure 4.13 compared to Figure 4.5). First and foremost, as mentioned in the introduction to this chapter, Brancalion et al. set a different threshold for excluding existing forest, and base that on the Hansen et al. dataset, which overall shows a higher tree cover in the tropics than the MODIS dataset used here. This results in a complete exclusion of the Amazon and Congo forests as well as forests on Borneo and in Indonesia. Second, large differences are found in Brazil’s Southeast region, coastal areas of Côte d’Ivoire and Ghana, and the eastern

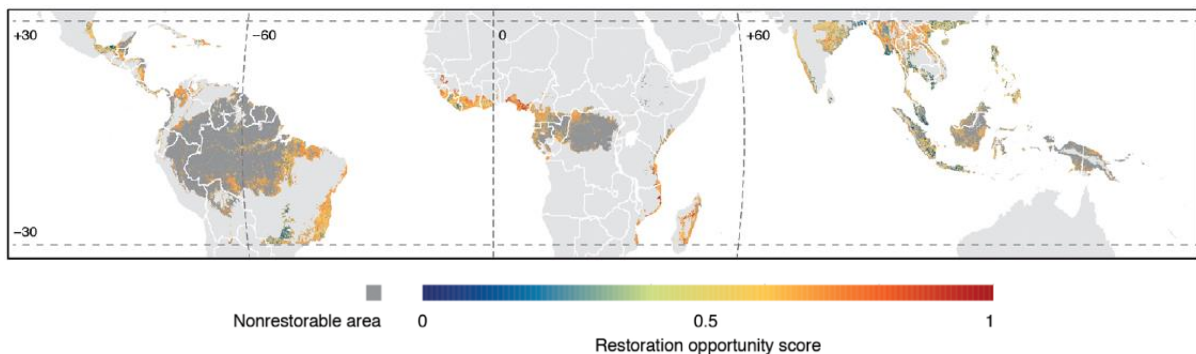


Figure 4.13 The Brancalion et al. restoration area map. Higher ROS (values ranging from 0 to 1) represent landscapes with higher potential restoration benefits and feasibility. Source: Brancalion et al. (2019), Fig. 1B

Indian states of West Bengal, Odisha, Bihar and Chhattisgarh, northern Vietnam, the Chinese provinces of Guangxi and Guangdong, and on the Indonesian islands of Sumatra and Java. These differences are due to the human modification index used in this study to exclude areas with higher degrees of human impact. The index used here combines multiple datasets of human modification such as built-up area, transport and agricultural area data while the Brancalion and colleagues only exclude urban areas. Lastly, they focus on lowland forests, i.e. forests below 1000 m.a.s.l, which is not a criterion in this study.

A map of reforestation potential for Southeast Asia published by Zeng et al. (2020) compared well with the estimates of this study. The authors estimate a restoration potential for 121 million hectares in Southeast Asian countries when only biophysical limitations are considered and 76.4 million hectares if more restrictive land use constraints are applied. The map presented in this study shows 105 million hectares of restoration potential for the same region. While the land use constraints in Zeng et al. (2020) result in the same amount of restoration potential on the island of Borneo, northern Vietnam, Lao and Thailand retain less potential in when compared to the area of opportunity maps from this chapter.

4.4.2 Comparison of the NPP-derived carbon accumulation rate to published literature

As there are no published models that increase tree cover over time as proposed by the model in this chapter, one of the key input variables, the carbon accumulation rate, is discussed in this section instead.

The aboveground carbon accumulation rate g_{RC} calculated from MODIS net primary productivity data for the tree growth model averages around 4.7 Mg C/ha·year across the tropics and is comparable to values from other tropical studies, for example Griscom et al. (2017) compiled a “natural forest growth rate” for the tropics of 4.8 Mg C/ha·year. Anderson-Teixeira et al. (2016) similarly calculate a mean aboveground net primary productivity which is very similar to the overall tropical mean accumulation rate from this study. Using the comprehensive a pantropical carbon database (TropForC), they estimate rates of 4.8 $\pm$ 0.7 and 5 $\pm$ 2.4 Mg C/ha·year for intermediate and mature broadleaf forests.

There are, however, studies reporting lower rates of carbon accumulation such as Cook-Patton et al. (2020) and Requena Suarez et al. (2019). The former modelled carbon accumulation rates for tropical forests in the range of 2 to 4.5 Mg C/ha·year, on the basis of a large dataset of published data. The latter, calculate for tropical rainforest in the Americas a carbon accumulation rate from 1.1 to 2.7 Mg C/ha·year for old and young growth secondary forest in their study, which is many times smaller than the equivalent from this chapter's methodology: When averaged over the same ecozone in the Americas the rate is 7.3 Mg C/ha·year in this chapter, although this could not be disaggregated by growth stage. Similarly stark discrepancies are found for Asia and Africa and the other ecozones tropical moist and dry forest, and tropical mountain system. Overall, the estimates from this chapter are 2.5 to 4 times as large as the growth rates calculated by Requena Suarez et al. (2019).

All these studies, however, use forest plot monitoring data unlike the present chapter, which uses the MODIS NPP remote sensing product to calculate the accumulation rate. The wide range on reference values must therefore be considered in view of the methodological differences.

4.4.3 Patterns in tree cover increase across the tropics

Across the tropics, 812 million hectares have the potential to increase or establish new tree cover according to the tree cover growth scenario presented in this chapter.

Almost half of this area is located in the tropical regions of Central and South America, a third in tropical Africa and the remainder in tropical Asia and Oceania. The top five countries by total area of opportunity are Brazil, the Democratic Republic of the Congo (DRC), Colombia, Peru, and Indonesia. Most of the opportunity for tree growth lies in the increase of tree cover rather than the establishment of new tree cover, the latter only affecting around 10 per cent of the total tropical area of opportunity.

According to the tree growth model, the percentage of area with tree cover rises across the tropics from 25.8 per cent in 2018 to 31.3 per cent after 100 years of tree growth. The greatest *relative* increases are predictably found in tropical Africa, since the reference year tree cover for the continent was the lowest out of

the three continents, followed by Asia and lastly the Americas. For example, in Africa, after a minimum of 50 years of tree cover growth, a quarter of the grid cells with regrowth potential have at least doubled their reference year tree cover.

Almost half of the additional tree cover area projected for the tropics was captured by the Amazon and Congo River basins as the two largest basins in the tropics. Thus, by country, Brazil, Colombia and Peru, as well as the DRC and the Central African Republic, which are home to the Amazon and Congo River basins, respectively, had the biggest additions in tree covered area when aggregated by country. The next largest increases were found in the Orinoco and Magdalena River basins in South America and Niger and Sanaga basins in Africa. The remainder of the additional tree covered area is distributed between more than 100 other major river basins as well as areas outside of MRBs. For example, in Madagascar, all of the opportunity for regrowth and thus all additional tree covered area is found outside of the two MRBs on the island (see Figure 4.5).

4.5 Conclusions

The area of opportunity for tree cover increase presented in this chapter is typically more conservative than previously published maps with regard to socio-economic constraints for example than Brancalion et al. (2019), but not Zeng et al. (2020). This is due to the use of a more comprehensive dataset of human land uses and impacts.

With regard to biophysical constraints, however, the presented tree cover growth scenario is both less and more conservative. It is less conservative as it includes large areas with dense tropical forest that still have the potential to increase their cover, such as the Amazon Forest. This is of advantage of the following chapter on the hydrological effects of tree cover increase. It is stricter, however, in the exclusion of grasslands, savanna and shrublands from the area of opportunity map.

The biggest addition in tree covered area takes place in the Amazon River and Congo River basins. Basins in Asia and Oceania are ranked only in the lower half of the top ten basins regarding additional tree cover. The main reason for this spatial pattern is the very low area of opportunity for tree growth in Asia and Oceania which follows on the one hand, from the higher human land use impacts in the region and on the other, from very high baseline tree cover. The fastest rate

of change in tree cover, i.e. the largest relative changes, were found in Africa as the continent combines both extended areas of opportunity for tree growth under the scenario and low reference year tree cover.

Chapter 5 Determining the infiltration-evapotranspiration trade-off over multiple decades of tree growth for the tropics and selected tropical watersheds

5.1 Introduction

This chapter presents the estimates for water balance, trade-off between change in water balance and change in infiltration (hereafter *trade-off*) and monthly runoff for the different stages of tree cover regrowth as modelled by the DTRIE model. Hence, it aims to accomplish **objective 3**, to “*examine the effect of tree cover growth on annual water quantity, monthly runoff and dry season flows and their relationships with the given environmental conditions*”, and **objective 4**, to “*examine where the trade-off between increased evapotranspiration and improved infiltration can deliver net positive outcomes for water quantity and regulation services*”.

After a brief outline of the methods used to run the DTRIE model with scenario tree covers and other scenario-adjusted input variables (section 5.2.1), the results section will first describe the effect of tree cover change on overall and second, examine the influence of other environmental variables.

Section 5.3.1 looks at the water balance across the tropics and within the set of large, major river basins of the world (MRB). The analysis of change in water balance answers the question how much more or less water leaves a grid cell through evapotranspiration (AET, composed of soil evaporation, plant transpiration and interception loss), and thus cannot contribute to runoff, or streamflow at a point of interest, until it falls again as rain. For this analysis, dams were identified as points of interest, because they reflect economically and socially important locations where water is used and where water quantity and seasonality are relevant to users. Dams fulfil different purposes such as hydropower generation or agricultural irrigation and they support around a quarter of global electricity production and 12 to 16 per cent of global food production (Mulligan et al., 2020).

Next, section 5.3.2 examines the effect of tree cover growth on water regulation by comparing monthly streamflow at a point of interest (POI) between the baseline and that of scenario tree cover conditions. In the DTRIE model, total

streamflow is the sum of overland, or surface flows (SF) and subsurface flows (SSF), both of which are affected by changes in tree cover. While changes in SF and SSF both affect the magnitude of total streamflow, only SSF affects the timing because it arrives at the POI with a lag, which is determined by watershed topography and soil properties along the flow path. This section will thus examine whether increasing tree cover produces more (or less) streamflow at the POI on an annual scale. Furthermore, it analyses whether the seasonal pattern of streamflow peaks and troughs occurs at different times of the year other than in the baseline.

In section 5.3.3, the spatial pattern of the sensitivity of water balance and effective infiltration to tree cover increase, i.e. the absolute change in either divided by the change in tree cover, is mapped. Effective infiltration is examined for the question of trade-off because it determines partitioning of effective rainfall into surface and subsurface flows. The latter enters the slow hydrological pathway and contributes to streamflow with a delay. Changes in effective infiltration are therefore explored to answer the question of how much more (or less) water can enter the slow hydrological pathway and thus potentially contribute to baseflow, which is relevant in seasonally dry areas, where this water may redistribute streamflow seasonally and thus increase dry season flows. Subsequently, this section explores which environmental factors influence these sensitivities, testing the effects of mean annual temperature, total annual rain, rainfall and temperature seasonality, reference year tree cover and aridity index.

Finally, the discussion will address how these sensitivities relate to the trade-off debate by bringing together the results from the dam watershed experiment and those derived for larger basins on the tropical scale. It will also briefly touch upon the special case of cloud forests, and conclude by placing the findings from this chapter in the context of other published research.

The chapter answers the following research questions:

- 1) How does tree cover growth affect annual water balance on tropical scale and in selected major river basins, (see section 5.3.1, p. 111)
- 2) How does tree cover growth affect streamflow seasonality and streamflow quantity in the following dry season (see section 5.3.2, p. 117)

3) How do other environmental factors influence the sensitivity of water quantity and regulation services to tree cover growth? (see section 5.3.3, p. 125)

5.2 Methods: Applying the hydrological model to multiple decades of tree growth

The hydrological model DTRIE developed in Chapter 3 is run with the scenario vegetation cover maps created in Chapter 4. In the first step, the model is run separately for each vegetation cover type, following the methodology of GLEAM (Martens et al., 2017), i.e., as if the grid cell were only of that cover type, in order to produce plant transpiration or soil evaporation, interception loss (except in the case of bare cover), water balance, effective infiltration and subsurface runoff. In the second step, for each of the three vegetation cover types the output variables are scaled according to their respective scenario cover fractions and, in step 3, these are summed up to create the output variable for the complete pixel (see Figure 5.1).

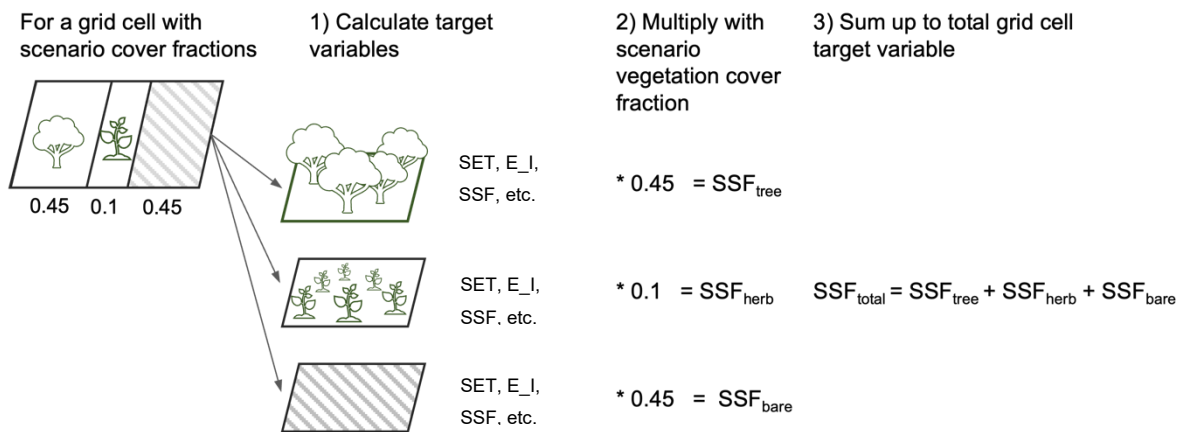


Figure 5.1 Schematics of variable calculations with scenario vegetation covers. In this example, SSF is calculated for a grid cell with scenario tree cover fraction of 0.45, herbaceous cover fraction of 0.1 and bare cover fraction of 0.45. SSF_{tree} , SSF_{herb} and SSF_{bare} are the SSF values for a purely tree-covered, herb-covered and bare grid cell, respectively.

The hydrological model is run with the same climatological inputs for temperature (T), rainfall (P) and net radiation (R_n) as in the baseline. The variables adjusted to the scenario vegetation cover conditions are:

- Interception loss (E_i) and effective rainfall P_{net} (which is $P - E_i$);
- Net radiation available for SET (which is input net radiation R_n less the energy required to evaporate interception loss water volume E_i ;

- Leaf area index seasonality (LAI_{seas});
- Rooting depth and derived soil moisture store volumes (plant available, AW store, and unavailable water stores, UAW store);
- Throughflow velocity, v_T , to account for the impact of enhanced organic matter and macropore development on soil hydrology.

5.2.1 Brief description of input variable adjustments to the scenario conditions

Interception loss, LAI seasonality and the volume of the plant available water store (AW_{pot}) are adjusted to scenario tree (herbaceous, or bare) conditions cover by first filtering all grid cells with a “high” cover fraction of the cover type in the reference year. These are then considered representative of the cover type. “High” tree cover is defined as more or equal to 70 per cent cover. Grid cells are further grouped by climate class so that finally, the variable mean, for example of LAI seasonality, of a group of grid cells with > 70 per cent tree cover is considered representative of LAI seasonality for a “typical” forest in a certain climate class. A sensitivity analysis for the choice of the 70 per cent threshold is presented in Appendix A2.2.

LAI seasonality and interception loss are furthermore also grouped according to their forest cover type, which has been mapped across from ESA CCI to Hengl et al.’s potential natural biome types. In this mapping procedure, ESA forest types are assigned an equivalent forest type from the Hengl map based on each classification’s detailed description. This procedure and the lookup table are described in more detail in Appendix A1.3.

As introduced in section 3.2.1.2, throughflow velocity v_T is derived from the saturated hydraulic conductivity of lower soil layers (0.3 – 2 m below surface) derived from the dataset of Montzka et al. (2017), which is used here as matrix flow velocity here, and is then adjusted to scenario vegetation cover conditions with the help of a macropore factor as identified by Gao et al. (2018). This factor increases the velocity, based on the assumption that vegetation cover promotes the creation of macropores which have higher flow velocities than matrix flow. Throughflow velocity is adjusted analogously to the process described in Figure 5.1, where first, it is adjusted for each cover type separately. As opposed to the

weighted mean used in Figure 5.1, grid cell throughflow velocity is the weighted median of the separate velocities. For tree cover, throughflow velocity is multiplied with a macropore factor of 10^3 , for herbaceous cover with 10^2 . No adjustment is made for the bare cover fraction, which is assumed to have no macropores.

5.2.2 Outline of methods used in the streamflow calculations

Streamflow at a point of interest (POI, for the purpose of this study these are dams), is calculated on a monthly timestep for a small set of dam watersheds in section 5.3.2. The set of watersheds has been selected to represent a range of dam purposes, namely water supply, hydroelectric power and agricultural irrigation as classified by the Global Reservoir and Dam Database (GRanD) and is briefly described in Appendix A3.1.

For a given month, the total runoff (or “streamflow”) at the POI is the sum of all the watershed’s pixels’ overland flows (SF) and subsurface flows (SSF). SF is composed of R_1 , R_2 and R_3 , which leave the soil within the month of their creation, and subsurface flows (SSF) is a lagged contribution from a previous month (or the same month if there is no lag). Both volumes SF and SSF are first converted from their original unit mm to m^3 per pixel so that the final watershed total reflects the correct volume. For example:

$$SF [mm] = SF [m^3/(m^2 * 1000)]$$

(Eq. 5-1)

Then

$$SF [m^3/pixel] = SF [m^3/m^2] * \text{pixel surface area } [m^2]$$

(Eq. 5-2)

Pixel surface area is calculated in m^2 with the function `cellSize()` from the R package *terra* because raster pixel surface area is not constant for the geographic CRS (EPSG: 4326). For example, a pixel resolution of $1 * 1$ degree ($^\circ$) at the equator covers around $111 \text{ km} * 111 \text{ km}$, but at a latitude of 24°N it covers only $111 \text{ km} * 101 \text{ km}$.

5.2.2.1 Calculation of surface flows, SF

SF for a given month i is

$$SF(i) = R_1(i) + R_2(i) + R_3(i)$$

(Eq. 5-3)

It is assumed that all surface flow (SF) will reach the nearest downslope stream pixel within the same month. This assumption is based on a simplified representation of all surface flow as *shallow concentrated flow* over a forest floor with heavy ground litter and the maximum downslope distance to the nearest stream pixel d_{STREAM} (see description in section 5.2.2.2). The stream network is derived from HydroRIVERS. As per the USDA-NRCS National Engineering Handbook, the range of flow velocities over forest floor for slopes from 0.005 to 0.65 m/m is 0.06 (155,520 m/month) to 0.66 m/s (1,710,720 m/month). The flow over “forest with heavy ground litter and hay meadows” was chosen because it represents the slowest of the given flow velocities (Kent et al., 2008). The longest distance d_{STREAM} across all the watersheds for which this is calculated is 47,668 m (mean: 11,779 mm). This means that all water is fast enough to reach the nearest stream within one month.

Furthermore, it is assumed that upon reaching a stream pixel, streamflow has also reached watershed outlet (POI), a process representation that is sometimes called “instantaneous routing”. The Bhumibol dam’s watershed (described in section 5.3.2.1) can demonstrate that this is plausible. For example, dry and wet season flow velocities for the Ping River just below the Bhumibol dam range from 1.07 to 1.34 m/s (2773 to 3473 km/month) and the flow length of the Ping River upstream of the dam is approximately 480 km (Namsai et al., 2021). Therefore, all water in the stream can reach the dam point of interest within the month.

5.2.2.2 Calculation of subsurface flows, SSF

Subsurface flow, however, occurs in deeper soil layers and at slower velocities and may reach the nearest stream pixel (and thus the POI) with a lag. As a reminder, SSF stems from the soil stored water that is unavailable to plants, the UAW store. It is the amount of water drained by gravity each month, leaving behind only the water content at the wilting point (WC_{WP}) (see p. 32 & p. 38 for details). After each month, it is assumed that the SSF volume leaves the grid cell of origin and starts traveling towards the nearest stream pixel as throughflow at a velocity defined by the subsequent cells’ hydraulic conductivity.

The lag time, lag_{SSF} , is the number of months it takes the subsurface flow water to travel between a pixel j and its nearest downslope stream pixel. lag_{SSF} is calculated as follows:

$$\text{lag}_{\text{SSF}} = d_{\text{STREAM}} / v_T \quad (\text{Eq. 5-4})$$

where v_T is the vegetation adjusted throughflow velocity of pixel j and d_{STREAM} the distance between pixel j and the downslope stream pixel nearest to pixel j . For each month, the SSF is the sum of SSF volumes from the current and preceding months. A pixel's lag_{SSF} value determines for which preceding month the pixel SSF is contributed to the total SSF (see Figure 5.2a). For example, for pixels with $\text{lag}_{\text{SSF}} = 0$, the current month's SSF is contributed. The upper limit for lag_{SSF} is 11 months. Capping the lag at 11 months, or rather, at less than one year effectively excludes SSF from certain pixel groups (either too far, or too low a throughflow velocity, or both) from contributing the total watershed SSF. However, this is deliberate because this research is focused on the effects on streamflow in the *following* dry season, as per **research question 2** of this chapter (*"How does tree cover growth affect streamflow seasonality and streamflow quantity in the following dry season"*). A discussion of the implications of the cap is presented in Appendix A.3.2.

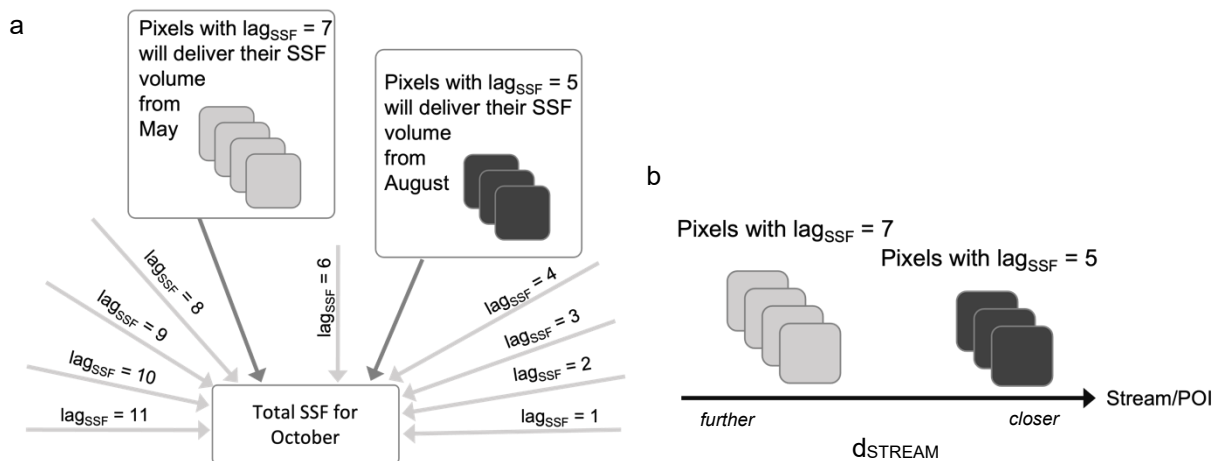


Figure 5.2 a) Schematics of the contributions of groups of pixels with different lag_{SSF} values to the total SSF for the month of October; two example groups are described, but the remaining groups with other lag_{SSF} values contribute in the same way; b) simplified illustration of the distance to the stream/POI d_{STREAM} for two groups of pixels with the same throughflow velocity v_T . Light grey squares symbolise all pixels with a lag_{SSF} of 7 months, dark grey squares are all pixels with a lag_{SSF} of 5 months.

The distance d_{STREAM} is calculated based on the HydroSHEDS void-filled digital elevation model (DEM) at spatial resolution of 30" and HydroRIVERS stream

data for the selected watersheds in the R programming language using the package “whitebox” (the whitebox package is a frontend for the command line programme WhiteboxTools developed by Lindsay (2016)). The distance d_{STREAM} is the distance of each raster pixel to the nearest stream pixel along the downslope flow path. The DEM was pre-processed to remove artefact topographic depressions and flat areas, otherwise stream flow can be erroneously interrupted. The D8 flow algorithm was used to create flow pointer grid required for the workflow. This pointer specifies the direction of flow out of a pixel, which in the case of the D8 flow algorithm, is the steepest neighbour downslope (O’Callaghan and Mark, 1984). Dam reservoirs are considered stream pixels for the purpose of this calculation as otherwise distance is inflated; the extent of dam reservoirs in the selected watersheds is obtained from the GRanD database (V1.3). Before the downslope distance to stream is calculated, all input data are reprojected to the World Equidistant Cylindrical Projection (EPSG: 4087).

5.2.3 Summary of the tree cover inputs used in this chapter

Chapter 4 identified areas with the potential for tree cover growth in the tropics and applied a data-derived growth rate to incrementally increase tree cover in these areas over multiple decades. The maps of potential fractional tree cover from chapter 4 are used as vegetation cover inputs to the hydrological model, DTRIE, in the present chapter. In the following section, a short description of the fractional tree cover maps created in chapter 4 are presented as background for the interpretation of the results of this chapter.

The tree cover growth scenario identified 812 million hectares across the tropics with the potential to increase or establish new tree cover. Most of this potential lies in the increase rather than the establishment of new tree cover, which only affects around 10 per cent of the total tropical area of opportunity.

The largest relative increases were modelled for Africa, as the continent combines both extended areas of opportunity for tree growth under the scenario with low baseline tree cover (see Figure 5.3). For example, in Africa, after a minimum of 50 of tree growth, a quarter of the grid cells with regrowth potential have at least doubled their reference year tree cover (see Figure 5.4).

The greatest additions in tree cover take place in the Amazon River and Congo River basins. The next largest increases were found in the Orinoco and Magdalena River basins in South America, and the Niger and Sanaga basins in Africa. Basins in Asia and Oceania are ranked only in the lower half of the top ten basins regarding additional tree cover. Much of the additional tree cover area is distributed between more than 100 major river basins (MRBs) other than the aforementioned. It also occurs outside of MRBs.

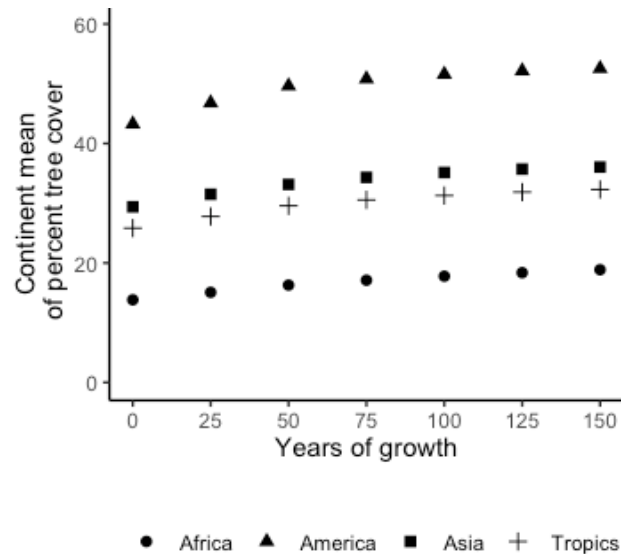


Figure 5.3 Timeseries of continental mean tree cover (%), and mean tree cover for the entire tropics. This figure has already been presented in chapter 4 and is included here for convenience.

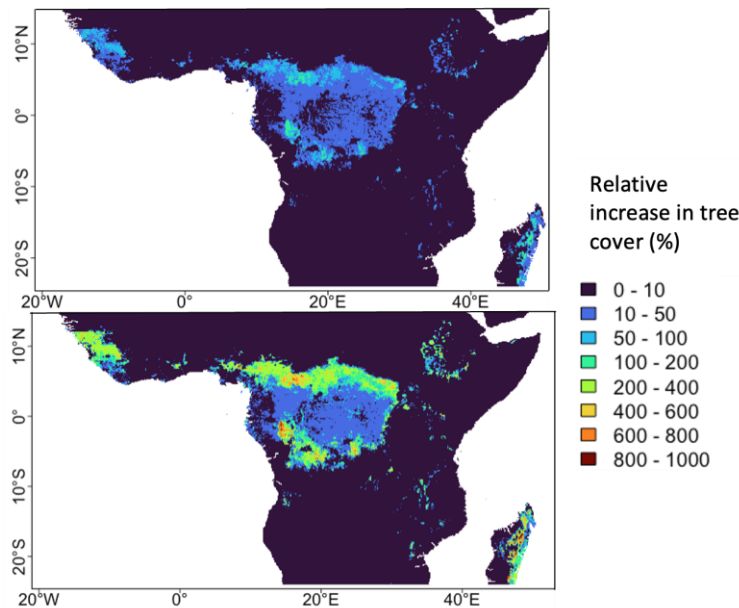


Figure 5.4 Relative increase in tree cover (%), i.e. the increase in tree cover as percentage of baseline tree cover for tropical Africa. Top: after 25 years of tree cover growth. Bottom: after 125 years of growth. This figure has already been presented in chapter 4 and is included here for convenience.

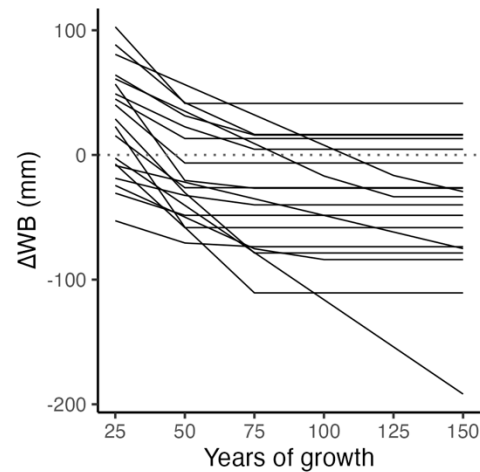


Figure 5.5 Change in water balance (mm) over time for 20 randomly selected grid cells across the tropics. Generally, water balance declines throughout the scenario. Negative values mean the baseline water balance exceeds the scenario values.

5.3 Results

5.3.1 Effects of the tree cover growth scenario on water quantity

The results presented in the following section will inform answers to the **research question 1** of this chapter (*How does tree cover growth affect annual water balance on tropical scale and in selected major river basins?*).

5.3.1.1 Changes in annual water balance, AET and infiltration across the tropics

The annual total per pixel water balance is shown in Figure 5.6a, b & e for the example of scenario run 100, i.e. after 100 years of tree cover growth as modelled in Chapter 4. Particularly high values are modelled for Central America, either side of the northern Andes mountain range, the western coastlines of India and Myanmar, as well as large parts of the islands of Sumatra, Java, Borneo and New Guinea.

Water balance most commonly declines with tree cover increase, as is shown in Figure 5.6c, d & f for the example of 100 years of tree cover growth. Here only annual isolated areas in South America show an increase in water balance, which is typically no higher than 50 mm. Figure 5.5 illustrates the same trend for a set of randomly selected grid cells across the tropics over time. Between the baseline and the first scenario run at 25 years, there are also however, many grid cells with an increase in water balance. This is an artefact resulting from the fact that actual remote sensing input data are used in the calculation of baseline variables whereas for the scenario inputs variables must be adjusted to the scenario conditions. This is because per-pixel data are not available for potential conditions of the scenario. This issue is explored in section 5.3.1.2 using the example of MRBs and discussed further in section 5.4.2.1 (see also Appendix A2.5).

Complementing the spatial patterns in Figure 5.6, the change in actual evapotranspiration (Δ AET) naturally shows the inverse pattern to water balance in Figure 5.7 (left-hand panels). Effective infiltration, on the other hand, follows essentially the water balance pattern. It exhibits overall stronger responses than AET in terms of magnitude. Decreases in effective infiltration are found, for example, in the north-western Amazon sub-basins, the eastern side of the Andes range, and southern parts of the Orinoco basin. Increases in effective infiltration are modelled for the central and south-western regions of the Amazon basin.

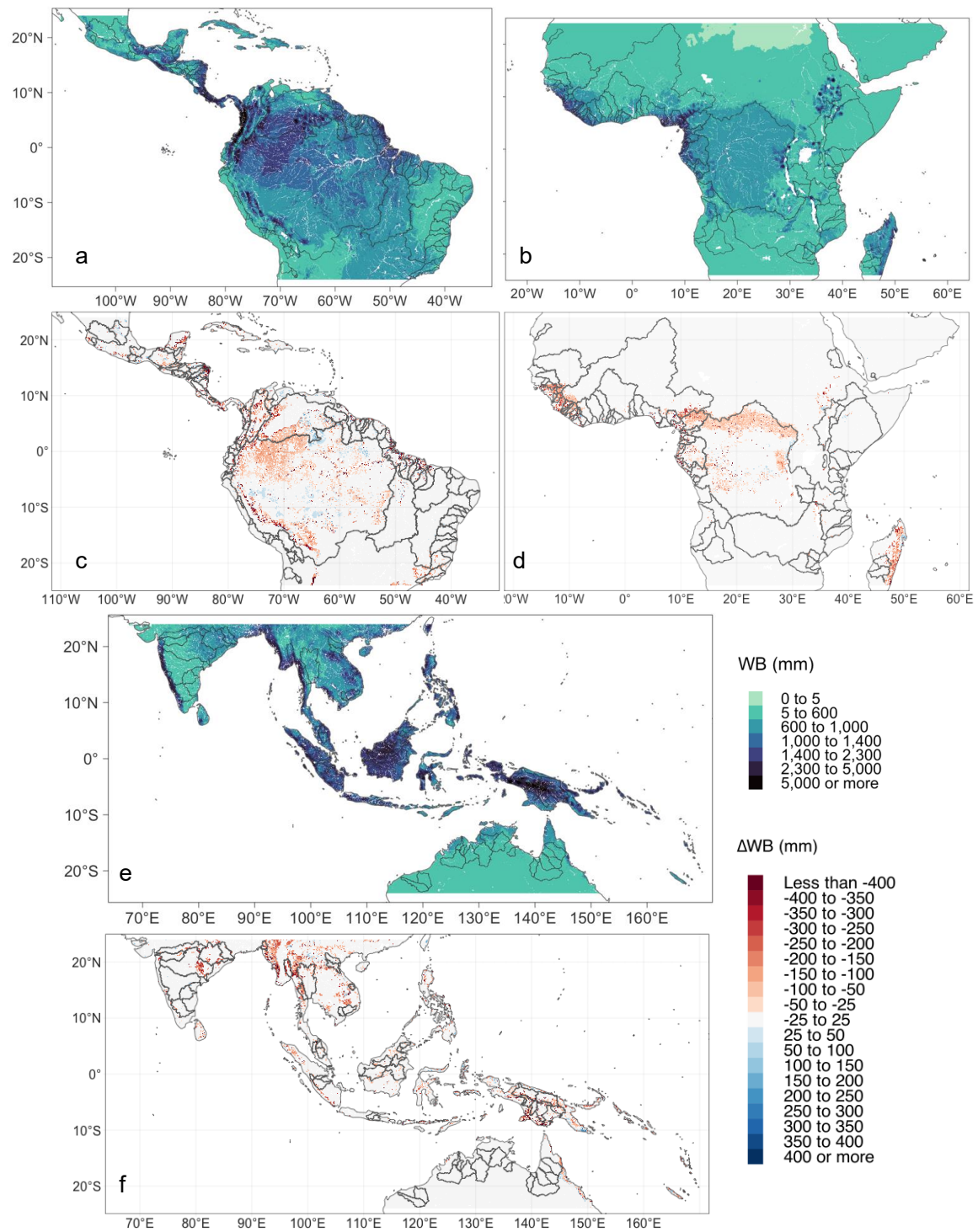


Figure 5.6 a, b, e) Annual total water balance (WB, mm) and c, d, f) change from the baseline (ΔWB , mm) after 100 years of tree cover growth for tropical regions in the Americas (a, c), Africa (b, d) and Asia and Oceania (e, f). Lines delineate MRBs. ΔWB is negative where the baseline is bigger than scenario. In most grid cells water balance is reduced by the scenario.

