Multi-model investigations of the biogeophysical effects of historical and future land-cover changes on climate

A thesis submitted to attain the degree of

DOCTOR OF SCIENCES of ETH ZURICH
(Dr. sc. ETH Zurich)

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2016
Abstract

Vegetation plays an important role in the climate system by determining the biogeophysical properties of the land surface, such as its albedo, emissivity, evapotranspiration rate and roughness length. Since these properties depend on the plant type, their modifications through human-induced land-cover changes (LCC) affect the surface energy budget and the water cycle, and can therefore lead to changes in climate conditions. However, some questions are still unresolved regarding the overall biogeophysical effect of LCC on climate, due to the many mechanisms at play and their geographically-varying nature. This explains for example the high uncertainties regarding the climatic effect of the expansion of agricultural areas which occurred at the expense of forests over the northern mid-latitudes during the industrial period, or of the deforestation that is projected to occur in the future over tropical areas, especially in the Amazon Basin.

The aim of this thesis is thus to reduce these uncertainties. To achieve this goal, I primarily base my analyses on simulations run by recent climate models, which include state-of-the-art land surface models representing the energy and water fluxes at the land-atmosphere interface. Emphasis is put on comparing the results from multiple models, so as to assess the robustness of their overall conclusions. Moreover, I also confront these model findings with observational evidence of the effect of deforestation on climate in order to identify their most realistic aspects.

In Chapters 2 and 3 of this thesis, I look at how the LCC that have occurred during the industrial period over the northern mid-latitudes (mainly North America, northern Eurasia and South Asia) have locally modified surface air temperature. To do so, I adapt a recently introduced statistical method which aims to extract the climate impact from the LCC forcing in simulations where other climate forcings are also imposed. In Chapter 2, I first demonstrate the suitability of this reconstruction method to study the local impacts of LCC on albedo, the latent heat flux and surface air temper-
ature, and show that it gives very similar results to the factorial experiment approach that is traditionally employed, even if it tends to underestimate them.

This method is then applied to numerical climate simulations from about 1850 until today from 17 recent global climate models part of the LUCID and CMIP5 model intercomparison projects. This analysis shows that a great majority of models agree that historical LCC have led to an increase in albedo, especially under the presence of snow over mid-latitudes, which drove a decrease in temperature in winter in these regions. In contrast, there is less model agreement on the sign of the changes in latent heat flux, and therefore in summer temperature since the evapotranspirative cooling plays a more important role in this season. Overall, the majority of the investigated models indicate that historical LCC led to a summer warming over mid-latitude regions, which contrasts with the results from most previous studies.

A comparison of these model findings with observational evidence of the local effect of deforestation on surface air temperature over North America is also conducted. It reveals that none of the analysed models are able to reproduce the pronounced impact of deforestation on the diurnal cycle of temperature shown by observations. However, overall the more recent CMIP5 models perform better at capturing its warming effect during daytime in the warm season, which suggests a positive effect of recent model developments.

In Chapter 3, I develop on these results and concentrate on the five CMIP5 models that are able to represent the daytime warming effect of deforestation during summer over North America in order to investigate the impact of LCC on extremely warm temperatures. Contrary to most previous modelling studies, this observation-constrained analysis indicates that deforestation has led to substantial local increases in the intensity of daytime hot extremes over many regions in the world, and especially in the northern mid-latitudes. Over the areas of North America and Eurasia where the tree cover has diminished by at least 15% since pre-industrial times, I estimate that the biogeophysical effects of deforestation are responsible for a third of the total warming of the hottest day of the year by present-day, but accounted for most of it before 1980. This underlines the importance of considering LCC for regional-scale detection/attribution purposes, and suggests that future re-/afforestation policies could help locally mitigate hot extremes.

In the following chapter, I examine how possible scenarios of deforestation in the Amazon basin may influence future climate conditions in this region through biogeophysical mechanisms. For this purpose, one control and three perturbed experiments reflecting different levels of deforestation are run with the Regional Climate Model COSMO-CLM coupled to the land surface model CLM. These simulations show that surface air temperature increases over deforested areas because of reduced evapotranspiration, and that this increase is almost proportional to the imposed deforestation rate. Besides, I find that deforestation leads to a reduction in precipitation on average over the
Amazonian region, even if the opposite behaviour is simulated over its eastern part because of an enhanced moisture input from the Atlantic Ocean.

In a second time, these results are compared with those from 28 previous studies that investigated the biogeophysical impacts of Amazon deforestation on the regional climate. This meta-analysis shows that a great majority of the considered experiments agree that surface air temperature will increase and precipitation will decrease in response to deforestation in this region. More recent studies are found to show a similar sensitivity to full deforestation scenarios than older ones (+1.3°C and -0.8 mm/d), but exhibit a lower spread. Overall, based on the current literature I find it rather unlikely that drastic reductions in the rainfall amounts related to the presence of tipping points will occur during the 21st century in response to the biogeophysical effects of deforestation alone, i.e. if the additional effect of global warming is not considered.

In summary, the findings of this thesis confirm the importance of LCC for regional climates. The employed multi-model approach and the confrontation of model results with observational evidence of the effect of deforestation highlight some robust impacts of LCC on climate, but also point out some model deficiencies and remaining uncertainties related to this research topic. More investigation is required to further diminish these uncertainties, for example regarding the more general impact of future LCC in a global warming context. However, I believe that the methodologies employed in this thesis and the obtained results can provide solid direction to address these questions.
Résumé

La végétation joue un rôle important dans le système climatique en déterminant les propriétés biogéophysiques de la surface des continents, telles que son albédo, son émissivité, son taux d’évapotranspiration et sa rugosité. Comme ces propriétés varient selon le type de plante, leurs altérations par des modifications du couvert végétal (MCV) d’origine humaine affectent le bilan énergétique à la surface et le cycle de l’eau, et peuvent donc modifier le climat. Cependant, certaines questions restent non résolues quant à l’effet biogéophysique total des MCV sur le climat, en raison des nombreux mécanismes impliqués et de leur caractère changeant selon les régions. Ceci explique par exemple les larges incertitudes entourant l’impact climatique de l’expansion des surfaces agricoles au détriment des forêts qui a eu lieu sous les latitudes moyennes septentrionales pendant la période industrielle, ou de la déforestation tropicale qui est annoncée pour les prochaines décennies, particulièrement dans le bassin amazonien.

Le but de cette thèse est donc de réduire ces incertitudes. Pour y arriver, je me base essentiellement sur l’analyse de simulations réalisées avec des modèles climatiques récents, qui incluent des modèles de surface terrestre de pointe capables de représenter les flux d’eau et d’énergie à l’interface entre la surface continentale et l’atmosphère. L’accent est mis sur la comparaison des résultats de plusieurs modèles, afin d’évaluer leur robustesse. De plus, ceux-ci sont confrontés à des données d’observation de l’effet de la déforestation sur le climat, pour en identifier les aspects les plus réalistes.

Dans les Chapitres 2 et 3 de cette thèse, j’examine comment les MCV qui ont eu lieu pendant la période industrielle sous les latitudes moyennes septentrionales (principalement en Amérique du Nord, Eurasie du Nord et Asie du Sud) ont localement modifié la température de l’air en surface. Pour cela, j’adapte une méthode développée récemment qui vise à extraire l’impact climatique du forçage dû aux MCV dans des simulations également soumises à d’autres forçages. Dans le Chapitre 2, je démontre premièrement que cette...
méthode de reconstruction est appropriée pour étudier les impacts locaux des MCV sur l’albédo, le flux latent et la température de l’air en surface, et montre qu’elle donne des résultats très similaires à ceux de l’analyse par plan factoriel qui est traditionnellement employée, même si elle a tendance à les sous-estimer.

Cette méthode est ensuite appliquée à des simulations numériques représentant le climat d’environ 1850 à nos jours, réalisées par 17 modèles climatiques globaux ayant pris part aux projets d’intercomparaison de modèles LUCID et CMIP5. Il en ressort que selon une grande majorité d’entre eux, les MCV historiques ont mené à une augmentation de l’albédo, en particulier sous les latitudes moyennes en présence de neige, ce qui a conduit à une diminution de température en hiver dans ces régions. Par contre, il y a moins d’unanimité sur le signe de la réponse du flux latent, et donc des températures en été puisque l’effet refroidissant de l’évapotranspiration joue un rôle plus important en cette saison. Au final, la majorité des modèles analysés indique que les MCV historiques ont entraîné un réchauffement en été sous ces latitudes, ce qui contraste avec les résultats de la plupart des études précédentes.

Ces résultats obtenus avec des modèles sont également confrontés avec des observations de l’effet local de la déforestation sur la température de l’air en surface collectées en Amérique du Nord. Ceci révèle qu’aucun des modèles analysés n’est capable de reproduire l’impact prononcé de la déforestation sur le cycle journalier des températures qui est indiqué par les observations. Cependant, globalement les modèles plus récents de CMIP5 sont plus performants pour capturer son effet réchauffant durant la journée pendant la saison chaude, ce qui suggère un effet positif des développements récents des modèles climatiques.


Dans le chapitre suivant, j’examine comment des scénarios possibles de dé-
forestation dans le bassin amazonien pourrait influencer les futures conditions climatiques de cette région par des mécanismes biogéophysiques. Dans ce but, une simulation de contrôle et trois autres forcées par différents niveaux de déforestation sont réalisées avec le modèle climatique régional COSMO-CLM couplé au modèle de surface terrestre CLM. Ces expériences révèlent que la température de l’air en surface augmente au-dessus des zones déforastées en réponse à une évapotranspiration réduite, et ceci de manière presque proportionnelle au taux de déforestation imposé. En outre, je trouve que la déforestation entraîne une réduction des précipitations en moyenne sur la région amazonienne, même si le comportement contraire est simulé sur sa partie orientale en raison d’un renforcement de l’apport d’humidité depuis l’Océan Atlantique.

Dans un second temps, ces résultats sont comparés avec ceux de 28 études précédentes qui se sont penchées sur les impacts biogéophysiques de la déforestation amazonienne sur le climat régional. Cette méta-analyse montre qu’une grande majorité des expériences considérées convient que la température de l’air en surface va augmenter et que les précipitations vont diminuer en réponse à la déforestation dans cette région. Les études plus récentes indiquent une sensibilité à la déforestation totale similaire aux plus anciennes (+1.3°C et -0.8 mm/jour), mais présentent une dispersion moindre. Globalement, d’après la littérature existente je conclue qu’il est plutôt improbable que des réductions drastiques des pluies liées à l’existence de points de bascule surviennent pendant le XXIème siècle en réponse aux seuls effets biogéophysiques de la déforestation, c’est-à-dire si l’effet supplémentaire du réchauffement climatique n’est pas pris en compte.

En résumé, les conclusions de cette thèse confirment l’importance des MCV pour le climat régional. L’approche multi-modèle employée et la confrontation de ses résultats avec des données d’observation de l’effet climatique local de la déforestation surlignent certains aspects robustes des impacts des MCV sur le climat, mais attirent également l’attention sur certaines lacunes des modèles ainsi que sur des incertitudes toujours existantes dans ce domaine de recherche. Des travaux plus approfondis seraient nécessaires pour les réduire encore plus, par exemple pour mieux comprendre l’impact plus général des futures MCV dans un contexte de réchauffement climatique global. Cependant, je pense que les méthodologies employées dans cette thèse et les résultats obtenus peuvent fournir des orientations claires pour répondre à ces questions.
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Introduction

For more than 20 years, international summits have recommended efforts to better preserve forests across the world in order to address a number of environmental problems, including climate change. The Earth Summit held in Rio de Janeiro in 1992 can be considered as a starting point in this process, as it resulted in the release of the "Forest Principles", a series of recommendations to conserve forests and develop sustainable forestry, but also in the entry into force of the United Nations Framework Convention on Climate Change (UNFCCC). This legally-binding international treaty was created in order to pursue the broad objective of "stabilization of greenhouse gas concentrations in the atmosphere at a level that would prevent dangerous anthropogenic interference with the climate system", following accumulating scientific evidence for undergoing climate change driven by anthropogenic greenhouse gas (GHG) emissions (IPCC, 1990). The UNFCCC now involves 197 countries or governing entities in the world, which meet every year during the so-called Conference of the Parties (COP) in order to evaluate advances made in dealing with climate change. That is during the eleventh session of the COPs, in 2005, that the implementation of the global mechanism called "Reducing emissions from deforestation and forest degradation" (REDD) first came under negotiation. Its enforcement in the subsequent years constituted a first political recognition of the role of forests in the climate system, and of their importance for climate mitigation.

This recognition focuses on the role of forests acting as carbon sinks,
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whose perturbations by deforestation influence climate by emitting GHG (biogeochemical effects). However, there is now scientific evidence supporting the fact that deforestation as well as other types of land-cover changes (LCC) can also affect the climate system by modifying the radiative, hydrological and aerodynamic properties of the land surface, thereby altering its exchanges of water and energy with the atmosphere (see e.g. Mahmood et al., 2014; Bonan, 2008a). These so-called "biogeophysical effects" are however usually not considered in land use planning policies nor in the context of climate mitigation strategies. This is related to the fact that they actually are more of an umbrella term which involve many different mechanisms, whose impacts vary depending on the type of LCC, the location and the time of the year. These partly tend to offset each other, all the more once averaged globally and annually. Because of this plural nature, it is difficult to summarise the perturbations imposed on the climate system through the biogeophysical effects of LCC with a single metrics, as can be done with GHG emissions for their biogeochemical aspects. Besides, it leads to higher uncertainties on their overall climate impact; there is for example only low consensus in the literature whether the biogeophysical effects of past LCC actually cooled or warmed the regions over which they occurred, and through which mechanisms (de Noblet-Ducoudré et al., 2012; Kumar et al., 2013a). However, many studies suggest that their consequences for the local climate may have been as strong as those of the concomitant biogeochemical effects (e.g. Avila et al., 2012; Brovkin et al., 2004; Chase et al., 2001; Pitman and Zhao, 2000). These findings, together with the large LCC that are being forecasted for the course of the current century, highlight the need for a better understanding of these processes. The aim of this thesis is to advance scientific knowledge on this topic by confronting different pieces of evidence, in order to extract some robust answers, and also point at some remaining uncertainties.

This introduction starts with a description of the role played by vegetation in the climate system through its influence on the land water and energy balances (Section 1.1). Then, I review some results from observational studies which investigated the local effects of LCC on surface energy fluxes and climatic variables (Section 1.2). Then, I give an overview of past, ongoing and possible future LCC that occurred, are currently occurring, and are likely to occur in the future (Section 1.3). Here I also conduct a short review of the scientific evidence of their impacts on climate, as well as of remaining open questions on the topic. Eventually, in Section 1.4, I draw a detailed list of the objectives of this thesis and announce its outline.
1.1 The role of vegetation in the climate system

The most scrutinized of the climate variables include for example the temperature, humidity, the amount of precipitation under various forms or even the sunshine hours that are observed over continental areas, and constitute specific measures of the amount of energy and water at the interface between the land surface and the atmosphere, and of fluxes thereof. Since plants are precisely located at this interface, they participate to these land-atmosphere fluxes by exchanging water and energy with their environment. Thereby, they play a crucial role in two essential components of the climate system, namely the surface energy budget and the water cycle. This role is determined by various specific biogeophysical properties of plants, which differ from those of bare soil. Many modelling experiments demonstrated their importance in setting surface climate conditions. For example, Kleidon et al. (2000) compared two idealised model simulations, one called "green planet" in which all ice-free land surfaces are artificially covered with highly productive vegetation, and another one called "desert world" in which all the vegetation has been replaced by bare soil. They found that the presence of vegetation led to large changes in surface energy fluxes, resulting in lower surface air temperatures by more than 1 °C on average over land in the "green planet" simulation compared to the "desert world" one, and also to a considerably more active hydrological cycle with notably a doubling of precipitation over land. In this section, I review the various biogeophysical mechanisms which were involved in these results and through which vegetation can take part in the establishment of local climate conditions. In contrast, I will not address in detail the climatic role of plants through their biogeochemical properties, which refer to their more well-known impacts on the carbon and nitrogen cycle as well as on aerosol emissions. These are indeed out of the scope of this thesis, and will only be sporadically mentioned for comparison purposes with the biogeophysical properties.

1.1.1 The radiative properties of vegetation determine the energy amounts absorbed and emitted by the land surface

Plant albedo controls how much solar radiation is absorbed by the land surface

Fig. 1.1 displays the energy fluxes that are exchanged between the atmosphere and the land surface, and gives estimates of their annually and globally-averaged magnitudes in the present-day climate. The big yellow arrow on the upper-left part of this figure materialises the radiative energy flux that comes from the Sun into the Earth’s atmosphere under the form of shortwave radiation. It amounts to ∼325 W/m² on a global average over the land surface, and constitutes the energy input for the climate engine. An
Figure 1.1: Best estimates for the magnitude of the annual mean energy balance components averaged over land, together with their uncertainty ranges, representing climatic conditions at the beginning of the twenty-first century. The surface thermal upward flux contains both the surface thermal emission and a small contribution from the reflected part of the downward thermal radiation. Units are W/m$^2$. From Wild et al. (2015).

important part of this flux is reflected by clouds or other non-transparent aerosols along its journey through the atmosphere, or absorbed by the different molecules that constitute it (also cloud droplets and aerosols, as well as ozone and water vapor). On average, only $\sim$57% of this initial flux reaches the Earth’s surface. This fraction is referred to as incoming shortwave radiation ($SW_{in}$). Over land, an average amount of $\sim$26% of this remaining energy is directly reflected and called outgoing shortwave radiation ($SW_{out}$), while the rest is absorbed by the surface. In fact, the ratio $SW_{out}/SW_{in}$, called albedo and noted $\alpha$, depends on the radiative properties of the local land cover type, which thereby determine the amount of energy absorbed by the land surface.

While deserts and bare soils generally have albedo values of about 0.35, vegetation appears darker from space and therefore has lower albedo values, ranging between 0.05 and 0.25 (see for example Chapter 13 of Bonan, 2008b). Therefore, the presence of plants leads on average to the absorption of more solar radiation. One consequence is that it tends to warm the land surface locally. Besides, since the land surface is almost at equilibrium, the absorp-
tion of more radiative energy means that more energy is emitted back to the atmosphere under the form of turbulent heat fluxes (as described more in detail in Section 1.1.2), which thus enhances convective activity and therefore leads to more cloud development and precipitation formation.

**Plant emissivity determines how much infrared radiation is re-emitted from the land surface**

As any body whose absolute temperature is greater than zero, the Earth’s surface emits a radiative flux towards the atmosphere, with a magnitude that depends on its temperature. Since the Earth’s surface is colder than that of the Sun, compared to solar rays this flux is constituted of less energetic infrared radiation (in orange on Fig. 1.1), and thus has a higher wavelength than the incoming solar radiation. Part of this ‘thermal infrared’ flux is subsequently absorbed in the atmosphere by the greenhouse gases (water vapour, CO$_2$, methane, N$_2$O, ozone, etc.). This maintains the temperature of the molecules of the atmosphere, which hence also emit longwave radiation in all directions, resulting in incoming longwave radiation at the surface ($LW_{in}$). This induces an additional heating of the surface besides that of the solar radiation, and constitutes the greenhouse effect which naturally raises the temperature of the Earth by about $30^\circ$C. The overall outgoing longwave radiative flux ($LW_{out}$) is constituted of the emitted thermal infrared radiation, whose magnitude is related to surface temperature through the Stefan-Boltzmann law, as well as of a small part of $LW_{in}$ that is reflected by the land surface. We can hence write, as in Chapter 13 of Bonan (2008b):

$$LW_{out} = \epsilon \sigma T_s^4 + (1 - \epsilon)LW_{in}$$

$\sigma$ stands here for the Stefan-Boltzmann constant, $T_s$ is the absolute temperature of the land surface (in K), while $\epsilon$ stands for its emissivity. Note that the right term on the right-hand side is comparatively small because $\epsilon$ is close to 1, and that it is sometimes omitted in the definition of $LW_{out}$ and instead implicitly subtracted from the $LW_{in}$ term beforehand. However, the definition of $LW_{out}$ used in Equation 1.1 is consistent with the estimates of energy fluxes provided on Fig. 1.1.

Emissivity values are positive and at most equal to 1, which is by definition the case for a blackbody. Nonetheless, most natural surfaces behave as gray bodies and hence have emissivities inferior to 1. However, these values slightly differ from one land cover type to another, and also depend on the considered wavelength of the light spectrum. For example, for wavelengths of 8-10 µm (corresponding to long-wavelength infrared radiation), Wang et al. (2005) report emissivity values of $\sim$0.98 for snow and ice, $\sim$0.95 for leaf, bark and dry grass, but only $\sim$0.8 for sand. Therefore, the presence of vegetation can have an impact on surface temperature through two
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countering effects: while the higher emissivity of vegetation leads to more thermal emission and thus has a cooling effect, on the other hand it entails a higher absorption of incoming longwave radiation, which tends to warm the land surface compared to a case where it would be covered with desert. A few modelling studies have reported that overall, surface temperatures are significantly lower over more densely vegetated areas (e.g. Voldoire, 2006; Levis et al., 2000). However, because of its countering effects on the surface energy budget, the emissivity likely plays a lesser role in the climate system compared to other biogeophysical properties. It has therefore received less attention, which is why I will also not focus on it in the rest of this thesis.

Ultimately, the net amount of energy that is absorbed by the land surface depending on its radiative properties (both albedo and emissivity) is called net radiation \( R_{\text{net}} \), and can be summarised as:

\[
R_{\text{net}} = SW_{\text{in}} - SW_{\text{out}} + LW_{\text{in}} - LW_{\text{out}}
\]

1.1.2 Plant transpiration regulates the surface energy partitioning and leads to a more active water cycle

On a global average, \( R_{\text{net}} \) hence amounts to \( \sim 70 \text{ W/m}^2 \) over land. Since we do not observe an increase in surface temperature corresponding to this magnitude, the surface energy balance must be maintained by the loss of energy through other fluxes. Most of the energy absorbed by the surface is used to evaporate water contained in the soil, intercepted by vegetation during precipitation events or from open water surfaces. Over land, this endothermic process occurs either through direct evaporation, either through transpiration of plants, and is hence often referred to as "evapotranspiration". It consumes \( \sim 38 \text{ W/m}^2 \) on a global average, leading to an upward flux of water vapour. The fate of this water vapour is to be eventually condensed again somewhere in the atmosphere, leading to cloud development and possibly to precipitation formation. This occurs through the opposite exothermic process, hence from an energetic perspective evapotranspiration (noted \( E \)) is considered as a latent heat flux referred to as \( \lambda E \), with \( \lambda \) denoting the latent heat of vaporisation of water. This illustrates the close link between the land surface energy and water budgets.

Most of net radiation that is not converted into latent heat also eventually warms the atmospheric layers above the surface, which is the reason why it is called "sensible" heat (\( H \)). The difference between net radiation and the sum of the latent and sensible heat fluxes is the ground heat flux (\( G \)), which tends to bring the temperature differences between the surface and the subsurface to equilibrium. It can therefore lead to variations in the soil heat content, which can be mathematically expressed as \( \frac{dH_s}{dt} \). Overall, the Surface Energy Balance (SEB) can thus be expressed as follows:

\[
\frac{dH_s}{dt} = R_{\text{net}} - (\lambda E + H)
\]
1.1. THE ROLE OF VEGETATION IN THE CLIMATE SYSTEM

\[ R_{\text{net}} = \lambda E + H + G + \frac{dH_s}{dt} \]  

(1.3)

Since its average magnitude is very low compared to the other components of the energy budget, the ground heat flux is usually neglected. Besides, on climatological timescales the change in soil heat content is usually also very small, which leads to a reduced mathematical form of the SEB:

\[ R_{\text{net}} = \lambda E + H \]  

(1.4)

Through its impacts on both the water cycle and surface temperature, the partitioning of \( R_{\text{net}} \) between \( \lambda E \) and \( H \) can hence influence climatic conditions. The fraction of net radiation going into \( \lambda E \) is called the evaporative fraction; it is determined by water availability over land, which is highly related to the amount of soil moisture (Seneviratne et al., 2010). However, plant transpiration is additionally affected by other controls specific to vegetation, which explain an important part of the spatio-temporal variability of \( E \) (see e.g. Wang and Dickinson, 2005). The transpiration process occurs through microscopic pores located mostly on the epidermis of the leaves of plants and called stomata, where the water that was taken up by the roots of the plants and brought up to the leaves is evaporated into the atmosphere (see the photograph on Fig. 1.2). The water flux that is transpired through stomata is quantified by the stomatal conductance. In addition to being controlled by many environmental factors that determine the "demand" for evapotranspiration (e.g. the vapor pressure deficit in the air close to the leaves), the stomatal conductance is influenced by many physiological parameters through which plants regulate the "supply" of soil water to the atmosphere:

- the root depth, through which plants can increase the availability of soil water for evapotranspiration by accessing that stored deeply in the ground. This notably enables evapotranspiration to be sustained under conditions where the upper soil layers become water-depleted;

- the Leaf Area Index (LAI), which is defined as the one-sided green leaf area per unit of ground surface area (in \( \text{m}^2/\text{m}^2 \)). Higher LAI values mean a higher amount of stomata, and thus tend to lead to higher evapotranspiration rates;

- additional plant-specific physiological controls of the stomatal conductance reflecting the plant "strategies" regarding water-use. For example, plants tend to limit their stomatal conductance by closing their stomata when the air is getting dry or when the leaf water content drops below a threshold, in order to enable the input of water by the xylem sap to keep up with the demand for evapotranspiration from the air, and thus to avoid leaf dessication (see e.g. Chapter 17 of Bonan, 2008b);
• the specific phenology of the considered plant species. Vegetation activity has a pronounced seasonal cycle under mid- and boreal latitudes, especially in the case of crops for which it exhibits a peak followed by a quick decline after harvest.

![Microscopic photograph of a leaf epidermis on which one can observe a dozen of closed stomata. By absorbing water into their membranes, the pair of guard cells that surrounds each stoma can expand, which increases its opening and thereby favours the entering of CO$_2$ into the leaves and the release of water into the atmosphere. The size of a stomata is typically 50 µm.](http://images.fineartamerica.com/images-medium-large-5/2-stomata-on-epidermis-of-rose-leaf-power-and-syred.jpg)

**Figure 1.2:** Microscopic photograph of a leaf epidermis on which one can observe a dozen of closed stomata. By absorbing water into their membranes, the pair of guard cells that surrounds each stoma can expand, which increases its opening and thereby favours the entering of CO$_2$ into the leaves and the release of water into the atmosphere. The size of a stomata is typically 50 µm. Photo credit: Google (http://images.fineartamerica.com/images-medium-large-5/2-stomata-on-epidermis-of-rose-leaf-power-and-syred.jpg).

On average, plants have higher evapotranspiration rates than bare soil because 1) their roots increase the access to soil water, 2) their high leaf area constitute a wider interface for transpiration, and 3) their lower albedo (Section 1.1.1) results in more radiative energy being absorbed and made available for conversion into latent heat flux. Kleidon et al. (2000) found for example that evapotranspiration over land was amplified by a factor 3.5 globally in their "green planet" simulation compared to the "desert world" one. This firstly leads to a limitation of surface temperatures, because the energy used for evapotranspiration is not converted into sensible heat which would warm the lower layers of the atmosphere. Besides, it has important consequences for the water cycle. On a global average, evapotranspiration indeed sends as much as $\sim$65% of the water input to the land surface through precipitation back to the atmosphere (Trenberth et al., 2007). This is the most important contribution to the atmospheric water budget over land, the remaining $\sim$35% originating from the water vapour transport from the oceans. Once evapotranspired, water vapour can then be transported further in the atmosphere and contribute to precipitation elsewhere over land. This succession of episodes of precipitation and evaporation is often referred to as "precipitation recycling", and leads to the redistribution of water within continental surfaces. Since plant transpiration is estimated
to account for between 45 and 90 % of total continental evapotranspiration (Jasechko et al., 2013; Dirmeyer et al., 2006), vegetation plays a crucial intermediary role in establishing the current water cycle, and especially in reducing aridity over water-limited regions. Thereby, plants can maintain the climate conditions necessary for their subsistence, leading to a positive feedback which maintains the activity of the water cycle. Lastly, Kleidon et al. (2000) found that the increased atmospheric moisture in their "green planet" experiment also impacts the radiative budget of the land surface by increasing cloud cover and the atmospheric water content.