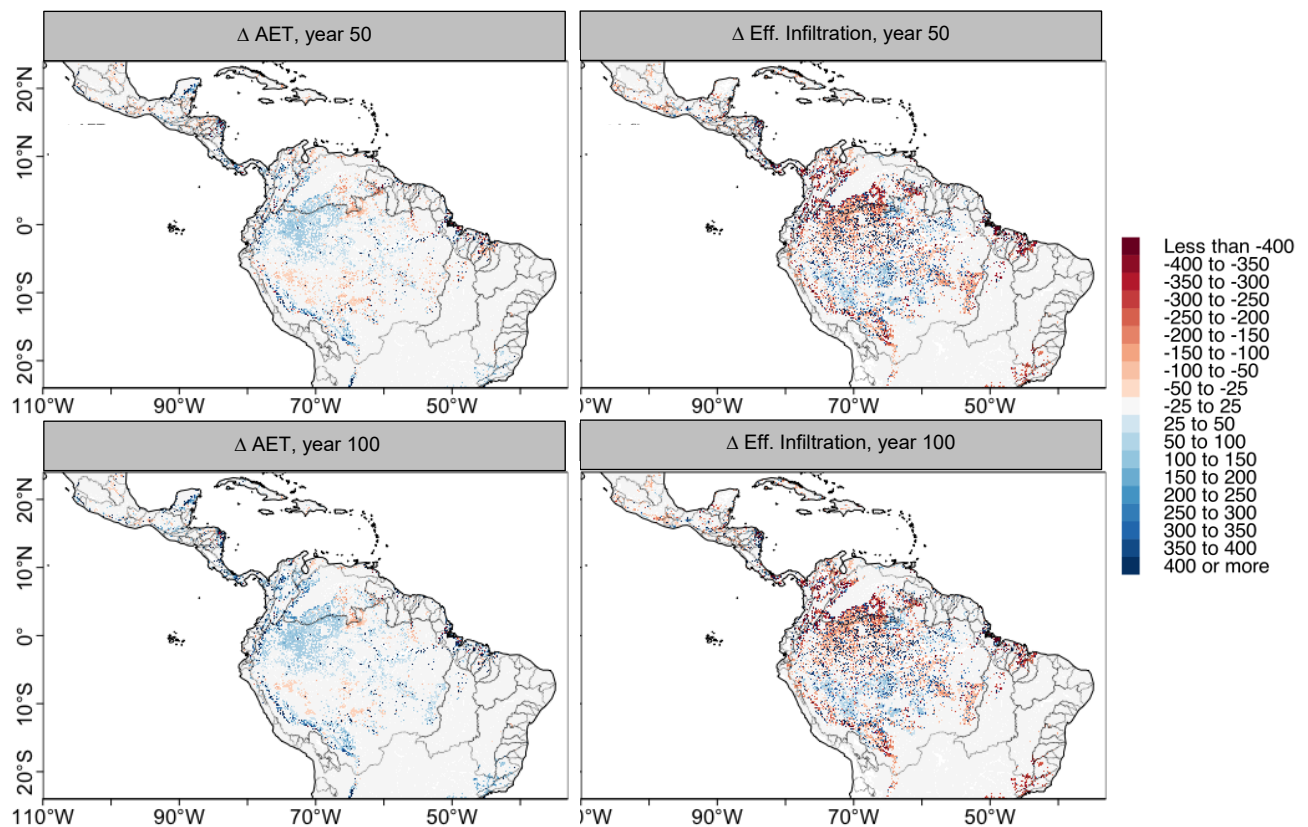


Figure 5.7 Absolute change in AET (left-hand panels) and effective infiltration (right-hand panels) for tropical Central and South America at 50 and 100 years of tree cover growth. Legend shows change in mm.

5.3.1.2 Changes in annual water balance for MRBs

Figure 5.8a depicts the absolute change in water balance over the years of tree growth for the basins of the major river basins of the world (MRB) dataset, with the seven most decreasing basins highlighted (A1 through A7). Some basins exhibit rapid change early on and then level off (for example A1, A2 or A6), others decline in a more consistently (for example, A3, A5, or A7). Figure 5.8b traces the relative change in water balance (as percentage of baseline water balance).

Basin P3 (= A3) registers the highest relative decrease in water balance with almost - 20 per cent, while the remaining basins tend to level off at around - 10 per cent change from the baseline. The three basins A3, A5 and A7 (which are the same as P3, P5, and P7) show both high absolute and relative change in water balance. All highlighted basins are described in brief in Table 5-1.

As rainfall remains unchanged between baseline and scenario, change in water balance is due solely to changes in Actual Evapotranspiration (AET), as water balance is calculated by subtracting AET from total rainfall. AET is composed of

SET (soil evaporation and plant transpiration) and E_i (interception loss). SET and E_i are affected differently by the scenario, as illustrated in Figure 5.9 for the basins presented in Table 5-1.

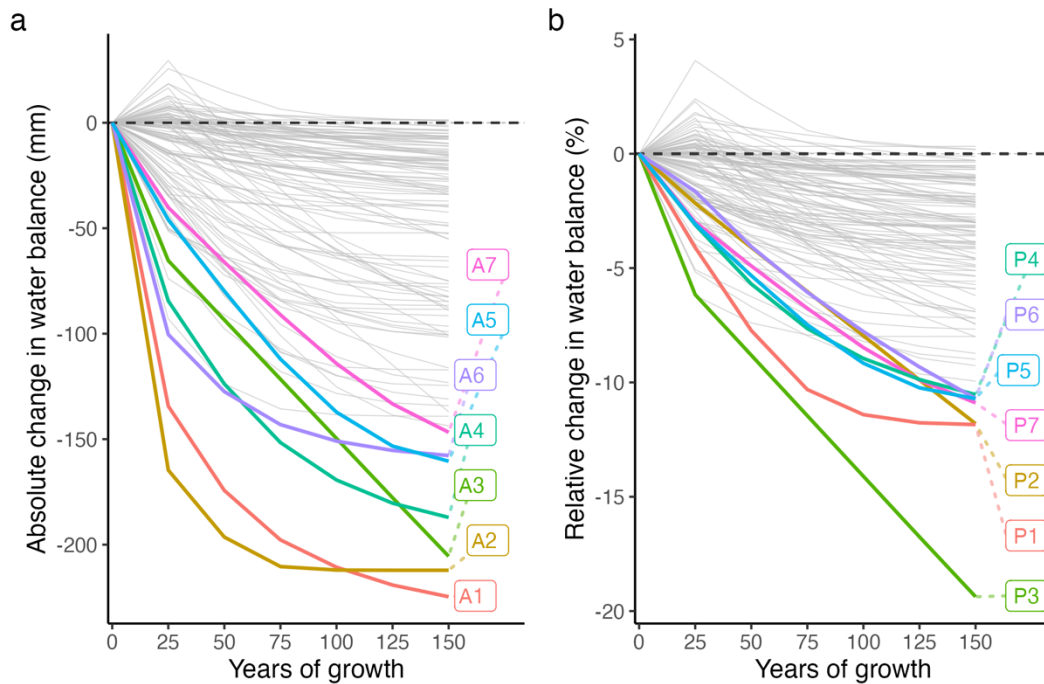


Figure 5.8 Trends in annual water balance over years of tree cover growth for major river basins of the world: a) absolute change in water balance (mm) from baseline; b) relative change in water balance as percentage of baseline water balance; basins with the highest absolute and relative changes are highlighted basins (A1-A7 and P1-P7). Note that A3 = P3, A5 = P5 and A7 = P7, all others differ. MRB where regrowth area of opportunity is less than 5% of basin area are excluded.

Furthermore, basin responses can be grouped by E_i changes (higher or lower gains) and SET changes (higher or lower loss, or low gains) (see Table 5-2 and Figure 5.9c and d). However, even the higher SET decreases are typically offset by increases in interception loss (E_i gain), for example in basins A2, A3/P3 and P2, which lead to an overall increase in AET, as AET is the sum SET and E_i , and thus a decrease in water balance.

Tree cover growth has a smaller effect on the annual sum of SET (see Figure 5.9a) as compared to interception loss, which rises gradually over time for most of the highlighted basins (see Figure 5.9b). This is emphasised again by Figure 5.10a, where SET responds almost not at all to tree cover change until at least 20 per cent of tree cover are added (in percentage points, not relative terms) and from then onwards it declines. ΔE_i on the other hand increases steadily with tree cover, although there is some variability in the response (see Figure 5.10b).

Table 5-1 Characteristics of the basins highlighted in Figure 5.8 and 5.9. Where the same basins are highlighted, ID column marks A.x/P.x, otherwise, plots with IDs A.x are basins highlighted in Figure 5.8a (absolute change); plots with IDs P.x are those highlighted in Figure 5.8b (relative change). Basin area (mio ha), Aridity index (dimensionless), Annual total P = total annual precipitation (mm), P seasonality = CV of rainfall (%), Net radiation = Mean net radiation (W/m²), Increase tree cover = percentage change between year 100 and baseline (%); for example, a 100% increase means tree cover has doubled, MRBID = ID assigned by the Major River Basins of the World dataset. Sources: WorldClim v.2.1 (Fick and Hijmans 2017), CERES EBAF, GRDC 2020 v2, Zomer and Trabucco (2022).

ID in plot	Basin name	Countries	Basin area (mio ha)	Aridity index	Annual total P (mm)	P seasonality (CV, %)	Net radiation (W/m ²)	% Increase tree cover (year 100)	MRBID
A1	Atrato	Colombia, Panama	3.58	2.77	4208	28	175.7	16	3205
A2	Jurado	Colombia, Panama	0.09	1.86	2984	46	188.6	28	3413
A3/ P3	Corubal (also Koliba)	Guinea, Guinea-Bissau	2.43	0.83	1734	114	162.6	187	1210
A4	Patia	Ecuador, Colombia	2.23	2.05	2480	35	191.6	35	3421
A5/ P5	Sarstoon	Guatemala, Belize	0.22	2.03	3403	61	182.8	63	4242
A6	San Juan	Colombia	1.53	3.35	4641	17	171.1	7	3424
A7/ P7	Moa (also Makona)	Sierra Leone, Guinea, Liberia	1.96	1.54	2558	74	176.5	99	1225
P1	Saint John River	Guinea, Liberia, Ivory Coast	1.62	1.37	2150	63	173.6	34	1237
P2	Little Scar-cies (also Kaba)	Sierra Leone, Guinea	1.86	1.28	2347	95	172.1	161	1220
P4	Saint Paul River	Guinea, Liberia	2.03	1.37	2239	69	177	58	1238
P6	Sanaga	Central African Republic, Nigeria, Cameroon	13.3	1.13	1663	72	174.6	94	1239

Table 5-2 Overview of the which basins gain or lose in AET components.

	High loss in SET	Low loss in SET	Gain in SET
High gain in E _i	A/P3, P2, A2	A/P7, A/P5	none
Low gain in E _i	none	P4, P6	A1, A4, A6, P1

MRBs with high relative change in water balance (P1, P2, P4 & P6, marked in reds) increase their E_i less so than those where absolute changes in water balance are high (MRBs marked in blues and greens). Lastly, Figure 5.10c and d

illustrate the *sensitivity* of SET and E_i to tree cover increase under different aridity and rainfall regimes. The plots show that the higher the annual rainfall total, the more an additional unit of tree cover will increase E_i . For SET, the pattern indicates that lower aridity indices (in the context of these basins, these MRBs are perhaps best called *less humid*) can result in decreases in SET with additional tree cover. In contrast, in even more humid basins (indicated by higher aridity indices) tree cover increase will have a positive effect on SET, similar to E_i .

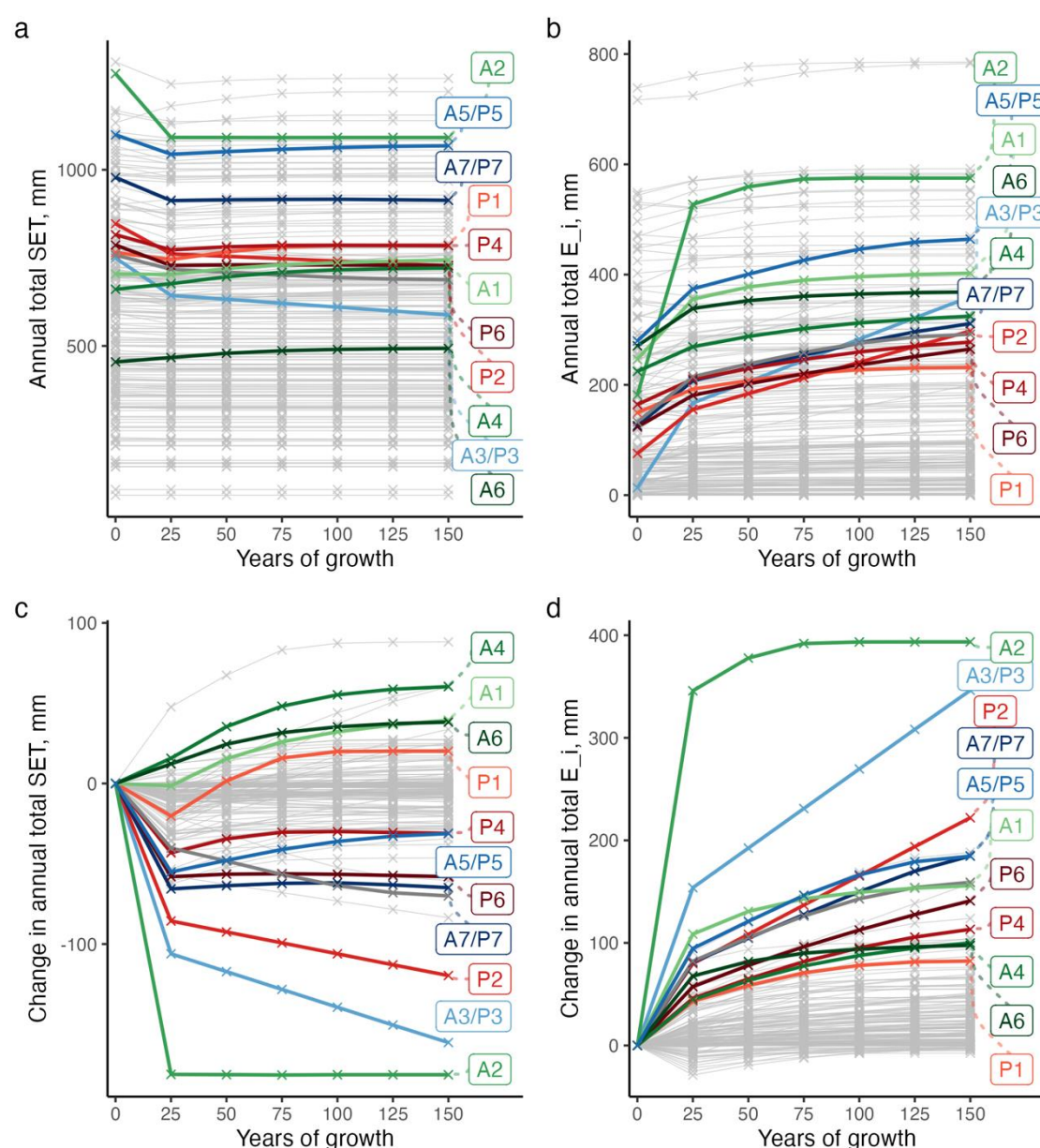


Figure 5.9 Trends in evapotranspiration variables over years of tree cover growth for major river basins of the world: a) annual sum of soil evaporation & plant transpiration (SET) in mm, b) annual sum of interception loss in mm, c) change (absolute difference) in annual total SET in mm, d) change in annual total interception in mm. Labels A1-7 and P1-7 correspond to highlighted basins in Figures 5.8 and Table 5-1, but note the differing colour code.

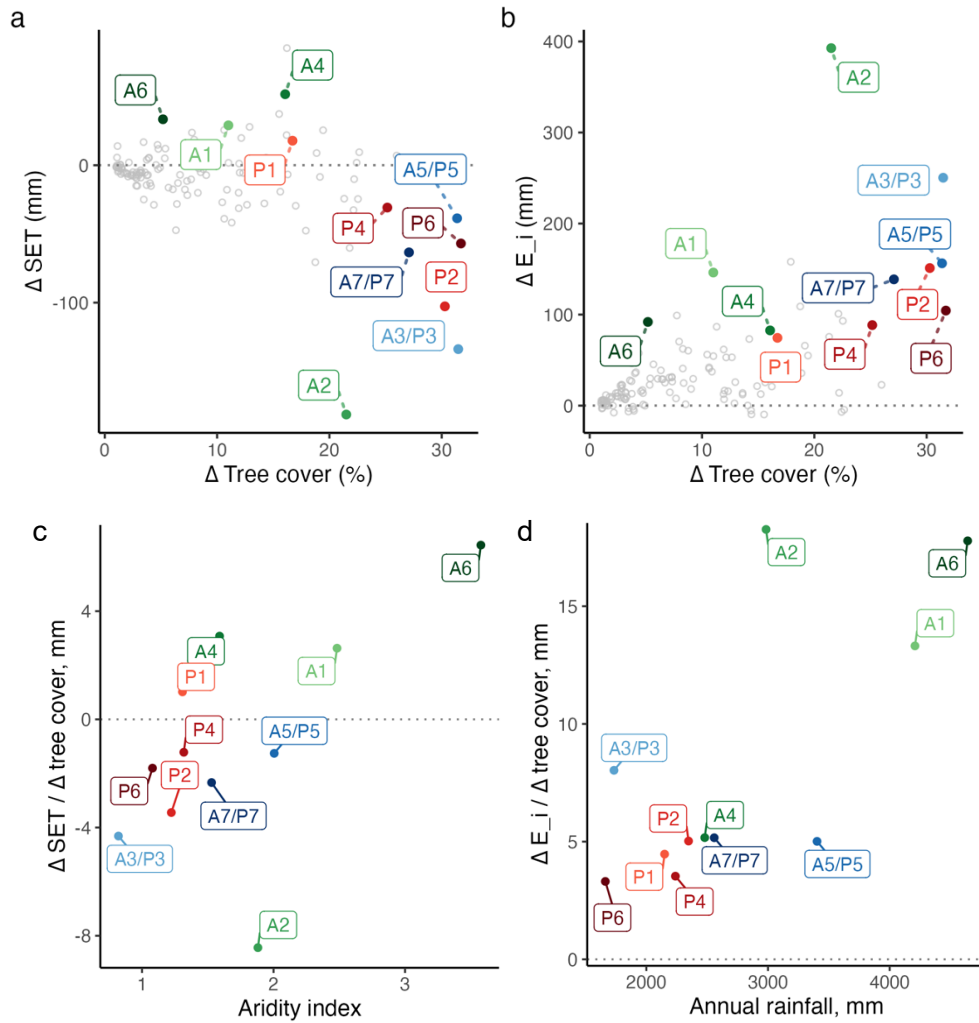


Figure 5.10 Scatter plots of change in a) SET and b) E_i against change in tree cover (percentage points) for major river basins of the world and c) change in E_i per unit change in tree cover (mm/%) and annual rainfall total and d) between change in SET per unit change in tree cover (mm/%) and annual aridity index for MRBs. Plots c & d) thus measure the sensitivities of SET and E_i to tree cover increase and only show the highlighted MRBs, while plots a & b show all MRBs. All variables are basin median values.

5.3.2 Effects of the tree cover growth scenario on water regulation services

In this section, the effect of the tree cover growth scenario on monthly streamflow at outlets of ten selected dam watersheds is examined in response to **objective 3**, by addressing **research question 2** of this chapter. This analysis is conducted for multiple timesteps of tree cover growth (25 to 150 years) to reflect how post-restoration hydrological changes evolve over time. For the monthly streamflow at a point of interest, lag times (lag_{SSF}) of subsurface flow (SSF) become relevant, in contrast to the previous sections concerned with changes in annual water

quantity based on water balance. Because the calculation of the lagged SSF was computationally intensive, I decided to study mostly smaller dam watersheds in this section. The focus on dam watersheds stems from the fact that this is where water is used and thus changes in quantity and timing are relevant, rather than other types of watershed outlets such as confluences.

The section is divided into the following parts: first, a brief introduction of the ten selected dam watersheds, second, an attempt at verifying the streamflow estimates by comparing baseline model discharge to reference discharge data from the Global Runoff Data Centre (GRDC, 2020); and third, the description of change in runoff between the reference year (baseline) and the various timesteps of the tree cover growth scenario.

5.3.2.1 Description of the selected dam watersheds

The ten dams and their watersheds are briefly described in Table 5-3 and their locations are shown in Figure 5.11. Their locations were obtained from the GOODD dam database (Mulligan et al., 2020).

On an annual scale, the watersheds of the three dams Bhumibol, Tabsalao and Tiznados are less humid, as measured by the annual *aridity index* by Zomer and Trabucco (2022). In the remaining dam watersheds, annual rainfall is on par with or exceeds the PET demands on an annual scale. It is noteworthy that for the selected watersheds, the term aridity index is somewhat misleading as all are classified as humid according to the climate classification by Zomer and Trabucco (2022). The index is calculated as P/PET , therefore values above 1 indicate more rainfall than PET demands. The following text will, however, refer to it as *aridity index* in keeping with the naming of the dataset. The monthly pattern of the aridity index illustrates that all watersheds, except that of the Paraibuna dam, have higher PET demands than rainfall available for at least several months of the year (see Appendix A3.1). When the aridity index in the Paraibuna dam watershed is low, it is still very close to 1, signifying that water limitation is not an issue.

The area that has been identified by the tree cover growth scenario developed in Chapter 4 as suitable for tree cover growth varies from 28 (in the Tiznados watershed) to 95 per cent (in the Mape watershed) of the respective watersheds' areas. A minimum share of 20 per cent is thus ensured, in keeping with Bosch and

Hewlett's (1982) early findings that with a lower share, effects on streamflow are unlikely to be detectable.

Total rainfall ranges from 1288 to 2232 mm/yr with the highest values found in Bamendjin, Mape, and Srinagarind dam watersheds, and the lower values located in Tiznados, Bhumibol and Tabsalao watersheds.

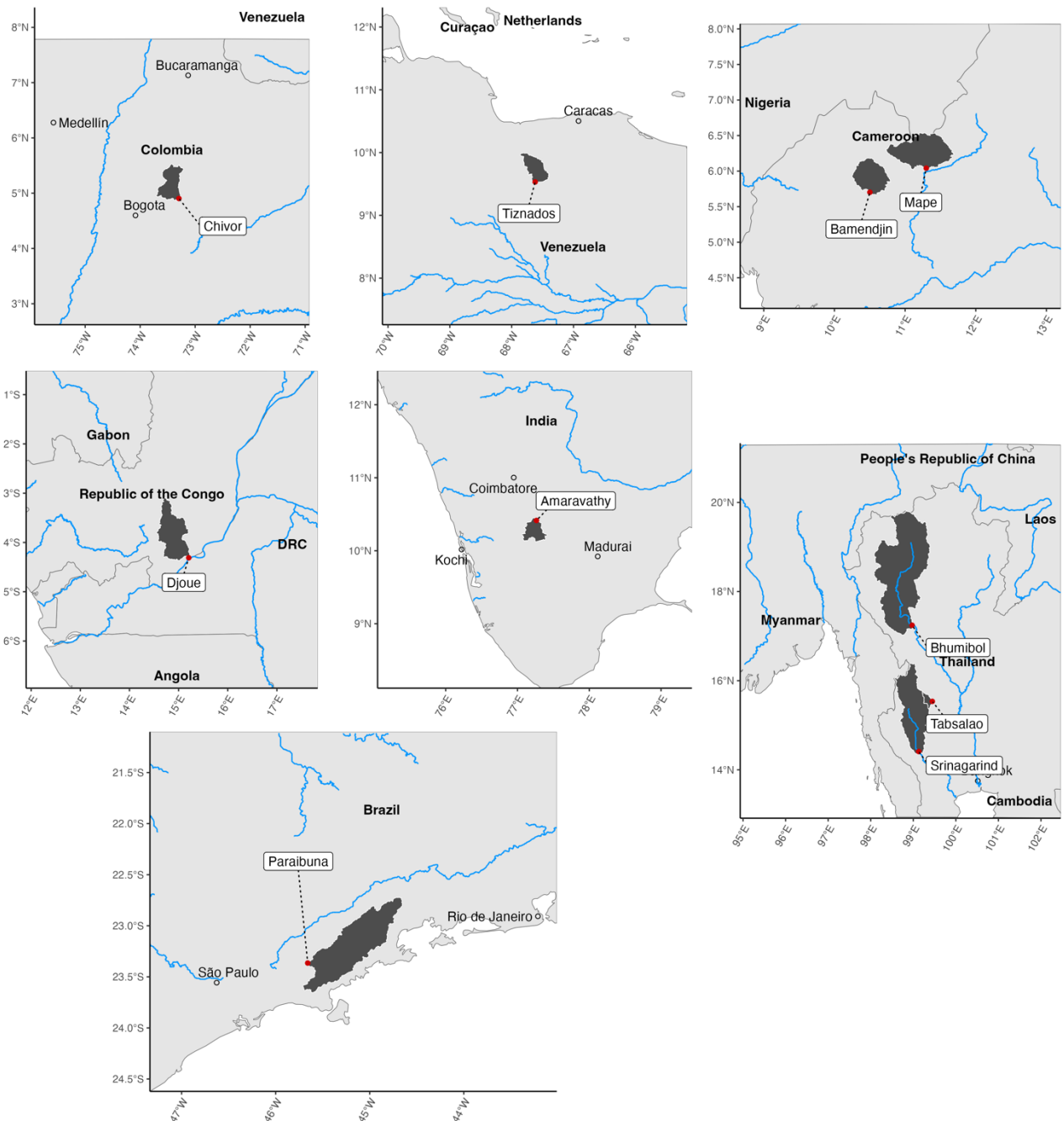


Figure 5.11 Watersheds of selected dam in dark grey with their respective GRanD dams marked in red; blue lines are rivers. Sources: Dam watersheds: Global Georeferenced Database of Dams (GOODD, Mulligan et al. 2009); dams: GRanD database; Rivers: Major named rivers, GRDC.

Table 5-3 Selected dam watersheds with corresponding IDs from the GOODD database, dam & river names watershed area and country. Environmental properties include the watershed means of the annual aridity index (dimensionless, P/PET), annual total rainfall (mm) and the share of watershed area with an opportunity for regrowth. Dam and river name and main use are extracted from the GRanD database; watershed area is based on GOODD dam watersheds in the first instance and on re-extracted watersheds in some cases. There is no GRanD dam near GOODD ID dam 1017960; therefore dam name, river and main use are extracted from FAO Aquastat data. Additional information, such as GRanD ID and main dam use can be found in Appendix A3.1

Dam name	Country	Total area (km ²)	Regrowth area (%)	Aridity index	Annual rain (mm)	River name	GOODD ID
Tiznados	Venezuela	1,441	28	0.66	1288	Tiznados	1012364
Chivor	Colombia	2,415	36	1.33	1769	Bata Chivor	1012023
Paraibuna	Brazil	4,091	82	1.32	1753	Paraibuna	1003540
Mape	Cameroon	3,767	95	1.13	2055	Mape	1002328
Bamendjin	Cameroon	2,201	35	1.34	2232	Noun	1017710
Djoue	Republic of the Congo	6,173	34	1.32	1740	Djoue	1017960
Amaravathy	India	800	62	0.98	1796	Amaravathy	1023176
Bhumibol	Thailand	26,160	48	0.64	1289	Ping	1025865
Tabsalao	Thailand	522	81	0.75	1482	Sakae Krang	1025900
Srinagarind	Thailand	10,998	91	0.92	1903	Quae Yai	1025877

5.3.2.2 Comparison of model estimate and GRDC streamflow data

The baseline discharge at the dam watershed outlet is compared to multiple years of monthly mean discharge data from the Global Runoff Data Centre (GRDC) for four dam watersheds with nearby GRDC gauge stations in Figure 5.12. Because the DTRIE model calculates streamflow for undammed watersheds, its estimates are compared to GRDC data from before the construction of the respective dam for all GRDC stations except Kibassi, where no records prior to damming exist. To convert streamflow to discharge the total monthly streamflow volume in m³ was divided by the number of seconds in a month (with a standard number of 30 days in a month).

Mean monthly runoff from the model is well within the range of GRDC monthly means for Paraibuno/Santa Branca station and for Srinagarind during months with high runoff. At the Bamendjin, Kibassi and Srinagarind locations, the model mean runoff peaks slightly earlier in the year than the GRDC runoff. For the

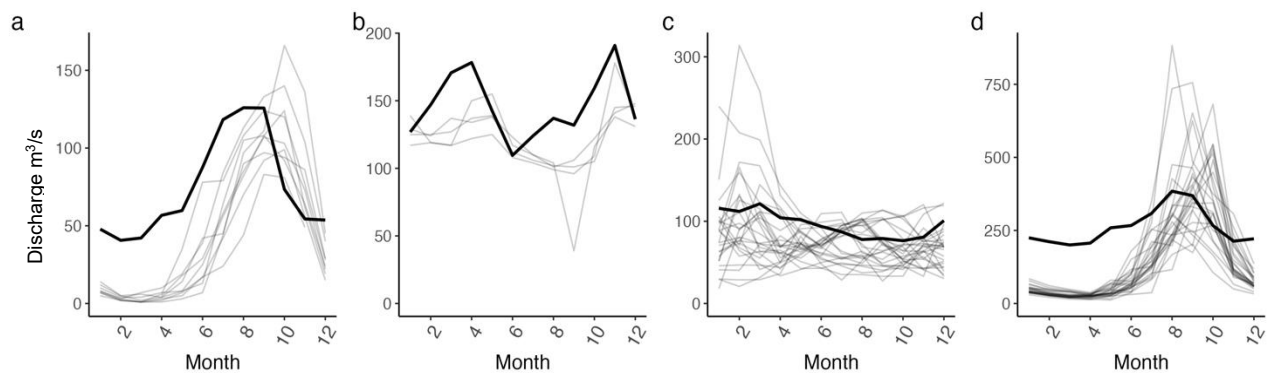


Figure 5.12 Average monthly discharge in m^3/s at GRDC gauge stations near the selected GOODD dams for a) Bamendjin (GRDC station Bamendjin), b) Djoue (GRDC station Kibassi), c) Paraibuna (GRDC station Santa Branca) and d) Srinagarind (GRDC station Srinagarind dam). Black line = monthly mean discharge for the baseline (2018) according to the model; grey lines = monthly mean GRDC discharge for multiple years. Where possible, GRDC runoff excludes values after the dam construction year. The GRDC data used for Bamendjin (or Bamendjin) spans the years 1965-1974; for Kibassi (Djoue) 1969-1972; for Santa Branca (Paraibuna) 1952-1978 and for Srinagarind 1952-1978.

Bamendjin location, for example, the GRDC data suggest highest flows in October whereas the model pulls these forward into August. Furthermore, the model overestimates runoff in months with lower flows. This is the case at the Srinagarind location, where model discharge in January is $250 \text{ m}^3/\text{s}$ compared to the GRDC long-term mean of $30 \text{ m}^3/\text{s}$. Overall, however, the DTRIE model estimates runoff values that are well within the range of possible values as measured at GRDC gauging stations.

5.3.2.3 Change in total annual streamflow

Although the watershed dam analysis is designed to answer the **research question 2** on changes in monthly streamflows, it is worthwhile to first describe the effect of the tree cover growth scenario on the annual total of streamflow. This analysis will enable a better interpretation of the monthly patterns presented in section 5.3.2.4.

As Figure 5.13a illustrates, the effect of tree cover growth on total annual streamflow presents itself in three different ways. In one group, which includes Bhumibol, Srinagarind, Tabsalao, Amaravathy and Chivor dam watersheds, streamflow increases with the scenario. A second group increase sharply between the baseline and year 25, and the levels off. This group comprises the Mape, Bamendjin, Djoue and Paraibuna dam watersheds. Lastly, the watershed of the Tiznados dam increases sharply to its high point in year 25 and then

declines in annual streamflow. As has been shown in previous sections for MRB and HB4 basins, the annual water balance typically declines with the tree growth scenario because AET increases. This is also the case for these dam watersheds (Figure 5.13b), barring an initial jump in water balance in year 25 in the watersheds of Djoue, Chivor and Tiznados dams (this jump is explained as an artefact caused by the different input datasets between baseline and scenario in Appendix A2.5).