1.1.3 The roughness length of vegetation affects the transmission of energy fluxes to the atmosphere

Both sensible and latent heat fluxes tend to mix the heat and water vapour content within the boundary layer. If their magnitude depends on the amount of energy available and on the evapotranspiration rate at the surface, they are also influenced by its aerodynamic properties. They are indeed transmitted through turbulent convection, which is triggered when wind blows over the land surface and encounters objects which slow it down by exerting a friction force. The ability of these objects to create turbulence is characterised by its roughness length, which is primarily determined by the height of the objects (Chapter 14 of Bonan, 2008b). The presence of plants hence increases the roughness length of the land surface compared to bare soil and therefore enhances turbulence, i.e. the "demand" for evapotranspiration, leading to more important turbulent heat fluxes. On the contrary, roughness is diminished if the vegetation is removed, and the following restriction of the transport of energy between the surface and the atmosphere tends to bring the surface energy budget out of equilibrium. However, the energy that remains close to the surface tends to warm it, which increases its temperature and therefore outgoing longwave emission, thereby maintaining the equilibrium. This can be described mathematically by combining Equations 1.1, 1.2 and 1.4 to re-write the Surface Energy Balance:

$$SW_{in} - SW_{out} + \epsilon LW_{in} = \epsilon T_s^4 + \lambda E + H.$$  \hspace{1cm} (1.5)

This new equation illustrates better the possible partitioning of the radiative energy absorbed by the land surface into either thermal emission or the release of sensible or latent heat, as well as the role played by the physiological controls and the aerodynamic characteristics of vegetation in this partitioning.

In summary, vegetation tends to decrease surface temperature and to result in a more active water cycle because of its aerodynamic (related to roughness) and physiological (related to the control of evapotranspiration)
properties, which facilitate the transfer of energy and water from the land surface to the atmosphere. Besides, due to its specific radiative properties (i.e. its low albedo), it can absorb more solar energy than bare soil, which also goes in the direction of making the water cycle more active, but on the other hand tends to warm the land surface locally. Furthermore, since the presence of vegetation can affect cloud cover and the atmospheric water vapour content, this can lead to atmospheric feedbacks which in turn also modify the surface energy budget.

1.2 Observed effects of land-cover changes on local climate

In the previous section, I have reviewed the various biogeophysical properties through which the presence of vegetation affects the local surface climate. However, these properties very much depend on the plant type, therefore variations in vegetation cover can lead to changes in climate conditions. In this section, I review some observational findings which demonstrated the effect of LCC on local climate through modifications of the biogeophysical properties of the land surface. Since LCC commonly involve the removal of primary vegetation, like forests or natural grasses, and its replacement by shorter vegetation types, especially for agricultural purposes, I give particular attention to the impact of the conversion of forests into open land (i.e. cropland or pasture).

1.2.1 Deforestation locally increases albedo

As forests are darker than cropland and grassland, they have lower albedo values. This contrast is amplified in the presence of snow, because of the masking effect of tall vegetation. This is illustrated in Fig. 1.3, which shows the seasonal variations in albedo over measurements sites located in different boreal ecosystems of North America. During the warm season, coniferous forests have albedo values of \( \sim 0.1 \), while both the aspen site and the grassland sites exhibit values of \( \sim 0.2 \). This means that the additional absorption of solar radiation by forests compared to grassland ranges between 0 and \( \sim 15\% \). In contrast, in winter the albedo of grassland is increased up to \( \sim 0.8 \) due to the presence of snow, whereas that of forests is only slightly modified. Under such conditions, forests thus absorb about four times more solar radiation than short vegetation types. These results are confirmed by the study by Li et al. (2015), who compared satellite measurements of albedo over forest patches and surrounding open land and interpreted these results as a space-for-time analogy showing the local effect of deforestation on albedo (see Fig. 1.4a, d). Their global analysis also demonstrates that the increased absorption of solar radiation by forests compared to open land is maximal under mid-to-high latitudes and during
the cold season, where forests tend to lead to a local surface warming and to make more energy available for convection through turbulent heat fluxes compared to grassland and cropland. In contrast, their results show that the albedo differences between forest and open land tend to become unsignificant over tropical areas, although some studies suggest that they can remain substantial locally (see for example the smaller-scale study conducted in Amazonia by von Randow et al., 2004).

Figure 1.3: Daily averaged albedo over 10 measurement stations located in boreal North America for 1995; showing two grass sites, an aspen site, and an average of seven conifer sites. From Betts and Ball (1997).

1.2.2 The effect of deforestation on evapotranspiration depends on the region and the time of the year

In Section 1.1.2, I have listed the physiological controls imposed by vegetation on transpiration. However, there is an important variability in these controls amongst plant species, which leads to substantial differences in the measured evapotranspiration values between forests and short vegetation types within one biome. However, these differences depend on the background climate conditions and also vary both along the year and within one day. Using the methodology previously described in Section 1.2.1 but applied to satellite-based evapotranspiration retrievals, Li et al. (2015) found that deforestation leads to lower evapotranspiration rates in tropical areas, especially during daytime (see Fig. 1.4b, c, e and f). This effect is amplified during the dry season because short vegetation types suffer from water limitation in the upper soil layers, whereas deep-rooted
trees can still access water stored deeper in the soil and thereby sustain important transpiration rates. These satellite-based results are confirmed by site-level in situ measurements of surface fluxes with the eddy covariance technique (e.g. von Randow et al., 2004), while other studies by Baker et al. (2008) and Markewitz et al. (2010) showed that the deeply-rooted trees of the Amazon could sustain elevated evapotranspiration rates during drought conditions lasting for 1-2 years.

Under boreal latitudes, the plant activity is overall lower and differences in evapotranspiration between forests and open land are almost zero. Over mid-latitudes, except during the cold season Li et al. (2015) found more elevated evapotranspiration rates over forests than over open land, which are partly offset by more important evapotranspiration over short vegetation types during nighttime. However, a study conducted by Teuling et al. (2010) and based on eddy-covariance in situ measurements over central and western Europe revealed that evapotranspiration is slightly higher over grassland and cropland than over forests during summer in this region (Fig. 1.5).
this difference is amplified during heatwave conditions because trees exert a stronger physiological control on their stomatal conductance, whereas the transpiration rate of grassland and cropland directly increases in response to the elevated evaporative demand. Nevertheless, these differential water-use strategies lead to a quicker decrease of soil moisture availability for cropland and grassland, hence Teuling et al. (2010) suggest that transpiration may become higher over forests if heatwave conditions last long enough (Fig. 1.6). These contrasting pieces of evidence highlight the issue of the uncertainties about observational products for evapotranspiration and in particular of the consistency between the various techniques to measure it, which has for example been described by Mueller et al. (2013). Therefore, further work involving the analysis of more extensive and independent datasets need to be realised in order to understand better the potential impact of deforestation on local evapotranspiration rates. More generally, this also depends on possible anthropogenic intervention for land management purposes, for example to relieve crops from water stress by irrigation.

In summary, due to the multiplicity of the intervening physiological parameters and the diversity of plant species, how changes in land-cover (excluding those in land management) affect evapotranspiration rates highly depends on the considered ecosystems and the time of the year. Consequently, the understanding of how they impact local climatic conditions is relatively uncertain and leads to disagreement between models that explicitly represent vegetation-climate interactions, as will be described more in detail in Section 1.3.

1.2.3 Deforestation reduces the roughness length

Since trees are taller than crops or grasses, they have a higher roughness length. Therefore, they exert more friction on the wind blowing over the land surface and enable a better mixing of water and energy in the lower layers of the atmosphere by enhancing turbulent fluxes. For example, Gash and Nobre (1997) observed less vertical mixing over deforested areas than over unperturbed forest patches in Amazonia during the night, when boundary layer development is less affected by the partitioning between sensible and latent heat fluxes but more by the aerodynamic properties of the land surface. This tends to lead to a local increase in surface temperature, and thus to higher thermal emission under the form of longwave radiation. Moreover, the reduction of both latent and sensible heat fluxes implies a local weakening of the water cycle, because less energy and moisture are available in the atmosphere for convective activity and cloud development.
**Figure 1.5:** Radiation and energy exchange over forest and grassland, on average over a network of ∼20 eddy covariance flux towers located in western and central Europe. The balance of incoming and outgoing shortwave and longwave radiative fluxes (\(SW_{in}\), \(SW_{out}\), \(LW_{in}\) and \(LW_{out}\)) determines the net radiation \(R_n\) available for latent (\(\lambda ET\)), sensible (\(H\)) and ground (\(G\)) heat fluxes. The residual (\(\epsilon = R_n - \lambda ET - H - G\)) encompasses both missing balance terms and bias. *Upper row* Flux climatologies. *Lower row* Heatwave days (HWD) anomalies. The vertical lines indicate 95% confidence limits for medians determined by bootstrapping. From Teuling et al. (2010).

### 1.2.4 Summary: Spatio-temporal patterns of the local climate effect of deforestation

#### Impacts on temperature at the land surface

The overall local biogeophysical impact of LCC on climate results from the aggregated effects of changes in albedo, evapotranspiration and roughness, whose relative importance vary in space and time and which partly tend to counteract each other. In the previously mentioned global analysis conducted by Li et al. (2015), the authors also looked at the local effect of deforestation on remotely sensed Land Surface Temperature (LST). They found that the effect of deforestation on LST is largely dependent on the
1.2. OBSERVED EFFECTS OF LCC ON LOCAL CLIMATE

Figure 1.6: Conceptual model for latent heat flux evolution over grassland and forest during drydown. **a** Relation between soil moisture storage depletion and midday latent heat flux $\lambda ET$. **b** Temporal evolution of $\lambda ET$ during a drought event. Values for $\lambda ET$ during stage I drying are taken from Fig. 1.5, with dashed lines corresponding to the hypothetical situation of drydown under average conditions and thick lines corresponding to climatologies plus heatwave days (HWDs) anomalies. The points indicate independent observations of $\lambda ET$ and soil moisture for Oensingen (grassland) and Wetzstein (forest) for HWDs in 2003 and July 2006. The conceptual model suggests that the sharp drop in $ET$ corresponding to stage II drying occurs for higher soil moisture values and earlier during the drought event over grasslands than over forests. The observations for the grassland site confirm the nonlinear behaviour of the model, while soil moisture depletion at the forest site was not sufficient to induce sensitivity to soil moisture. Adapted from Teuling et al. (2010).

Over mid-to-high latitudes, there is a clear contrast between the effect of deforestation during daytime and nighttime in the warm season. During...
the night, Li et al. (2015) found that it diminishes LSTs, which they interpret as the consequence from the higher heat capacity of forests, which can hence lose heat more slowly and keep releasing it during the night, thereby maintaining higher temperatures in their canopies. However, deforestation leads to an increase in LST during the day because of the observed evapotranspiration cooling, which is partly offset by a weak albedo-driven warming. Zaitchik et al. (2006) and Teuling et al. (2010) also observed higher LSTs over agricultural areas compared to forests after analysing snapshot satellite images captured over western Europe during summer. Moreover, they found that these differences were amplified during the extremely hot and dry summer of 2003. In contrast, Li et al. (2015) observed that deforestation leads to a diminution in LST during daytime in the cold season over these latitudes, because the warming effect of the albedo increase is enhanced in the presence of snow and exceeds the effect of the decrease in evapotranspiration. The regional analyses conducted by Lee et al. (2011) and Zhang et al. (2014) support the findings from Li et al. (2015), but for surface air temperature. Lee et al. (2011) compared in situ measurements collected over more than 30 forest sites and neighbouring
weather stations (located over short vegetation) in North America, and also observed a contrast between the local warming effect of deforestation between daytime and its local cooling effect during nighttime in the warm season (Fig. 1.8). Consistently with the results from Li et al. (2015), they also found a lower effect of deforestation on surface air temperature during daytime in the cold season, as well as year round under high latitudes. Zhang et al. (2014) confirmed all these results for some measurement sites located over eastern Asia, and so did Alkama and Cescatti (2016) in their larger-scale satellite-based analysis. The differential response of daytime and nighttime near-surface temperature to local deforestation, and thus the resulting increase in its diurnal cycle, hence appears to be a robust feature over mid-to-high latitudes. However, the various listed studies do not agree on the relative magnitude of the deforestation-induced changes in temperature during daytime and nighttime. As a consequence, they deliver contrasting conclusions on its impact on daily mean temperature for temperate and boreal areas: while Lee et al. (2011) indicate a year round mean cooling effect, the satellite-based studies of Li et al. (2015) and Alkama and Cescatti (2016) rather suggest the opposite behaviour most of the year, except during winter when the effect of albedo dominates.

Figure 1.8: Seasonal cycle of mean daily maximum and minimum temperatures for the mean of more than 30 eddy-covariance measurement sites located over forests (solid lines) and their corresponding neighbouring surface stations located over open land (dashed lines) in North America for 28-45° N (blue lines) and 45-56°N (red lines). From Lee et al. (2011).
Impacts on cloud cover and the water cycle

Given the high evapotranspiration rates of tropical trees and their ability to sustain them during dry conditions due to their deep roots (see Section 1.1.2), forest clearing potentially leads to changes in surface climatic conditions. Some mesoscale simulations suggested that the temperature gradients created by scattered deforestation patterns affect the development of convective clouds and precipitation by triggering mesoscale circulations between forested and deforested patches (Garcia-Carreras and Parker, 2011; Baidya Roy, 2009; Wang et al., 2000). These were however not simulated during the wet season because of the prevalence of large-scale synoptic conditions. The observational evidence from Wang et al. (2009) showing deeper convection associated to the development of deeper clouds over forests in Rondônia goes in the direction of these modelling results. Likewise, some localised rainfall enhancement has been reported over deforested patches in this region (Negri et al., 2004).

1.3 The extent of past, present and future land-cover changes, and their climate impact

The climate effects of historical (and future) LCC is often explored with the help of climate models, which can be defined as sets of mathematical equations that are resolved numerically to simulate some components of the climate system and their interactions. Some of them include Land Surface Models (LSMs), which represent the water and energy transfers at the land surface: from the soil to the lowest levels of the atmosphere, including the vegetation and its canopy. In particular, they compute the partitioning of the energy budget and hydrological processes at the surface depending on its biogeophysical properties, and in response to the atmospheric forcing. In return, the processes they simulate can feed back on the atmosphere when they are used as lower boundary conditions for the atmospheric components of climate models. Current LSMs commonly include an explicit representation of vegetation and a parameterisation of different vegetation types, which hence enable the investigation of the impact of changing vegetation on climate. In this section, I review some results from the scientific literature about the consequences of historical LCC on climate through biogeophysical effects, or about their possible impact in response to forecasted changes in land cover in the future.

1.3.1 Historical land-cover changes

The development of agricultural societies around 10,000 BC increased the need for wood for heating and construction purposes, as well as land in order to grow crops and raise cattle. It therefore resulted in large-scale
1.3. CLIMATE IMPACT OF PAST, PRESENT AND FUTURE LCC

Figure 1.9: Global combined cropland and pasture area according to Kaplan et al. (2009) (KK10), Pongratz et al. (2008) (PEA), and the extended HYDE 3.1 datasets (Hurtt et al., 2011; Klein Goldewijk et al., 2011). From Schmidt et al. (2012).

Transformations of the landscape by humans, who started to remove forests and other types of primary vegetation to replace it by cropland and pastures. If reconstructions of the evolution of agricultural areas and forests over the last three centuries can be partly based on historical records, such documentation is lacking for anterior periods. Instead, historians have used estimates of population data and assumptions about the area of land required per capita (e.g. Kaplan et al., 2009; Pongratz et al., 2008; Klein Goldewijk et al., 2011). Differences in these assumptions have therefore resulted in a large spread in the reconstructions for the last millenia, as shown in Fig. 1.9. However, these tend to agree better from the end of the nineteenth century onwards, when more historical data are available. In this thesis, I will study the climate impact of historical LCC starting about 1850, therefore my investigation is relatively few impacted by the presented uncertainties in historical reconstructions.

The evolution of the area covered by cropland and primary vegetation between 1850 and 2005 according to the HYDE 3.1 dataset is visible in Fig. 1.10. It for example shows that extensive LCC have occurred over this period following the establishment of new settlements in western North America. Primary vegetation has indeed mostly been removed between the Atlantic Ocean and the Rocky Mountains in favour of cropland, which now occupy $\sim 3/4$ of the Great Plains. Similarly, cropland have extended over large parts of central and eastern Europe and Asia after the economic development of the European empires and the Soviet Union. As a result of the local increase in population, agriculture has also tremendously developed at the expense of primary vegetation in India, southeastern Asia, Patagonia, as well as some parts of Australia. The development of agriculture was also accompanied by technology changes towards its intensification. Especially, irrigation by humans enables to relieve crops
from water stress, affecting evapotranspiration and therefore surface temperature as well as the whole water cycle. Despite some modelling indication that the historical climate impact of irrigation has been substantial (e.g. Cook et al., 2015; Sacks et al., 2009), this method — as well other land management technologies — are still not represented in most climate models. For this reason, in this thesis I will focus on the climate impacts of anthropogenic changes in land cover rather than in land management practices.

Brovkin et al. (2004), Matthews et al. (2004) and Pongratz et al. (2010) have simulated that these historical LCC have led to a global cooling through biogeophysical mechanisms, by the same order of magnitude as the global warming driven by the release of 180±80 GtC in the atmosphere that they entailed (which represents ~30% of the cumulated anthropogenic emissions between 1750 and 2011, see IPCC, 2013). However, the comparability of the climate effects of biogeochemical and biogeophysical processes is limited for several reasons. First, while the former have well-distributed impacts around the globe, the latter mostly have regional effects that are centered over the areas of intense land cover perturbation, in addition to possible localised remote effects through teleconnections (Pongratz et al., 2010; Gedney and Valdes, 2000). Secondly, the former have been traditionally summarised with the radiative forcing metrics, which quantifies the global imbalance in the energy budget at the top of the atmosphere from the various emitted GHGs and aerosols, the imposed albedo changes as well as the natural variations in solar irradiance, in order to compare their global
1.3. CLIMATE IMPACT OF PAST, PRESENT AND FUTURE LCC

warming (or cooling) potential. Nevertheless, Davin et al. (2007) argued that this concept is inappropriate to describe the biogeophysical impacts of LCC because they involve non-radiative processes, like the modification of evapotranspiration and roughness length. These indeed affect temperature and the water cycle without modifying the net amount of incoming energy, and their overall impact on temperature and the water cycle depends on the considered region, time of the year and specific climate conditions, in relation with the phenology of the local vegetation. Because of these differences in the involved processes and in the spatial scales at which they act, existing studies have focused on the regional responses to the biogeophysical effects of past LCC. Thus, Pongratz et al. (2010), Brovkin et al. (2004) and Matthews et al. (2004) found that they were regionally as important as the associated biogeochemical impacts. However, their spatial distribution and magnitude differed substantially amongst studies.

The LUCID project (Land-Use and Climate, IDentification of robust impacts) was launched in order to reduce uncertainties about the biogeophysical impact of historical LCC since the mid-nineteenth century. While the seven coupled land-atmosphere climate models involved in this project showed a noisy precipitation response, on an annual average they all simulated a regional cooling over mid-latitudinal areas that had experienced deforestation and cropland expansion, with a magnitude similar to that of the effect of increased GHG concentration (de Noblet-Ducoudré et al., 2012). All models agreed that the cooling was driven by the albedo increase in winter. However, variations in the surface energy partitioning were found to be more important in summer. Because of the model spread on the changes in evapotranspiration following deforestation, there was a low agreement on the mechanisms underlying the overall temperature change in the warm season, despite six out of seven models indicating a cooling. Boisier et al. (2012) found that more than half of this spread arose from differences in model parameterisations, while the rest came from differences in the way the reconstructed maps of vegetation were interpreted in terms of land cover distributions by the various models. Furthermore, Kumar et al. (2013a) investigated the local biogeophysical impacts of historical LCC in more than 15 Global Circulation Models (GCMs) that took part in the Coupled Model Intercomparison Project Phase 5 (CMIP5), and found high model disagreement on the resulting summer temperature change over North America. These results highlight the need for a better evaluation of the representation of the impacts of LCC on surface fluxes and temperature in land surface models, underlining the relevance of conducting model intercomparison efforts and also calling for a confrontation between results from models and from appropriate observational products.

Besides, either within the LUCID project or employing similar protocols
(Pitman et al., 2012; Avila et al., 2012), either using a detection/attribution framework (Christidis et al., 2013), some modelling-based studies showed that historical LCC have significantly impacted temperature extremes. This is very plausible considering that land-atmosphere processes highly regulate their occurrence (e.g. Seneviratne et al., 2012, 2006), and given the role of vegetation in controlling the surface energy balance (see Sections 1.1 and 1.2). However, these studies came to the same mixed conclusions on the sign of this impact and on the underlying mechanisms than those looking at the effect on mean climate.

1.3.2 Recent and ongoing land-cover changes

![Figure 1.11: 2012 tree cover (green), and areas which have experienced forest loss (red), gain (blue), as well as both loss and gain with loss and gain enhanced for improved visualisation (magenta), between 2000 and 2012. All map layers have been resampled for display purposes from the 30-m observation scale to a 0.05° geographic grid. From Hansen et al. (2013).](image)

Over the last part of the twentieth century, some forest regrowth has been occurring in the eastern part of North America, western Europe and China, driven by land abandonment and afforestation policies. However, in the same time cropland and pastures have encroached on tropical forests of Amazonia, equatorial Africa, southern Asia and Indonesia. These ecosystems experienced 32% of the global forest cover loss between 2000 and 2012 with the highest forest loss to gain ratio of all climatic zones, and are undergoing increasing deforestation rates (see Figure 1.11 and Hansen et al., 2013). Most of the decline in the tropical forest cover is currently occurring in South America. In particular, the Amazonian region has undergone sustained deforestation rates since the 1970s, which are estimated to have led to the clearing of more than 800’000 km$^2$ of forest (13% of the original extent) by 2001 (Soares-Filho et al., 2006).

Given the specific biogeophysical properties of tropical trees, and particularly their high evapotranspiration rates, these large-scale forest clearings
have led to modifications of the local climatic conditions. In Section 1.2.4, I have for example mentioned the satellite-based study of Alkama and Cescatti (2016) who observed that the changes in forest cover between 2000 and 2012 reported by Hansen et al. (2013) have mostly led to local increases in daily mean surface air temperature around the globe, except over boreal latitudes in the cold season, and despite constrained effects on daily minimal and maximal temperature. Besides, I have listed some variations in hydrometeorological variables that have been observed in response to local changes in land cover in Amazonia. In addition, there is conflicting evidence about the larger-scale changes in rainfall amounts over the twentieth century in this region (d’Almeida et al., 2007). Chen et al. (2001) suggested that the increase in precipitation observed in reanalysis datasets over the Amazonian basin between the 1950s and the 1990s were due to interdecadal changes in the global circulation, which brought more moisture from the ocean over the rainforest and thereby counteracted the tendency of deforestation to weaken the water cycle through reduced precipitation recycling. However, Henderson-Sellers and Pitman (2002) added that global warming may have contributed to this observed reorganisation of the large-scale circulation, but also that deforestation may have played a role in the overall rainfall increase by triggering mesoscale circulations which actually accelerated the water cycle. In summary, despite relatively good process understanding of the local hydrometeorological changes due to existing deforestation in Amazonia, their large-scale evolution results from the addition of the effects of global warming and interannual variability, whose respective contributions are hard to disentangle given the current limitation on observations.

1.3.3 Scenarios for the future

How the land cover will evolve over the course of the twenty-first century depends on future population growth and the development of the world’s economy, which will determine the needs for food and other land resources. Moreover, active policies may or may not be implemented to protect natural reserves, restore degraded land or even to reforest large areas in order to counteract the increasing atmospheric carbon concentration. There hence exists a wide range of scenarios for future LCC, which are therefore expected to translate into very different climate impacts. In order to assess all these possibilities, the scientific community has outlined a few scenarios based on different assumptions that could be directly used to force climate models (van Vuuren et al., 2011; Nakicenovic et al., 2000). Depending on these storylines, the global forest cover may be either further reduced in favour of the expansion of cropland and intensively used pastures (Riahi et al., 2011), or widely increased to sequester carbon (Thomson et al., 2011). Furthermore, large-scale vegetation shifts may occur as a natural consequence of global warming, but assessing their feedbacks on climate remains outside the scope of this thesis.
Brovkin et al. (2013) and Boysen et al. (2014) investigated the climatic impacts of some scenarios of future LCC in a multi-model context. They concluded that these will be exceeded by the consequences of fossil fuel emissions during the twenty-first century, contrary to the historical period where both had similar contributions. Besides, their results suggest at first that the biogeophysical impacts of future LCC will remain small, despite being significant over areas of maximal perturbation. However, this limited signal is at least partly due to the small-scale implementation of LCC in the analysed climate models, because the numerous intermediary steps which were required to translate the scenarios presented by van Vuuren et al. (2011) into vegetation maps directly usable by climate models largely reduced the original land-use signal (Di Vittorio et al., 2014).

![Figure 1.12: Differences between years 2100 and 2005 in fractions of cropland plus pasture in the scenarios RCP2.6 (left) and RCP8.5 (right). From Brovkin et al. (2013), after data from Hurtt et al. (2011).](image)

The analysed scenarios agree that most of the land-cover changes expected during the twenty-first century will occur in tropical and subtropical areas, pursuing present trends (see Fig. 1.12). Many scientific publications have focused on the multiple impacts of future tropical deforestation because of its importance for biodiversity as well as the carbon and hydrological cycles. Amazonia, which holds about 40% of the remaining world’s tropical forests, has for example received particular attention. The removal of large fractions of forest in this region is expected to impact the local climate in many aspects, including through biogeophysical processes. These will likely be dominated by a reduction in the evapotranspiration cooling of forests, which are expected for example to lead to modifications in the water cycle (e.g. d’Almeida et al., 2007). The results of Boisier et al. (2015) suggest that these perturbations of the local climate conditions are of even higher importance in the context of global warming, because using observation-constrained CMIP5 climate projections for the twenty-first century they found that it would likely lead to a significant strengthening of the Amazonian dry season.
As for now, there is no clear observational evidence for a change in basin-scale precipitation amounts despite ongoing deforestation in this region, potentially because of global warming and interdecadal variability acting as confounding factors (see Section 1.3.2). The current scattered deforestation pattern has induced some local hydrological changes, possibly redistributing local precipitation or even enhancing it. However, it was hypothesised that as the fraction of the original forest being cut down keeps increasing, a tipping point could be reached after which a drastic decline in basin-scale precipitation amounts would occur because of reduced precipitation recycling, as illustrated in Fig. 1.13. Moreover, it is unknown whether the global-scale circulation would reduce or amplify these regional perturbations of the water cycle by increasing or decreasing atmospheric moisture input into the Amazonian basin.

Figure 1.13: Schematic representation of the hydrological impact of different extents of clearing (in dark gray) in Amazonia. The horizontal water vapor flux transfers moisture into the region and in the case of no deforestation (a), this flux is sustained by precipitation recycling, maintaining high indices of rainfall. Areas of local deforestation (b) are too small to affect rainfall, but runoff increases and evapotranspiration decreases. Areas of regional deforestation (c) are large enough to influence circulation, strengthening convection and potentially increasing rainfall. A basin-wide deforestation scenario (d) would impose a severe decline on evapotranspiration and then on precipitation recycling, weakening the hydrological cycle in Amazonia as a whole. From d’Almeida et al. (2007).

There is a long history of investigating the biogeophysical impacts of Amazonian deforestation with climate models, starting in the 1980s. The first studies aimed to quantify the climate sensitivity to the complete removal of the rainforest. Following the evolution of land surface models and the implementation of new GCM parameterisations, more and more studies were published to provide new assessments. This let appear an overall agreement that full deforestation would increase surface temperature and decrease precipitation, but also a substantial spread between the different estimates (d’Almeida et al., 2007). Up to now, it is uncertain how this
historical development affected the magnitude of the simulated changes. In the same time, the increase in resolution of climate models, the improvement in their abilities to describe the structure and the spatial distribution of vegetation, as well as the availability of economically-based scenarios of future LCC enabled to evaluate the biogeophysical impact of more realistic projections of deforestation for the Amazonian climate. However, the resulting increase in computing resources led to the conduction of shorter simulations and thereby brought out another type of uncertainty, related to the importance of the diagnosed signal in view of interannual variability. So far, the eventuality of a deforestation-driven tipping point in this crucial region for the Earth’s climate and biodiversity can consequently neither be confirmed nor rejected.