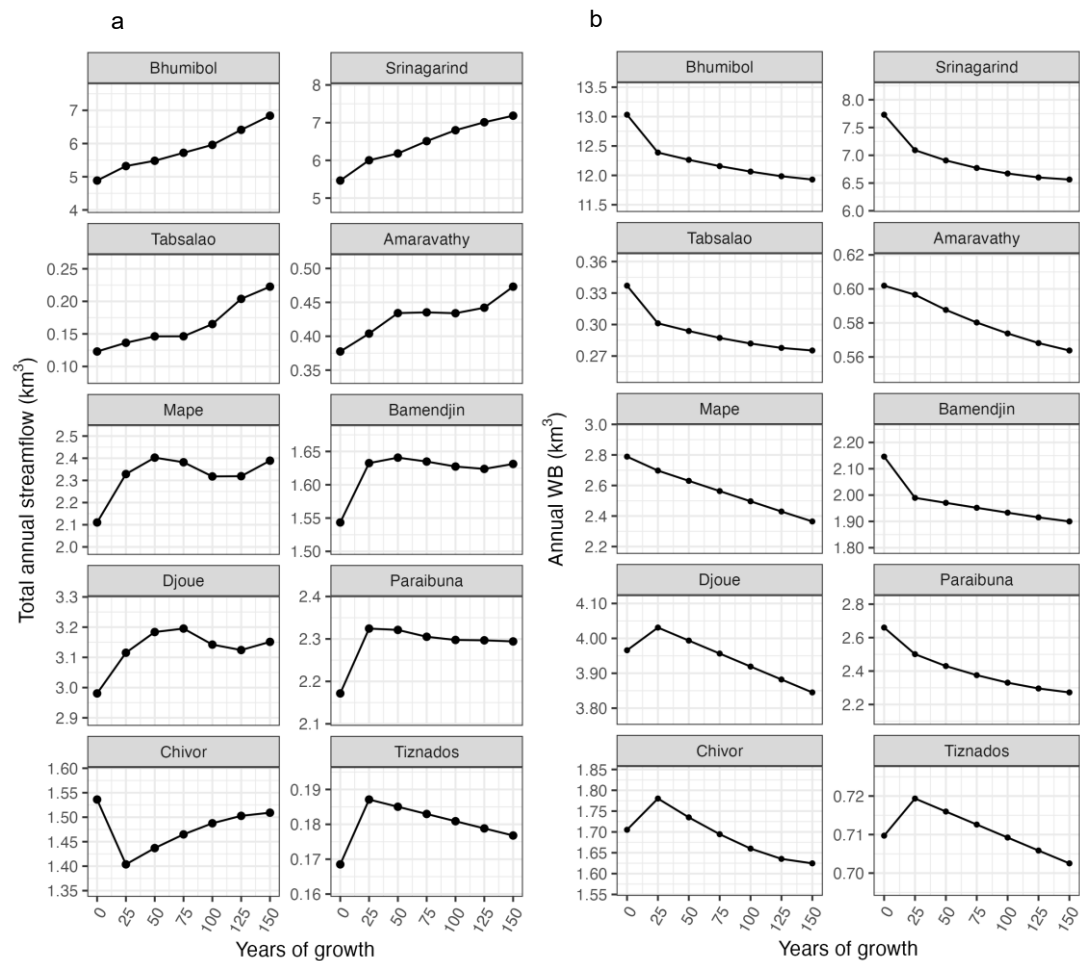


Figure 5.13 Effect of the tree cover growth scenario on annual hydrological variables for the dam watersheds. a) total annual streamflow (km³) from the dam watersheds for baseline (year 0) and following scenario intervals; b) total annual water balance (WB, km³). The water balance is the sum of all pixel WB values for the year.

As such, the effect of tree cover growth on annual streamflow totals seems at first counter-intuitive. However, it will be shown in section 5.4.2.1 that this is expected from the model because it is a consequence of the way the lagged subsurface flow contribution to monthly streamflow is calculated. Furthermore, annual streamflow will not be used to assess the changes in annual water quantity in the dam watersheds, because this is already done via water balance. The focus of

the dam watershed analysis is on the monthly timestep analysis and the annual total streamflow is presented only to contextualise the findings regarding streamflow variability as measured by the coefficient of variation.

5.3.2.4 Change in watershed streamflow on a monthly scale

This section explores the effect of tree cover growth on the changes in monthly streamflow and its coefficient of variation (CV) at the dams to address **research question 2** of this chapter: *How does tree cover growth affect streamflow seasonality and streamflow quantity in the following dry season?* The CV is calculated as follows from the standard deviation (σ) the mean (μ):

$$CV = \frac{\sigma}{\mu}$$

(Eq. 5-5)

Figure 5.14 illustrates the shifts in water availability over the year for all scenario runs, from 25 to 150 years of tree cover growth.

First, the change in CV over time is examined in the left-hand panel of Figure 5.14. Tree cover growth affects the CV in three ways: 1) CV increases, which is the case for Srinagarind, Mape, Bamendjin, Chivor and Paraibuna; 2) CV decreases, which is the case for Bhumibol and Tabsalao; and 3) it remains largely unchanged, which is the case for Amaravathy, Djoue and Tiznados. The greatest absolute changes in CV are modelled for the two watersheds of the Srinagarind and Paraibuna dams.

To complement the patterns in CV, the timeseries of monthly streamflow for the different scenario runs are depicted in Figure 5.14 (right-hand panel). This will aid the interpretation of results in section 5.4.2.2 because an increase in CV can also be the result of an overall increase in total annual streamflow, which is in fact modelled for some watersheds (see in Figure 5.13a).

For Srinagarind and Paraibuna, the amplitude of the monthly streamflow pattern increases over the years, and results in more streamflow when baseline streamflow was already high in the baseline, and less when it was low. A similar pattern, albeit less stark, can be identified for the watersheds of Mape, Bamendjin and Chivor dams. In contrast, the watersheds of Bhumibol and Tabsalao and to some extent Amaravathy show an increasing magnitude of monthly streamflow,

although there are no seasonal shifts (see Figure 5.14 a, c, d). The remaining watersheds Djoue, Tiznados and Amaravathy do not respond to tree cover growth with changes in the monthly distribution of streamflow.

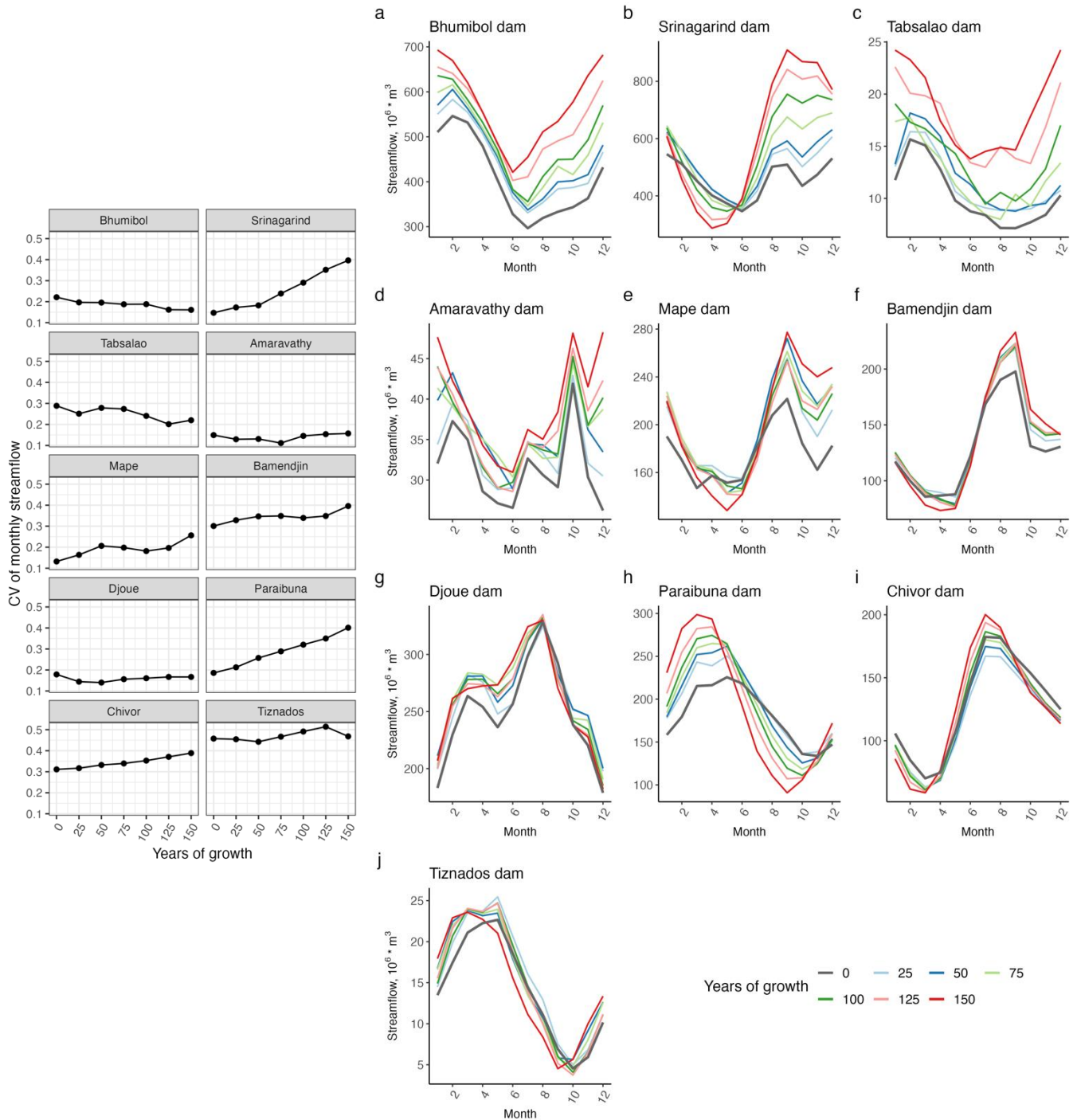


Figure 5.14 Effects of tree cover growth on monthly streamflow at the dam. The left-hand panel shows the coefficient of variation (CV) of monthly streamflow at each dam from year 0 (baseline) to 150 years of tree cover growth. Right-hand panel: Plots a-j) show the monthly streamflow at the dams (million m^3) with the line colour indicating the years of tree cover growth; year 0 (in grey) is the baseline. The watersheds of Bhumibol, Tabsalao, Amaravathy, Djoue and Tiznados experience a decline or not change in CV, while all others increase.

5.3.3 Environmental drivers of the changes in water quantity and regulation services following tree cover growth

The following three sections focus on the sensitivities of hydrological variables. First, the sensitivity of water balance to the threshold used in the delineation of regrowth areas in chapter 4 is examined. The last two sections then present the results relevant to **research question 3** of this chapter (*How do other environmental factors influence the sensitivity of water quantity and regulation services to tree cover growth*).

5.3.3.1 Sensitivity of the water balance change to the tree cover threshold of the tree growth scenario

As established in Chapter 4 section 4.2.1.1, the tree cover growth scenario uses an upper threshold of 80 per cent tree cover in the reference year, i.e. grid cells with higher tree cover than 80 per cent are not areas of opportunity for tree cover growth, but lower tree cover thresholds were also briefly visualised (Figure 4.2, p. 79). While a tree cover threshold of 80 per cent may include grid cells in the regrowth scenario that are in fact already fully forested (or appear fully forested to the remote sensing instrument), a lower threshold risks overlooking grid cells that have potential for increase in cover if human pressures (e.g. selective logging) are removed. The effect of the different thresholds on the absolute change in basin tree cover (Δ Tree cover, in percentage points) was examined in section 4.3.2.4. In brief, for 106 of the 196 MRBs in the analysis, the 80 per cent threshold resulted in higher tree cover increases from the baseline to the scenario year (on both pixel level and as basin mean) and for 90 basins it made no difference. The differences in basin means of Δ Tree cover between the two thresholds diminished over the scenario runs and was never greater than 15 percentage points.

This section now examines the effects of two thresholds 70 (hereafter *group 1*) and 80 per cent (hereafter *group 2*) on the change in water balance from the baseline. For all major river basins of the world, Figure 5.15 illustrates the divergence between the two cut-offs over multiple timesteps of tree cover growth. All in all, most basins show higher percentage changes in water balance from the baseline in *group 2* (80 per cent threshold) compared to *group 1*; *group 1* values

for percentage change in water balance amount to on average 77 per cent of their respective *group 2* counterpart (median = 89%, 25th percentile = 52%, 75th percentile = 100%). This means limiting the analysis to grid cells meeting the 70 per cent reference year tree cover threshold would in lower relative changes in water balance.

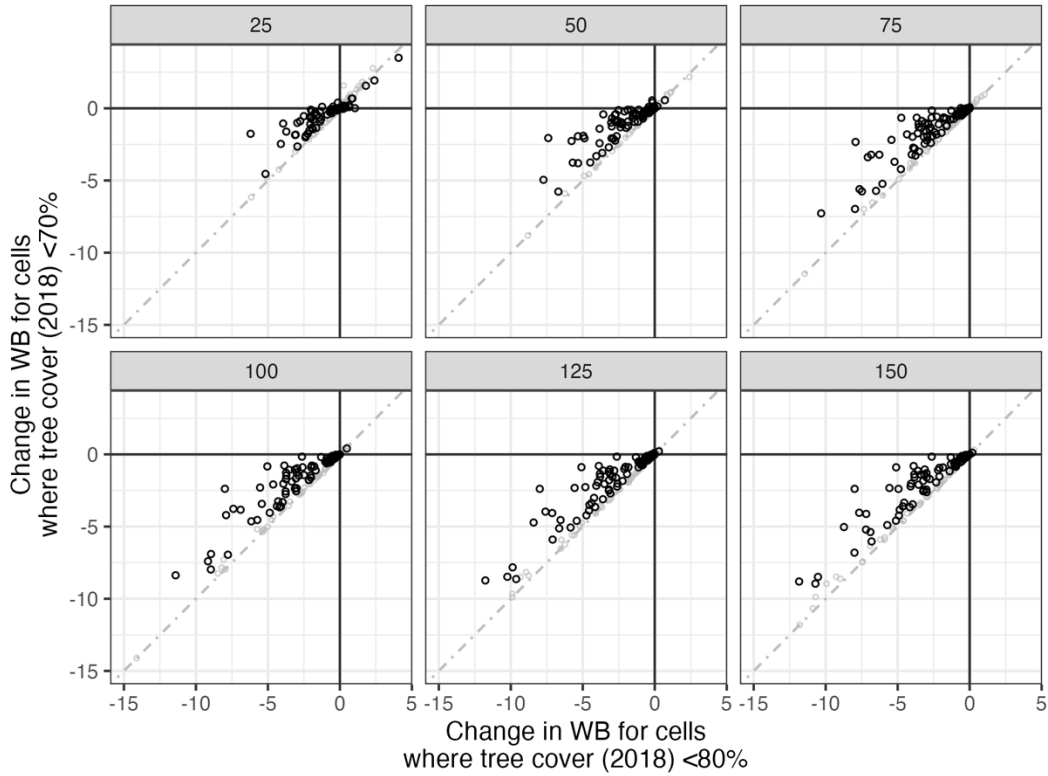


Figure 5.15 Percentage change in water balance between scenario and baseline for tree cover threshold, 80% (x-axis, “group 2”) plotted against the percentage change for the tree cover threshold of 70% (“group 1”). Each circle is an MRB. Percentage change is aggregated as the mean over major river basins of the world. Bold black circles represent basins where the % change water balance of group 1 is less than 90% that of the respective group 2 value; grey circles represent basins where this discrepancy is less than 10%. The dot-dashed grey line is the 1:1 line. Facet numbering (25-150) reflects years of tree growth.

5.3.3.2 Sensitivity and elasticity of water balance to tree cover increase

Figure 5.16 shows the spatial pattern of water balance change (in mm) per unit tree cover change (in percentage points), and in the bottom plot, both water balance and tree cover change are shown in normalised units. The former will be referred to as *general hydrological sensitivity* (H_s). When relative change in water balance is analysed per relative change in tree cover (e.g. as in the lower plot in Figure 5.16), the term *hydrological elasticity*, E_{WB} , is used. To enable comparison with other literature, the variable S_f , absolute hydrological sensitivity, is introduced, which is defined by Zhang et al. (2017 Eq. 2) as the absolute values of

E_{WB} . As an absolute value visualises the strength of the individual relationships are better, but does not include direction, therefore E_{WB} is used to show the direction of the effect where needed. Note that while S_f could have been referred to as *absolute elasticity*, but it is referred to as *sensitivity* to align with Zhang et al. 2017, Hou et al. 2023, and others.

$$H_s = \frac{\Delta WB}{\Delta \text{Tree cover}}$$

(Eq. 5-6)

$$E_{WB} = \frac{\% \Delta WB}{\% \Delta \text{Tree cover}}$$

(Eq. 5-7)

$$S_f = |E_{WB}|$$

(Eq. 5-8)

$$\% \Delta WB = \frac{100 * \Delta WB}{\text{Baseline WB}}$$

(Eq. 5-9)

$$\% \Delta \text{Tree cover} = \frac{100 * \Delta \text{Tree cover}}{\text{Baseline tree cover}}$$

(Eq. 5-10)

$$\Delta WB = WB_{\text{year}_k} - WB_{\text{baseline}}$$

(Eq. 5-11)

$$\Delta \text{Tree cover} = \text{Tree cover}_{\text{year}_k} - \text{Tree cover}_{\text{baseline}}$$

(Eq. 5-12)

where WB is water balance and year_k is the scenario run (25, 50, ...150).

The spatial pattern in both plots of Figure 5.16 is very similar, with higher decreases in water balance sensitivity and elasticity, for example, in the north-western Amazon and southern Orinoco basins, the northern belt of the Congo basin and several western African basins. Increases in water balance are located in more central areas of the Amazon and Congo basins, as well as in a more scattered manner, in central parts of the Mekong basins (i.e. northern Laos).

On pixel level, general hydrological sensitivity H_s ranges from - 46.14 mm to 6.9 mm (1st percentile and 99th percentile, respectively, absolute minimum and

maximum are - 128.93 to 76.42 mm) with a median value of - 0.34 mm. Hydrological elasticity E_{WB} ranges between - 1.35 and 0.33 per cent (1st percentile and 99th percentile, respectively, absolute minimum and maximum are - 2.99 and 1.59 per cent), with a median value of - 0.015 per cent across the tropics. Thus, changes in water balance are more often negative than positive with tree cover growth and the magnitude of decreases recorded are larger than the increases in water balance (see also Figure 5.17).

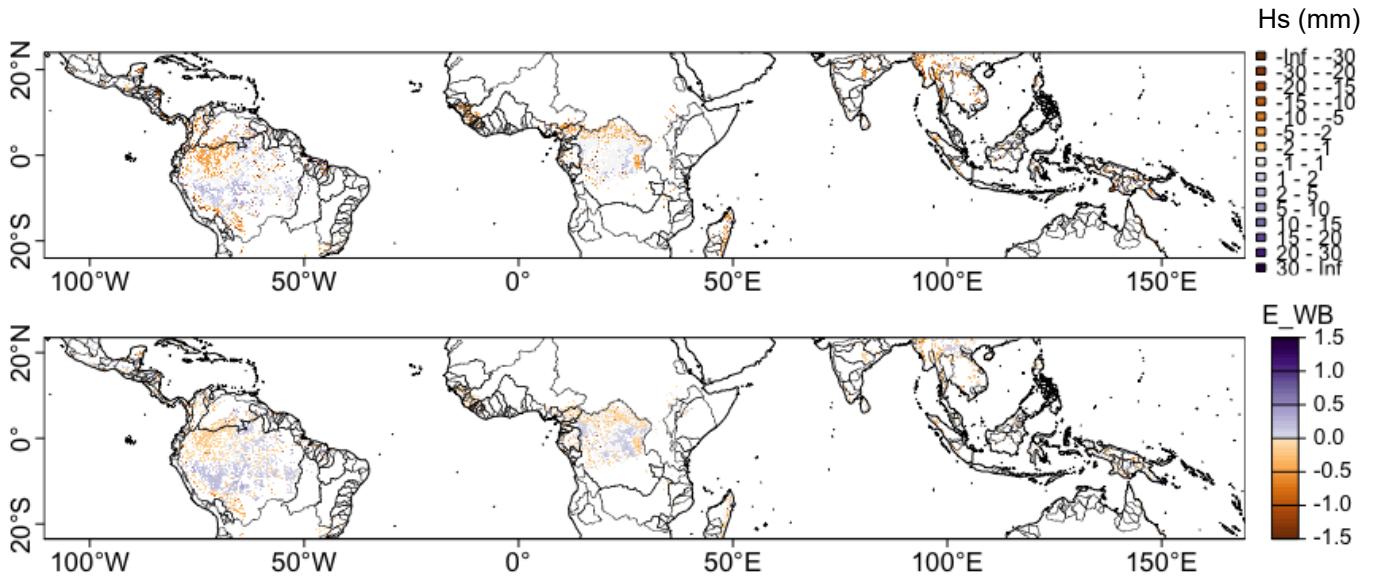


Figure 5.16 Top: Water balance change (mm) per change in tree cover (percentage points), or general water balance sensitivity; bottom: relative change in water balance (%) per unit relative change in tree cover (%) E_{WB} , or water balance elasticity. Both plots present averages over all scenario runs (25-150 years). Lines delineate MRBs and general coastlines. Grid cells with a tree cover increase of less than 5 percentage points (for the top plot) or less than 1 % relative increase (for the bottom plot) are excluded.

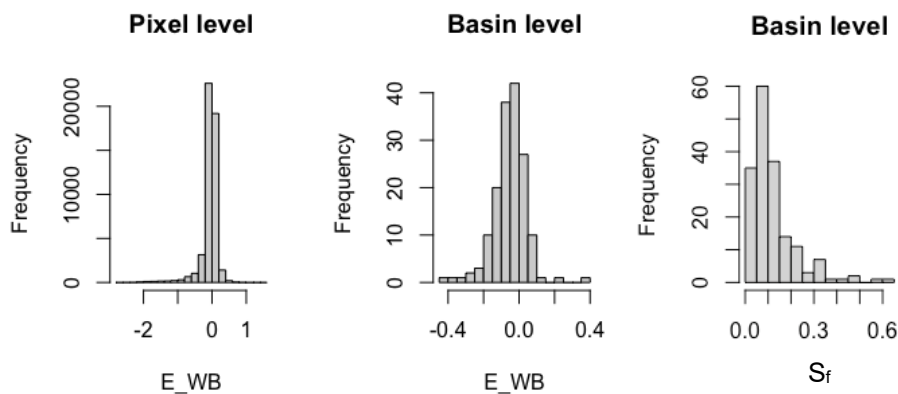


Figure 5.17 Frequency distributions of hydrological elasticity, E_{WB} across the tropics, on pixel level (left panel) and on basin level (centre panel); frequency distribution of S_r on the basin level (right panel). On basin level, the basin the median is used.

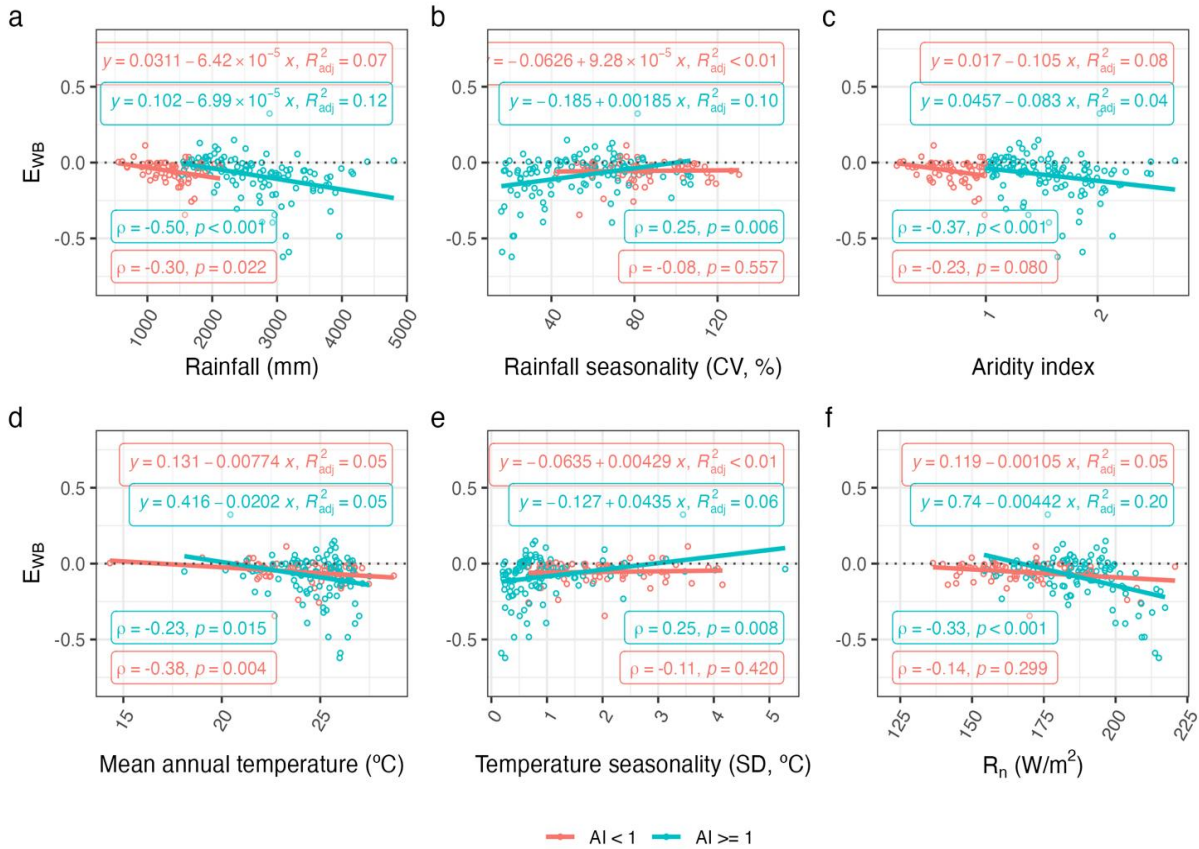


Figure 5.18 Relationship between elasticity of water balance to tree cover increase, E_{WB} with environmental conditions for HB4s: a) total annual rainfall (mm), b) rainfall seasonality (CV, %), c) aridity index (dimensionless), mean annual temperature (°C), temperature seasonality (SD, °C), and net radiation R_n (W/m^2). Red scatter and lines represent basins where the annual aridity index (AI) is below 1, turquoise scatter and lines represent basins where annual aridity index exceeds 1. Values are basin medians for HydroBasin level 4 (HB4) basins which have at least 5 % of regrowth area.

The relationships between hydrological elasticity E_{WB} , and thus S_f , are affected by the aridity index (see Figure 5.18c and Figure 5.19c). E_{WB} and aridity have a weak negative correlation (Spearman's $\rho = -0.32$, $p < 0.001$, not shown in plot); S_f has a moderate positive correlation (Spearman's $\rho = 0.57$, $p < 0.001$, not shown in plot) with the aridity index (see Figure 5.19c).

The relationships with the remaining environmental variables were examined in groups of HB4s with an aridity index (AI) below versus above 1 indicating water- or energy-limitation (AI < 1 versus AI ≥ 1), as is widely used (e.g. Hou et al., 2023). Whether disaggregated by the aridity index threshold or not, the relationships are not linear. The grouping does highlight, however, that for water-limited basins (represented by red scatter and lines), temperature and rainfall seasonality do not affect E_{WB} and the remaining variables, very slightly decrease E_{WB} (see Figure 5.18b, e). In contrast, energy-limited basins (represented by turquoise scatter and lines) respond with *higher* E_{WB} to increases in rainfall and

temperature seasonality, and respond with *lower* E_{WB} to gains in annual rainfall, net radiation and MAT (see Figure 5.18a, f, d).

The patterns shown in Figure 5.19 for S_f are very similar to those for E_{WB} , as S_f is the absolute value of E_{WB} . For most basins, the effect of tree cover increase on water balance is low, but the distribution is heavily right-skewed and has a long tail (see Figure 5.17; the 90th percentile of S_f is 0.25).

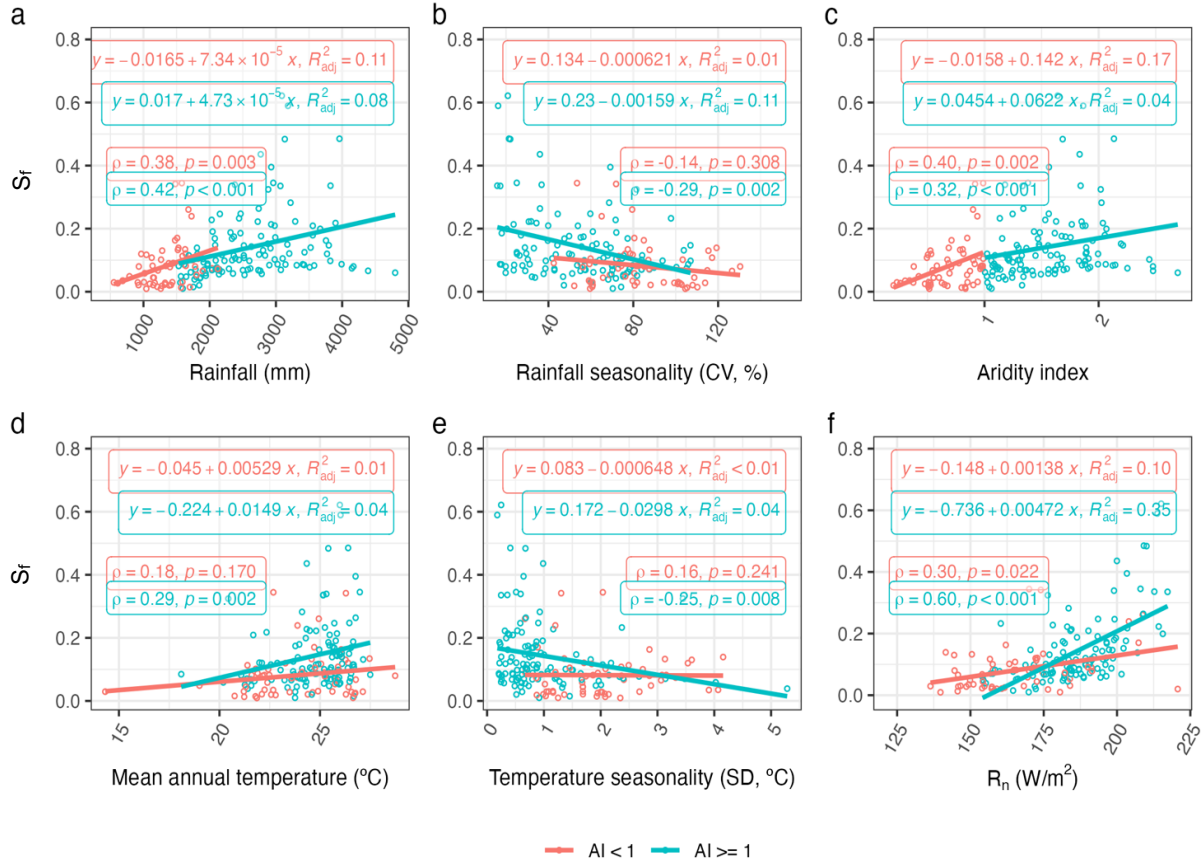


Figure 5.19 Relationship between sensitivity of water balance to tree cover increase, S_f with environmental conditions for MRBs: a) total annual rainfall (mm), b) rainfall seasonality (CV, %), c) aridity index (dimensionless), mean annual temperature (°C), temperature seasonality (SD, °C), and net radiation R_n (W/m²). Red scatter and lines represent basins where the annual aridity index (AI) is below 1, turquoise scatter and lines represent basins where annual aridity index exceeds 1. Where AI < 1 is defined by Hou et al. 2023 as water-limited, versus AI ≥ 1, which is energy-limited. Values are basin medians for HydroBasin level 4 (HB4) basins which have at least 5 % of regrowth area.

The relationship of both sensitivity and elasticity of water balance and the size of the basin is illustrated in Figure 5.20. While there is a significant moderate correlation in both cases for the more humid, energy-limited basins (AI ≥ 1), the relationship between either pairs of variables is not very linear, even after log transforming the basin size variable, as is demonstrated by the low coefficients of determination ($R^2 = 0.19$ for S_f and 0.17 for E_{WB}). There is no correlation and no linear relationship between the variables in the case of water-limited basins (AI < 1).

For both variables and in both cases, the best description of the pattern is a convergence toward zero, i.e. sensitivity and elasticity to tree cover change get closer to zero with increasing basin size.

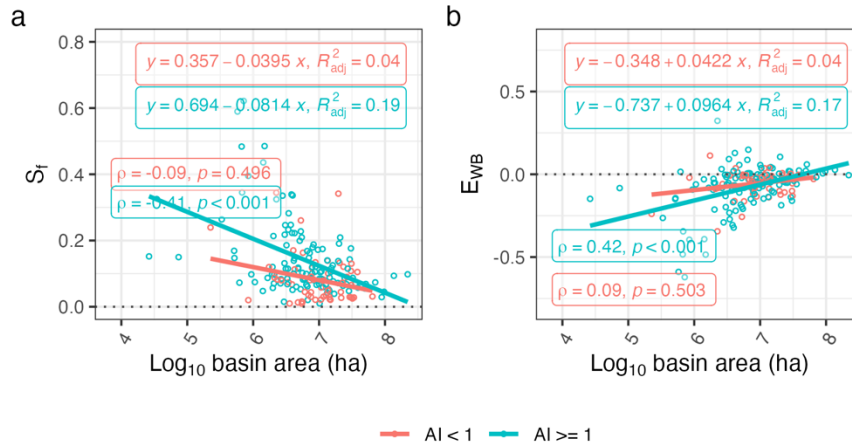


Figure 5.20 Relationship between a) sensitivity of water balance to tree cover increase, S_f , and b) elasticity of the same, E_{wb} , and the basin size (log hectares). All other plots specifics are the same as Figures 5.18 and 5.19.

Hydrological sensitivity S_f is generally very low, with a 90th percentile value of 0.25, meaning in 90 per cent of the basins, a one per cent relative increase in tree cover engenders a 0.25 per cent change in water balance. In sixteen basins S_f is higher than 0.25 and they can be considered relatively highly hydrologically sensitive. These basins are all coastal and located predominantly in insular Southeast Asia and Taiwan, two are in South America, and two in West Africa (see Figure 5.21).

Common traits within this hydrologically highly sensitive group are high net radiation, high baseline tree cover and mean annual temperature, as well as moderate to high aridity index and annual rainfall. Most notably, they have very low temperature and rainfall seasonality (see Figure 5.22a). It is noteworthy, however, that the five basins presented in Figure 5.22a are all located in insular Southeast Asia (Figure 5.21, bottom plot) and thus may share similar environmental traits due to proximity. These commonalities have been confirmed in other regions as well, however, although there is slightly more spread with regards to net radiation and rainfall seasonality (see Figure 5.23).

Of the hydrologically very sensitive basins, all but the Taiwanese basin (see Figure 5.21, bottom panel, Pfaffstetter ID 4370) have negative E_{wb} values in the

range from - 0.6 to - 0.1 per cent, which means their water balance decreases with tree cover increase. The Taiwanese basin, in contrast, shows a relative increase in its water balance by 0.3 per cent. This basin shares most of the previously identified common traits, however, its MAT is the lowest in the group (20.4 °C), temperature seasonality is highest in the group (3.4 °C), rainfall seasonality is comparatively high and mean radiation comparatively low (but not an extreme value among the hydrologically very sensitive basins) (see Figure 5.23). This basin technically spans the entire island of Taiwan, but water balance was only calculated for the part south of 24°N.