1.4 Objectives

As discussed in the previous sections, LCC can affect climate conditions through many processes. In particular, biogeophysical mechanisms involving the modification of the local albedo, evapotranspiration rate and roughness length can alter the surface energy budget and water cycle, resulting in significant climate changes over regions where the vegetation cover is extensively perturbed. However, because some of these mechanisms are poorly constrained and tend to counteract each other, there are large uncertainties associated to their overall climate impacts (e.g., Mahmood et al., 2014). For this reason, the overarching aim of this thesis is to improve the understanding of the biogeophysical effects of some past and future LCC on regional mean and extreme climate conditions. In order to achieve this purpose, it is essential to use climate models which properly simulate the effect of vegetation on land-atmosphere fluxes. In this thesis, the presented analyses are therefore based on results from the most recent generation of climate models, which use a state-of-the-art representation of land surface processes. Besides, in order to assess the robustness of these model findings, I compare various models between each other, with the already existing literature, as well as with recent observational evidence of the effect of deforestation on surface climate conditions. In particular, I address the following research questions:

- How did regional mean and extremely warm temperatures respond to historical land-cover changes over mid-latitudes according to the newest generation of climate models?
- How do these results compare with indication from present-day observations?
- How will local precipitation and temperature likely evolve following future Amazonian deforestation? In particular, what is the likelihood
of reaching a tipping point in the hydrological cycle of the Amazonian basin during the twenty-first century?

This thesis is organised in five chapters and three appendices. Chapters 2 to 4 are each constituted of articles that are either published in scientific journals (Chapter 2 and 4) or in preparation (Chapter 3), and can be read as stand-alone scientific contributions. The various chapters can be summarised as follows:

- **Chapter 2:** **Historical land-cover change impacts on climate: comparative assessment of LUCID and CMIP5 multi-model experiments,** (Lejeune et al., 2017). Here, I demonstrate the suitability of a recently developed method to analyse the local climate impacts of LCC in climate model simulations. I then apply this method to 17 recent climate models, in order to reassess the outcomes of the LUCID project which showed that historical mid-latitude deforestation since the Industrial Revolution led to a regional cooling in winter, but to a more uncertain temperature response during the warm season. Eventually, I confront these model results with present-day observations to pinpoint at some robust features and remaining uncertainties, as well as to some biases of the analysed models.

- **Chapter 3:** **Historical deforestation increased the risk of heat extremes in northern mid-latitudes,** (Lejeune et al., in preparation). In this chapter, I use the results from Chapter 2 to select the models that are able to reproduce the observed daytime warming effect of deforestation over mid-latitudes. I then base on this selection to quantify the most realistic contribution of historical LCC to the increase in intensity of daytime hot extremes since the Industrial Revolution.

- **Chapter 4:** **Influence of Amazonian deforestation on the future evolution of regional surface fluxes, circulation, surface temperature and precipitation,** (Lejeune et al., 2015). In order to investigate the precipitation and temperature response which may follow possible future deforestation in the Amazon region, I first analyse four climate simulations performed with the regional climate model COSMO-CLM² and forced with four different vegetation maps reflecting different deforestation states. Then, I also compare the outcomes from these model simulations with the results from the existing literature, in order to better assess their robustness.

- **Chapter 5:** **Conclusions and outlook** I draw some conclusions from the scientific analyses presented in the previous chapters, announce some of their implications, and indicate possible directions for future research on this topic.
Historical land-cover change impacts on climate: comparative assessment of LUCID and CMIP5 multi-model experiments

Journal of Climate, 30, 1439–1459, doi:10.1175/JCLI-D-16-0213.1 *
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Abstract  During the industrial period, many regions experienced a reduction in forest cover and an expansion of agricultural areas, in particular North America, northern Eurasia and South Asia. Here results from the Land-Use and Climate, IDentification of robust impacts (LUCID) and CMIP5 model intercomparison projects are compared in order to investigate how land-cover changes (LCC) in these regions have locally impacted the biogeophysical land surface properties, like albedo and evapotranspiration, and how this has affected seasonal mean temperature as well as its diurnal cycle. The impact of LCC is extracted from climate simulations including all historical forcings, using a method that is shown to capture well the sign and the seasonal cycle

*This publication was slightly changed from its original version by adapting the spelling and the wording in order to ensure consistency throughout this thesis.
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of the impacts diagnosed from single-forcing experiments in most cases. The model comparison reveals that both the LUCID and CMIP5 models agree on the albedo-induced reduction of mean winter temperatures over mid-latitudes. In contrast, there is less agreement concerning the response of the latent heat flux and, subsequently, mean temperature during summer, when evaporative cooling plays a more important role. Overall, a majority of models exhibit a local warming effect of LCC during this season, contrasting with results from the LUCID studies. A striking result is that none of the analysed models reproduce well the changes in the diurnal cycle identified in present-day observations of the effect of deforestation. However, overall the CMIP5 models better simulate the observed summer daytime warming effect compared to the LUCID models, as well as the winter nighttime cooling effect.

2.1 Introduction

Since the beginning of the Industrial Revolution, the world’s population has tremendously increased, thereby strengthening the demand for more agricultural land. Consequently, forests and natural grasslands have been replaced by crops and pastures over large parts of the world (Ramankutty and Foley, 1999; Foley et al., 2005; Pongratz et al., 2008; Klein Goldewijk et al., 2011; Hurtt et al., 2011). This mostly occurred over the eastern part of North America and the Great Plains, northern Eurasia, and less extensively over India, eastern Asia and South America, as well as more recently in tropical areas. These historical land-cover changes (LCC) have impacted climate through both biogeochemical effects (i.e., through an increase in atmospheric carbon dioxide concentration) and biogeophysical effects (i.e., modifications of the biogeophysical properties of the land surface) (Brovkin et al., 2004; Findell et al., 2007; Pongratz et al., 2010; de Noblet-Ducoudré et al., 2012; Kumar et al., 2013a).

The Land-Use and Climate, IDentification of robust impacts (LUCID) model intercomparison project specifically aims to quantify these biogeophysical effects on climate. de Noblet-Ducoudré et al. (2012) found that six of the seven General Circulation Models (GCMs) taking part in LUCID indicate an all-year cooling through biogeophysical mechanisms over the affected mid-latitudinal regions (North America and Eurasia) during the industrial era, which almost cancelled out locally the warming driven by the concomitant increase in atmospheric CO$_2$ concentration. They identified the higher albedo of anthropogenic croplands and pastures compared to primary forests as an important cooling property in each model, particularly in winter over snow-covered areas. However, de Noblet-Ducoudré et al. (2012) underlined the low inter-model consistency on the responses of the latent and sensible heat fluxes to historical modifications of the albedo, roughness
length, leaf area index, root depth, and stomatal resistance of the vegetation.

The fifth Phase of the Coupled Model Intercomparison Project (CMIP5) offers an opportunity to reassess the climatic impacts of LCC in the context of more recent, fully-coupled GCMs. Indeed, a transient LCC forcing based on the reconstruction of Hurtt et al. (2011) was included in more than 15 of the CMIP5 models. However, the classical approach to extract LCC effects based on factorial experiments (e.g., by comparing experiments with and without the LCC forcing) is not applicable to CMIP5 since most models only provide so-called all-forcings experiments. To overcome this challenge, Kumar et al. (2013a) developed a methodology to extract the LCC forcing from such experiments. It consists in comparing the evolution of climatic variables over neighbouring grid cells, which experienced different rates of LCC but were similarly affected by other forcings. Similar approaches had beforehand already been applied to observations (e.g., McPherson et al., 2004; Ge, 2010; Loarie et al., 2011; Wickham et al., 2012). Interestingly, Kumar et al. (2013a) found a much lower model agreement about the impact of historical LCC on summer temperature than in LUCID studies. Only about half of the models they considered indeed showed a mean cooling effect over North America, while the other half showed a mean warming effect. They evaluated the reconstruction method that they developed by comparing its results to those of the factorial experiment approach, but this comparison remained limited to one single model and only two ensemble simulations. Even if they found a good similarity between both methodologies, it does not ensure that this result can be generalised to all models. It also does not completely rule out the possibility that the reconstruction method may actually show the climate impacts of other forcings instead of extracting those of LCC. Moreover, Kumar et al. (2013a) chose to focus on the consequences of LCC for summer temperature, even if the LUCID studies revealed effects of at least similar magnitude in other seasons (Boisier et al., 2012; de Noblet-Ducoudré et al., 2012). Besides, some recent observational studies demonstrated that the impact of deforestation on air and surface temperatures over mid-latitudes has an opposite sign during daytime and nighttime (e.g., Lee et al., 2011; Vanden Broucke et al., 2015; Li et al., 2015), a feature which was mostly overlooked in previous modelling studies.

Consequently, in this study we intend to answer three research questions:

- Is the reconstruction method based on Kumar et al. (2013a) able to assess the historical LCC impacts on albedo, latent heat flux and surface air temperature, and are its estimates comparable to those of the method using factorial experiments? (Section 3.2.3.1)

- Do the CMIP5 models confirm the results from the LUCID project regarding the impact of LCC on surface air temperature during the industrial period? (Section 3.2.3.2)
• Are model results consistent with present-day observations of the impact of deforestation on temperature, and especially its diurnal cycle? (Section 3.2.3.3)

2.2 Data and Methods

2.2.1 Description of the reconstruction method

To extract the LCC signal from single transient simulations, we employ a method based on Kumar et al. (2013a) with some modifications. This method, illustrated in Fig. 2.1, assumes that LCC constitute a spatially heterogenous forcing with essentially local climate impacts (i.e., this method cannot be applied to simulations with large-scale homogeneous forcings and will work only to the extent that local effects outweigh possible remote effects). In contrast, other forcings like greenhouse gases (GHG) are assumed to have a more homogeneous and larger-scale impact on climate.

For a given model, we therefore separate between grid cells for which the mean tree fraction between a pre-industrial and a present-day period has decreased by at least 15% (the high-LCC grid cells) and the others (the low-LCC grid cells). In a next step, for each high-LCC grid cell we look at a bigger box of 5X5 grid cells centered over it. Then, to disentangle the impact of LCC from that of other forcings between the pre-industrial and present-day periods in this high-LCC grid cell, we compute the difference in the mean temporal changes in climatic conditions over the high-LCC grid cells and those over the low-LCC grid cells contained within the corresponding bigger box. Looking at temporal changes also allows us to cancel out at least partly possible spurious effects due to climatic gradients unrelated to LCC within a bigger box (e.g., due to topography). We require each bigger box to contain at least three high-LCC and three low-LCC grid cells (and at least eight in total) and also the ratio of the number of its high-LCC grid cells over the total number of its land grid cells to be as close as possible to 0.5. If these criteria are not fulfilled, the size of the bigger boxes is increased to 7X7 or even 7X9 grid cells. We found that using this protocol compared to a fixed bigger box increases the ability of the reconstruction method to disentangle the impact of LCC from climate changes due to other forcings and internal variability (see the next section). The choice of a threshold of 15% to separate between high- and low-LCC grid cells was also made in order to optimise the method (more details are also given in the next section).

Contrary to Kumar et al. (2013a), we did not conduct our analysis on model data regridded to a common 2.5°X2.5° resolution but kept them in their native grid, nor did we separate high- from low-LCC grid cells in CMIP5 simulations based on the increase in crop cover according to the dataset from Hurtt et al. (2011). We have made these decisions because 1) deforestation leads to a clearer climatic signal than the expansion of croplands, since forests exhibit a distinct influence on the surface climatic variables compared
2.2. DATA AND METHODS

To short vegetation types that are typical of agricultural areas, whereas crops overall behave more similarly to natural grasslands (Ambrose and Sterling, 2014; Zhao and Jackson, 2014); 2) we found that the LCC impacts could be better disentangled from those of other forcings and internal variability if the method is based on the decrease in tree fraction rather than on the increase in crop fraction; 3) even if they were based on vegetation datasets that are the same for each intercomparison project, the analysed models interpret those differently and thus did not uniformly prescribe the LCC forcing; and 4) we observed that after regridding the reconstruction method would extract LCC impacts that were somewhat attenuated. More developed justifications for these methodological choices are provided in the next section (section 3.2.3.1), following a comparison of the reconstruction method with that using factorial experiments.

Figure 2.1: Illustration of the methodology employed to reconstruct the impact of land-cover changes in the model grid cell highlighted in blue, using all-forcings simulations. The numbers indicate the change in tree fraction between the pre-industrial (PI) and present-day (PD) periods in each grid cell. Red grid cells are high-LCC grid cells in which the tree fraction has decreased by more than 15%, while green grid cells are low-LCC grid cells in which the tree fraction has decreased by less than 15% or increased. Light blue grid cells are ocean or lake grid cells.

LCC impact = $\Delta X_{\text{high-LCC}}^{\text{PI-PD}} - \Delta X_{\text{low-LCC}}^{\text{PI-PD}}$

2.2.2 LUCID simulations

The LUCID project aimed to identify the robust biogeophysical impacts of LCC that have occurred since the mid-nineteenth century. We have analysed six models from this project, listed in Table 2.1. They all ran four experi-
ments with five 30-yr ensemble simulations each and used prescribed interannually and seasonally varying Sea Surface Temperatures (SSTs) and sea ice extent. Each model was provided with a map showing the change in the extent of both crops and pastures between 1870 (pre-industrial conditions) and 1992 (present-day conditions). This map was obtained by combination of the crop area reconstructed by Ramankutty and Foley (1999) and the pasture area from Klein Goldewijk (2001). It was then adapted by each model center depending on their "natural" vegetation distribution as well as their own interpretation of these prescribed land-use transitions. For each model, the mean grid cell fraction covered by each land cover type over the high-LCC grid cells during the pre-industrial period is shown in Fig. 2.2a for North America (30-60°N, 230-310°E), while the differences in the change in these fractions from the pre-industrial to the present-day periods between the high- and low-LCC grid cells are shown in Fig. 2.2b. In the body of this article we show only results for North America, but respective analyses for Eurasia (40-60°N, 20-100°E) and South Asia (5-35°N, 65-115°E) are systematically provided in the Appendix A (see its Figs. A.2-A.5 in this case).

The first (second) experiment was called PD (PI) and used land cover, GHG concentrations, SSTs, and sea ice extent reflecting present-day (pre-industrial) conditions. A third experiment (PDv) used the same forcings as PD, apart from land cover, which was set to pre-industrial conditions. Similarly, the fourth experiment (PIv) was conducted by prescribing the same forcings as in PI, except for land cover, which was set to present-day conditions. To isolate the climate impacts of historical LCC from those of other forcings which evolved concomitantly, the LUCID studies looked at the difference between two experiments differing only in terms of land cover map under both pre-industrial and present-day GHG concentrations and SSTs (i.e., Plv-PI and PD-PDv; see, e.g., Pitman et al., 2009; de Noblet-Ducoudré et al., 2012; Boisier et al., 2012). However in this study, we use a reconstruction algorithm that aims to isolate the climate impacts of LCC in simulations where both land-cover and other forcings are varying. In the case of LUCID simulations, we hence apply it to the difference between the PD and PI experiments. In order to quantify to which extent this reconstruction method may also capture climate variations not due to LCC, we also apply this algorithm to the differences between simulations sharing the same land cover map but differing in terms of GHG concentrations, SSTs, and sea ice extent (PD-PIv and PDv-PI).
Table 2.1: List of the LUCID models analysed in this chapter.

<table>
<thead>
<tr>
<th>Model name</th>
<th>Institution</th>
<th>Reference</th>
<th>Resolution (latitude × longitude)</th>
<th>Ensemble size</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARPEGE</td>
<td>Centre National de la Recherche Météorologique</td>
<td>Salas-Mélia et al. (submitted 2005)</td>
<td>64 × 128</td>
<td>5</td>
</tr>
<tr>
<td>CCSM</td>
<td>National Center for Atmospheric Research</td>
<td>Collins et al. (2006)</td>
<td>96 × 144</td>
<td>5</td>
</tr>
<tr>
<td>ECHAM5</td>
<td>Max-Planck-Institut für Meteorologie</td>
<td>Roeckner et al. (2006)</td>
<td>91 × 180</td>
<td>5</td>
</tr>
<tr>
<td>IPSL</td>
<td>Institut Pierre-Simon Laplace</td>
<td>Marti et al. (2010)</td>
<td>72 × 96</td>
<td>5</td>
</tr>
<tr>
<td>SPEEDY</td>
<td>International Centre for Theoretical Physics</td>
<td>Strengers et al. (2010)</td>
<td>91 × 180</td>
<td>5</td>
</tr>
</tbody>
</table>

* Interpolated data were analysed since original data stored in the native grid were partly missing
CHAPTER 2. HISTORICAL LCC

Figure 2.2: Land-cover changes in the LUCID models in North America (30-60°N, 230-310°E). Left Mean fraction of each land-cover type over high-LCC grid cells in the 1870 vegetation maps (corresponding to pre-industrial conditions). Right Changes in land-cover fractions between the vegetation maps of 1870 and those of 1992 (representative of present-day conditions) over high-LCC grid cells, minus those same changes over low-LCC grid cells. A negative value for the tree bar means, for example, that the tree fraction has decreased more over high- than over low-LCC grid cells between the pre-industrial and present-day periods.

2.2.3 CMIP5 simulations

Many models involved in CMIP5 included LCC as a forcing in their historical all-forcings simulations, which covered the 1860-2005 period (Taylor et al., 2012). We have analysed 11 of these models (listed in Table 2.2), selecting only those which provided land cover information, as well as surface air temperature, albedo and latent heat flux outputs at monthly resolution. They are all coupled models that compute SSTs interactively and simulate land surface processes explicitly. To represent historical LCC, they adapted the dataset developed by Hurtt et al. (2011) based on Klein Goldewijk et al. (2011), which provides maps of the land-use states and transitions between cropland, pasture, primary land and secondary (recovering) land between 1500 and 2005 at 0.5° resolution. We have used the reconstruction method to extract the climate impacts of historical LCC between two 30-yr time slices of each all-forcings simulation: 1862-1891 (pre-industrial period) and 1975-2004 (present-day period). The mean grid cell fraction covered by each land cover type over the high-LCC grid cells in North America during the pre-industrial period is shown in Fig. 2.3a, while Fig. 2.3b shows how it evolved over the high-LCC grid cells compared to the low-LCC ones by the present-day period.
Table 2.2: List of the CMIP5 models analysed in this chapter.

<table>
<thead>
<tr>
<th>Model name</th>
<th>Institution</th>
<th>Reference</th>
<th>Resolution on land (latitude × longitude)</th>
<th>Ensemble size</th>
</tr>
</thead>
<tbody>
<tr>
<td>CanESM2</td>
<td>Canadian Centre for Climate Modelling and Analysis</td>
<td>Arora et al. (2011)</td>
<td>64 × 128</td>
<td>5</td>
</tr>
<tr>
<td>CCSM4</td>
<td>National Center for Atmospheric Research</td>
<td>Gent et al. (2011)</td>
<td>192 × 288</td>
<td>6</td>
</tr>
<tr>
<td>CESM1-CAM5</td>
<td>National Center for Atmospheric Research</td>
<td></td>
<td>192 × 288</td>
<td>3</td>
</tr>
<tr>
<td>CESM1-FASTCHEM</td>
<td>National Center for Atmospheric Research</td>
<td></td>
<td>192 × 288</td>
<td>3</td>
</tr>
<tr>
<td>GFDL-CM3</td>
<td>NOAA Geophysical Fluid Dynamics Laboratory</td>
<td><a href="http://www.gfdl.noaa.gov">http://www.gfdl.noaa.gov</a></td>
<td>90 × 144</td>
<td>5</td>
</tr>
<tr>
<td>HadGEM2-ES</td>
<td>Met Office Hadley Centre</td>
<td>Collins et al. (2008)</td>
<td>145 × 192</td>
<td>4</td>
</tr>
<tr>
<td>MPI-ESM-LR</td>
<td>Max-Planck-Institut für Meteorologie</td>
<td>Raddatz et al. (2007); Marsland et al. (2003)</td>
<td>96 × 192</td>
<td>3</td>
</tr>
<tr>
<td>MPI-ESM-MR</td>
<td>Max-Planck-Institut für Meteorologie</td>
<td>Raddatz et al. (2007); Marsland et al. (2003)</td>
<td>96 × 192</td>
<td>3</td>
</tr>
<tr>
<td>NorESM1-M</td>
<td>Norwegian Climate Centre</td>
<td>Bentsen et al. (2013)</td>
<td>96 × 144</td>
<td>3</td>
</tr>
</tbody>
</table>
2.3 Results and Discussion

2.3.1 Part 1: Evaluation of the reconstruction method

Comparison with the factorial experiment approach

Because of their specific experimental design, the LUCID simulations are appropriate to compare the reconstruction method and the factorial experiment approach. The former can indeed be applied to the difference between LUCID simulations where both the land cover and the CO$_2$/SST/sea ice forcings differ (PD-PI). As for the latter, which consists of comparing a simulation forced by LCC only with a control (or an all-forcings simulation with another one forced by all forcings except LCC), one can apply it to the difference between two simulations differing only in terms of vegetation map (PD-PDv or PIv-PI). Therefore, in this section we compare the impacts of LCC as estimated with both methods in each of the analysed LUCID models. By design, the reconstruction method only computes the climate impacts of LCC over high-LCC grid cells. For comparison purposes, we therefore also consider these impacts according to the factorial experiment method over high-LCC grid cells only. We have computed them using two different sets of experiments forced by CO$_2$, SSTs and sea ice reflecting either pre-industrial or present-day background climate conditions (i.e. both PD-PDv and PIv-PI). However, consistently with de Noblet-Ducoudré et al. (2012), we have found small differences between these two estimates, therefore here we only show the mean of them.
Changes in albedo and latent heat flux  Fig. 2.4 (as well as Figs. A.6 and A.7) compares the reconstructed regional mean impacts of LCC on seasonal mean albedo, latent heat flux (LH), and surface air temperature to those estimated by the factorial experiment approach. Using two-tailed t-tests, we also looked at whether the impacts estimated by the factorial experiment method were significantly different from zero and whether those computed by the reconstruction method were significantly different from zero and from the noise induced by possible confounding factors of the method (e.g. CO$_2$).

Overall, there is a very good concordance between the domain-averaged estimates of both methods for albedo and LH, as revealed by the high coefficients of determination of the regression lines between them (shown on the bar charts). The reconstruction method captures the sign as well as the seasonal cycle of the LCC impacts computed with the factorial experiment method. Besides, both methods almost always agree on the significance of the impacts and never show significant impacts of opposite signs. However, there is a systematic underestimation of the LCC impacts by the reconstruction method compared to the factorial experiment one, with the slopes of the regression lines ranging between 0.66 and 0.84. This can be expected from the design of the method, because it looks at differences between grid cells that underwent important LCC and others that underwent less important ones, whereas the factorial experiment method investigates differences between a world with and another without LCC. In addition to this, it could indicate that this difference due to the methodology is not compensated by positive feedbacks resulting from the interactions between LCC and the CO$_2$/SST/sea ice forcings, which would reinforce the impact of LCC in simulations where all forcings are simultaneously imposed.

Changes in surface air temperature  Overall, we see a good concordance between the two methods for seasonal mean temperature (see third panel of Fig. 2.4 and also Figs. A.6 and A.7). The reconstruction method captures the sign of the impacts estimated by the factorial experiments method for a majority of models and seasons. It also reproduces well the seasonal variations for the ARPEGE, IPSL and SPEEDY models. Differences in the sign of the LCC impacts may arise where these are equal to no more than 0.2°C, but in these cases at most one method shows significant results.

However, for almost all models and all seasons the LCC impacts on mean temperature are even more underestimated by the reconstruction method compared to the factorial experiment one than in the case of LH and albedo (the slopes of the regression lines can be as low as 0.37 over Eurasia). This suggests that the LCC-induced changes in temperature are less localised than those in land surface properties. In fact, if part of the local impacts on temperature over high-LCC grid cells had propagated to the neighbouring grid
cells that experienced less important LCC and that are located in the same bigger boxes, they would have been more underestimated by the reconstruction method than the impacts on albedo and LH. There is some modelling evidence supporting the fact that LCC can also affect temperature away from the perturbed areas, contrary to LH and albedo that directly reflect the local characteristics of the land surface. The simulations of global-scale deforestation by Davin and Noblet-Ducoudré (2010) showed that this is especially the case for the albedo-induced radiative cooling, which can propagate to other regions because it decreases temperature and hence humidity in the whole tropospheric column, whereas changes in surface roughness and evapotranspiration impact temperature mostly locally and close to the surface. The LCC-induced temperature changes over high-LCC grid cells may hence have partly propagated to the neighbouring grid cells through the same mechanisms, even if we note that the overall good agreement between both methods indicates that they have mostly remained local.

We remark that our estimates of the impact of LCC according to the factorial experiment method may slightly differ from those of de Noblet-Ducoudré et al. (2012), because in their analysis they consider larger regions that include both high- and low-LCC grid cells. The potential larger-scale impact of the albedo-induced cooling (Davin and Noblet-Ducoudré, 2010) may play a more important role over low-LCC grid cells, which could explain why de Noblet-Ducoudré et al. (2012) reported a cooling effect of LCC in all seasons in the CCAM and CCSM models for a larger domain in North America, whereas we computed a slight warming effect in SON over high-LCC grid cells only for these two models.

To conclude, we acknowledge that one advantage of the factorial experiment approach is its ability to assess the impacts of LCC in other regions than those which underwent important perturbations, whereas the reconstruction method focuses on the local consequences for the high-LCC grid cells. However, the reconstruction method is more appropriate to track what the effects of changes in a particular vegetation type are, even if it cannot fully disentangle different land-cover transitions in its current design. Besides, we argue that one relative disadvantage of the factorial experiment method is that it may miss possible interactions between LCC and other forcings which are simultaneously imposed on the climate system. Although these have likely remained negligible in the LUCID simulations, because the small differences between the estimates of the factorial experiment method under either pre-industrial or present-day conditions suggest that changes in background climate during the industrial period did not have a primary influence on the impacts of LCC, this may however be different in the future, when important changes in temperature are expected, especially on land (Pitman et al., 2011; Collins et al., 2013).
Results and Discussion

Signal-to-noise ratio of the reconstruction method

To assess to which extent possible confounding factors of the reconstruction method (e.g., other forcings and artefacts due to climatic gradients unrelated to LCC within the bigger boxes) may distort its estimates of the impacts of LCC, we apply it to the differences between LUCID experiments which are not forced by the same GHG concentrations, SSTs and sea ice extents but share the same land cover map. This enables us to quantify the noise of the method in these simulations: that is, climate changes that were extracted by the method even if they are not due to LCC. It can then be compared to the signal obtained when applying the method to the differences between simulations where all forcings are different (PD-PI), as this is the case for the analysed CMIP5 simulations.