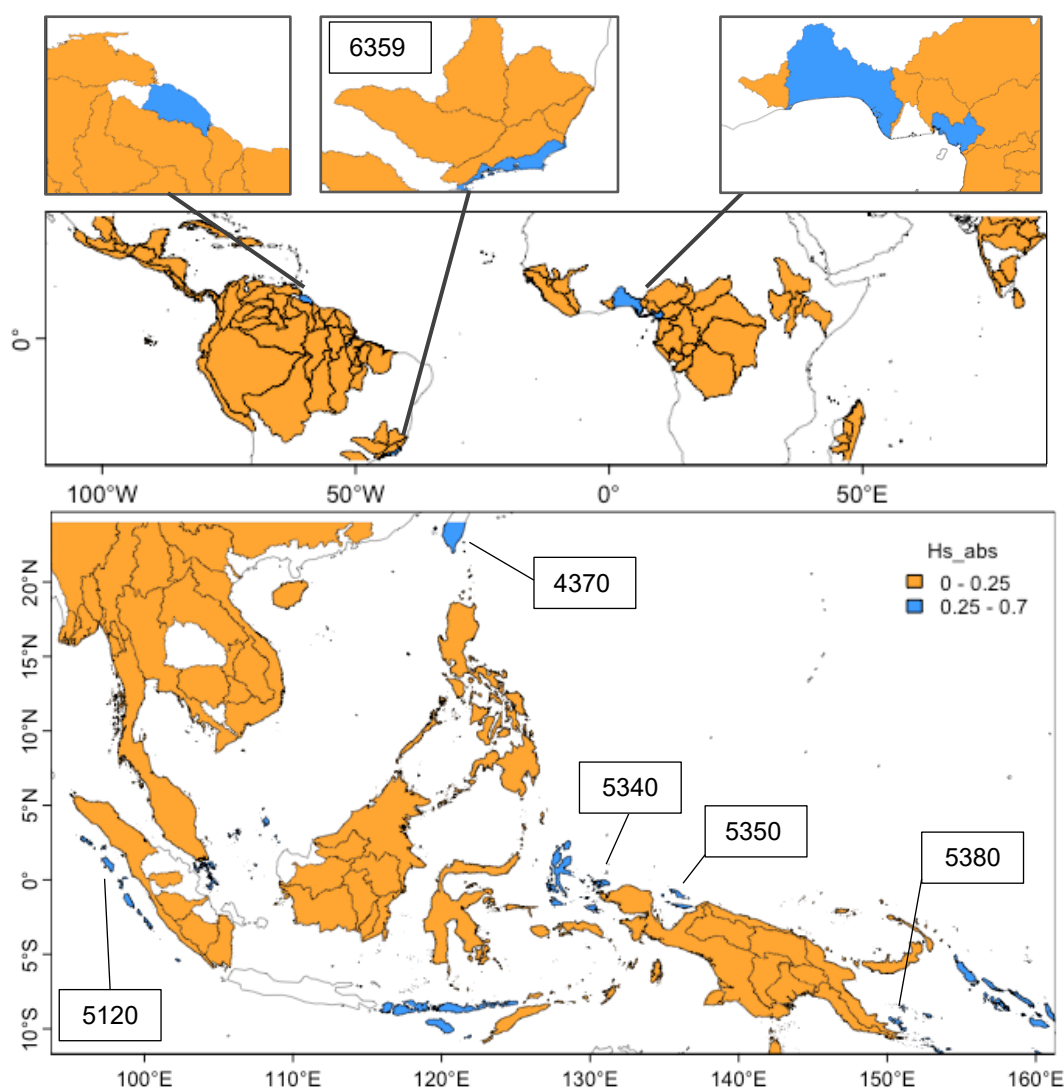


Figure 5.21 Map of water balance sensitivity to tree cover increase, S_r . HB4 with $S_r > 0.25$ are marked in blue, others are orange. Several basins in insular south-east Asia are labeled with their unique Pfaffstetter ID (in boxes), as assigned by the HydroBASINS level 4 dataset. Only HB4s with a minimum share of 5 per cent of basin area with regrowth potential are included.

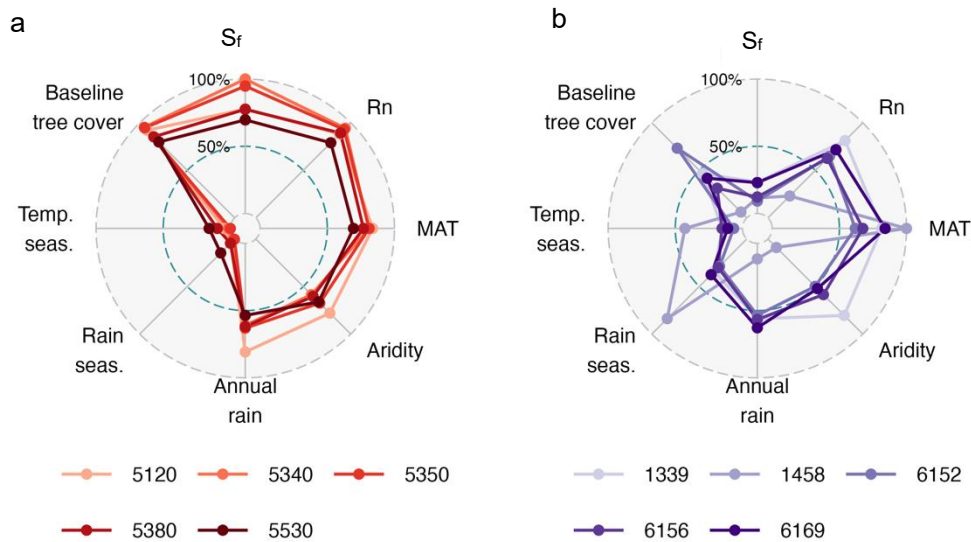


Figure 5.22 Radar charts of environmental conditions for two sets of HB4s: a) the five hydrologically most sensitive HB4s (with $S_f > 0.4$) and b) hydrologically more resistant HB4s (with $S_f < 0.25$). Environmental variables are, in clockwise order from the top: hydrological sensitivity, net radiation, mean annual temperature, aridity index, total annual rainfall, rainfall seasonality, temperature seasonality and baseline tree cover. The five most sensitive basins share the common traits low temperature and rainfall seasonality and high baseline tree cover, while the less sensitive basins exhibit more variability. Line colour represents the Pfaffstetter ID assigned by HydroBASINS. All variables are rescaled to 0-1 because of the different units and ranges. This was done before subsetting according to the S_f threshold so that a value of 0 in a variable represents the minimum over all HB4s, not just the 5 shown in the plots. The five basins for plot b were randomly selected from the subset with $S_f < 0.25$. Only HB4s with a minimum share of 5 per cent of basin area with regrowth potential are included.

5.3.3.3 Sensitivity of effective infiltration and AET to tree cover increase

The following section explores the sensitivity of effective infiltration to tree cover increase. Effective infiltration determines the partitioning of effective rainfall into surface and subsurface flows. As the latter enters the slow hydrological pathway and contributes to streamflow with a delay, the examination of effective infiltration becomes relevant to the trade-off question. The results from this section will respond to **research question 3** of this chapter.

The spatial pattern of the sensitivity of effective infiltration to tree cover change is shown in Figure 5.24 for all three tropical regions. The change in effective infiltration ranges from - 68 to 140 mm per percentage point increase in tree cover (1st percentile = - 29 mm, 99th percentile 51 mm). With a median value of - 1.43 mm, negative changes are most common across all three continents, but some clusters of increasing effective infiltration are found in the central and southern parts of the Amazon basin, the central and northern Congo basin, and northern Lao,

density are compared. For example, the belt of infiltration decreases in the Congo basin (orange pixels) traces where lower baseline tree cover is increased by the scenario. Here, the effect of increasing interception loss (E_i) dominates. Within the area surrounded by this belt, as well as in the southern Amazon basin and in Southeast Asia baseline tree covers were higher, which results increased effective infiltration in the scenario (purple pixels). In these areas, the effect of tree cover increase is dominantly an improvement of soil water storage capacity rather than change in E_i .

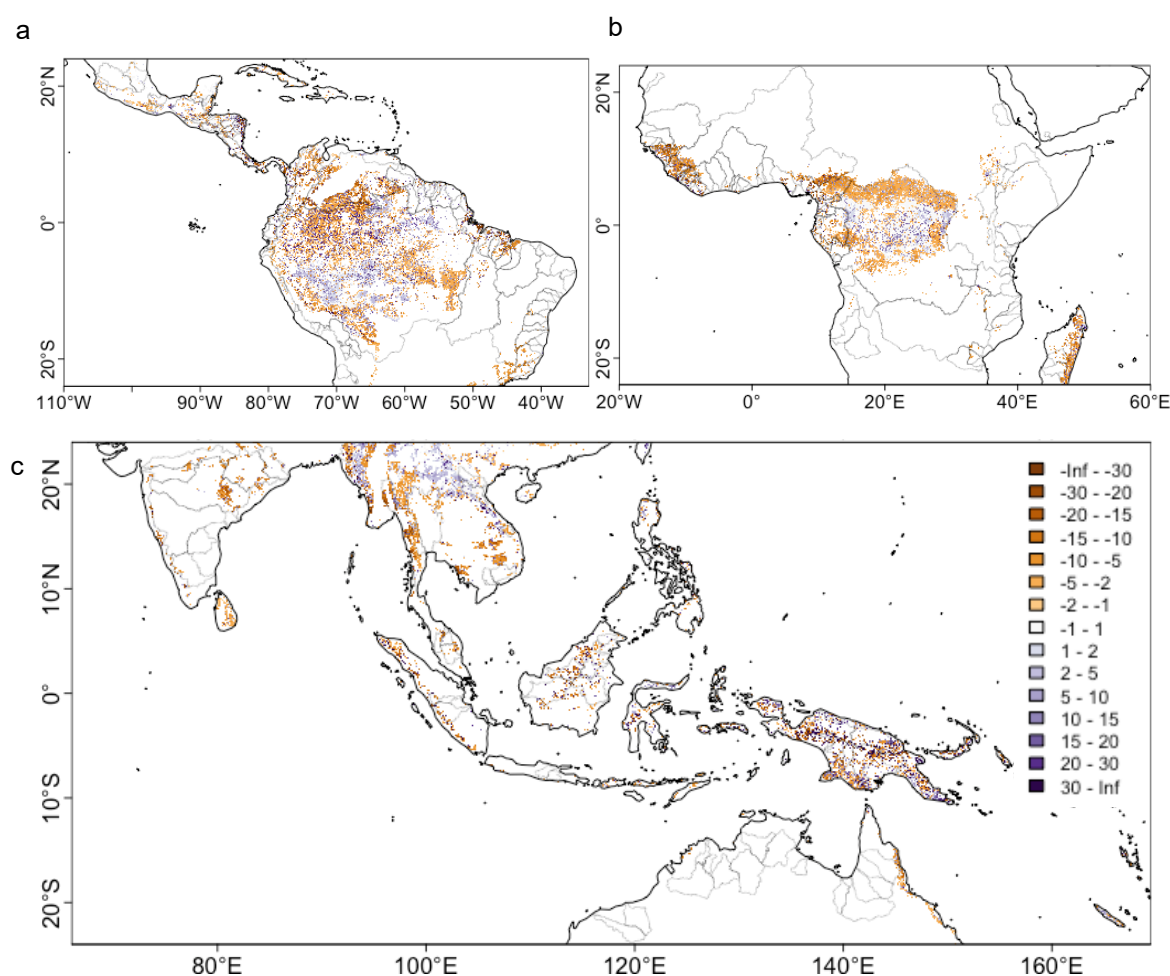


Figure 5.24 Sensitivity of effective infiltration to tree cover change (mm/%), presented as change in effective infiltration per unit change tree cover. Positive values (shown in purple) occur when the scenario exceeds the baseline value. Colour scale is identical for all plots. Faint grey lines delineate MRBs. Averaged over all scenario runs.

A map of the sensitivity of AET is not shown separately because its spatial pattern is the opposite of that of water balance sensitivity, which has already been presented in Figure 5.16.

Figure 5.25 examines the sensitivities of AET and effective infiltration on the spatial level of MRBs for two example years, 50 (a) and 100 (b). Over the years of tree cover growth, all MRBs gradually register differences closer to 0 in these two variables compared to the baseline (compare plot a to b), because tree cover continues to rise but the absolute change in variable levels off. The general pattern is that effective infiltration more often decreases than increases, but for AET increases are dominant and only very few basins decrease in AET. These negative AET changes are an artefact of the “raw value” baseline and will be discussed in section 5.4.2.1.

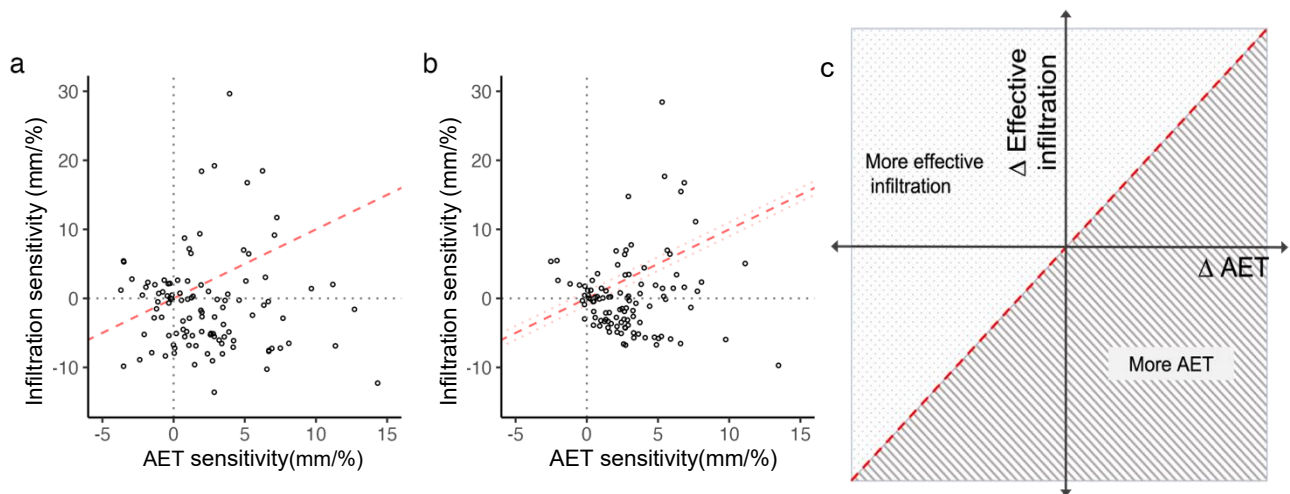


Figure 5.25 Sensitivity of effective infiltration versus that of AET to tree cover change for a) 50 years and b) 100 years of tree cover growth for MRBs. Both variables are presented as absolute change in the variable (mm) per unit change in tree cover (%). Plot c is a conceptual diagram to help the interpretation of plots a-b by indicating where a basin would be plotted if it received overall more infiltration (above the red dashed line), or loses more to AET (below the red line) through the scenario. Each point represents one MRB. Red dashed line represents the 1:1 line, where change in infiltration and AET are in equilibrium. MRB where regrowth area of opportunity is less than 5% of basin area are not shown.

For year 50, in 36 out of 112 basins the change in quantity of effective infiltration (per change in tree cover) outweighs the change in AET; these MRBs are plotted above the red dashed line, thus overall, the number of MRBs where changes in AET exceed those in effective infiltration is greater. This indicates that AET is more sensitive to tree cover change than effective infiltration. The 36 MRBs where effective infiltration is more sensitive, on the other hand, are located in insular Southeast Asia, continental East Asia (Lao & Vietnam), and also to a large degree in Central and South America, but notably, not in Africa. At 100 years of tree cover growth, only 30 MRBs show this behaviour.

An initial investigation into the environmental properties of these two groups is presented in Figure 5.26, with several of the previously examined variables.

While the spread in both groups tends to be large, especially for the group where AET is more sensitive and which outnumbers the other, there are some key differences. Baseline tree cover and aridity index are significantly higher in the group with higher infiltration sensitivity ($p < 0.001$), while rainfall and temperature seasonality are lower. Neither the share of regrowth nor basin size (not shown in plot; median basin size for $\Delta \text{AET} > \Delta \text{effective infiltration}$ was 2.96 million ha compared to 2.74 million ha for the other group; non-significantly different with $p > 0.05$ and Mann-Whitney $U = 1072$, $N = 112$) differed significantly between the groups.

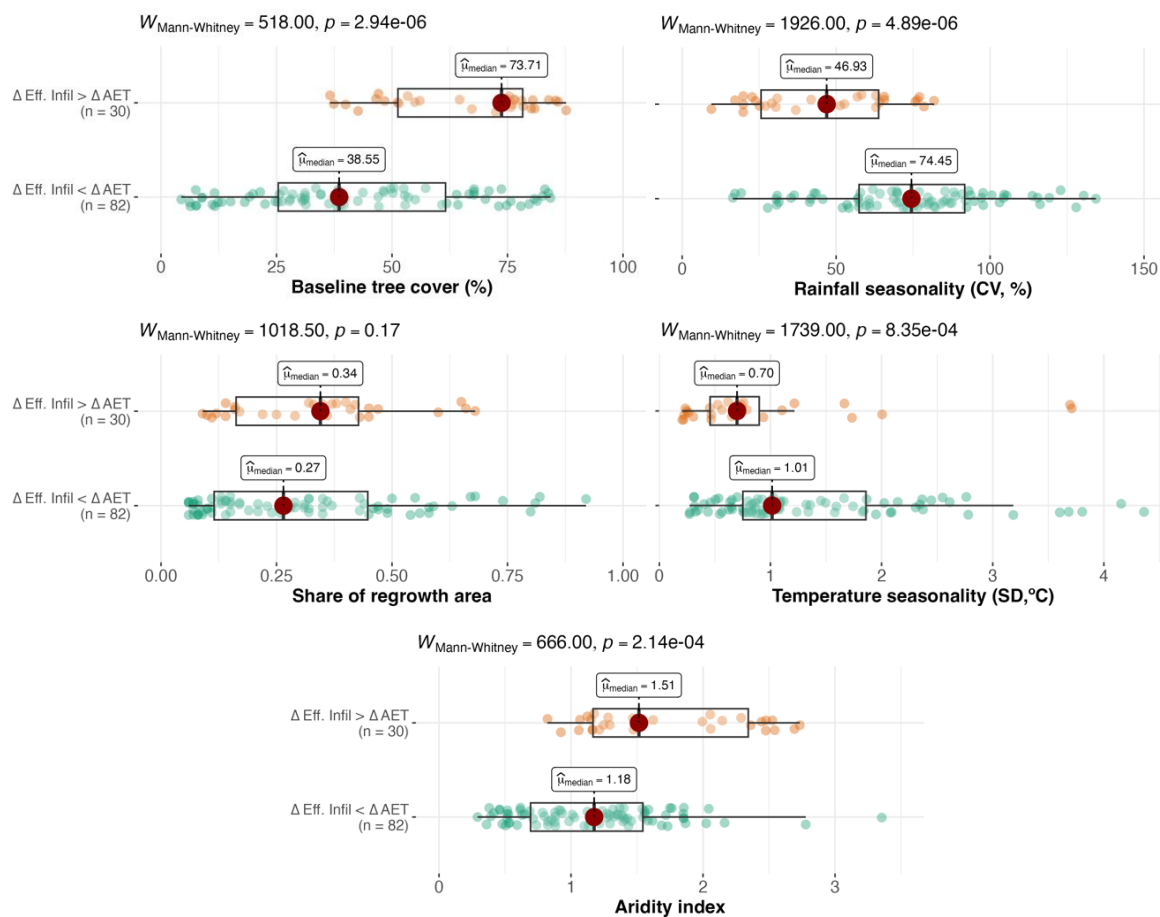


Figure 5.26 Comparison of baseline tree cover and share of regrowth area for two groups MRBs for year 100. Baseline tree cover is significantly higher in the group with sensitivity of effective infiltration ($\Delta \text{effective infiltration}$) $>$ sensitivity of SET (ΔAET). The share of regrowth area does not differ significantly between groups. The differences between groups in other variables are significant, but not very big. The non-parametric Mann-Whitney U test was performed in all cases. The sensitivity measured is the variable's sensitivity to tree cover change.

5.4 Discussion

5.4.1 General effects of the tree cover growth scenario on water quantity

The changes in water quantity, measured as annual water balance modelled by DTRIE broadly agree with those reported by for example Hoek van Dijke et al. (2022) for several tropical basins. They modelled regional water availability due to global tree restoration on the basis of the Bastin et al. (2019) restoration map using an ensemble of data-driven Budyko models and provide streamflow and AET estimates. As my study modelled streamflow only for a small subset of dam watersheds, AET values will be compared instead as their increase or decrease is proportional to the water balance decrease or increase, which is used here as a proxy for water quantity.

For most basins, DTRIE agrees well with results from Hoek van Dijke and colleagues: In the Kapuas basin (on the island of Borneo), DTRIE models and increase in AET of up to 7 mm after 150 years, equal to relative increase of around 1 per cent, while Hoek van Dijke et al.'s (2022) results estimate an increase of 9.8 mm (± 6.9 mm, equivalent of 0.7 per cent). In the Congo basin, the agreement is surprisingly good, even though the share of basin area with restoration/regrowth potential is five times higher in the restoration map used by DTRIE. Here, it is worth remembering that the Congo basin receives a lot of tree cover *increase*, rather than *new* tree cover under the tree cover growth model (the merits of including already forested areas in the scenario were discussed in section 5.3.3.1 and Chapter 4). The good agreement with the Hoek van Dijke et al. (2022) results therefore shows that the impact of including already forested areas in the model is limited as their tree cover increases are limited. In other basins, Hoek van Dijke et al.'s use of the Bastin et al. (2019) map means the effect of restoration is not comparable. For example, in the Orinoco basin, much of the restoration potential occurs in the Llanos grasslands, while grasslands and savanna are explicitly excluded from tree growth in this thesis. Furthermore, since, the authors assume full tree cover after restoration, their estimates may be higher than those from DTRIE. This is because DTRIE models the hydrological effects of incremental tree growth based on a data-driven growth rate, which means

basins reach full tree cover not right away, as is common in many other models, but after a number of years commensurate with the forest type and climate.

5.4.2 Changes in water regulation

5.4.2.1 Changes in annual total runoff at the dams

A brief discussion of annual totals for runoff (in this case, streamflow at a point of interest/POI) and water balance is warranted for two reasons: 1) annual water balance is much higher than total annual streamflow and 2) while the annual basin means for water balance decline, the total streamflow at the dam increases (see Figure 5.13).

The first finding is a consequence of the equations used in the calculation of water balance and total streamflow. Water balance (WB) is calculated as $WB = P - AET$, and therefore captures all water that can become runoff. Total streamflow on the other hand, is calculated as the sum of overland flows (surface flows R_2 and R_3) and the lagged subsurface flow (SSF, or throughflow). However, because of the lag time (lag_{SSF}), which is capped at 11 months (see section 5.2.2.2 for an explanation), the total streamflow variable does not necessarily capture the entire amount produced in one year. Essentially, this cap emulates that a quantity of SSF is still “in transit” and therefore not contributing to the streamflow in the timeframe relevant to **research question 2**, which is concerned with flows in the following dry season.

The total streamflow variable was introduced for the analyses on the monthly scale. With it, the DTRIE aims to identify the change in the *timing* of water, especially in the following dry season – rather than the annual total water quantity – at the dam. It is not necessary to calculate the change in annual total water quantity via total streamflow, because this can be established separately with the water balance for the annual scale. Therefore, the fact that total annual water balance exceeds total annual streamflow is an expected outcome of the model but not an issue because the variable total annual streamflow is not used in the analysis.

The second finding, that total streamflow increases with growing tree cover seems also counter-intuitive at first, because we expect the overall water quantity to decline, as shown by the water balance trend (see Figure 5.13b). The answer

to this question also lies in the lag times. As is depicted in Figure 5.27, lag times (lag_{SSF}) generally *decrease* with growing tree cover through increases in throughflow velocity v_T . Total annual streamflow rises in some watersheds when more pixels decrease their lag_{SSF} below 12 months and thus start contributing to total streamflow.

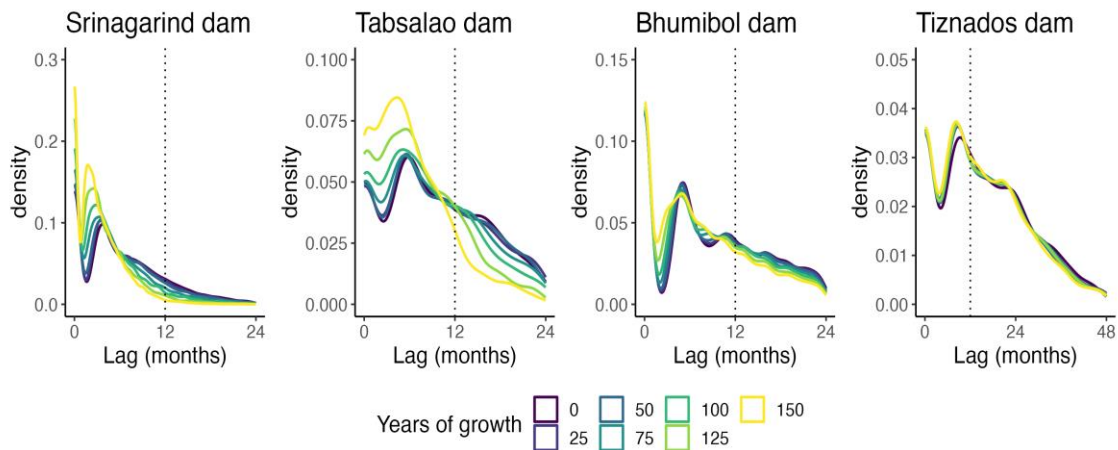


Figure 5.27 Effect of lag_{SSF} on the total streamflow variable over the scenario runs for three dam watersheds in Thailand and Tiznados dam watershed in Venezuela. When lag times decrease to ≤ 11 months they start contributing to total streamflow. lag_{SSF} are capped at 24 and 48 months for illustrative purposes. The dotted line represents a lag_{SSF} of 12 months in all plots.

The lag time is also the cause of the Tiznados dam watershed's decline in streamflow, which is unexpected in the context of the other dam watersheds' responses. In the Tiznados watershed, lag_{SSF} values are much higher than 12 months (see and tree cover increase does not shorten the lag time enough within the 150 years of the final scenario run for many pixels to contribute their SSF to total watershed SSF within the year).

A third issue that needs to be discussed is the slight dip in water balance for the first scenario run (25 years of growth) in several watersheds (see Figure 5.13b). This artefact is a consequence of the use "raw" data to calculate the baseline variables (such as AET) in DTRIE, compared to the inputs averaged over climate classes and forest types that are used in the scenario runs. A test was conducted with *alternative* baseline inputs created with the same procedures as the scenario inputs and the absence of the year 25 artefact was confirmed. The decision to use raw, or pixel level values was made to reflect the reality in the baseline better and enable comparisons with other AET products (see discussion in Chapter 3), even though it results in the described artefact when changes between baseline

and scenario are examined. An *alternative* baseline AET map is shown in Appendix A2.5 for comparison for South America.

5.4.2.2 Changes in monthly water availability

The following section discusses the different responses in monthly streamflow to answer **research question 2** (*How does tree cover growth affect streamflow seasonality and streamflow quantity in the following dry season*) of this chapter. It will demonstrate that a higher share of regrowth area and higher humidity are the causes of larger (or any) increases in the seasonality of streamflow with the help of two case studies, the first including three dam watersheds in Thailand, the second, two dam watersheds in Cameroon.

The Thailand case study focuses on the watersheds of the Bhumibol, Tabsalao and Srinagarind dams, which are comparatively close to each other, with Tabsalao located roughly in between the two other dams (they are roughly 400, 200 and 150 km NNW and WNW from Bangkok, see also Figure 5.11). These dams highlight the effect of both annual humidity and the share of regrowth area on seasonal shifts in monthly runoff. As demonstrated in section 5.3.2.4, the Srinagarind dam watershed experiences a large increase in runoff amplitude, i.e. increasing high runoffs and decreasing lower ones, while the other two dams show no change in amplitude (see Figure 5.14, right-hand panel). The coefficient of variation (CV) of monthly runoff in Srinagarind increases. While Tabsalao and Bhumibol's CV decreases slightly, it only does so because these watershed's total annual streamflow also increases. Therefore, the pattern for Bhumibol and Tabsalao can be summarised as not increasing in seasonality.

In both Srinagarind and Tabsalao watersheds the share of area with regrowth potential is about twice that of Bhumibol (see Table 5-3). The effect this has on the distribution of runoff over the year becomes apparent when the change in throughflow velocity (v_T) and lag times (lag_{SSF}) and is examined. Because the regrowth area share is greater in Srinagarind and Tabsalao, more pixels experience a change in throughflow velocity and shorten their lag times. This is evident in Figure 5.28, where the lines representing the frequency of different values in different scenario years differ much more for these two dams compared to the Bhumibol watershed.

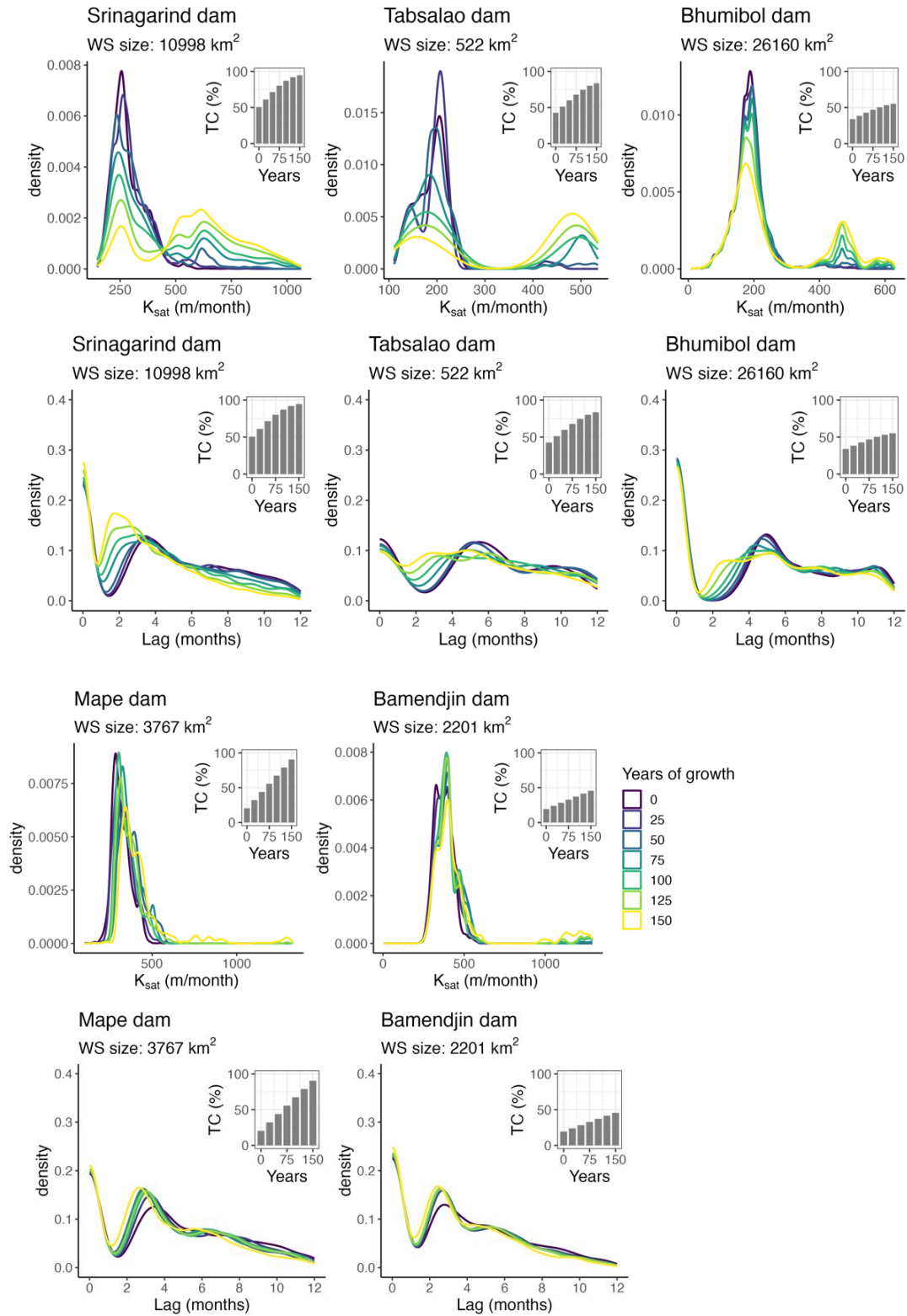


Figure 5.28 Density plots of throughflow velocities v_T (labelled " K_{sat} ", m/month) and lag times (in months) of the three dams in Thailand (top) and two in Cameroon (bottom) illustrating the changes in the variables over multiple years of tree cover growth. The small inset bar chart shows the mean watershed tree cover (TC, %) from baseline (year 0) to 150 years of tree cover growth. Lag times are calculated for each watershed pixel by multiplying the downslope distance to the nearest stream with the throughflow velocity. Note that density plots can be interpreted like histograms, their advantage being that they are stackable.

The reason why the Tabsalao and Srinagarind watersheds do not respond in a more similar way is, again, a difference in watershed aridity index, which is higher in Srinagarind than in Tabsalao (see Table 5-3). Bhumibol and Tabsalao watersheds, on the other hand, have comparable mean annual aridity index values (and monthly patterns, see Appendix A3.1). The higher excess of P over PET in the Srinagarind watershed in combination with the great number of pixels with shortened lag times results in more streamflow being “moved up” in the calendar year. In contrast, in the Tabsalao watershed, the lag of pixels may have shortened, but not much runoff is created that could be affected by this. Lastly, in the Bhumibol watershed, neither are there many changes in lag times, nor is there a lot of streamflow to which these lag changes could be applied.

The second case compares the two adjacent watersheds of the Mape and Bamendjin dams in Cameroon. Here, both watersheds increase in CV of monthly runoff (see Figure 5.14, left-hand panel) and annual total streamflow does not increase much after the first increase to year 25 values. Together, this indicates that streamflow becomes less evenly distributed over the year. However, even though the aridity index, baseline tree cover and watershed size are very similar, their monthly streamflow patterns respond slightly differently. The Mape dam watershed shows greater increases in CV. This can be attributed to the much larger share of regrowth area in Mape watershed, - 95 per cent, compared to Bamendjin's 35 per cent. Figure 5.28 also supports this as it shows that the lag times for Mape dam decrease in more pixels than in the Bamendjin watershed.