We computed the noise for all ensemble members and in both possible combinations of experiments (PD-PIv and PDv-PI). For each variable, we then compared the mean noise estimates to the mean signal computed from all ensemble members. Regarding albedo, the regional mean signal-to-noise ratios are equal to \( \sim 100 \) on average for all models and all seasons and are even seldom inferior to 10, for both North America (Fig. 2.5a) and Eurasia and South Asia (Figs. A.8 and A.9). This demonstrates the very good ability of the reconstruction method to disentangle regional mean albedo changes over high-LCC grid cells that are due to LCC from those due to its possible confounding factors. Only over a minority of individual grid cells is the signal not high enough to be distinguished from the noise. The domain-averaged ratios are also high for the latent heat flux, ranging mostly between 10 and 100 (Fig. 2.5b), except for some estimates where the reconstructed signal is low (i.e., ARPEGE and ECHAM5 in specific seasons over Eurasia and South Asia). For mean temperature, the regionally-averaged ratios are typically equal to 10 and always exceed 2 (Fig. 2.5c), with the exception of ECHAM5 in JJA and SON over Eurasia and South Asia as well as IPSL in SON, for which the reconstructed signal is almost zero. This analysis demonstrates the overall good ability of the method to extract the regionally-averaged impact of LCC on seasonal mean temperature in all-forcings simulations, given that this impact is large enough. It hence confirms that the basis assumption according to which LCC mostly affect grid cells individually whereas other forcings affect all grid cells within a bigger box in a rather similar way is verified. This therefore means that even if the impact of LCC on temperature is not completely local, its spatial fingerprint is still smaller and distinguishable from that of other forcings. Besides, the presented signal-to-noise analysis shows that possible spurious signals due to climatic gradients unrelated to LCC only have a very limited influence on the diagnosed LCC impacts. In the next sections, we use these noise estimates to assess the significance of the reconstructed impacts in both LUCID and CMIP5 simulations. We acknowledge that other possible confounding factors that were included in CMIP5 simulations may increase
the noise of the method (e.g., the aerosol forcing), but we are unfortunately not in possession of simulations which would enable us to test this hypothesis.

**Sensitivity of the reconstruction method to the choice of parameters**

We first tested the sensitivity of the computed impacts of LCC and of their signal-to-noise ratios to the choice of the threshold used to differentiate between high- and low-LCC grid cells, as well as to the size of the bigger box. For North America, we found that the choice of the threshold significantly affects the sign of the estimated impact of LCC only in one case, where it remains low (MAM LH in IPSL, see Figs. A.10-A.12). However, we find that selecting higher thresholds overall tends to increase the magnitude of the impacts with both methods, which is consistent with the fact that it implies a higher difference in the decrease in tree fraction between high- and low-LCC grid cells. Eventually, we selected the threshold of 15% as well as a varying bigger box approach because for all models they enable us to avoid low signal-to-noise ratios and often even to maximize them (see Figs. A.13 and A.14), while keeping a reasonably high number of both high- and low-LCC grid cells.

We also remark that in a few cases we find a better agreement between estimates of both methods when the reconstruction is computed by discriminating land grid cells depending on the increase in crop cover they experienced, rather than on the decrease in tree fraction (e.g., for temperature in the CCAM model, see Fig. A.15). However, this is not a general rule and we in contrast also find that basing the method on the decrease in tree fraction overall gives higher signal-to-noise ratios (Figs. A.13).

### 2.3.2 Part 2: Reconstructed LCC effects in LUCID and CMIP5 models

**Seasonal mean albedo**

Most LUCID and CMIP5 models indicate that historical deforestation entailed an increase in albedo in all seasons (Fig. 2.6). Only CCAM, CanESM2, GFDL-CM3 and MPI-ESM-LR show some non-significant changes in some seasons. For all LUCID models and 10 out of 11 CMIP5 models, the season where albedo increases most in North America and Eurasia is DJF because of the snow-masking effect. This is not the case in the subtropical South Asia domain; hence, we find lower LCC-driven albedo increases and no model agreement on a seasonal pattern there (Figs. A.19-A.21). Albedo changes over North America are, on average, ~30% higher in LUCID than in CMIP5 models (+0.045 on average in DJF and +0.012 in JJA, against +0.035 and +0.01 for CMIP5 models). We attribute this to differences in the vegetation
maps because the decrease in tree fraction between high- and low-LCC grid cells is higher for LUCID models compared to CMIP5 ones (33% versus 25% of additional deforestation on average, see Figs. 2.2b and 2.3b). In contrast, we find no indication that the sensitivity of albedo to the deforestation rate is significantly different among LUCID and CMIP5 models (as estimated with a linear regression between albedo changes and the deforestation rates).

**Seasonal mean latent heat flux**

A majority of LUCID and CMIP5 models simulate a decrease in LH due to deforestation, although the inter-model agreement is less clear than for albedo changes. We find impacts on LH of the same magnitude in LUCID and in CMIP5 models. They are maximal in JJA, with a multi-model mean reduction by between -2 and -3W/m^2 over North America, while it ranges between -1 and -2W/m^2 in SON and does not exceed -1W/m^2 in DJF and MAM. However, LH increases in at least one season for 3 out of 6 LUCID models and 5 out of 11 CMIP5 models. The model disagreement is also strongest in JJA, during which CCAM, IPSL and SPEEDY as well as GFDL-CM3, the two IPSL and the two MPI models from the CMIP5 project show a decrease in LH by more than 4.5W/m^2, whereas ARPEGE and HadGEM2-ES show significant increases in LH that even exceed 3W/m^2 in the case of the latter model.

Overall, the mean decrease in LH is consistent with the albedo-driven decrease in net radiation, but over North America albedo changes only explain 4% of the inter-model variance in the changes in LH in JJA for CMIP5 models (against 18% for LUCID models). This therefore suggests that CMIP5 models do not share a consistent response of the partitioning of available energy between the latent and sensible heat fluxes. This was already clearly reported in the context of the LUCID models (de Noblet-Ducoudré et al., 2012).

We find lower changes in LH over Eurasia and South Asia (see Figs. A.18-A.19 and A.22-A.23), which we at least partly relate to the lower differences in the decrease in tree fraction between high- and low-LCC grid cells experienced in these regions (-21% in the CMIP5 models and -29% in the LUCID ones in Eurasia, against -16% and -25% in South Asia, respectively). However, while we find a qualitatively similar model spread in Eurasia compared to North America, this is not the case for South Asia, where only ARPEGE simulates some significant increase in LH in DJF in response to historical LCC. This shows that there is a higher model agreement that evapotranspiration diminishes after a reduction in tree cover in subtropical and tropical regions.
CHAPTER 2. HISTORICAL LCC

Seasonal mean temperature

All models show that historical LCC entailed a cooling of the surface air temperature in winter in the mid-latitudes. This cooling is significant for all but one models over North America (lower panel of Fig. 2.6) and for all but two models over Eurasia (Fig. A.18). This demonstrates that the mid-latitude winter cooling previously reported in LUCID studies is also a robust feature in the CMIP5 models. The multi-model mean cooling is of about -0.3 and -0.4°C over North America, and -0.3 and -0.2°C over Eurasia for LUCID and CMIP5, respectively. We find that albedo changes are the dominating mechanisms for changes in surface air temperature in DJF when snow covers large areas and vegetation is mostly dormant, with 31% of the inter-model variance in LCC-induced temperature changes over North America being explained by changes in albedo (32% over Eurasia). The robust winter cooling is therefore consistent with the robust increase in albedo mentioned in a previous section.

In JJA, vegetation activity is highest and modifications of LH explain 32% of the inter-model variance in T over North America (16% over Eurasia), while the role of albedo is of a relatively lower importance (only 18% of the explained variance for North America and 11% for Eurasia). Consequently, there is less model agreement about the response of surface air temperature to LCC in the warm season. There are indeed as many LUCID models for which the reconstruction method indicates a significant cooling than a significant warming over both North America and Eurasia, with almost zero impact on average. As for CMIP5 models, the multi-model mean indicates an increase in surface temperature by ~0.1°C. Out of 11 models, 10 show a significant warming effect over North America and 5 over Eurasia, whereas only HadGEM2-ES shows a significant cooling effect in both regions. These results clearly show that, for a majority of CMIP5 models, during summertime high-LCC grid cells have warmed more than the surrounding areas during the industrial period. This also suggests a lower agreement about the regional-scale impact on surface air temperature (i.e., over all land grid cells) among CMIP5 models over mid-latitudes, compared to what was concluded in LUCID studies.

Over both North America and Eurasia, the impact on surface air temperature in MAM and SON is intermediate between those in DJF and JJA for all models. Most of them indicate a cooling effect of LCC in MAM, which equals about 0.15°C on average over both regions. The impact in SON is often of the same sign as in JJA but of lower magnitude, and multi-model mean changes almost equal zero.

In the subtropical South Asian region, the increases in albedo and decreases in LH simulated by almost all models have counteracting effects on temperature, leading to model disagreement on the simulated impacts of LCC on this variable (Fig. A.19). In contrast with the mid-latitudinal regions, we find no clear seasonal pattern in this domain, with individual models often
showing impacts of the same sign all year long.

### 2.3.3 Part 3: Comparison of model results with observations

In this section, we compare changes in surface air temperature simulated by the LUCID and CMIP5 models in response to historical LCC with present-day observations of the local effect of deforestation. Most of these observations purely rely on a spatial comparison between vegetation types, as opposed to our model analysis, which also emphasises temporal changes. However, in agreement with de Noblet-Ducoudré et al. (2012), we found that changes in background climate during the industrial period did not have a primary influence on the effects of LCC, which means that present-day LCC should impact temperature in the same direction as those that have occurred since 1870. For these reasons, we expect present-day observations of the effect of deforestation to indicate what the sign of the reconstructed temperature response to simulated land-cover perturbations should be.

We used the observational data from Lee et al. (2011), who compared air temperature measurements over forest and open land sites located close to each other (∼30 km on average) in the United States and Canada. Since they showed a clear contrasted effect of deforestation on daytime and nighttime temperature, we have investigated whether models are able to capture this feature. To do so, we selected 22 observational sites located within high-LCC grid cells for at least one of the analysed models, and computed the average difference in daily minimum (Tmin) and maximum (Tmax) temperature between forest and open land.

**Nighttime temperature**

The in situ observations indicate a cooling effect of deforestation during nighttime over mid-latitudinal North America, whereas the ability of the models to reproduce this behaviour strongly depends on the considered season (lower panel of Fig. 2.7). Open land is cooler than forests by almost 2°C on average along the year among the selected sites, with very few of them that depart from this behaviour (see also Figs. 2.8 and 2.9). This has also been observed by Vanden Broucke et al. (2015) for three paired sites over western Europe. Besides, some studies investigated the impact of deforestation on remotely sensed land surface temperatures (LSTs), either by comparing pixels that are mostly covered with forests versus with open land (Wickham et al., 2012; Peng et al., 2014; Zhao and Jackson, 2014; Li et al., 2015), or by comparing areas over which the forest cover evolved differently over the observation period (Alkama and Cescatti, 2016). These studies also show a cooling effect of deforestation during nighttime over temperate and boreal mid-latitudes (e.g., Zhao and Jackson, 2014; Li et al., 2015), although it is in some cases less pronounced (Peng et al., 2014; Alkama and Cescatti, 2016). The reasons
invoked for the lower nighttime temperatures over open land in these studies are its lower roughness length, which reduces turbulence and can thus bring less heat from the atmosphere to the surface if the boundary layer is stable (Lee et al., 2011), interactions between its lower evapotranspiration rates, cloud formation, and radiation, as well as variations in heat capacity (Peng et al., 2014; Vanden Broucke et al., 2015).

The amplitude of the reconstructed LCC effects on temperature from model simulations is lower than in the observations, which can be expected since they were obtained by comparing model grid cells that underwent partial deforestation, whereas observations intend to capture its full local effect. We find that, in agreement with observations, the 11 CMIP5 models simulate a significant decrease in Tmin in response to historical LCC during wintertime, while only 3 models out of 6 from the LUCID project reproduce this feature. In contrast, only one CMIP5 model (HadGEM2-ES) simulates a cooling of Tmin due to deforestation during summer, against two LUCID models (ARPEGE and SPEEDY).

**Daytime temperature**

Contrary to their results for nighttime, the in situ observations overall show higher values of Tmax over open land compared to forests and especially during the warm season, when the multi-site average indicates a daytime warming impact of deforestation by almost 1.5°C (higher panel of Fig. 2.7), while only few sites experience the opposite behaviour (Fig. 2.10). This effect is less strong in winter, with a multi-site average increase in Tmax of about only 0.5°C over open land compared to forests and more spatially heterogeneous results (see also Fig. 2.11). The findings from Vanden Broucke et al. (2015) for Europe go in the same direction as those of Lee et al. (2011) regarding summertime; nonetheless, they show a slight cooling effect of deforestation in winter. Similarly, during summertime, Alkama and Cescatti (2016), Li et al. (2015), Zhao and Jackson (2014), Peng et al. (2014) and Wickham et al. (2012) found higher daytime LSTs over open land than over surrounding forests for mid-latitudes, but observed more contrasted results during wintertime, and especially latitudinal variations that the poorer spatial coverage of the in situ data may not allow to capture. The higher daytime temperatures over open land during summer were explained by its lower roughness (Lee et al., 2011; Vanden Broucke et al., 2015) and its lower evapotranspiration rates (Peng et al., 2014; Li et al., 2015). This is counteracted by its higher albedo, which makes the difference in daytime temperature between open land and forests be almost zero during winter or at high latitudes (Lee et al., 2011), or even negative (Vanden Broucke et al., 2015; Li et al., 2015).

In the light of these observational results, we conclude that on average CMIP5 models are performing better at simulating the warming effect of deforestation on Tmax during the warm season: five of them exhibit this feature in JJA and four during SON, while that is not the case for any of the
LUCID models. All the analysed models show a cooling effect of historical LCC during winter, which is significant for 3 from the LUCID and 8 from the CMIP5 project. This is in contrast with the results of Lee et al. (2011) but concurs more with the other previously mentioned observational studies.

Because of their contrasted results on the effect of mid-latitudinal deforestation on daytime temperature, the various observational studies partly disagree on its impact on daily mean temperature. Consequently, this complicates the evaluation of the response of this variable to deforestation in the models presented in section 2.3.2. However, these different pieces of observational evidence show more uniform conclusions regarding the effect of deforestation on the Diurnal Temperature Range (DTR), therefore we will now look at whether these are in agreement with model results.

**Diurnal temperature range**

The in situ measurements indicate a diurnal asymmetry in the impact of deforestation on temperature over mid-latitudes, which is more pronounced in summer. As a result, they show an increase in the Diurnal Temperature Range (DTR) over open land compared to forests. This feature is also present in other observational studies and is particularly robust during the warm season. However, it contrasts very strongly with model results (Fig. 2.12 and Fig. A.24 for Eurasia). In fact, none of the analysed models simulate this behaviour: about half of them actually show a reduction of the DTR in response to deforestation, while the other half suggest almost zero effect on average throughout the year, even if they may exhibit some small increases for specific seasons (e.g., SPEEDY or CanESM2 in summer, HadGEM2-ES in autumn or IPSL-CM5A-LR in winter). Over South Asia, we find that only SPEEDY and CanESM2 simulate an increase in both Tmax and DTR and either a decrease or no change in Tmin during most of the year (Fig. A.25). These two models hence better reproduce the observational results from Zhang et al. (2014), who extended the analysis of Lee et al. (2011). In particular, they included some sites located in tropical South Asia and South America, where they also observed higher Tmax over open land but similar Tmin values compared to forests. However, they report these features for the whole year, contrary to what SPEEDY and CanESM2 simulate. In general, we find that many models simulate a significant influence of deforestation on the seasonal cycle of surface air temperature. There is no robust evidence for this in the in situ observations, even if LST-based observational studies suggest that this may be the case for daytime at high latitudes.