5.4.3 Sensitivity of water balance and effective infiltration

5.4.3.1 Magnitude of hydrological sensitivity in the tropics

Section 5.3.3 described the sensitivity and elasticity of water balance to tree cover change, as well as the sensitivity of effective infiltration to tree cover change for the HydroBASINS level 4 river basins dataset (HB4). For water balance, it was shown that most HB4s share a comparatively low sensitivity to tree cover increase. While basin changes (S_f) of up to 0.62 per cent in water balance per one per cent increase in tree cover were found, the median across all assessed basins is 0.06. Previous reviews by and reviews have found hydrological sensitivities: Most recently, Hou et al. 2023 found higher sensitivities of 1.24 per

cent in streamflow per 1 percent forest increase. For the subset of tropical basins, this decreases to an average of 0.28, however, the sample only includes two basins in the forestation dataset (Glenmorgan, Ootacamund B; Nilgiri), which are located close to each other and are likely to have very similar environmental conditions. In an earlier review, Zhang et al. (2017) found a median sensitivity of 1 per cent across all the studied watersheds where forestation, i.e. tree cover increase, occurred. Similar to Hou et al. 2023, the subset of tropical watersheds is small: only around four watersheds are located between -23.5° S and 23.5° N (this study's definition of tropical), as confirmed by a visual assessment of the paper's Figure 1. The absence of the tropical region, with its distinct climate characteristics (such as described by Köppen-Geiger climate types Af, Am, Aw) in the literature on hydrological sensitivities greatly decreases comparability with this study's results. Some specific characteristics of the tropical region and how they relate to hydrological sensitivity are examined in the following section.

5.4.3.2 Relationships of hydrological sensitivity with environmental variables

The effects of annual rainfall, mean annual temperature, temperature seasonality, rainfall seasonality, net radiation, aridity index, baseline tree cover and basin size on these sensitivities and elasticities are discussed in the following to answer **research question 1** of this chapter (*How does tree cover growth affect annual water balance on tropical scale and in selected major river basins?*).

The results presented in this chapter have at many points demonstrated the importance of watershed annual rainfall and aridity index (P/PET, also called *wetness* or *humidity* index) for overall hydrological (i.e. water balance) sensitivity (see section 5.4.3) as well as change in water regulation (see section 5.4.2).

In this regard, the results deliver strong support for the findings of Bentley and Coomes (2020), who showed that the sensitivity of river flows to forest growth is lower when the annual precipitation is low, which itself covaries with the aridity index. Conversely, very humid basins, i.e. those with higher rainfall than PET demands, will experience larger decreases in river flow. The results from this chapter add to these findings specifically from a large watershed and tropical perspective, which was a distinctly underrepresented region in the Bentley and Coomes (2020) study.

This contrasts the conclusions of work by Hou et al. (2023) and reviews by Zhang et al. (2017) and Li et al. (2017) who found hydrological sensitivity to be greater in more arid conditions.

Zhang et al. (2017) split their dataset into different energy and water regimes along the aridity index, water- (WL), energy-limited (EL) and equitant (EQ), and sensitivity increased from EL to WL. On the other hand, in DTRIE results show the opposite pattern, meaning that water-limited basins show the lowest median sensitivity out of the three groups (note that the definition of energy- versus water-limited differs here from the one used in section 3.5.2.2 on p. 66 and following). Given that a general conclusion in Zhang et al. 2017 is that sensitivity is highly variable, the lower median for WL watersheds may be due to the smaller sample size of such watersheds. The range of values present in EL and EQ watersheds (represented by 79 and 63 watersheds) and consequently the median, are much larger than those of the WL watersheds, which are only represented by 35 watersheds. This study's findings for forest gain (as opposed to forest loss) are also only based on around four tropical watersheds (as confirmed by a visual assessment of the paper's Figure 1), which may further limit the comparability, especially since the authors do not provide the aridity index for the examined watersheds.

Hou et al. (2023) and Lit et al. 2017 also found higher sensitivities in drier basins. However, the comparability of their results to this study may be limited because basins may have too different aridity index (P/PET) ranges. Hou et al.'s dataset is skewed toward drier basins, with a median aridity index of 0.66, while the basins in this study represent more humid areas with a median aridity index of 1.24. In Lit et al.'s study, the maximum aridity index is 2 compared to this study's 2.7. It may be that the basins in their dataset are simply not humid enough to enable a robust comparison with the results of this study. More work is needed therefore on such basins.

However, when measuring sensitivities in absolute terms, as two of these reviews, Lit et al. 2017 and Zhang et al. 2017, rainfall becomes the dominant driver of water balance, especially in drier climates. Since all three review papers include no or very few watersheds with annual rainfall totals near the 5,000 mm/yr of the HB4 basins used in the analysis in this chapter it is difficult to compare the

findings. Their sample includes few watersheds with annual rainfall above 2,500 mm and when it does, the watersheds are outside of the tropics. In fact, the watersheds used in these reviews and by the Hou et al. (2023) study cover the range of the watersheds considered comparatively water-limited in this study's sample. This means the referenced studies are unlikely to capture the hydrological sensitivity to tree cover change for the energy-limited ($AI > 1$) watersheds of this study. While the aridity index was chosen in both this chapter and the referenced studies to enable better comparability among watersheds with varying rainfall totals, the annual rainfall total is still a relevant grouping variable in itself. It is likely that the underrepresentation of watersheds with annual rainfall totals matching the watersheds analysed in this chapter is the cause of the diverging conclusions on the effect of the aridity index on hydrological sensitivity. This study is one of the first which models these changes for watersheds with annual rainfall above 2,500 mm and further work would therefore be beneficial to corroborate its results.

For the 16 highly sensitive basins (with sensitivity values $S_f > 0.25$), the relationships with the aforementioned environmental variables were examined in more detail. Here, a strong link between high aridity index (i.e. very humid), net radiation, baseline tree cover, and somewhat moderate to high rainfall and mean annual temperature was described. Notably, the highly sensitive basins were unlikely to have high seasonality in rainfall or temperature.

It bears repeating, however, that the aforementioned 16 highly sensitive basins are all located near the coast or span an entire island (Note that this does not mean that coastal, flooded forest or mangrove land cover types were reforested, because these are excluded from the tree growth scenario). Furthermore, many of them are found in insular Southeast Asia and may thus somewhat inflate the effects of environmental variables on hydrological sensitivity. In fact, final analyses revealed that three of the 16 highly sensitive HB4 inherited data gaps from the GLEAM interception loss input, which resulted in them having less than 5 per cent of the basin area affected by change in water balance, although they did meet the requirement of having 5 per cent under regrowth area. These basins are three of the island basins of Indonesia, but apart from the basin with Pfaffstetter ID 5350, which is shown in Figure 5.22a they do not feature prominently in the

analysis (the other two basins have the HydroBASINS Pfaffstetter IDs 5130 and 5220). Overall, the fact that several, although not all, of these highly sensitive basins have comparatively few pixels available for the determination of water balance sensitivity leads to the conclusion that a higher cut-off with regards to basin percentage affected by the tree growth scenario is needed for this analysis. It is also worth mentioning that many of those HB4s span clusters of multiple islands. This is of no concern to the results of this study, however, because water balance was calculated, rather than streamflow at a singular point of interest.

Basin size and hydrological sensitivity are moderately negatively correlated, but the effect is not linear; rather, both variables get closer to zero with increasing basin size (see Figure 5.20). A similar response is found in Zhang et al. (2017) (see Figure 5.29b) for basins larger than 1000 km² (the comparison with this subset of basins is warranted because in this thesis, all but four of the assessed HB4 basins were larger than 1000 km²). In Hou et al. 2023, sensitivity seems to increase with basin size but as Figure 5.29c illustrates, this may be on account of two very large outlier basins.

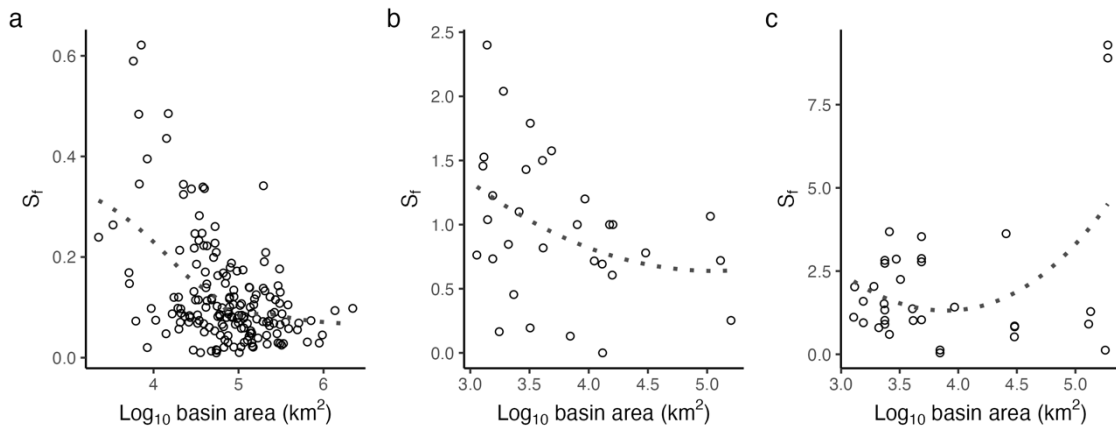


Figure 5.29 Relationship between hydrological sensitivity, S_f , and log-transformed basin area (km²) for a) DTRIE, b) Zhang et al. 2017 and c) Hou et al. 2023 for basins larger than 1000 km². Note that for b and c) only forestation basins were included, while basins where deforestation was studied were excluded. Figures b and c were created from the datasets provided in the paper's supplementary material.

Zhang et al. 2017 begin to explain the inverse relationship between hydrological sensitivity and basin size as a consequence of the greater potential for topographical, climate, vegetation and over all heterogeneity in larger basins. More heterogeneous landscapes may have increased buffering capacity attenuating the effects of forest cover changes. However, the Zhang study (as well as the

Hou et al. 2023 study) examines runoff or streamflow for their hydrological sensitivity questions, while the DTRIE results in this study calculate the sensitivity of water balance (the justification to use water balance are essentially resource constraints and explained in the methods section 5.2.2). As water balance has not been routed through the basin yet it makes sense that basin heterogeneity would not be the driving factor behind the DTRIE S_f relationship with basin size. Furthermore, the effects of other basin characteristics reflected in DTRIE (soil depth, plant available water fraction, hydraulic conductivity, baseline tree cover and the share of regrowth area of opportunity) on hydrological sensitivity, S_f , were examined and no effects of these variables on S_f , nor relationships with basin area were found. This further underscores that basin heterogeneity and buffering capacity are not responsible for the inverse relationship between basin size and S_f .

The most promising explanation for this behaviour is a simple statistical one: When basins are smaller, outliers may have a greater impact on basin medians than in larger basins, potentially resulting in higher medians. In contrast, outliers in larger basins are more likely smoothed out by the larger number of pixels available for analysis.

5.4.3.3 Hydrological sensitivity in a cloud forest environment

In all but one of the highly sensitive basins water balance decreased with tree cover increase. The basin that showed an increase is located in Taiwan and has both high temperature and rainfall seasonality as a consequence of the highly variable topography, contrasting the general pattern described in the previous section. The increase in water balance in Taiwan is, although surprising in the context of the other hydrologically sensitive basins, expected, because of the presence of cloud-affected montane forests at higher altitudes across the island (Mulligan, 2011; Schulz et al., 2017). As described in section 2.2.1, cloud affected forests can intercept significant amounts of cloud water, which can add to water balance as stemflow and throughfall (Bruijnzeel and Proctor, 1995; Gomez-Peralta et al., 2008; Sáenz and Mulligan, 2013). Likewise, their typically lower temperatures, high cloud cover and relative humidity results in lower AET (Bruijnzeel et al., 2011). This makes areas where cloud forests can occur more likely than others to respond with an *increase* or at least lower decreases in water balance when afforested, as opposed to non-cloud affected areas.

DTRIE does not model cloud forest interception, because it uses rainfall as an input, which does not include fog (the CHELSA climatology used is a precipitation input and fog is not counted as precipitation). However, DTRIE can capture the lower AET gains in cloud forest areas via the temperature and net radiation, which would be reflected in a comparatively low decrease in water balance. The likely reason for the registered small increase is the use of the different input datasets between baseline and scenario described in section 5.3.1.1 (also see the Appendix A2.5 for a comparison of AET estimates between these two procedures).

For another country that is home to montane cloud forests, Colombia, this did not happen, even though some areas of opportunity were identified in potential cloud forest areas (for a map of cloud affected forests in Colombia, see Sáenz and Mulligan, 2013; or Wilson and Jetz, 2016). It is likely that the absence of a high water balance sensitivity in Colombian basins comparable to that of Taiwan is due to the differences in tree cover increase. For example, the Magdalena River basin in Colombia, although much larger than the Taiwan basin, has a substantial upstream area with high cloud forest probability, similar to Taiwan. Equally, in both basins tree cover growth does take place in cloud forest suitable areas. However, the basin mean increase in tree cover, for example in year 100, is 15 per cent, compared to that in Taiwan of only 4.8 per cent. Since H_s is the change in water balance divided by the change in tree cover (see (Eq. 5-6), higher tree cover changes lead to lower sensitivity.

5.4.3.4 Implications of changes in sensitivity for the trade-off debate

Section 5.3.2 addressed the sensitivity of effective infiltration and how it compares to the sensitivity of AET to tree cover increase, and section 5.4.2.1 examined the effects of tree cover increase on the distribution of streamflow throughout the year. These two parts are now combined to address the question of *where* the trade-off between enhanced AET and changes in water regulation services has *what kind of outcome*, thus responding to **objective 4** of this study. The measures to group the outcomes are water quantity and its regulation, or distribution across the year, measured with the coefficient of variation (CV), and illustrated in Figure 5.30.

Across most examined watersheds, annual water quantity generally declined through tree cover growth, in accordance with the range of published evidence on the matter (Farley et al., 2005; Filoso et al., 2017; Ochoa-Tocachi et al.,

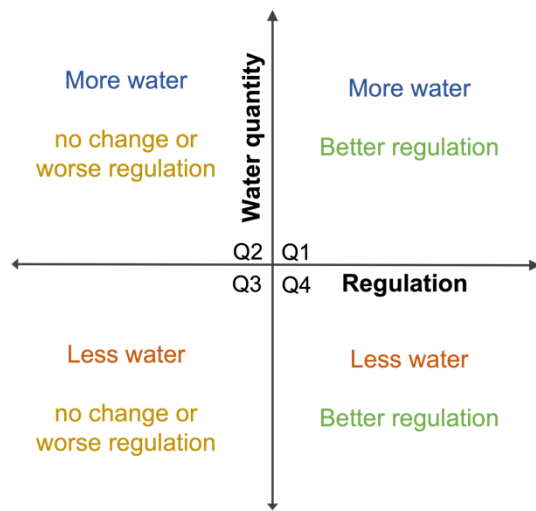


Figure 5.30 Schematic of the potential outcomes of the trade-off. Better regulation is defined as a lower CV of monthly streamflow.

2016). There was only one watershed where the opposite was true, and it is likely the effect of cloud frequency significantly reducing the impact of tree cover growth on AET (see section 5.4.3.3). This means that most tropical watersheds are likely situated in the quadrants Q3 and Q4 of Figure 5.30. Only those home to cloud forests would be located in Q1 or Q2.

Regarding water regulation, even if the benefits of change in effective infiltration

outweigh the impact of increased AET on annual water balance, as was elaborated in section 5.3.3.3, it does not necessarily mean that the monthly variability of streamflow is lessened, or more specifically that dry season flows will be augmented. Where this occurs, however, is useful information in combination with the insights from section 5.4.2, which demonstrated that more humid watersheds with higher regrowth area shares are prone to greater seasonal shifts in their seasonal runoff patterns, increasing the CV of monthly streamflow.

In DTRIE, effective infiltration can become SET, which is a component of AET, or subsurface flow (throughflow), which arrives at a downstream point of interest with a delay, thus via a slower hydrological pathway. Higher effective infiltration therefore means potentially greater amount of water in this slow hydrological pathway, which, depending on the watershed size, topography and soil, could contribute to dry season flows as baseflow. Therefore, in a watershed where effective infiltration *gains* outweigh the *losses* of increased AET caused by tree cover, more water enters the slow hydrological pathway, creating the potential for a change in the monthly distribution of streamflow.

If watershed humidity and area under regrowth are also high, the watershed may experience greater seasonality in streamflow at a point of interest (as was

demonstrated in section 5.4.2.2). In this case, the watershed would be situated in quadrants Q2 (or Q1, if it has cloud forest), on account of the higher CV of streamflow. Conversely, drier watersheds, such as those of the Bhumibol and Tabsalao dams, would find themselves in Q4. While CV of streamflow is a good initial measure for the regulation services, a more thorough examination of the changed to dry season flows may still be useful, though sensitive to the definition of *dry season*. The Srinagarind dam watershed, for example, increases its streamflow CV steadily with tree cover growth, but dry season flows - when defined as the flows during months of $P < PET$ (here, November through April) - are indeed higher than the baseline for three out of the five dry months. This means the Srinagarind dam watershed would be in Q4.

Finally, the relationship between streamflow seasonal shifts, or streamflow CV, with humidity and regrowth area is stronger where baseline subsoil K_{sat} (hydrological conductivity) is lower. In watersheds where baseline K_{sat} , and thus the throughflow velocity with which lagged subsurface flow travels to the POI, is high, tree cover growth will only increase the amount of water entering the slow hydrological pathway. For example, the Chivor dam watershed has the highest K_{sat} value of all the dam watersheds, because the dominant soil type is the highly permeable Andosol. Although the watershed is as humid as Bamendjin and Djoue dam watersheds and has a similar share of regrowth area, its response in terms of the seasonality of monthly streamflow does not change much.

5.5 Conclusion

The tree cover scenario developed in Chapter 4 provided a test bed to model the changes in water balance, AET, and effective infiltration and thus the amount of water in the slow hydrological pathway, which is vital for the study of dry season flow changes under forestation.

DTRIE results showed that water balance declines in most basins, except for very few basins where the effect of cloud frequency may be present, and others where the increase is evened out again over the years of the tree growth scenario. In doing so, DTRIE results confirmed the wider consensus in literature that reforestation leads to lower water yield. For the several basins with a water balance increase, which at some point receded to baseline levels, it could be

demonstrated that this is an artefact of the use of “raw” values for the baseline run in DTRIE, whereas the scenario run, naturally, must use inputs adjusted to the scenario tree cover conditions. Additionally, caution still must be applied when using DTRIE in cloud forest areas, because many of the data inputs may not reflect some of the forest type’s properties well. For example, the growth rate (calculated in section 4.2.2) may need specific careful validation because its data sources, MOD17, relies on remote sensing instrumentation that is negatively affected by cloud cover in these regions.

In most basins that were part of the analysis of hydrological sensitivity, water balance was found to be largely *insensitive* to tree cover increase: for 90 per cent of them an increase in tree cover by one percentage point resulted in a change in water balance of 0.25 mm or less. For the remaining basins, the greatest water balance change did also not exceed 0.6 mm per unit tree cover change. The hydrological elasticity (defined as relative change in water balance per relative change in tree cover) ranged between - 1.35 and 0.33 per cent. A one per cent increase in tree cover (relative to baseline tree cover) therefore caused between a 1.35 per cent decrease and a 0.33 per cent increase in water balance.

The few highly sensitive basins are characterised by high net radiation, baseline tree cover and mean annual temperature, as well as moderate to high aridity index and annual rainfall; they also commonly have very low temperature and rainfall seasonality. Basin size was negatively correlated with hydrological sensitivity (S_f). It was also noted that many of these basins are located in coastal areas and frequently in insular Southeast Asia, which may somewhat inflate the relative importance of the environmental factors.

Effective infiltration more often decreased than increased with tree cover on both pixel and basin level, while AET typically increased (but also not exclusively). The basin level sensitivity of effective infiltration was compared to that of AET to identify where tree cover growth may have the potential to augment dry season flows. To achieve that, the sensitivity of effective infiltration must exceed that of AET, because only then is there more water in the slow hydrological pathway. Several basins met these conditions, and they had a significantly higher baseline tree cover and aridity index than the group where AET sensitivity exceeded that of effective infiltration. Furthermore, their rainfall and temperature seasonality were

lower and again, basin size did not differ significantly between groups, and neither did the share of basin area under regrowth.

On the scale of mostly smaller dam watersheds, all of them seasonally dry, it was demonstrated that a higher aridity index and larger shares of the basin area under regrowth increase, result in redistribution of streamflow throughout the year, often increasing the coefficients of variation of streamflow. However, this did not necessarily result in lower dry season flows, because the number of months the streamflow amplitude is moved forward in the calendar year depends strongly on watershed topography and soil. For example, watersheds with high hydraulic conductivities (K_{sat}) in the subsoil, such as are common in Andosols, would benefit less from the increases in throughflow velocity following tree cover increase. Therefore, these watersheds would experience smaller changes in their streamflow seasonality.

Combining the insights from both small dam watershed and larger basin analyses, the conditions for different outcomes regarding water quantity and regulation under tree cover growth were explored. While *more water* in general is unlikely except for when significant shares of cloud forest are present in the basin, *less water* but *better regulation* was linked to less humid watersheds, while *less water* and *worse or similar regulation* was linked to more humid watersheds (i.e. higher aridity index) with larger areas under regrowth. The latter two conditions may be moderated, however, by topography and soil properties, which are highly watershed specific, in which case an enhancement of dry season flows, which is a more specific measure of regulation than streamflow CV, is possible.

Chapter 6 Conclusions

In this concluding chapter the key findings of the thesis will be summarised and translated into policy- and planning relevant recommendations on where forestation and restoration projects are likely to have a more positive or negative hydrological outcome with respect to annual total water balance and intra-seasonal flow regulation. The chapter will then conclude by illustrating the contributions of this thesis to wider research in the water-forest nexus and more specifically, the infiltration trade-off debate, and finally, I will examine the limitations of this research, and key requirements for future research.

6.1 Summary of the study's key findings

1) The newly developed DTRIE model was shown to perform well when compared to estimates of water balance and AET produced by other models, and other published reference values: Although DTRIE AET is typically somewhat lower than that of GLEAM or MODIS it captured both the magnitude and seasonality of the key variables water balance and AET when compared to the results from other studies for several basins. Compared to GLEAM values, annual DTRIE AET was between 36 and 271 mm/yr lower when averaged over a selection of basins. On a monthly timestep, seasonality was well reflected with a correlation coefficient between 0.75 and 0.93. Differences between DTRIE and MODIS basin means were lay between -102 to 390 mm/yr, which is a consequence of the seasonality mismatch also demonstrated by the correlation coefficients for monthly AET totals, which ranged from -0.78 to 0.53.

2) A realistic scenario for the growth or restoration of tree cover in the tropics was developed, producing a map of areas of opportunity for tree cover growth. This map identified 812 million hectares of land area across the tropics with the potential to increase or establish new tree cover. Almost half of this area is located in Central and South America, a third in Africa, and the remainder in Asia and Oceania. Most of the opportunity for tree cover growth lies in the *increase* of tree cover in already forested areas rather than “new” growth in areas without forest. This reflects the conservative socio-economic constraints of the tree cover growth scenario.

3) The tree cover growth model produced potential fractional tree cover maps for 25, 50, 75, 100, 125 and 150 years into the future. After 100 years of tree growth, the model estimated an increase in tropical forest cover from 25.8 (current/2018) to 31.3 per cent (in 2118), with greatest relative increases occurring in Africa. The basins of the Amazon and Congo Rivers captured the largest additions in tree covered area, followed by the Orinoco, Magdalena, Niger and Sanaga river basins.

4) Changes in water balance were predominantly negative, as a result of increasing AET. Only very few basins exhibited an increase in water balance (because AET decreased), and it was demonstrated that in almost all cases this likely an artefact due to different data inputs between baseline and scenario.

5) The sensitivity of water balance to tree cover increase (hydrological sensitivity) was determined for different climates. Overall, when averaged to a basin level, water balance was found to be comparatively insensitive to tree cover increase. The maximum change in water balance per unit change in tree cover (S_f) was 0.6 mm, although 90 per cent of the examined basins registered changes below 0.25 mm. The few highly sensitive basins were shown to have high net radiation, baseline tree cover and mean annual temperature, as well as moderate to high aridity index and annual rainfall, but very low temperature and rainfall seasonality. Basin size was negatively correlated with hydrological sensitivity (S_f).

6) The sensitivities of effective infiltration and AET were compared. Most basins showed an increase in AET (per unit change in tree cover), while effective infiltration changes could be negative or positive. A subset of several basins was identified where the increase in effective infiltration with forestation outweigh the losses from increased AET (both variables per unit change in tree cover). This group was examined because of its potential to see dry season flow increases through tree cover growth, even though annual water balance may decrease. These basins were found to have significantly higher baseline tree cover and aridity index values than the group where AET losses exceeded gains in effective infiltration.

7) On a set of seasonally dry tropical dam watersheds the intra-annual variation in streamflow, measured by the coefficient of variation (CV) of streamflow, was found to increase under tree cover growth. In more humid watersheds (i.e. those

with a higher aridity index) and those with a larger share of their area under restoration, the CV of monthly streamflow increased more steeply over the years.

8) An increase in streamflow CV did not automatically mean that dry season flows were reduced. Some basins experienced both higher streamflow seasonality *and* higher dry season flows. Aridity index and area under regrowth only determined that streamflow is more (or less) likely to shift between months, and the amount of streamflow available to these shifts. To which months the streamflow is moved is highly watershed specific and depends on topography, basin size, drainage network morphometry, and soil properties.

9) Lastly, the synthesis of the findings from larger basins and dam watersheds provided the following characterisations of seasonally dry watersheds where water quantity increased or decreased, and water regulation improved or remained unchanged or worse. *More water* was generally rare on a basin level, and is only expected in basins with cloud forest cover, because there, forestation results in lower changes in evapotranspiration. *Less water* but *better regulation* was linked to less humid watersheds, while *less water* and *worse (or similar) regulation* was linked to more humid watersheds with larger areas under regrowth.

6.2 Translating the findings into recommendations for the planning of reforestation projects and their guiding policies

As discussed in section 5.4.3.4 there are four combinations of hydrological outcomes of forestation and forest restoration project (see Figure 6.1):

O1) There is *more* water, and it is *more evenly distributed* throughout the year

O2) There is *more* water, but it is *less evenly distributed* throughout the year

O3) There is *less* water, and it is *less evenly distributed* throughout the year

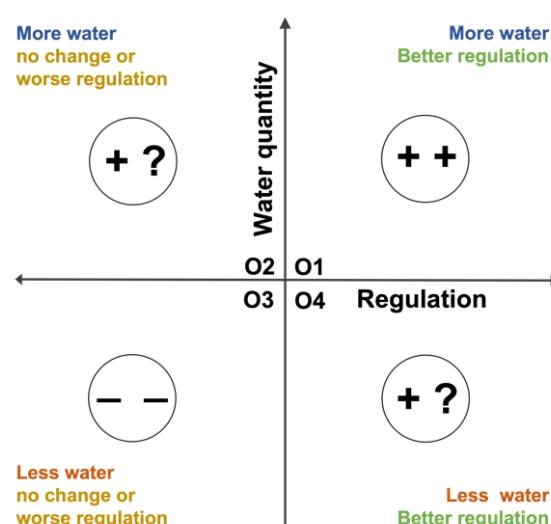


Figure 6.1 Schematic of the hydrological outcomes of tree cover increase. O1-O4 refer to outcomes 1-4 described in the text.

O4) There is *less* water, but it is *more evenly distributed* throughout the year.

Whether an increase in annual water quantity is a desirable outcome, or whether the reduction thereof is a negative one is highly context dependent. However, it is difficult to imagine a case where outcome 3 is considered positive. Similarly, the trade-off debate generally assumes that an increase in dry season flows in seasonally dry areas, in the first instance indicated by a more even distribution of water of moderate peak flows and consistent baseflows, is positive (Jones et al., 2022). As such outcomes O1 and O4 are most likely considered positive.

To illustrate where these largely more positive and more negative hydrological outcomes could follow forestation projects, I will revisit some the watersheds examined in Chapter 5.

Outcomes 1 and 2 are unlikely for most forestation areas of opportunity because water quantity has mostly been found to decrease, and only where cloud forests make up a significant part of the forest is it likely to increase (Jarvis and Mulligan, 2011; Letts and Mulligan, 2005). While we can consider the increase in water quantity and improvement in regulation (O1) as generally desirable, outcome O2 may also be acceptable in certain cases. For example, in watersheds with larger dams, typically those of hydropower plants, the regulation function may be less important than the overall water quantity, because the dam itself fulfils the regulation function. Both in South America and Southeast Asia, some cloud-affect forest likely occurs in the watersheds of larger hydropower dams. For example, in northern Vietnam, there are several large dams along the Da River (e.g. GRanD ID 7204, see Lehner et al., 2011), whose basins likely have cloud forest cover in their upstream reaches according to a map produced by Wilson and Jetz (2016). In the diagram of Figure 6.1 these dam watersheds may be situated in O1 or even O2 (more water but less well regulated), if the area under regrowth and humidity are both high enough.

An example for a dam watershed that could be found in the O3 quadrant is that of the Tiznados dam in northern Venezuela (GRanD ID 2282, examined in Chapter 5). As was demonstrated in section 5.4.2.1, this watershed's water balance, like all others', declines with tree growth. Because of the watershed's soil properties and drainage network, however, subsurface flow is extremely slow and not

likely to change much with forestation according to DTRIE. It is therefore likely that the Tiznados dam watersheds would see *less* water and *no change in regulation* under forestation.

The final outcome O4 (less water but better regulation) could be expected in watersheds where humidity is lower (but still classified as humid with an aridity index > 0.65) and less area is under forestation. This outcome is relevant for regions with less developed dam infrastructure where smaller scale (i.e. non-industrial) irrigated agriculture is prevalent. In the absence of the regulation and storage service provided by a dam, a more even distribution of streamflow throughout the year at the expense of some decrease in water quantity may be acceptable. A country heavily reliant on irrigated rice (paddy rice) cultivation is Madagascar, which only has six larger dams, with comparatively low reservoir volumes according to the GRanD database. Paddy cultivation, however, requires larger volumes of water at specific times of the cropping cycle, and equally, is prone to damage by flooding (Dröge et al., 2022; van Meerveld et al., 2021). In a socio-economic and environmental setting such as this, better regulation of streamflow may outweigh the loss of water quantity on an annual scale.

6.3 Contributions of the thesis to the trade-off debate and the forest-water nexus

With the DTRIE hydrological model and the outputs of the updated, incremental tree cover growth model, this study was able to confirm the consensus based on paired-catchment scale research that reforestation decreases water quantity for large watersheds and across the tropics. Large watersheds, variously defined as larger than 100 or 1,000 km² (Li et al., 2017; Zhang et al., 2017), are under-represented in the literature because of a *de facto* size limit on paired-catchment style studies (see section 2.2.1). The tropical region also features less in this field because of the comparatively intensive data input requirements for most hydrological models, which are often not met in data scarce tropical regions. By applying a spatially distributed hydrological model based only on publicly available remotely-sensed data products, the study was able to overcome these limitations and examine major rivers basins of the tropics, responding to both of the identified research gaps.

Secondly, this study is also the first academic study to reflect tree cover growth as the long-term, incremental process that it is. Because tree cover is increased with a data-driven growth rate, a more realistic picture of fractional tree cover at various management-relevant time steps can be produced. This is a fundamental shift away from previous studies, such as for example Hoek van Dijke et al. (2022), who completely bypass the growth process and simply assumed full tree cover if an area is considered suitable for restoration. In contrast, the approach developed here is capable of translating the spatial variation in baseline tree cover and forest specific growth rates into a more realistic scenario tree cover map with appropriate levels of heterogeneity in tree cover density.

By using this type of tree cover map we can assess the hydrological effects of reforestation at individual time steps, which may well be before the pixel(s) reach full tree cover. Conversely, in some environments, 100 per cent tree cover is not attainable in 200 years, in which case it may be of less concern to planners and practitioners what the effects of a project on water quantity are. In short, this type of map is vital when the question is, for example, *how much less (or more) water can be expected from this reforestation project in 50 or 75 years*. The simplified, instant full tree cover approach, however, may be sufficient to outline a general worst-case/best-case outcome. These are, however, often less useful in project planning and implementation, especially when multiple stakeholders are involved, as is common for reforestation and land restoration projects. This approach also sets more realistic expectations for the time it takes for hydrological benefits to accrue from forestation investments, which may be beyond the generation making the investment.

Third, DTRIE presents a novel approach to model the effect of tree cover on sub-surface flows because it adjusts soil moisture store volumes and throughflow velocities to the presences of tree cover. The baseline soil store volume is based on root depth and depth to bedrock spatial data, as opposed to other hydrological or evapotranspiration models such as GLEAM. Those often conceptualise the soil store as a fixed number of layers of specific depths, depending on the type of vegetation (tree, herbaceous and bare cover) (Martens et al., 2017; Miralles et al., 2011). Furthermore, the throughflow velocity, which determines how fast sub-surface flows travel to the nearest stream pixel, is in the baseline derived from

lower soil layers' hydraulic conductivity, K_{sat} and in the scenario, adjusted with a factor reflecting the increased presence of so-called macropores following from increased tree cover (Gao et al., 2018). In doing so, DTRIE integrates valuable insights from plot-scale soil science into large scale hydrological modelling.

6.4 Limitations of the study

To examine the response of annual water balance and dry season flows to the slow process of tree cover growth, DTRIE was specifically designed as a monthly timestep equilibrium (as opposed to transient) model. Hence it is not suitable for event-based rainfall-runoff modelling or flood modelling. Typically, the effect of tree cover change on stormflow generation is most relevant at the local scale, which is why this is commonly monitored or modelled in a paired-catchment approach.

Savanna and grasslands areas were specifically excluded from DTRIE scenarios for a variety of reasons detailed in section 4.2.1.2, principally the intrinsic value of these biomes, and the fact that they provide livelihoods for a sizeable part of the population in the tropics (Delzeit et al., 2019). The presented tree cover growth scenario and model therefore should not be applied to model tree cover growth in these areas.

Although wherever possible datasets were specifically chosen for their performance in mountain environments (for example, the CHELSA as opposed to WorldClim products), hydrological outputs may still have reduced accuracy because of the coarse resolution of some inputs. Both leaf area index (LAI) seasonality and GLEAM interception loss are provided at a 0.25 degrees resolution and may degrade the performance in and near mountain ranges.

Lastly, DTRIE outputs are very sensitive to the rainfall input, so the choice of input data may affect the absolute estimates, but less so the changes over time. Several global gridded rainfall datasets differ particularly in extremely wet places, such as for example the Pacific coast of Colombia.

6.5 Further research needs

6.5.1 Integrating moisture recycling into DTRIE

Moisture recycling, also called *precipitation* or *evaporation recycling*, which is the

“contribution of land evaporation to local and remote precipitation” (van der Ent et al., 2014) was beyond the scope of this research project. However this process can contribute an average of 40 per cent of rainfall over land and is especially relevant in the tropics (Ellison et al., 2017; Keys et al., 2016). Evaporation from the Amazon forest, for example, contributes to 70 per cent of the precipitation in the Río de la Plata basin; the Congo forest provides moisture that falls as rain in the Sahel, and receives, in turn, moisture evaporated over eastern Africa (van der Ent et al., 2010). The effects of tree cover change on moisture recycling is an expanding field (Li et al., 2018; Wang-Erlandsson et al., 2018) and most recently, the previously discussed research by Hoek van Dijke et al. (2022) modelled the effects of large scale tree cover increase on these atmospheric feedbacks. Their findings revealed a large impact of including moisture recycling when modelling water balance under tree restoration. For example, in their study, in the Amazon basin, the change in streamflow becomes positive for large groups of pixels when moisture recycling is considered, while otherwise it is mostly neutral on a pixel level. As basin average for the Orinoco basin, they found that moisture recycling lessened the difference from the baseline from - 40.8 to - 28 mm/yr. In baseline estimates from DTRIE for the reference year 2018 (presented in chapter 3), moisture recycling is captured by the rainfall input. In contrast, in the scenario runs analysed in chapter 5, the effect of moisture recycling is underestimated because the rainfall remained unchanged from the baseline.

In future research, the combination of Hoek van Dijke et al.’s (2022) moisture recycling approach with this study’s incremental tree cover growth in a novel application of DTRIE could improve the accuracy of the magnitude of water balance and streamflows following from the large scale restoration scenario in the tropics.

6.5.2 Improving the tree model’s socio-economic constraints through assimilating indigenous land tenure data

The tree cover growth scenario presented in this study attempted to produce a conservative map, with stricter socio-economic constraints than in most published literature, because this has frequently been a point of contention. For example, Fleischman et al. (2022) authored a thorough rebuke of the map of ecosystem restoration opportunities published by Strassburg et al. (2020) because it

risked the displacement of marginalised people. Similarly, Erbaugh et al. (2020) highlights the fact that 294.5 million people live on the tropical forest restoration opportunity land identified in the WRI restoration opportunity map (Potapov et al., 2011) and these populations depend to a large extent on the natural environment (Fedele et al., 2021).

Overlooking the realities of local communities and their livelihoods in reforestation projects is likely to result in conflict. Integrating these issues into restoration area maps such as the one produced in this study is by no means sufficient; restoration and reforestation projects and practitioners must themselves ensure communities' participation in governance. However, considering these topics even as early as in an exercise in mapping of opportunities may help communicate the issue better to decision-makers (Gnacadja and Vidal, 2022).

However, in this study, the socio-economic constraints are so far drawn from land cover and use maps that have a minimum resolution of 300 m because of the limitations in computing power governing this PhD project. This spatial scale is insufficient to represent smaller scale and transient land uses. For example, *shifting cultivation* (also called *slash and burn agriculture*) is a widespread practice in Southeast Asia and elsewhere, but they are usually mapped on spatial scales of 30 m or finer (Chen et al., 2023; Mananze et al., 2020).

Future applications can, however, expand the inputs for the socio-economic scenario component by adding specific datasets on community and indigenous land uses and tenure (Marshall et al., 2023). One such dataset is hosted by the Land-Mark Global Platform of Indigenous and Community Lands (Dubertret and Alden Wily, 2015). Reflecting these realities in the restoration opportunity map may help reduce the potential for land use conflicts, but should really be a priority in order to help safeguard indigenous and local communities' land rights.

6.6 Revisiting the aim of the thesis

The aim of this thesis was to advance the understanding of the relationships between tree cover growth and water provisioning and regulation services with specific attention to the trade-off between enhanced evapotranspiration and improved infiltration and regulation in the seasonally dry tropics. The thesis also aimed at identifying areas where net positive outcomes for water quantity and

regulation are likely or unlikely to be attainable, thus translating the findings into policy and planning relevant recommendations.

To achieve this aim, **chapter 2** introduced the literature and research into the effects of tree cover change on hydrological variables in general, and the infiltration trade-off hypothesis in specific. **Chapter 3** of the thesis then presented a new hydrological model, DTRIE (*Distributed TRade-off in Infiltration and Evapotranspiration*), for the monthly estimation of potential gains from infiltration and losses through evapotranspiration under tree cover increase. After assessing existing hydrological and landscape models' shortcomings in addressing the specific trade-off related questions, the DTRIE model was built on their foundations, adjusting and adding the relevant model components. The model was then used to produce baseline estimates for several hydrological variables for the reference year 2018. The verification of DTRIE estimates against other remote-sensing derived datasets for AET was shown to be satisfactory, both in terms of magnitude of annual and monthly totals and seasonality, delivering **objective 1** of this study.

Chapter 4 described a new map of tree cover growth potential across the tropics and a data-driven growth model in support of **objective 2**. The map of tree cover growth potential constitutes a major improvement to previous tree cover restoration maps with respect to socio-economic and biophysical constraints, alongside generally updating some of the biophysical inputs. In a novel approach, the model accumulated tree cover incrementally based on a growth rate derived from remotely sensed net primary productivity, producing potential fractional tree cover maps at multiple at 25-year intervals from 25 to 150 years.

The maps of potential fractional tree cover were then used as alternative, or scenario, inputs for tree cover in DTRIE in **chapter 5** in an effort to achieve **objective 3** and **objective 4**. First, the chapter outlined the hydrological effects of the tree cover growth model itself on both annual and seasonal water availability for the tropics and a small set of tropical dam watersheds. It then explored the general sensitivity of water balance and effective infiltration to tree cover change, and examined how these sensitivities in turn responded to a range of environmental conditions.

Lastly, the present chapter, **chapter 6**, translated the key findings into policy- and

planning relevant recommendations on where reforestation and restoration projects are likely to have a more positive or negative hydrological outcome in order to achieve **objective 5**.

6.7 Concluding remarks

In this thesis I developed two remote sensing data-driven models, an incremental tree cover growth model and DTRIE, the *Distributed TRade-off in Infiltration and Evapotranspiration* model. Both models were then applied to model the hydrological effect of tree cover growth in the tropics.

The area of opportunity for tree growth identified 812 million hectares of land area across the tropics with the potential to increase or establish new tree cover, half of which is located in Central and South America, a third in Africa, and the remainder in Asia and Oceania. The model estimated an increase in tropical forest cover from 25.8 (current/2018) to 31.3 per cent (in 2118), with greatest relative increases occurring in Africa.

The results of the DTRIE application confirm the findings from temperate regions and smaller scale catchment work that reforestation decreases water quantity. The only cases where an increase in water balance is plausible according to the model is cloud-affected forests, allowing for forests to be considered as “pumps”. Overall, however, the sensitivity of annual water balance to tree cover increase was low, except in very few basins where net radiation, baseline tree cover and mean annual temperature were high. These basins also had a moderate to high aridity index and annual rainfall, and exhibited low seasonality in temperature and rainfall.

In addition to overall annual water quantity, the timing of water availability was examined to answer the question under what conditions the distribution of streamflows across the year changes, and when dry season flows might be increased. In such cases, areas under tree cover could act as “sponges”, storing and more gradually releasing water back into streams as baseflow, because the changes in infiltration caused by the tree cover growth outweigh the changes in AET. The results showed that the changes in distribution of flows grew with humidity and the share of the basin with tree growth opportunity. Basin topography, soil characteristics and other factors then determined whether the altered flow

distribution across the year resulted in increased or decreased dry season flows. These results were put in context for a small set of basins where the application of DTRIE demonstrated the likely hydrological effects of reforestation or forest restoration activities.

In addition to the specific applications in this study, both models delivered important contributions to literature. For one, DTRIE addresses the dearth in model-based studies on the trade-off hypothesis. It provides a novel approach to model the effect of tree cover on subsurface flows through its adjustments to soil moisture store volumes and throughflow velocities to the presences of tree cover. The utility of DTRIE for the exploration of the trade-off hypothesis in the tropics has been demonstrated for the annual water balance and monthly streamflow response to tree cover change, but it is important to remember that DTRIE is not suitable for modelling on the time scale of rainfall events such as required by flood modelling. The tree cover restoration area map, called tree growth area of opportunity in this study, can be of use in other areas of research where the effect of tree cover density is relevant. Even if the incremental growth of tree cover is not important to a specific research project, the robust socio-economic and biophysical constraints at the core of the map constitute an improvement over many existing restoration maps.

In conclusion, because these two models can be run with publicly available remote sensing data products with good coverage in the tropics, they can help address two important general research gaps relating the infiltration trade-off debate: 1) the lack of tree cover change and hydrological studies on large spatial scales ($> 1,000 \text{ km}^2$), and 2) the scarcity of studies from the tropical region.

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Appendix 1: DTRIE model

A1.1 Alternative climatological precipitation inputs for DTRIE

List of alternative precipitation dataset

Table A- 1 lists the various medium to high resolution monthly climatologies for precipitation currently available. It also gives details on their temporal coverage, spatial resolution and type of data source as well as the respective reference publication.

Table A- 1) Several alternative medium to high resolution monthly precipitation climatologies and their suitability for DTRIE

Dataset name	Version	Coverage	Resolution	Data source	Reference
CHELSA (Climatologies at High Resolution for the Earth's Land Surface Areas)	v.2.1	1981 - 2010	1km	Reanalysis data + rain gauge	Karger et al. (2021, 2017)
WorldClim	v.2.1	1970-2020	1km	Rain gauge, interpolated (thin plate spline)	Fick and Hijmans (2017)
GPCP (Global Precipitation Climatology Project)	2	1981-2010	2.5°	Satellite + rain gauge	Adler et al. (2003)
CRU (Climatic Research Unit) CL	1.1 (revised 2022)	1961-1990	0.5°	Rain gauge	New et al. (2002, 1999)
CHPclim - High-quality monthly rainfall climatology	1	1980-2009	0.05°	Satellite + rain gauge, interpolated (inverse distance weighting, moving window)	Funk et al. (2015)
GPCC Climatology Version (Global Precipitation Climatology Centre)	1	1951-2000	0.25°	Rain gauge, interpolated	Schneider et al. (2014), Rustemeier et al. (2020)

Justification of the choice of CHELSA v2.1 as DTRIE input

CHELSA v.2.1 was chosen as monthly rainfall climatology because it performs better than WorldClim v.2.1 in areas with high topographic complexity and low weather

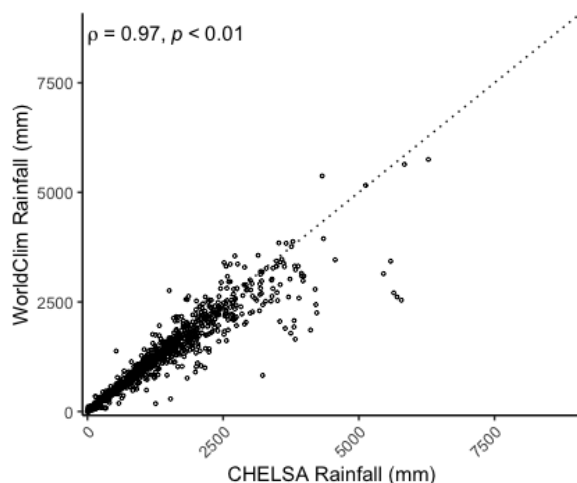


Figure A. 1 Annual total rainfall (mm) for a random sample of 1000 pixels across the tropics.

station density. At a 1 km (30 arcsec) resolution, it is also preferable over other climatologies such as the CHPclim, CRU and GPCC datasets, which have higher or much higher spatial resolutions (0.05 to 2.5° degrees).

The CHELSA algorithm uses statistical downscaling of ERA5 (ERA-interim in version 1) reanalysis data and applies bias correction with observational data, while WorldClim is interpolated from sta-

tion observations, integrating a set of covariates (Fick and Hijmans, 2017; Karger et al. 2017).

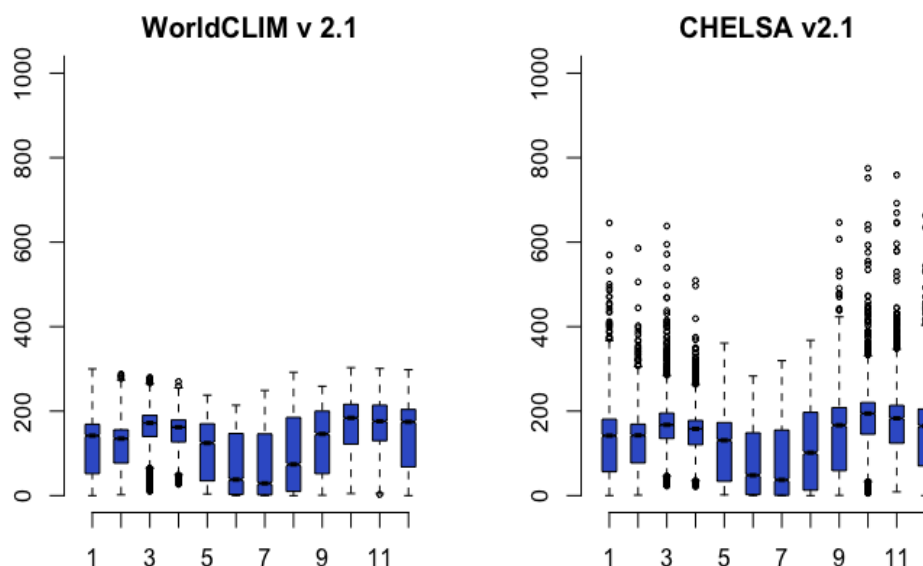


Figure A. 2 Box plots comparing WorldCLIM (left) and CHELSA (right) monthly rainfall amounts in the Congo River basin. As in the previous plot, the CHELSA values have a much larger variability and the monthly maxima are much higher. Basin mean monthly rainfall amounts do not differ as much, however.

Additionally, CHELSA includes orographic predictors, improving the overall precipitation predictions. Due to the inclusion of these predictors and because CHELSA v2.1 now integrates Beck et al.'s (Beck et al., 2020; Bobrowski et al., 2021) bias correction for systematic gauge undercatch, it outperforms WorldClim precipitation in mountainous areas, or lowland rainforest because these typically have low station density (Beck et al., 2020; Bobrowski et al., 2021).

Across the tropics, the scatter plot in Figure A. 1 underlines that WorldClim data can be less than half of CHELSA estimates. This is also visible in the boxplots in Figure A. 3 and Figure A. 2.

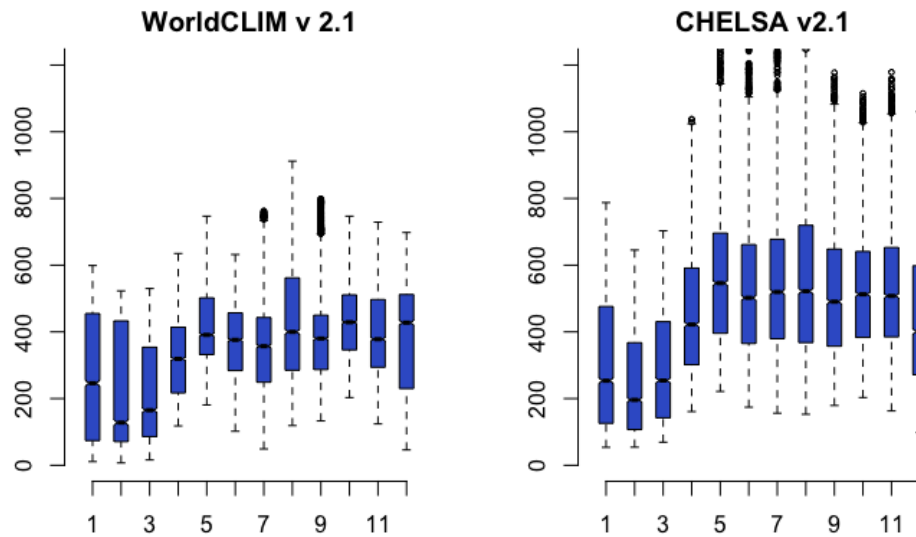


Figure A. 3 Box plots comparing WorldCLIM (left) and CHELSA (right) monthly rainfall amounts in the Atrato basin, Colombia. The CHELSA dataset registers much higher values in all but January through March. For example, the monthly rainfall basin mean for May in WorldCLIM is around 400 mm, compared to around 550 mm in CHELSA. The spatial heterogeneity of CHELSA is also greater.

A1.2 Comparison of annual total PET (mm) between DTRIE, GLEAM, FAO and CHELSA

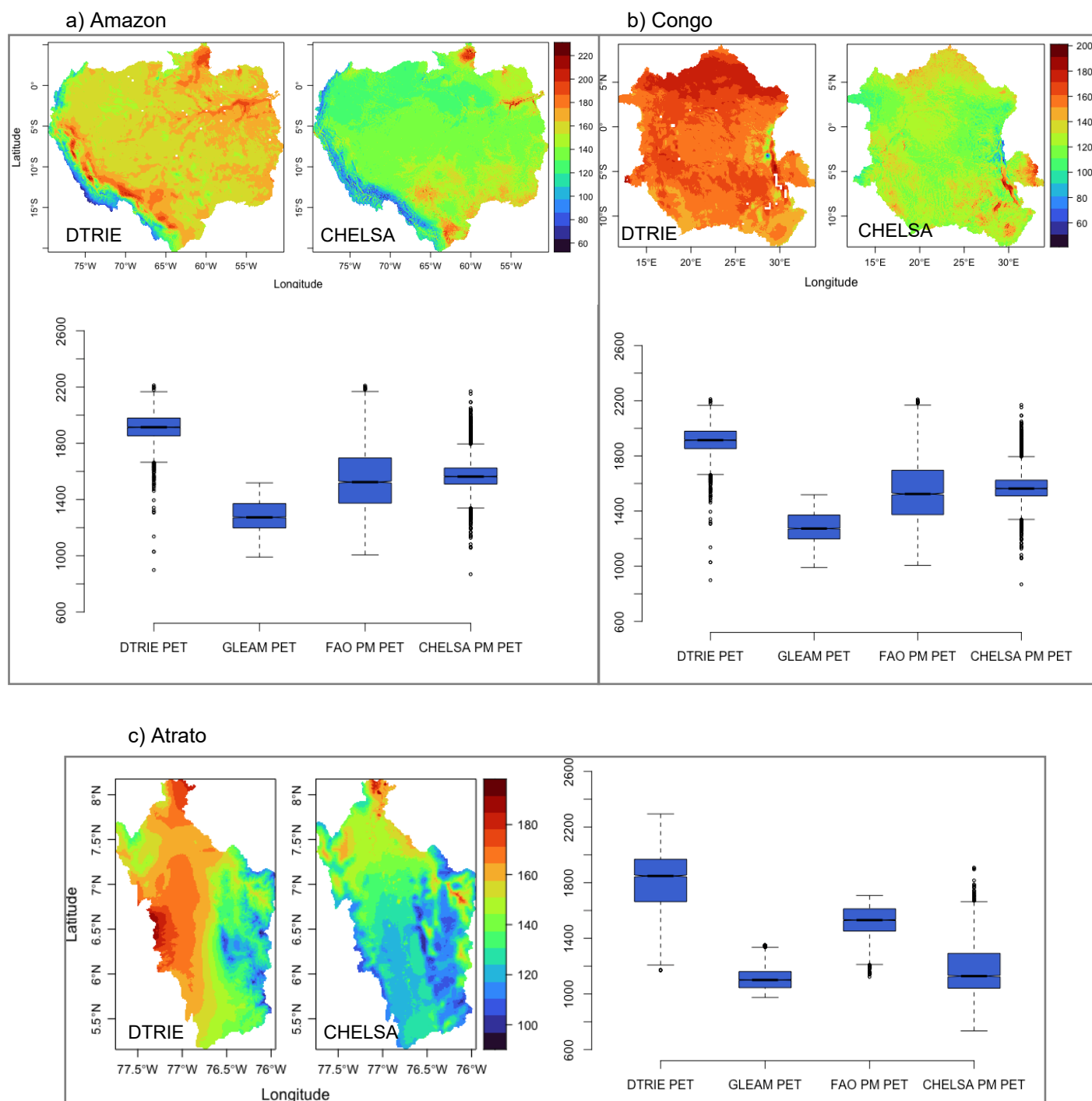
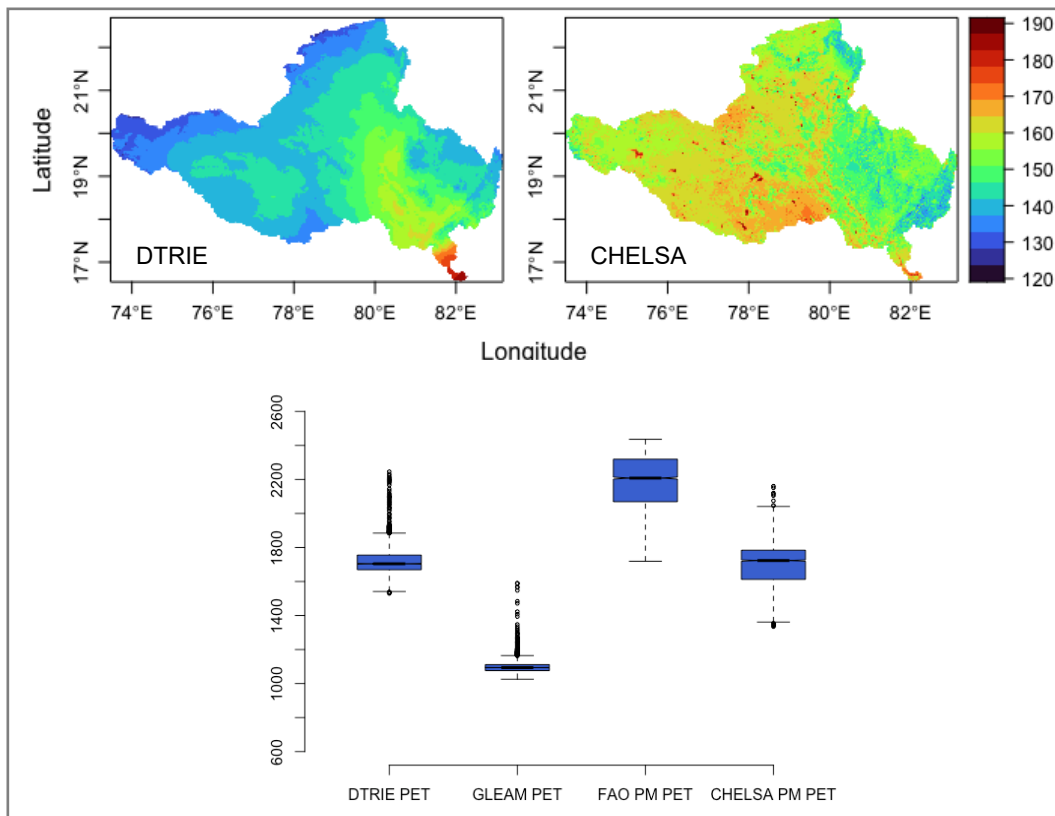


Figure A. 4 Comparison of annual total PET (mm) between DTRIE, GLEAM, FAO (PM) and CHELSA datasets for a) the Amazon River basin, b) Congo River basin, c) Atrato River basin. Maps show DTRIE (left) and CHELSA (right), while the boxplot compares all datasets. DTRIE is higher than all other datasets in all three basins. Sources: Zomer & Trabucco 2022 for FAO PET, CHELSA v.2.1, GLEAM v. 3.5.

a) Godavari



b) Kapuas

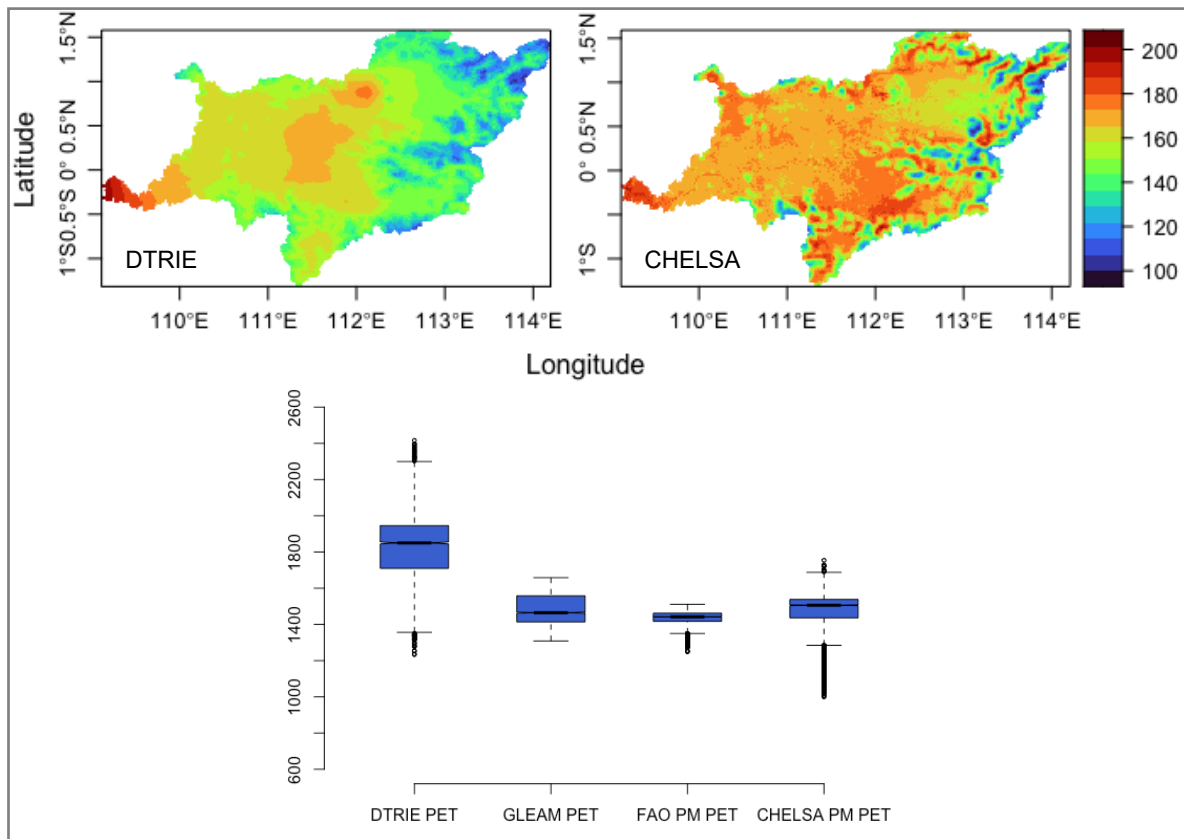


Figure A. 5 Comparison of annual total PET (mm) between DTRIE, GLEAM, FAO (PM) and CHELSA datasets for a) the Godavari basin, b) Kapuas basin. Maps show DTRIE (left) and CHELSA (right), while the boxplot compares all datasets. DTRIE PET is similar to CHELSA, higher than GLEAM and lower than FAO in Godavari; in the Kapuas basin, it is higher than all other datasets.

A1.3 Methodological notes on computing and software environment

1. Software and programming languages used

All computations were done on an Apple MacBook Air with an M1 processor running on macOS 12.6.5. The following lists all software and applications used with the version number in brackets. The R statistical software (R Core Team, 2021, v. 4.1.1) was used in the RStudio IDE (2023.03.0 Build 386), making use of the following packages: for general data processing: dplyr (1.0.10), janitor (2.2.0), ggplot2 (3.4.1), lubridate (1.9.2), data.table (1.14.3),

for geostatistical processing and plotting: terra (1.7-18), sf (1.0-9), ncdf4 (1.19), gdalUtils (2.0.3.2), whitebox (2.1.0), hydroGOF (0.4-0), with GEOS 3.11.0, GDAL 3.5.3, and PROJ 9.1.0.

For exploratory analysis, QGIS version 3.22. with GRASS plugins and SAGA Next Gen plugins was used.

2. General raster data processing:

All raster data was processed in R using the Rstudio IDE and R packages terra, sf, dplyr and data.table. Where necessary, data were reprojected to the standard WGS84 geographic CRS (EPSG: 4326) and cropped to latitudes between -24 and 24 degrees, which captures the tropics with a small buffer. Subsequently, data were cleaned and scaled in accordance with the supplied metadata and aggregated, and where necessary resampled, to the equivalent of a 1 km resolution at the equator (around 0.00883 degrees). Continuous data were resampled with bilinear and categorical with nearest neighbour interpolation. Where physical distances were calculated, data were reprojected to the World Equidistant Cylindrical CRS (EPSG: 4087).

3. Specific raster processing

3.1 Creating regional averages for variable interpolation & adjustment to scenario conditions

As the tree growth scenario and model are specifically designed to allow new tree cover in a pixel, several variables are be interpolated in order to reflect better the potential forest biome's characteristics rather than the non-forest biome characteristics of the reference year. To this end, these variables are grouped different by a grouping variable 1, either climate regions defined by two bioclimatic variables, mean

annual temperature (MAT) and total annual rainfall (TAR), or, in the case of AW and UAW stores, water table depth bands, as well as a grouping variable 2, forest cover type, and then averaged within all possible combinations of these two groups.

The variables affected include the carbon growth rate, carbon to cover conversion rate and reference maximum LAI and LAI seasonality, interception loss and volumes of the AW and UAW stores.

Grouping variable 1

The climate regions are calculated by categorising continuous annual total rainfall and annual mean temperature (MAT) into bands with bandwidths 1000 mm and 5 °C, respectively. The overall minimum for MAT in this study is set to -5 °C (which is band 1), the overall maximum is 40 °C. For annual total rainfall, the minimum is 0 mm and the maximum is 12,000 mm.

If a class is represented in less than 0.5% of the total non-NA area in the target area (tropics) it is excluded and affected pixels are reassigned the climate class value of the closest match in climate conditions.

For example, a pixel with MAT of 21 °C (and thus with a temperature band value of 6) and rainfall of 4600 mm (and thus with a rainfall band value of 5) has a climate class/region value of 605.

The digits for the rainfall slot have a leading 0 because the rainfall bands can go up to 12. For the above example, rainfall band 5 is therefore represented as “05”.

If climate class/region 605 does not make the area 0.5% cut-off it will be reassigned the climate class/region value of the most alike class that makes the cut-off, for example 505 or 606. Where multiple classes are available as alternatives, the class with the lower temperature band value is used.

The cuts used to convert the continuous water table depth to categorical bands are 0, 0.1, 1, 10, 25, 50, 75, 100 resulting in 8 classes, where class 1 represents a water table depth of 0 to 0.1 m.

Grouping variable 2

Because of the different naming conventions between ESA CCI land cover classes and Hengl et al's (2018) biomes, Table A- 2 presents a look-up table which maps ESA CCI land cover class(es) onto the equivalent Hengl et al. biome on account of

their respective name and descriptions. Some biomes are equivalent to multiple land cover classes. For example, to extract all grid cells needed to calculate a variable average for biome type 1 (tropical evergreen broadleaf forest), the respective baseline variable raster is filtered for all pixels that have ESA class 50 (tree cover, broadleaved, evergreen, closed to open). In the case of biome 2, pixels with ESA classes 50 and 60 are filtered.

Table A- 2 Cross-walking table between ESA CCI level 1 (global) land cover classes and Hengl et al. PNV biomes. Only ESA classes that are present in the tropics are listed

Hengl biome	Hengl biome name	ESA class	ESA land cover class name	included	Reason for exclusion
1	Tropical evergreen broadleaf forest	50	Tree cover, broadleaved, evergreen, closed to open	Yes	NA
2	Tropical semi-evergreen broadleaf forest	50 60	Tree cover, broadleaved, evergreen, closed to open; Tree cover, broadleaved, deciduous, closed to open;	Yes	NA
3	Tropical deciduous broadleaf forest and woodland	60	Tree cover, broadleaved, deciduous, closed to open	Yes	NA
4	Warm-temperate evergreen and mixed forest	90	Tree cover, mixed leaf type (broadleaved and needleleaved)	Yes	NA
8	Cool evergreen needleleaf forest	70	Tree cover, needleleaved, evergreen, closed to open	No	low percentage of cover in tropics
9	Cool mixed forest	90	Tree cover, mixed leaf type (broadleaved and needleleaved)	No	low percentage of cover in tropics
13	Temperate deciduous broadleaf forest	60	Tree cover, broadleaved, deciduous, closed to open	No	low percentage of cover in tropics
15	Cold evergreen needleleaf forest	70	Tree cover, needleleaved, evergreen, closed to open	No	low percentage of cover in tropics
16	Temperate sclerophyll woodland and shrubland	120 100	Shrubland; Sparse vegetation (tree, shrub, herbaceous cover (<15%); Mosaic tree and shrub (>50%) / herbaceous cover (<50%);	No	low percentage of cover in tropics
17	Temperate evergreen needleleaf open woodland	70	Tree cover, needleleaved, evergreen, open (15-40%)	No	low percentage of cover in tropics
18	Tropical savanna	110 60 50	Mosaic herbaceous cover (>50%)/ tree and shrub (<50%) Tree cover, broadleaved, deciduous, open (15-40%) Tree cover, broadleaved, evergreen closed to open	No	Not dense forest type; detailed reasoning to exclude savanna in chapter 3;

20	Xerophytic woods/scrub	120	Shrubland; Sparse vegetation (tree, shrub, herbaceous cover (<15%);	No	Not dense forest type; confusion with savanna possible
22	Steppe	130	Grassland	No	Not forest type
27	Desert	200	Bare areas	No	Not forest type

3.2. Adjustments to the plant available water store, *AW_pot*

The volume of the available water store (AW store, or *AW_pot*) is described section 3.2.2 (6).

Preliminary results yielded evapotranspiration values that were much lower in densely forested areas such as the central Amazon forests than published values. The low values were caused by the limited volume of the initial AW store, which could not capture the store volume of for example an extensive litter layer because *AW_pot* was calculated with the field capacity and wilting point water contents of mineral soil only. Therefore, the AW store under forest and herbaceous cover is increased to better reflect the presence of a litter layer by adding a soil volume equivalent of 1 m³ (or 0.5 m³ in herbaceous pixels) of soil with a high fraction of available plant water, which was defined as the 95th percentile of the tropical extent fraction of available plant water, $p_{95} = 0.19$. This adjustment is applied in pixels where the tree or herbaceous cover exceeds 50 %. Thus, for a pixel with more than 50 % tree cover, $1 \text{ m}^3 * 0.19 = 0.19 \text{ m}^3$ are added to the original *AW_pot* value.

The AW store is then adjusted to the scenario vegetation cover conditions in the following way as described in section 1 of this appendix.

A1.4 Annual baseline AET, water balance and effective infiltration averaged over HB4 basins

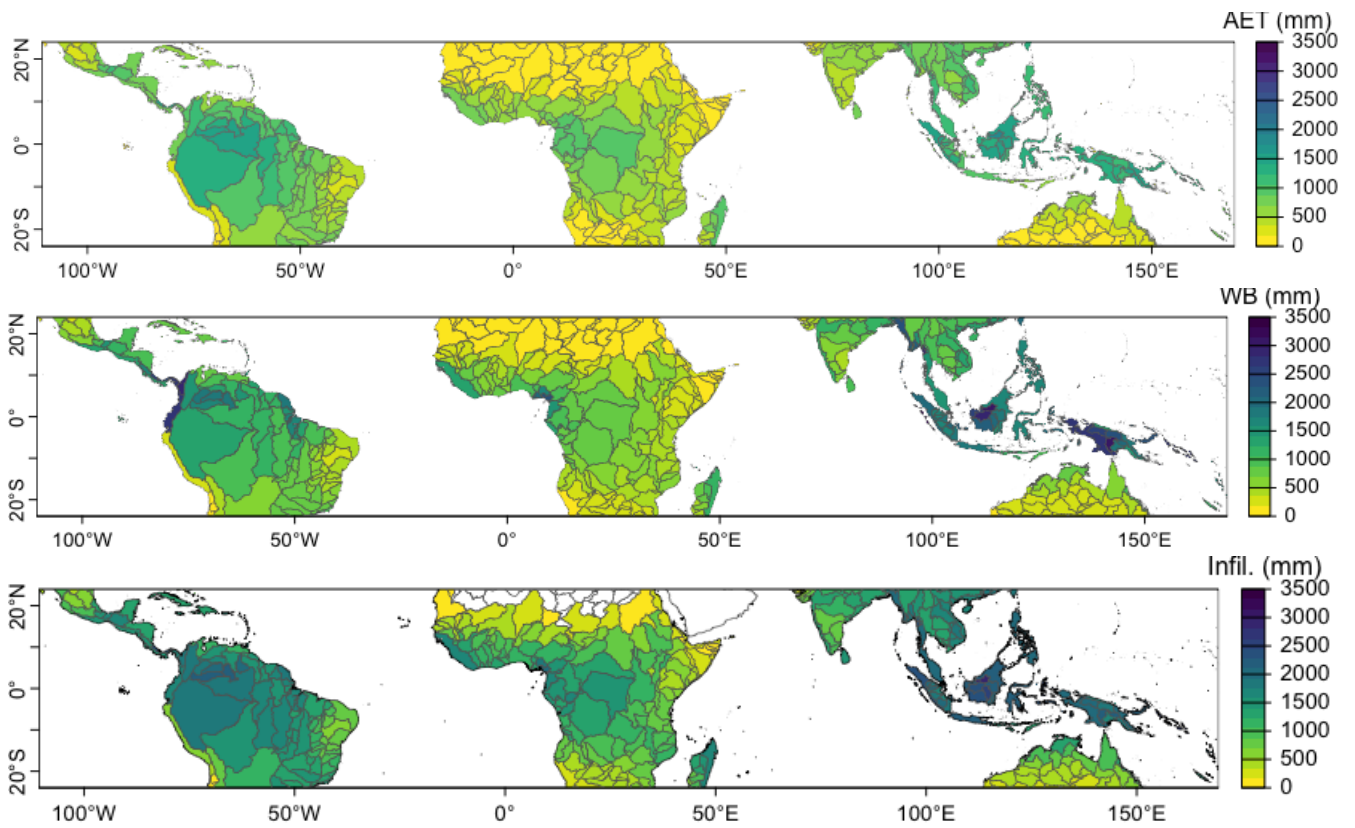


Figure A. 6 Annual AET (top), Water balance (centre) and effective infiltration (bottom) averaged over HB4 basins.

Appendix 2: Tree cover scenario and growth model

A2.1 Brief glossary for forestation and forest related terminology

Term	Definition
Forest	An area with a minimum of 0.5 hectares, covered with min. 10% of tree cover of trees higher than 5 m, without agricultural activity or human settlements (FAO, 2012b)
Afforestation	“Planting of new forests on lands that historically have not contained forests” (McCarthy et al., 2001)
Reforestation	“Planting of forests on lands that have previously contained forests but that have been converted to some other use” (McCarthy et al., 2001)
Forest landscape restoration, FLR	A landscape approach utilising many methods, considering both environmental and socio-economic needs; According to Chazdon and Guariguata (2016, p. 716) a “holistic process that aims to regain ecological integrity and enhance human well-being in deforested, human-impacted, or degraded forest landscapes”
Forest regeneration	Natural regeneration can occur where degradation is low and vegetation is able to recolonise on its own (Gann et al., 2019) Assisted regeneration is “a restoration approach that focuses on actively harnessing any natural forest regrowth capacity of biota remaining on site or nearby”. It requires addressing first the causes of degradation and then active interventions to restore damages. (Gann et al., 2019; Holl and Brancalion, 2020)
Forest regrowth	Cook-Patton et al. 2020 define natural forest regrowth as “the recovery of forest cover on cleared lands through spontaneous regrowth after cessation of previous disturbance or land use”
Natural forest regrowth	Also known as “passive restoration”, see natural forest regeneration spontaneous and without direct re-introduction (Gann et al. 2019 in Brancalion & Holl 2020)
Forest restoration	“ecological restoration is the process of assisting the recovery of an ecosystem that has been degraded, damaged, or destroyed”, typically with a focus on restoring ecological functions of a forest (Gann et al. 2019 in Brancalion & Holl 2020)
Forestation	“a change in land cover from a stable, non-forested state to a forested one, independent of the long-term history of forest cover.” (Bentley and Coomes 2020)

A2.2 Sensitivity analysis for tree cover threshold to classify “high” tree cover

The threshold to consider a pixel *highly forested* is set to a tree cover in 2018 of above 70 per cent. This threshold is used to filter pixels with a high certainty for good representation of the characteristics of dense forest. The filter created with this threshold is applied to data inputs into the tree growth and DTRIE models when a subset of pixels representative of forest is required; for example, when variables are averaged over climate classes in a gap-filling process. The result of this analysis is that both models are somewhat sensitive to this threshold in regions where annual rainfall is low, between 0 and 1,000 mm/year, but otherwise the choice is largely without effect.

In the following, two more thresholds in addition to the 70 per cent are compared in their effects on the variables LAI seasonality (Figure A. 8), interception ratio (Figure A. 7), net primary productivity mean (Figure A. 9) and the ratio of carbon to tree

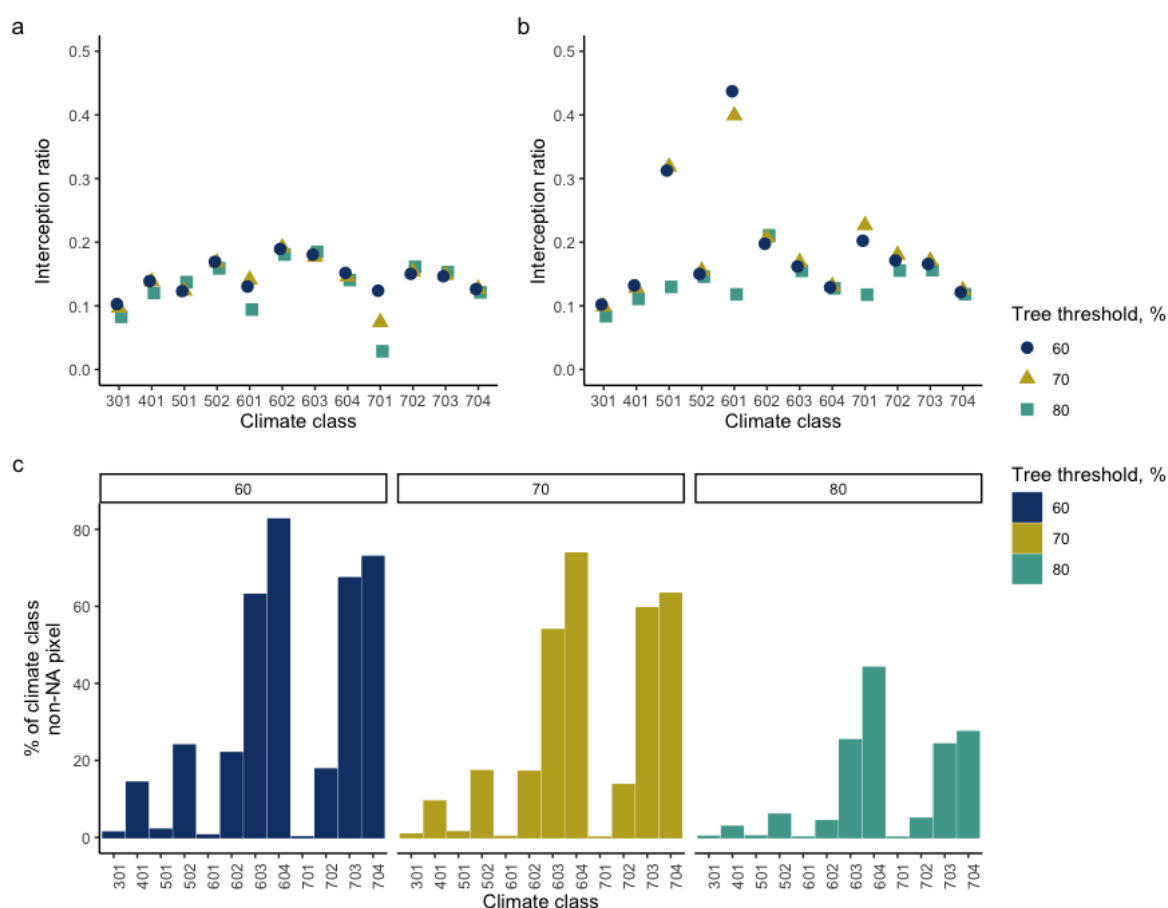


Figure A. 7 Interception ratio. Same parameters as previous Figure A.9. Again, there are very few differences between the tree cover thresholds.

cover (Figure A. 10). For the monthly inputs LAI seasonality and interception ratio

the sensitivity analysis is conducted for months January (a) and June (b) and considered representative of the full dataset.

The tree cover mask with the 60 per cent threshold selects the highest number of pixels in the LAI raster, followed by the 70 per cent mask, and the 80 per cent mask. As Figure A. 8c shows, the number of pixels between the 60 and 70 per cent mask does not differ much for any of the climate classes. Figure A. 8a and b illustrate the

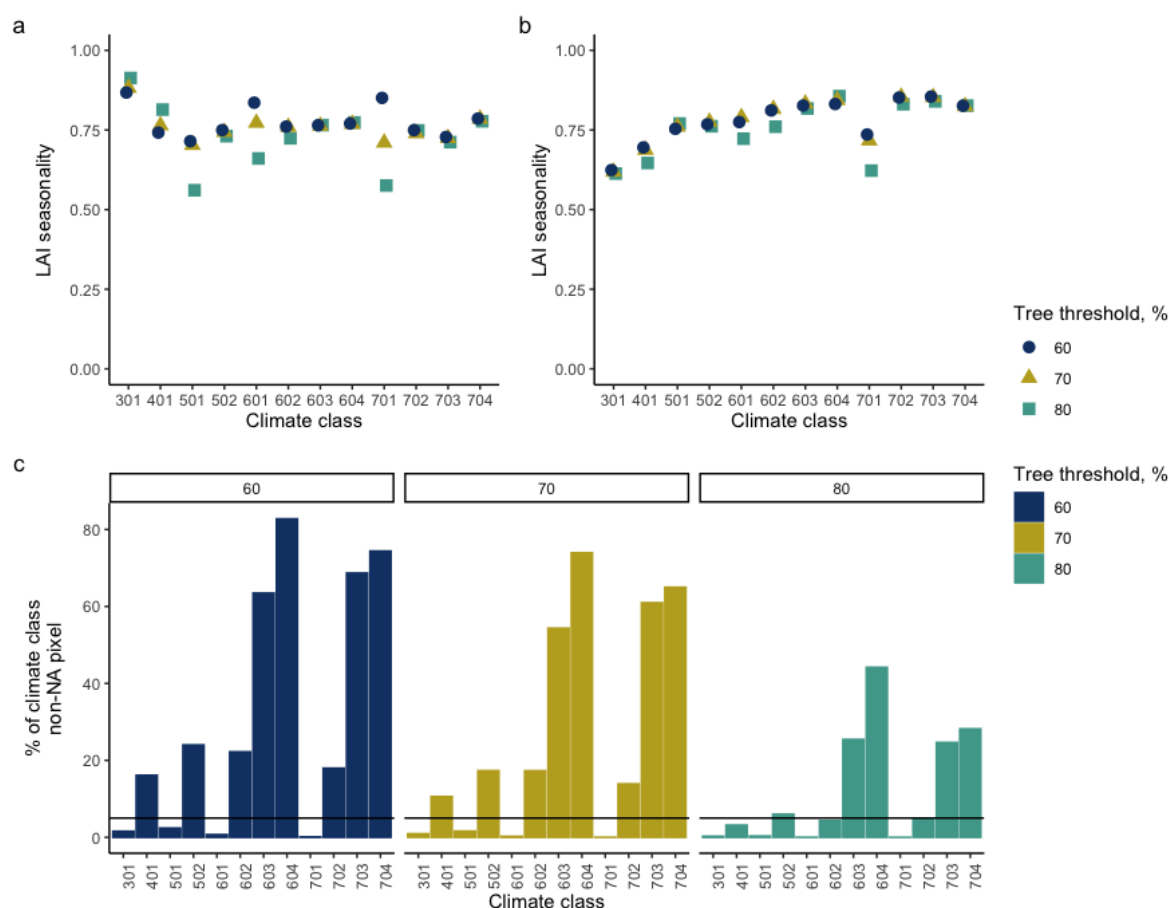


Figure A. 8 Comparison of different thresholds for "high" tree cover for LAI seasonality. a) Mean LAI seasonality for climate classes for the thresholds 60, 70, and 80 per cent tree cover for January; b) Mean LAI seasonality for climate classes for the thresholds 60, 70, and 80 per cent tree cover for June; c) count of non-NA LAI seasonality pixels in each climate class when the respective mask is applied. The number of non-NA pixels is the same across months for the variable

difference in means of LAI across the climate classes for January and June. Here, the threshold of 60 and 70 per cent again show very similar results, but the 80 per cent results differ somewhat. This threshold is unsuitable, however, because above 80 per cent tree cover, the MOD44B tree cover fraction product is affected by the saturation effect and does not accurately resolve differences in tree cover any longer.

Similar patterns are observed for the remaining variables examined. Interception ratio shows some small differences for climate class 501, 601 and 701 in both January (see Figure A. 7a) and June (see Figure A. 7b), but these are likely on account of the very small number of pixels in each climate class (see Figure A. 7c). The same climate classes show some variation between thresholds in the NPP (Figure A. 9a) and carbon-to-cover ratio plots (Figure A. 10a).

Climate classes 501, 601 and 701, reflect regions with very low annual rainfall, as is indicated by the last two digits in the class code, “01”. This code means that annual total rainfall is between 0 and 1,000 mm/yr. The explanation how climate classes are coded is given in Appendix A1.5 (above).

We can therefore say that DTRIE estimates are somewhat sensitive to the threshold used for the identification of pixels representative of forest types when the associated climate has very little annual rainfall. Otherwise, the choice threshold does not affect the value of the averaged and gap-filled variables examined here.

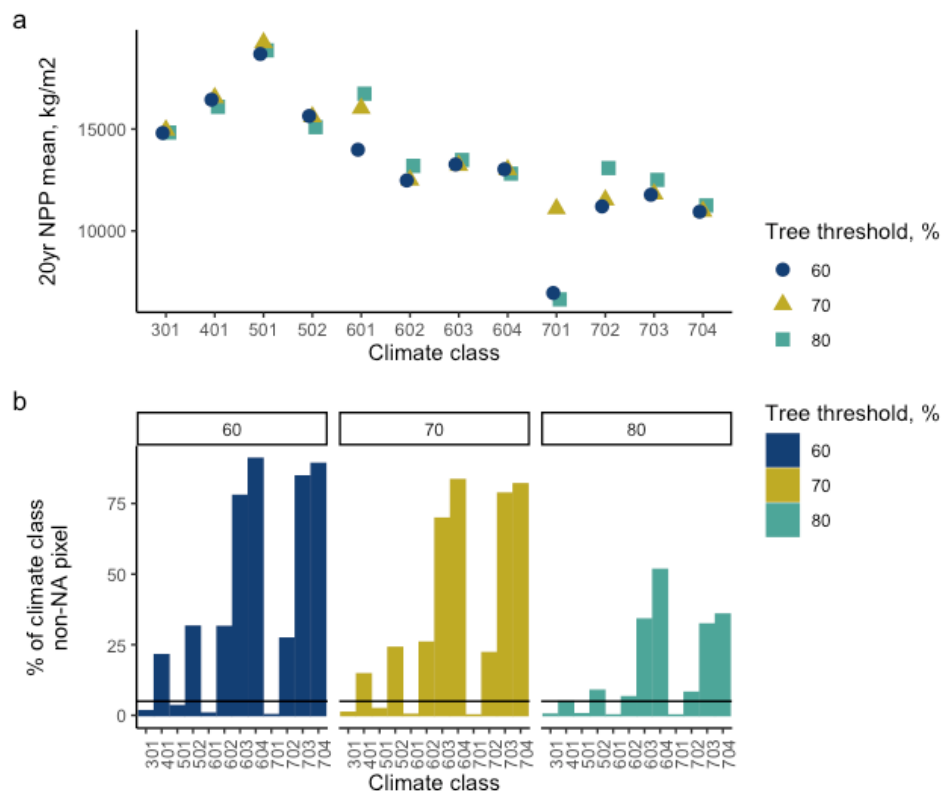


Figure A. 9 NPP (Net primary productivity) mean of 20 years (kg/m^2), otherwise same parameters as previous plots. Apart from class 701, there are practically no differences between the tree cover thresholds.

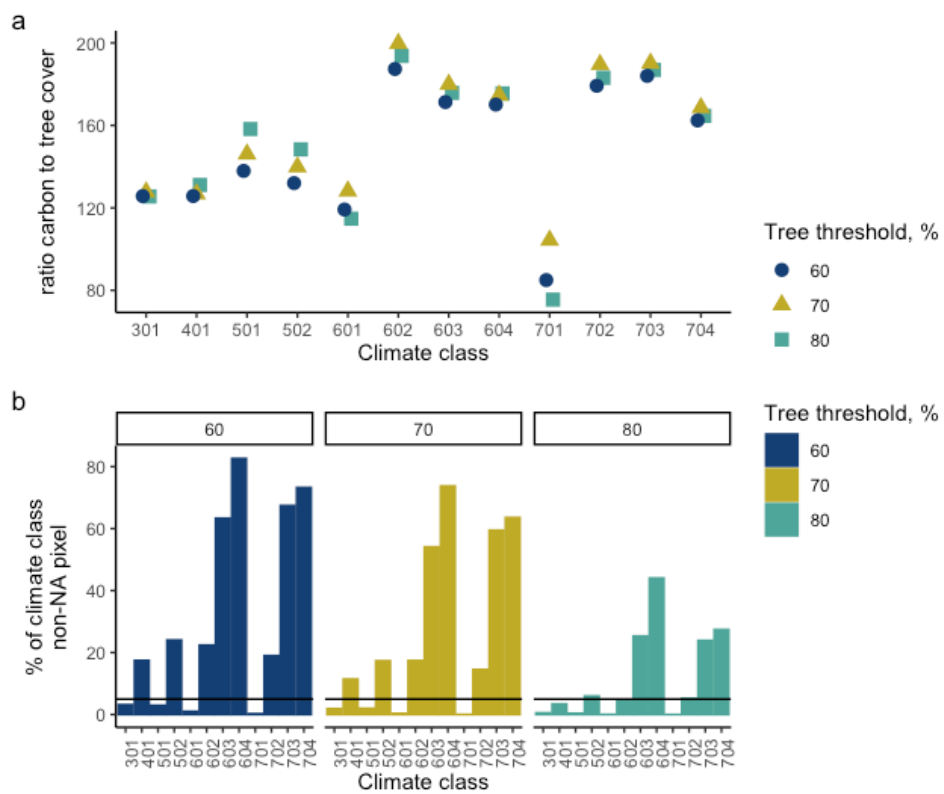
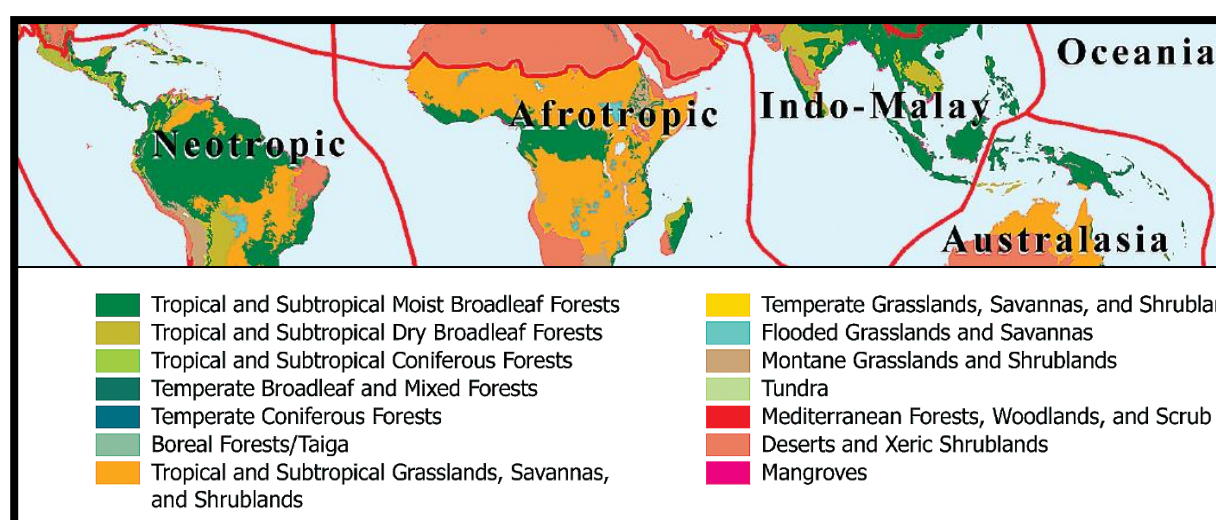
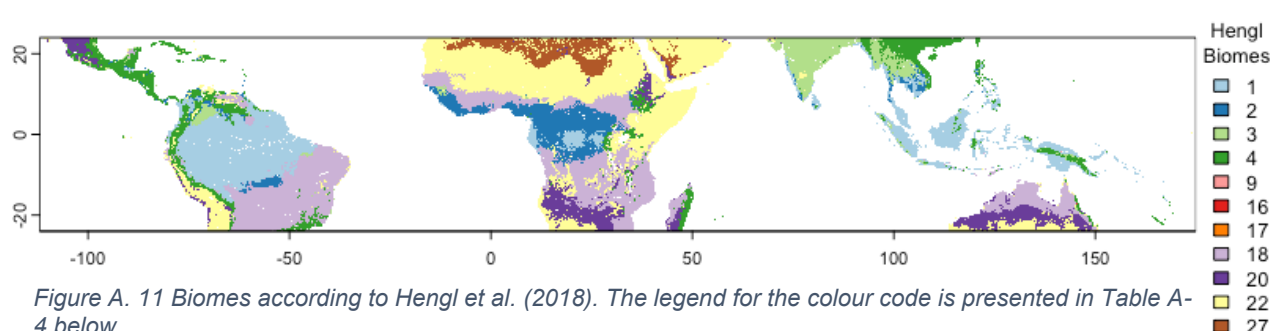


Figure A. 10 Ratio of carbon (MgC/km^2) to tree cover (%) otherwise same parameters as previous plot

A2.3 Comparison of the Hengl et al. (2018) biome map and Olson et al. (2001) biome/ecoregion map

As referenced to in chapter 5, the biome maps produced by Hengl et al. 2018 (hereafter *Hengl map*) do not differ much from the otherwise commonly used Olson et al. 2001 biome map (hereafter *Olson map*). Overall, the use of the Hengl map less to slightly less area of opportunity for forest cover growth.

A short visual comparison is presented below. Note the different colour codes. The names of the Hengl et al. (2018) biomes are presented in Table A- 3 below.



The main differences are:

The Hengl map identifies more savanna areas in South America, more savanna and xeric scrub type biomes in Madagascar. It also finds less forest type land in East Africa, the Yucatan peninsula of Mexico and Timor-Leste. In these regions, the *area of opportunity identified with the Hengl map will be lower* than if the Olson map were used.

Table A- 3 Biome codes and names for the map of Hengl biomes in Figure A.15

Hengl Biome code	Hengl biome name	Hengl Biome code	Hengl biome name
1	Tropical Evergreen Broadleaf Forest	15	Cold Evergreen Needleleaf Forest
2	Tropical Semi-Evergreen Broadleaf Forest	16	Temperate Sclerophyll Woodland And Shrubland
3	Tropical Deciduous Broadleaf Forest And Woodland	17	Temperate Evergreen Needleleaf Open Woodland
4	Warm-Temperate Evergreen And Mixed Forest	18	Tropical Savanna
8	Cool Evergreen Needleleaf Forest	20	Xerophytic Woods/Scrub
9	Cool Mixed Forest	22	Steppe
13	Temperate Deciduous Broadleaf Forest	27	Desert

More areas opportunity via the Hengl map are the consequence of the following differences. The Hengl map identifies less savanna, shrubland and grassland in Africa, for example in Ethiopia (however these areas are removed out by another biophysical constraint layer, the Dixon et al. (2014) WWF grasslands map). It also finds more forest type biomes in Southeast Asia, for example on New Guinea, and generally in coastal areas. In India, Gujarat and central southern Indian regions around Andhra Pradesh, Karnataka and Maharashtra have more forest type biomes in Hengl than in the Olson map. For example, the Great Rann of Kutch is classified as “deserts and xeric shrublands” in Olson, but as a potential tropical forest type in the Hengl map. In these areas, the Dixon et al. map (2014) did not present any grassland or savanna either, however, and therefore forestation opportunity was assumed.

In terms of overall area affected, less area of opportunity is identified with the Hengl map.

A2.4 Additional tree covered area for tropical countries and tropical basins

from GRDC's Major River basins of the world (MRB) dataset

Table A- 4 Additional tree-covered area by country, with area in million hectares with the two thresholds for area of opportunity delineation of 70 and 80 % tree cover in the reference year 2018. Countries with no increase in year 25 for either threshold are not shown. Only countries with the majority of land area between 24°S and 24°N are listed.

Country	Threshold 70%			Threshold 80 %		
	after 25 years	after 75 years	after 125 years	after 25 years	after 75 years	after 125 years
Angola	0.16	0.49	0.77	0.18	0.52	0.79
Argentina	0.04	0.12	0.14	0.09	0.22	0.24
Australia	0.42	1.25	1.97	0.49	1.42	2.14
Bangladesh	0.08	0.23	0.36	0.08	0.23	0.36
Belize	0.09	0.27	0.36	0.14	0.38	0.47
Bolivia	1.34	3.93	5.77	2.99	7.44	9.29
Brazil	4.69	13.84	19.71	21.59	46.92	52.79
Cambodia	0.36	1.07	1.6	0.46	1.29	1.83
Cameroon	1.93	5.76	8.88	2.91	7.79	10.92
Central African Republic	3.62	10.83	17.39	3.93	11.47	18.03
Colombia	2.24	6.59	9.4	6.15	14.29	17.1
Comoros	0.01	0.02	0.03	0.01	0.03	0.04
Costa Rica	0.09	0.28	0.39	0.15	0.41	0.53
Cuba	0.29	0.87	1.31	0.31	0.91	1.36
Democratic Republic of the Congo	5.84	17.36	25.69	13.93	33.84	42.17
Dominican Republic	0.05	0.16	0.23	0.07	0.18	0.26
East Timor	0.03	0.08	0.14	0.03	0.08	0.14
Ecuador	0.28	0.79	1.03	0.71	1.67	1.92
El Salvador	0.01	0.02	0.03	0.01	0.02	0.03
Equatorial Guinea	0.03	0.1	0.12	0.09	0.22	0.24
Ethiopia	0.75	2.23	3.47	0.83	2.37	3.62
France	0.02	0.06	0.09	0.07	0.16	0.18
Gabon	0.4	1.16	1.55	1.14	2.73	3.13
Ghana	0.07	0.2	0.33	0.07	0.21	0.34
Guatemala	0.4	1.18	1.64	0.47	1.33	1.78
Guinea	1.37	4.1	6.82	1.37	4.1	6.82
Guinea Bissau	0.12	0.36	0.61	0.12	0.36	0.61
Guyana	0.12	0.36	0.53	0.22	0.58	0.75
Haiti	0.02	0.07	0.11	0.02	0.07	0.11
Honduras	0.56	1.66	2.55	0.65	1.84	2.73
India	1.18	3.54	5.56	1.25	3.7	5.72
Indonesia	1.33	3.93	5.43	3.8	9.15	10.66

Country	Threshold 70%			Threshold 80 %		
	after 25 years	after 75 years	after 125 years	after 25 years	after 75 years	after 125 years
Ivory Coast	0.13	0.39	0.61	0.14	0.4	0.63
Kenya	0.07	0.2	0.28	0.09	0.23	0.32
Laos	1.1	3.26	4.44	1.46	4.03	5.21
Liberia	0.31	0.92	1.24	0.41	1.14	1.46
Madagascar	1.56	4.65	7.4	1.8	5.13	7.88
Malawi	0.04	0.13	0.19	0.04	0.13	0.19
Malaysia	0.07	0.19	0.23	0.42	0.97	1.01
Mali	0.01	0.02	0.03	0.01	0.02	0.03
Mexico	2	5.95	8.63	2.21	6.38	9.05
Mozambique	0.1	0.31	0.48	0.1	0.31	0.48
Myanmar	2.46	7.33	10.67	2.68	7.82	11.17
Nicaragua	0.39	1.17	1.79	0.46	1.32	1.94
Nigeria	0.67	2	3.22	0.7	2.07	3.29
Panama	0.18	0.52	0.75	0.31	0.83	1.06
Papua New Guinea	0.69	2.03	2.65	2.34	5.49	6.13
Peoples Republic of China	0.61	1.77	2.31	0.8	2.15	2.69
Peru	1.08	3.09	4.12	5.34	11.51	12.54
Philippines	0.39	1.15	1.56	0.6	1.65	2.06
Republic of the Congo	0.97	2.86	4.28	2.19	5.44	6.86
Sierra Leone	0.54	1.62	2.67	0.54	1.63	2.67
Solomon Islands	0.02	0.06	0.07	0.15	0.33	0.35
Somalia	0.01	0.04	0.06	0.01	0.04	0.06
South Sudan	0.4	1.21	1.99	0.41	1.22	2
Sri Lanka	0.21	0.62	0.96	0.21	0.63	0.98
Suriname	0.07	0.21	0.29	0.25	0.56	0.65
Tanzania	0.12	0.37	0.55	0.14	0.4	0.58
Thailand	0.72	2.14	3.11	0.86	2.45	3.43
Togo	0.02	0.06	0.1	0.02	0.06	0.1
Uganda	0.13	0.38	0.61	0.13	0.39	0.62
Venezuela	1.32	3.88	5.52	2.92	7.24	8.87
Vietnam	0.65	1.92	2.61	0.85	2.33	3.02
Zambia	0.01	0.03	0.05	0.01	0.03	0.05
Zimbabwe	0.04	0.1	0.15	0.04	0.11	0.16
Brunei	NA	NA	NA	0.02	0.05	0.05
Rwanda	NA	NA	NA	0.01	0.02	0.03

Table A- 5 Additional tree-covered area by MRB (major river basins of the world dataset), with area in million hectares with the two thresholds for area of opportunity delineation of 70 and 80 % tree cover in the reference year 2018. MRBs with no increase in year 25 for either threshold are not shown. Only MRBs entirely within the tropics are listed.

Basin	MRBID	Threshold 70%			Threshold 80 %		
		after 25 years	after 75 years	after 125 years	after 25 years	after 75 years	after 125 years
Congo	1209	10.32	30.73	46.75	20.34	51.23	67.24
Amazon (Also Amazonas)	3203	5.2	15.13	20.2	30.81	65.62	70.71
Orinoco	3234	1.52	4.49	6.4	3.68	8.9	10.82
Niger	1228	1.11	3.33	5.52	1.11	3.34	5.53
Sanaga	1239	1.07	3.21	5.08	1.26	3.61	5.48
Magdalena	3227	0.92	2.72	4	1.09	3.05	4.33
Usumacinta	4249	0.38	1.1	1.52	0.47	1.3	1.72
Ogooue	1233	0.37	1.07	1.44	1.1	2.62	2.99
Godavari	2307	0.34	1.03	1.7	0.34	1.03	1.7
Chao Phraya	2403	0.3	0.88	1.3	0.33	0.96	1.38
Corubal (Also Koliba)	1210	0.22	0.65	1.08	0.22	0.65	1.08
Panuco	4224	0.21	0.63	0.98	0.21	0.63	0.98
Tocantins	3247	0.18	0.55	0.85	0.26	0.72	1.02
Senegal	1242	0.17	0.51	0.85	0.17	0.51	0.85
Sittang	2321	0.17	0.51	0.71	0.18	0.53	0.74
Little Scarcies (Also Kaba)	1220	0.16	0.47	0.78	0.16	0.47	0.78
Jubba (Also Genale Wenz)	1308	0.16	0.49	0.74	0.18	0.52	0.77
Paraiba Do Sul	3237	0.16	0.47	0.72	0.18	0.51	0.76
Cross	1211	0.15	0.45	0.7	0.17	0.5	0.75
Moa (Also Makona)	1225	0.15	0.45	0.73	0.15	0.45	0.73
Mahanadi	2313	0.15	0.45	0.75	0.15	0.45	0.75
Lam (Also Xongka)	2416	0.15	0.45	0.59	0.2	0.55	0.7
Mae Klong	2420	0.15	0.46	0.67	0.18	0.52	0.72
Doce	3218	0.15	0.46	0.72	0.16	0.46	0.72
Saint Paul River	1238	0.14	0.41	0.62	0.15	0.44	0.65
Zambezi	1325	0.14	0.4	0.62	0.14	0.41	0.62
Lake Turkana	1911	0.14	0.41	0.64	0.15	0.43	0.66
Verde	4433	0.14	0.4	0.6	0.15	0.42	0.62
Papaloapan	4225	0.13	0.39	0.55	0.18	0.47	0.64
Ulua	4248	0.13	0.4	0.6	0.15	0.42	0.63
Catatumbo	3208	0.12	0.34	0.48	0.15	0.41	0.55
Pindare	3240	0.12	0.35	0.55	0.13	0.38	0.57
Mearim	3229	0.11	0.34	0.57	0.11	0.34	0.57

Basin	MRBID	Threshold 70%			Threshold 80 %		
		after 25 years	after 75 years	after 125 years	after 25 years	after 75 years	after 125 years
Ma	2419	0.1	0.3	0.37	0.15	0.39	0.46
Nyong	1232	0.09	0.27	0.33	0.16	0.42	0.48
Narmada	2316	0.09	0.26	0.43	0.09	0.26	0.43
Sao Francisco	3245	0.09	0.28	0.47	0.09	0.28	0.47
Patia	3421	0.09	0.26	0.39	0.11	0.31	0.43
Coco	4208	0.09	0.27	0.4	0.13	0.34	0.47
Patuca	4226	0.09	0.26	0.39	0.11	0.3	0.44
Tsiribihina	1321	0.08	0.25	0.41	0.08	0.25	0.41
Karnaphuli	2311	0.08	0.25	0.36	0.09	0.26	0.37
Hondo	4213	0.08	0.23	0.27	0.1	0.27	0.31
Sungai Fly (Also Fly River)	5434	0.08	0.25	0.33	0.28	0.67	0.75
Cavally	1204	0.07	0.2	0.3	0.09	0.24	0.34
Saint John River	1237	0.07	0.21	0.28	0.09	0.24	0.31
Sassandra	1240	0.07	0.21	0.35	0.07	0.21	0.35
Volta	1246	0.07	0.2	0.33	0.07	0.2	0.33
Atrato	3205	0.07	0.19	0.26	0.14	0.35	0.42
Candelaria	4204	0.07	0.2	0.25	0.07	0.2	0.25
Purari	5428	0.07	0.2	0.26	0.16	0.39	0.45
Loffa (Also Lofa River)	1221	0.06	0.18	0.26	0.07	0.2	0.28
Capim	3207	0.06	0.18	0.26	0.09	0.23	0.32
Grande De Mata-galpa	4212	0.06	0.19	0.29	0.07	0.2	0.3
Motagua	4221	0.06	0.18	0.28	0.07	0.19	0.29
San Juan	4240	0.06	0.17	0.27	0.07	0.2	0.3
Lempa	4415	0.06	0.18	0.28	0.06	0.18	0.28
Mamberamo	5423	0.06	0.19	0.26	0.27	0.64	0.71
Sepik	5432	0.06	0.19	0.24	0.27	0.62	0.67
Gambia	1215	0.05	0.15	0.26	0.05	0.15	0.26
Kouilou	1218	0.05	0.14	0.18	0.11	0.26	0.31
Mano (Also Mano River)	1222	0.05	0.14	0.2	0.05	0.15	0.21
Mangoky	1311	0.05	0.14	0.22	0.05	0.14	0.22
Araguari	3204	0.05	0.15	0.24	0.06	0.17	0.26
Cuyuni	3215	0.05	0.14	0.19	0.13	0.31	0.37
Jequitinhonha	3226	0.05	0.14	0.22	0.05	0.14	0.22
Chira	3407	0.05	0.14	0.21	0.05	0.14	0.21
Guayas	3411	0.05	0.13	0.17	0.06	0.15	0.19
Pulau (Also Eilanden)	5410	0.05	0.15	0.2	0.11	0.28	0.33

Basin	MRBID	Threshold 70%			Threshold 80 %		
		after 25 years	after 75 years	after 125 years	after 25 years	after 75 years	after 125 years
Great Scarcies (Also Kolente)	1217	0.04	0.13	0.21	0.04	0.13	0.21
Rufiji	1316	0.04	0.11	0.17	0.04	0.12	0.17
Brahmani	2301	0.04	0.11	0.17	0.04	0.11	0.17
Tapi	2322	0.04	0.13	0.21	0.04	0.13	0.21
Thu Bon	2428	0.04	0.12	0.16	0.06	0.16	0.2
Gurupi	3221	0.04	0.12	0.18	0.05	0.15	0.21
Itapecuru	3222	0.04	0.12	0.2	0.04	0.13	0.2
Armeria	4402	0.04	0.13	0.19	0.04	0.13	0.2
Santiago	4425	0.04	0.12	0.18	0.04	0.12	0.18
Cestos (Also Nuon)	1205	0.03	0.09	0.13	0.04	0.12	0.16
Pungwe (Also Pungoe)	1315	0.03	0.08	0.12	0.03	0.08	0.12
Ruvuma (Also Rovuma)	1318	0.03	0.09	0.15	0.03	0.09	0.15
Cauvery	2303	0.03	0.09	0.14	0.03	0.09	0.14
Digul (Also Uwimbu)	5408	0.03	0.1	0.12	0.08	0.19	0.21
Mitchell	5425	0.03	0.09	0.15	0.03	0.1	0.15
Geba (Also Kayanga)	1216	0.02	0.05	0.09	0.02	0.05	0.09
Ntem	1230	0.02	0.06	0.07	0.06	0.14	0.15
Nyanga	1231	0.02	0.07	0.1	0.07	0.16	0.19
Buzi (Also Budzi)	1302	0.02	0.07	0.11	0.02	0.07	0.11
Chew Bahir (Also Lake Stefanie)	1904	0.02	0.06	0.09	0.02	0.06	0.09
Krishna	2312	0.02	0.05	0.08	0.02	0.05	0.08
Dong Nai	2407	0.02	0.05	0.06	0.03	0.07	0.09
De Contas	3216	0.02	0.05	0.09	0.02	0.06	0.09
Paraguacu	3235	0.02	0.05	0.09	0.02	0.05	0.09
Mira	3417	0.02	0.05	0.07	0.03	0.08	0.09
Santa	3425	0.02	0.07	0.11	0.02	0.07	0.11
Sarstoon	4242	0.02	0.06	0.08	0.02	0.06	0.09
Choluteca	4403	0.02	0.05	0.09	0.02	0.06	0.09
Hari	5414	0.02	0.06	0.08	0.05	0.11	0.13
Kapuas	5415	0.02	0.06	0.07	0.08	0.19	0.21
Rajang	5429	0.02	0.06	0.08	0.11	0.26	0.28
Comoe (Also Komoe)	1208	0.01	0.04	0.07	0.02	0.05	0.07
Mbini (Also Woleu)	1223	0.01	0.03	0.04	0.04	0.09	0.1
Mono	1226	0.01	0.02	0.03	0.01	0.02	0.03
Utamboni (Also Mitemboni)	1245	0.01	0.02	0.02	0.02	0.06	0.06
Galana	1303	0.01	0.03	0.05	0.02	0.04	0.06

Basin	MRBID	Threshold 70%			Threshold 80 %		
		after 25 years	after 75 years	after 125 years	after 25 years	after 75 years	after 125 years
Lurio	1310	0.01	0.04	0.06	0.01	0.04	0.06
Pangani	1314	0.01	0.03	0.04	0.01	0.04	0.05
Save	1319	0.01	0.03	0.04	0.01	0.03	0.04
Tana	1320	0.01	0.03	0.04	0.02	0.05	0.06
Coppename Rivier	3213	0.01	0.04	0.05	0.03	0.08	0.1
Courantyne	3214	0.01	0.04	0.05	0.11	0.24	0.25
Essequibo	3219	0.01	0.03	0.04	0.03	0.08	0.09
Maroni	3228	0.01	0.03	0.03	0.07	0.14	0.14
Suriname Rivier	3246	0.01	0.03	0.03	0.02	0.05	0.06
Esmeraldas	3410	0.01	0.04	0.05	0.03	0.07	0.08
San Juan	3424	0.01	0.04	0.05	0.03	0.07	0.09
Tumbes (Also Tumbes)	3427	0.01	0.04	0.06	0.01	0.04	0.06
Goascoran	4412	0.01	0.03	0.05	0.01	0.03	0.06
Negro	4417	0.01	0.04	0.07	0.01	0.04	0.07
Paz	4419	0.01	0.02	0.04	0.01	0.02	0.04
Mahakam	5422	0.01	0.02	0.02	0.09	0.2	0.21
Bulungan	5404	NA	NA	NA	0.04	0.1	0.1
Perak	5310	NA	NA	NA	0.03	0.06	0.06
Pahang	5427	NA	NA	NA	0.03	0.07	0.07
Sembakung	5431	NA	NA	NA	0.03	0.06	0.07
Changuinola	4206	NA	NA	NA	0.02	0.05	0.06
Sixaola	4244	NA	NA	NA	0.02	0.05	0.05
Tano (Also Tanoe)	1244	NA	NA	NA	0.01	0.02	0.02
Oiapoque (Also Oya-pok)	3233	NA	NA	NA	0.01	0.02	0.03
Jurado	3413	NA	NA	NA	0.01	0.02	0.02
Suchiate	4429	NA	NA	NA	0.01	0.02	0.02
Kelantan	5416	NA	NA	NA	0.01	0.03	0.03
Kinabatangan	5417	NA	NA	NA	0.01	0.03	0.03
Kuantan	5419	NA	NA	NA	0.01	0.02	0.03
Lorentz	5421	NA	NA	NA	0.01	0.02	0.03

A2.5 Comparison of the effects of two pre-processing procedures for DTRIE inputs: “raw” value RS inputs versus scenario-averaged inputs

This section, demonstrate the effect on the use of a “raw” value baseline versus scenario-averaged baseline on hydrological outputs, in the case of AET. The conclusions also apply to all other DTRIE outputs.

Background:

For the baseline run, where hydrological variables are estimated for the reference year 2018, DTRIE uses actual remote sensing data products.

In the scenario runs, which model the hydrological effects of tree cover growth from 25 to 150 years, all inputs other than mean annual temperature and annual total rainfall are adjusted to reflect the effect of tree cover growth. The specific reasoning behind each adjustment has been described in Chapter 3, section 3.2, the respective methods applied to make these adjustments are described in chapter 3 and appendix A1.5.

Chapter 5 has also shown that the use of “raw” value baseline for AET and other variables results in artefacts regarding the difference between baseline and the scenario, i.e. a change where none is expected. For example, in some pixels, AET will first decrease between the baseline and year 25, and subsequently steadily increase. The below figures show the difference between variables produced with these two procedures for the example of annual and monthly baseline AET in South America.

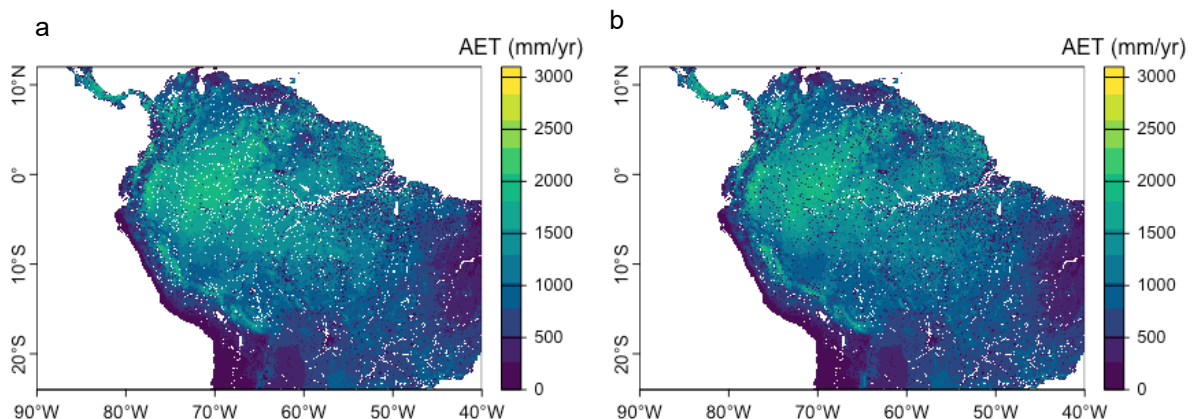


Figure A. 13 Effect of the use of “raw” RS inputs versus scenario-averaged inputs in DTRIE for the example of baseline annual total AET (mm/yr) in South America. a) “raw” value baseline AET, b) scenario averaged version of baseline AET.

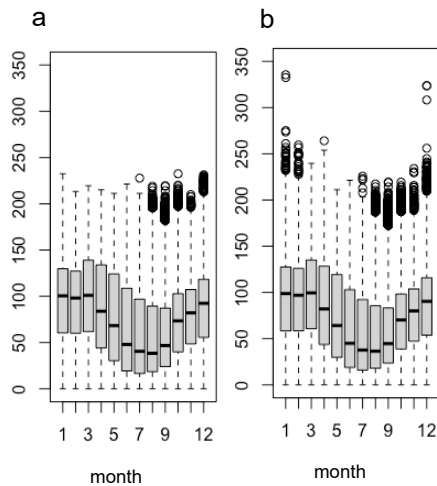


Figure A. 14 a) histogram of the monthly AET estimates when “raw” value inputs were used; b) histogram of the monthly AET estimates when scenario-averaged inputs were used

On an annual scale, both AET estimates agree well (see Figure A. 13). The monthly estimates underscore this agreement and show that the seasonal pattern does not differ either (see Figure A. 14).

Therefore, the overall difference between the two AET estimates is small, and mostly positive, meaning the “raw” value baseline is greater, as illustrated in Figure A. 15a for the annual scale. For 90 per cent of the values, the difference lies between -0.02 and 159.25 mm/yr (see also Figure A. 15b). The spatial pattern of the “raw” value baseline AET seems to indicate that where baseline tree cover is high, the “raw” value based AET value is higher.

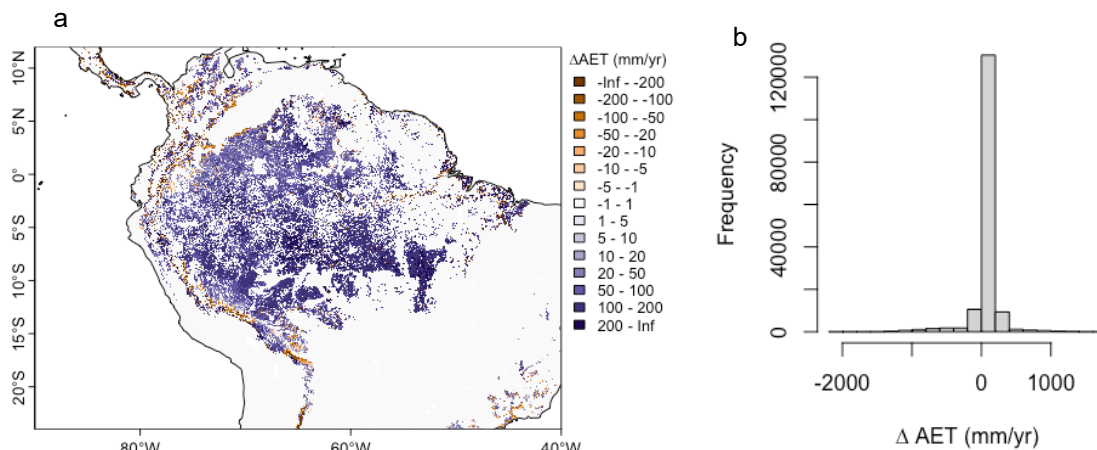


Figure A. 15 a) Absolute difference between the two estimates for baseline annual AET presented in Figure A. 17, Δ AET (mm/yr); b) histogram of the same; all pixels where Δ AET is between -1 and 1 mm/yr have been removed. Difference in AET is calculated as “raw” value baseline – “scenario averaged” baseline.

Appendix 3 DTRIE scenario application

A3.1 Additional information on the dam watersheds presented in Chapter 5

Table A- 6 Additional information for the dam watersheds presented in chapter 5 including the main use of the dam, and matching the GOODD database ID with the GRanD database ID. There is no GRanD dam near GOODD ID dam 1017960; therefore dam name, river and main use are extracted from FAO Aquastat data.

Dam name	Country	River	Main use	GRanD ID	GOODD ID
Tiznados	Venezuela	Tiznados	Irrigation	2282	1012364
Chivor	Colombia	Bata Chivor	Hydroelectricity	2300	1012023
Paraibuna	Brazil	Paraibuna	Hydroelectricity	2416	1003540
Mape	Cameroon	Mape	Hydroelectricity	3670	1002328
Bamendjin	Cameroon	Noun	Hydroelectricity	3672	1017710
Amaravathy	India	Amaravathy	Irrigation	5033	1023176
Bhumibol	Thailand	Ping	Irrigation	5146	1025865
Tabasalar	Thailand	Sakae Krang	Irrigation	5154	1025900
Srinagarind	Thailand	Quae Yai	Irrigation	5161	1025877
Djoue	Republic of the Congo	Djoue	Hydroelectricity, water supply	NA	1017960

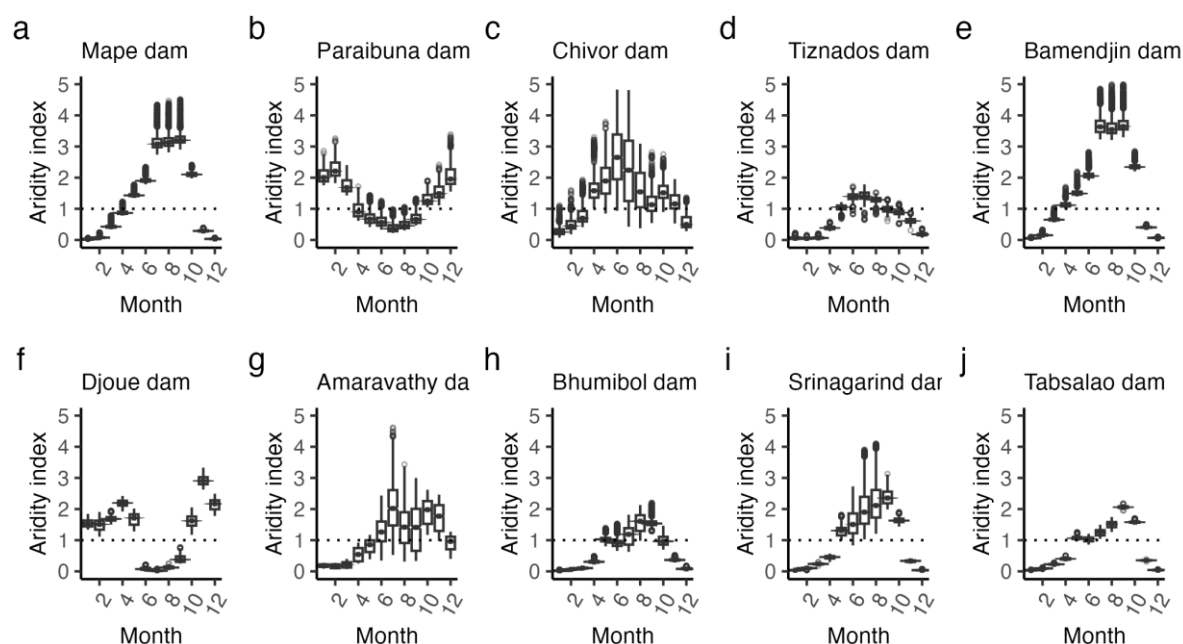


Figure A. 16 Monthly pattern of the aridity index for the selected dam watersheds. Aridity index data is derived from Zomer & Trabucco 2022 and calculated as P/PET where P is the total monthly precipitation and PET the potential evapotranspiration.

A.3.2 Implications of the upper limit for lag times

This sensitivity analysis assesses the implications of capping the lag times for subsurface flow (SSF) contributions to streamflows to below twelve months as first described in section 5.2.2.2 (p. 107 and following).

To recapitulate, this cap means that only those pixels of a watershed with a lag time of less than twelve months contribute their subsurface flow volume to the monthly stream discharge at the watershed outlet. This limits the streamflow contributions to the months of the target year (e.g. yr100, after 100 years of tree growth) and the preceding 11 months, to address research question “How does tree cover growth affect streamflow seasonality and streamflow quantity in the following dry season” (consider the target year 100 the year that contains the “following dry season”). This analysis is conducted in section 5.3.2 (p. 118 and following).

Introducing a maximum lag time allows for the examination of an equilibrium state of the model at each month of the target year and the contributions from the preceding 11 months. Without such an upper limit, contributions could come many more months and even years prior to the target year. As shown in Figure A. 17, the maximum lag time can amount to several years (the maximum lag time is found in Bhumibol dam watershed with ~600 months, i.e. ~50 years). This is an issue for the application of DTRIE because in such a case the target year conditions do not necessarily capture the tree cover conditions or subsurface flow volumes anymore. Instead, tree cover and SSF would have to be calculated for each of the years the additional lag time would include. However, this is beyond the intended scope of the analysis, which focuses only on the following dry season.

The following describes the implications of capping lag times for SSF contributions to streamflow at the POI (point of interest), using the baseline year as example. Generally, it would be expected that 1) in the current approach, the SSF contribution to monthly streamflows are lower because SSF from pixels with longer lag times are not considered; 2) watersheds containing more pixels with longer (“unconstrained”) lag times would be more strongly affected by this; and 3) additional SSF contributions may also be realised during dry season months, when streamflows are low, and thus affect the response to the research question for this section.

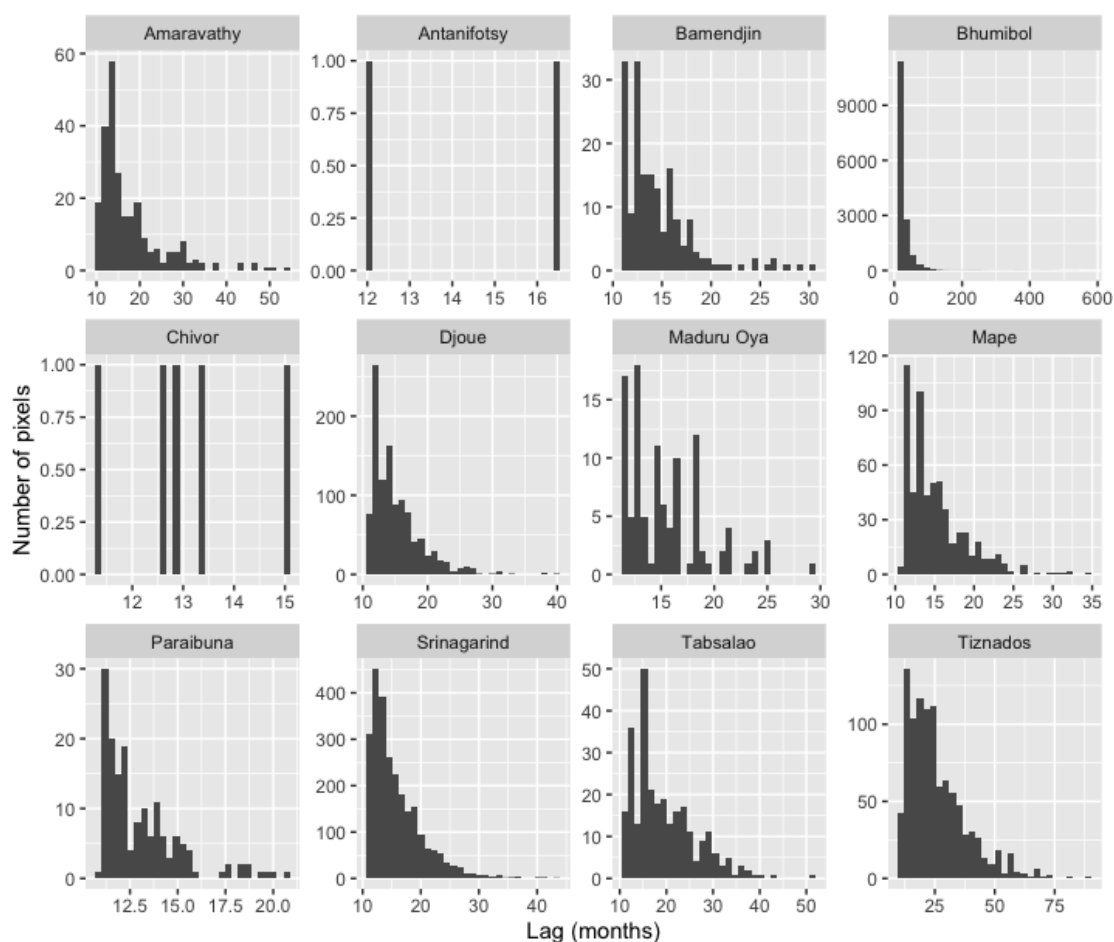


Figure A. 17 Histograms of the lag times greater than 11 months across the 12 tested watersheds. The plots exclude lag times of ≤ 11 months.

Table A- 7 Comparison of the number of pixels with lag times ≤ 11 months, versus those >11 months across the different watersheds.

Dam name	GOODD ID of dam	Number of pixels with lag > 11 months	Number of pixels with lag ≤ 11 months	Percentage of grid cells in watershed
Antanifotsy	1002237	2	7446	0.03
Chivor	1012023	5	12620	0.04
Paraibuna	1003540	148	28732	0.51
Bamendjin	1017710	179	11371	1.55
Maduru Oya	1036431	106	6692	1.56
Mape	1002328	580	16380	3.42
Amaravathy	1023176	237	6483	3.53
Tabsalao	1025900	278	6130	4.34
Djoue	1017960	1095	23530	4.45
Srinagarind	1025877	2441	38455	5.97
Tiznados	1012364	1010	8692	10.41
Bhumibol	1025865	15607	62142	20.07

The results of the analysis show that in nine of the twelve assessed watersheds less than five per cent of watershed pixels have lag times of 12 months or more (see Table A- 7). In terms of representation, the lag time upper limit of 11 months (inclusive, i.e. ≤ 11) is a therefore good choice, capturing most pixels for most watersheds. Three watersheds with higher shares in pixels with longer lag times are Bhumibol, Srinagarind and Tiznados. The first two being the largest of the 12 watersheds with 26,160 and 10,998 km², and the latter comparatively small with 1,441 km². Srinagarind and Tiznados were chosen as a representative of the group of three watersheds; the group of nine watersheds is represented by Amaravathy and Bamendjin dam watersheds.

Figure A. 18 (top) illustrates how much more SSF is contributed to the monthly streamflow compared to the original SSF with the lag time cap. In all three watersheds, the unconstrained lag times lead to higher SSF contributions (indicated by a ratio larger than 1). In Bamendjin, this difference is the lowest: the unconstrained SSF contributions are only up to 1.17 times that of the original SSF contributions. The Amaravathy dam watershed experiences a middling increase in SSF contributions ranging between 1.26 to 1.56 times that of the original value, similar to the Srinagarind watershed where this range is 1.16 to 1.52. In the Tiznados watershed, where around 10 percent of the watershed's pixel have lags greater than 11 months, the increases would be largest: 2.6 to 15.52 times the volume of the original SSF would be contributed to streamflow at the POI.

Figure A. 18 (bottom) puts this into perspective by using the total streamflow variable (which includes surface flow contributions). This can shed a light on whether the changes in SSF would affect total streamflow strongly, or whether SF is so dominant that SSF changes are not noticeable. Here it can be seen that in the Bamendjin watershed, the inclusion of pixels with longer lag times does not change seasonality, and the monthly magnitude is barely affected. All other patterns are closer to the patterns in the top plot, which means that the effect on total streamflow caused by longer lags is not overshadowed by the surface flow contributions to total flow, as is the case in Bamendjin. There is therefore the potential that unconstrained lag times lead to changes in streamflow its seasonality. This question is address by Figure A. 19, which revisits the monthly total streamflow pattern at the respective dams. It demonstrates that the additional SSF contributions in Bamendjin would not change

the streamflow seasonality much, because increased SSF contributions would add the baseline streamflow (called year 0 in the plot) at times when flows are already high. Here, only the overall magnitude would be affected. In Srinagarind, the unconstrained lags would also lead to an overall increase in magnitude, and a larger increase during the later months with low flows (June-July), thus possibly cutting short the low flow period. In Amaravathy, a similar effect is found. In the Tiznados watershed the largest additions would come predominantly during the low flow/dry season.

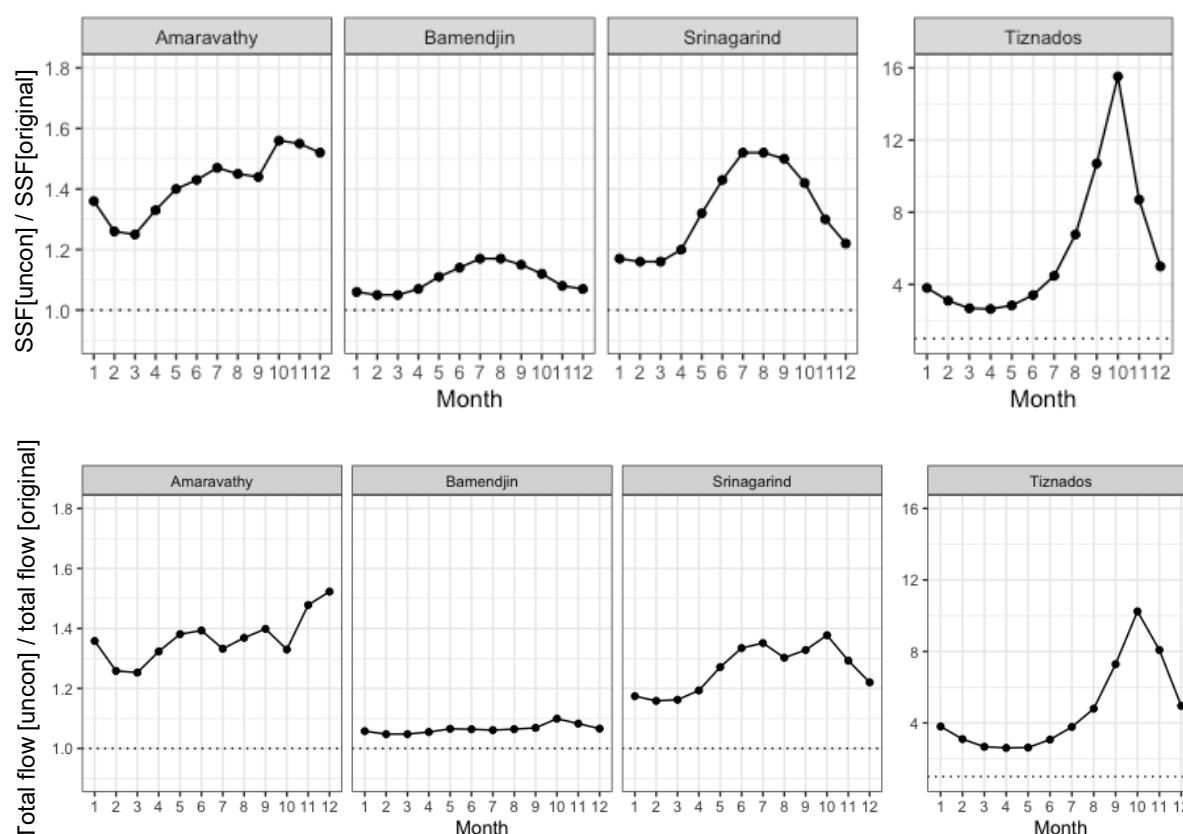


Figure A. 18 Effects of upper limit for lag times on SSF and total streamflow. Top: Comparison of the monthly SSF contributions from the watershed when lag times are unconstrained (i.e. greater than 11 months), to the contributions with the original constraint (i.e. less or equal to 11 months. Bottom: same plot with total (surface + subsurface) streamflow. The y-axis presents the ratio of the unconstrained version to the original version. The dotted line represents the case unconstrained = original SSF contribution.

In conclusion several expectations can be confirmed: the upper limit for lag times does indeed lead to lower SSF contributions to monthly streamflow; secondly, watersheds with more pixels with lags greater than 11 were more affected in their monthly streamflow pattern, low flows and overall magnitude.

However, as mentioned before, the scope of this analysis was to examine streamflows only for a target year and the following dry season. This scope enables a more practical and policy-relevant application and simpler interpretation:

It can answer the current research question “How does tree cover growth affect streamflow seasonality and streamflow quantity in the *following* dry season?”. The unconstrained approach, however would have to examine *x number of dry seasons* later, with *x* depending on basin characteristics.

This is because not constraining lags has the following consequence: tree cover is grown for *k* years

(as in the current approach), but depending on the basin size and topography, tree cover would also be needed for *x* number of years preceding *k* ($k > x$, with $x = \text{maximum lag time} / 12$) For example if $k = 100$, and maximum lag time (months) is 60, then tree cover and subsurface flow needs to be calculated for years 95 to 99 as well. A pixel with lag 48 would then contribute its year 96 SSF to the year 100 streamflow, a pixel with lag 36 would contribute its year 97 SSF. As many watersheds have maximum lags greater than this, the processing effort of the streamflow calculation would be much greater. On the other hand, the current implementation presents a good trade-off because by only using the preceding 11 months, tree cover can be assumed to be more stable, thus avoiding the need to calculate tree cover and SSF for multiple years.

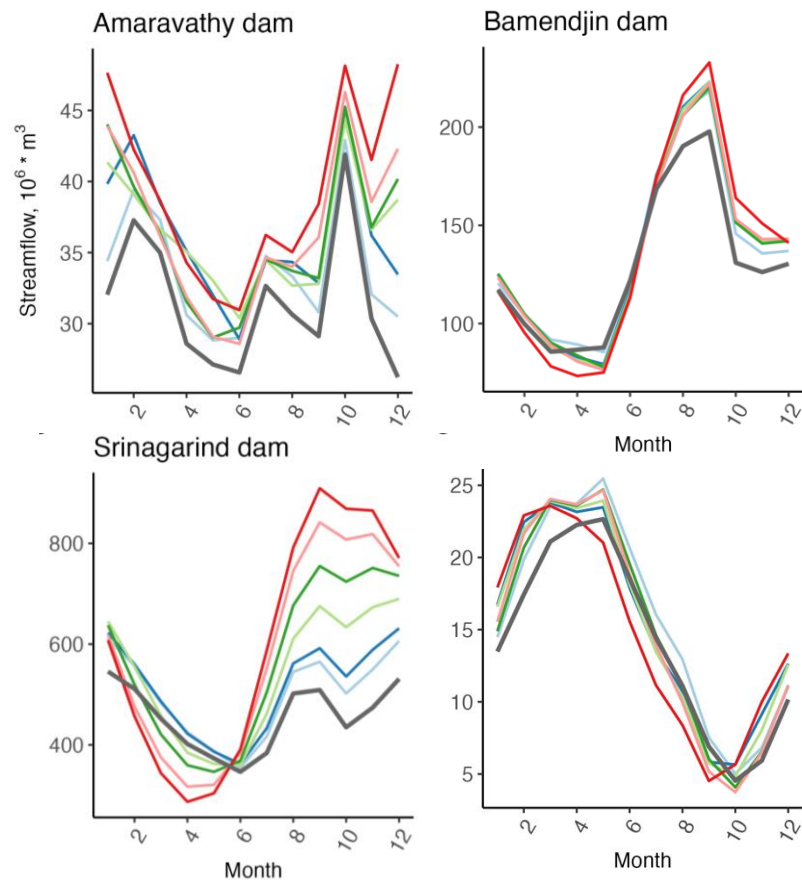


Figure A. 19 Total streamflow at the POI in million m^3 . Baseline streamflow is represented by the bold grey line (=year 0). Total streamflow is the sum of surface and subsurface flow at the point of interest (the dam). Note this plot is already presented as Figure 5.14 in the main text.

Investigating longer lag times and their effects on streamflow over multiple years presents an opportunity for a future application of DTRIE as a more transient model, updating tree cover inputs and SSF for each additional year included through extended lag times.

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