This comparison between models and observations would need to be extended more thoroughly in order to confirm its findings. Especially, more extensive observational datasets should be included, since the reported studies make use of temporally-limited data (between 3 and ∼15 years for the air temperature measurements, ∼10 years for the satellite observations), while the forest tower network used by Lee et al. (2011) also has a relatively poor
spatial coverage. Furthermore, more research should be done to reconcile the contrasting pieces of evidence on the impact of deforestation on temperature on a daily average or during daytime in the cold season. However, this primary evaluation suggests that all the analysed models have some deficiencies at representing the impact of deforestation on the diurnal cycle of temperature and thus highlights the need for more research to understand this poor performance.

2.4 Summary and Conclusions

We reconstructed the historical impacts of LCC on albedo, latent heat flux and temperature using all-forcings simulations from the LUCID and CMIP5 model intercomparisons. To do so, we used a method comparing climate change signals over neighbouring grid cells that experienced different rates of LCC but that were similarly affected by other historical climate forcings like CO$_2$.

First, using the LUCID simulations we showed that reconstructed estimates of LCC impacts compare well with results from factorial experiments explicitly isolating the LCC forcing. There is overall a very good concordance between the sign and the seasonal cycle of the LCC impacts estimated by both methods. We also found that, on average over the regions considered in this study, the impact of LCC on the analysed variables can easily be disentangled from that of other climate forcings with the use of the reconstruction method.

Second, we compared the reconstructed historical LCC effects from both LUCID and CMIP5 models. We found that they agree on an increase in albedo due to historical LCC. This increase is maximal in winter because of the snow-masking effect and lowest in summer. On the contrary, there is more disagreement about the sign of the change in LH in summer and spring. While the multi-model means of both LUCID and CMIP5 model subsets indicate a decrease in LH that is consistent with the increase in albedo, individual models do not share a consistent response of the partitioning between latent and sensible heat fluxes. The agreement about albedo changes leads to a homogeneous cooling effect of LCC among all models during winter. However, since the response of evapotranspiration plays a more important role in summer, there is more disagreement about the impact on temperature in this season. Overall, a great majority of the analysed models exhibit a local warming effect of LCC during summer, which contrasts with the results from previous LUCID studies.

In a third step, we compared our findings with observational evidence of the effect of deforestation on surface air temperature in North America. We find that none of the analysed models are able to represent both the observed warming effect of deforestation during daytime in summer and its cooling effect during nighttime, and therefore the resulting increase in DTR.
Given the relative scarcity of observations of the effect of deforestation on climate and the existence of contrasting observational results regarding its impact during daytime in winter, this primary model evaluation needs to be extended. However, it already reveals some model deficiencies that need to be investigated in more detail, for example by a joint analysis of the effect of deforestation on changes in albedo, LH and temperature in observations in order to disentangle the effects of different drivers of temperature changes, and evaluate the representation of these mechanisms in models.

In conclusion, for the first time we demonstrated extensively the suitability of the employed reconstruction method to study the effects of temporal LCC on albedo, surface fluxes, and surface air temperature. We then used it to identify similarities and differences in the historical impacts of LCC as simulated by 17 GCMs from the LUCID and CMIP5 model intercomparison projects. Thereby, we found that some results from LUCID studies are confirmed although substantial differences are also identified, especially regarding the impact of LCC during summertime. Besides, we extended this multi-model analysis with a comparison between model results and observations, which is to our knowledge new. This enabled us to highlight some fundamental issues with the representation of the LCC effects on the diurnal cycle of temperature in current land surface models. Nevertheless, it overall suggests that more recent CMIP5 models are closer to observations in that respect, hence underlining the positive effects of recent model developments.

2.5 Acknowledgments

We acknowledge partial support from the European Union through the projects FP7 EMBRACE (grant agreement No 282672), H2020 CRESCENDO (grant agreement No 641816) and ERC DROUGHT-HEAT (contract No 617518). We thank Victor Brovkin and an anonymous reviewer for their constructive comments on the manuscript. We also thank very much Juan Pablo Boisier, Ruth Lorenz, Nathalie de Noblet-Ducoudré, Andy Pitman and all LUCID modellers for providing LUCID data, as well as Xuhui Lee and colleagues for making the observational data available. We also acknowledge the World Climate Research Programme’s Working Group on Coupled Modeling, which is responsible for CMIP, and we thank the climate modelling groups who took part in this project for producing and making available their model output. For CMIP the U.S. Department of Energy’s Program for Climate Model Diagnosis and Intercomparison provides coordinating support and led development of software infrastructure in partnership with the Global Organization for Earth System Science Portals. Besides, we are very grateful to Urs Beyerle for his management of the CMIP5 database at ETH. Finally, we also thank Chris Jones, Vivek Avora, Ingo Bethke and Dave Lawrence for providing additional data from CMIP5 simulations.
Figure 2.4: Comparison of the reconstruction and factorial experiments methods showing LCC-induced changes in albedo (up), latent heat flux (middle) and daily mean temperature (bottom) over North America in LUCID models. The numbers on the left hand-side of each panel indicate the slopes of the regression line between the seasonal mean impacts diagnosed by the reconstruction vs the factorial experiments method, as well as the associated correlation coefficients. Dots indicate that results are statistically significant from zero in the case of the factorial experiments method and statistically significant from zero and the noise estimates in the case of the reconstruction method (at the 5% level, estimated with two-tailed t-tests considering the spread between ensemble members).
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Figure 2.5: Signal-to-noise ratios for seasonal mean albedo, latent heat flux, and daily mean temperature over North America in LUCID models. Small dots stand for individual grid cells, while big dots represent the domain-averaged signal-to-noise ratio.
Figure 2.6: Reconstructed impacts of LCC on seasonal mean albedo (top), latent heat flux (middle) and temperature (bottom) over North America in LUCID (left) and CMIP5 (right) models. The different colors refer to different seasonal averages. The number of ensemble simulations included in the analysis is indicated in black. LCC impacts are calculated based on the decrease in tree cover (threshold = -15). In the case of CMIP5, the multi-model mean (M-M M) was computed by giving to the two models of the IPSL family and the two models from the MPI family only half a weight, while models including the CLM land surface model (CCSM4, CESM1-CAM5, CESM1-FASTCHEM and NorESM1-M) were given a quarter of a weight each. Dots indicate that results are significantly different at the 5% level from zero as well as from the noise estimates computed for each ensemble member (according to a two-tailed t-test).
Figure 2.7: Impacts of LCC on the diurnal cycle of temperature, according to historical reconstructions from LUCID and CMIP5 models and from observations. Left, center As in the bottom panel of Fig. 2.6, but for Tmax (top) and Tmin (bottom). Right Observed difference in Tmax and Tmin between open land and forest, averaged over 22 paired sites in North America (data are from Lee et al., 2011). The vertical lines represent two standard deviations within the sites.
Figure 2.8: Top Differences in observed DJF Tmin between open land and forest for the selected 22 paired sites from Lee et al. (2011). The color indicates the magnitude of the difference, while the size of the dot indicates the number of years (between three and 13). Bottom Reconstructed DJF LCC impacts on Tmin for each model.
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Figure 2.9: As in Fig. 2.8, but for JJA.
Figure 2.10: Top Difference in observed JJA Tmax between open land and forest for the selected 22 paired sites from Lee et al. (2011). The color indicates the magnitude of the difference, while the size of the dot indicates the number of years (between three and 13). Bottom Reconstructed JJA LCC impacts on Tmax for each model.
Figure 2.11: As in Fig.2.10, but for DJF.
Figure 2.12: Top Seasonal cycle of the mean observed difference in daily maximum (red) and minimum (blue) temperatures between open land and forest over the selected 22 paired sites from Lee et al. (2011). The boxes indicate the interquartile range, while the whiskers show the range between the first and ninth deciles. Bottom Seasonal cycle of the reconstructed LCC impact for 6 LUCID models and 11 CMIP5 models over North America. The full lines indicate the results for the ensemble mean, while the dashed lines represent the spread between ensemble simulations (two standard deviations). Note the different Y-axis scale between the topmost plot and the others.
Historical deforestation locally increased the intensity of hot days in northern mid-latitudes

Abstract The effects of past and future land-cover changes on climate are disputed (Mahmood et al., 2014; Pitman et al., 2009). Modelling studies generally indicate that the biogeophysical effects of historical deforestation led to an albedo-induced cooling over mid-latitudes (de Noblet-Ducoudré et al., 2012), which is reflected by the negative radiative forcing from land cover change reported in the last IPCC report (IPCC, 2013). However this view has been recently challenged (Kumar et al., 2013a; Lejeune et al., 2017; Bright et al., 2017), and is not consistent with new observational evidence indicating a warming effect of deforestation during daytime (Lee et al., 2011; Li et al., 2015; Alkama and Cescatti, 2016). Here we show that historical deforestation has led to a substantial local warming of daytime heat extremes over the northern mid-latitudes using observation-constrained state-of-the-art climate

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model experiments. We estimate that moderate reductions in tree cover in these regions have contributed by at least one third to the local warming of the hottest day of the year by present-day since pre-industrial time, and were responsible for most of it before 1980. Our results imply that landscape changes need to be considered when studying past and future changes in heat extremes. Unlike previous studies emphasising the counterproductive effect of afforestation/re-forestation in temperate regions (Schwaab et al., 2015; Arora and Montenegro, 2011), these results highlight a potentially overlooked co-benefits of forest-based mitigation through local biogeophysical mechanisms, in addition to carbon dioxide removal.

3.1 Main

During the industrial period, large areas of primary vegetation like forests and natural grasslands were converted into croplands and pastures, in particular in northern mid-latitudes (Klein Goldewijk et al., 2011). These land-cover changes (LCC) have had substantial impacts on climate by altering the carbon stocks, which contributed to the increase in the CO$_2$ atmospheric concentration (biogeochemical effects IPCC, 2013), as well as by modifying land surface properties such as albedo, evapotranspiration and roughness, affecting the surface energy budget (biogeophysical effects Davin et al., 2007; de Noblet-Ducoudré et al., 2012; Kumar et al., 2013a; Lejeune et al., 2017). If the biogeophysical effects have had limited consequences at the global scale, they have impacted annual mean temperature by a similar magnitude as the concomitant increase in greenhouse gases (GHG) over the regions that have experienced important LCC (de Noblet-Ducoudré et al., 2012).

Some modelling studies indicated that the effects of historical LCC were even more pronounced for hot extremes. However they have revealed a strong model disagreement concerning the overall sign of these effects in mid-latitudes, despite more indication for a cooling effect. For example, three climate models out of four that took part in the model intercomparison project LUCID simulated that historical LCC had diminished the intensity of the extremely warm daytime temperatures over the northern mid-latitudes during summer (Pitman et al., 2012). However, one last model as well as a similar study using another model (Avila et al., 2012) showed the opposite effect. Furthermore, a detection/attribution study using the optimal fingerprinting method was conducted with the HadGEM2-ES model (Christidis et al., 2013). It simulated a global cooling trend of both mean and extreme temperatures due to historical LCC over the last half of the 20$^{th}$ century, which was detected in observations in the case of warm extremes.

In contrast with most modelling results, observational evidence suggests that deforestation locally increases daytime temperature over mid-latitudes. In situ observations over North America comparing neighbouring measurement sites located over different land cover types hence indicate that open
lands are overall warmer than forests during daytime in summer (Lee et al., 2011). This result has additionally been confirmed by global-scale studies based on satellite data that were collected under clear-sky conditions (Li et al., 2015; Alkama and Cescatti, 2016). Furthermore, satellite observations in the center of France showed that the higher surface temperatures over open lands compared to forests during daytime were exacerbated during heatwaves as opposed to normal summer conditions (Zaitchik et al., 2006). These findings based on spatial comparisons of present-day observations therefore rather suggest that historical deforestation may have amplified extremely warm temperatures during daytime. The implicit space-for-time analogy used to reach this conclusion is justified by the results from the LUCID project, which show that changes in background climate during the industrial period have had little influence on the sensitivity of regional surface temperature to LCC (de Noblet-Ducoudré et al., 2012).

In this study, we use observational data to constrain the historical impact of deforestation on hot extremes in 11 models that took part in the Coupled Model Intercomparison Project Phase 5 (CMIP5 Taylor et al., 2012, see list in Table 3.1) – i.e. the largest model subset used in this context. These recent, fully-coupled models all explicitly represent land surface processes and include historical LCC as a climate forcing, and were found to be generally able to reproduce the spatial distribution and the trend patterns of hot temperature extremes from the gridded observational dataset HadEX2 (Sillmann et al., 2013). We reconstruct the local impacts of historical deforestation on mean daily maximum surface air temperature (TX) in the warm season as well as on its yearly maximum value (TXx) which are simulated by these models from 1861 to 2000 compared to a pre-industrial control period. For this purpose, we use a recently developed methodology (Kumar et al., 2013a; Lejeune et al., 2017) based on a comparison of historical temperature changes over neighbouring areas that have experienced various deforestation rates (see 3.2). It compares very well with the more classical approach using factorial experiments over the analysed regions, while being less subject to interannual variability (see Fig. B.1).

We find that only 5 of the 11 CMIP5 models show consistency with in situ observations with respect to summer daytime temperature sensitivity to deforestation (Table 3.1). In the rest of this study, we therefore focus on the results of these selected models (CanESM2, IPSL-CM5A-LR, IPSL-CM5A-MR, MPI-ESM-LR and MPI-ESM-MR) and their multi-model mean (M-M M) on the ground that they capture more realistically the response of summer daytime temperature to deforestation, which is most relevant for our investigation of changes in hot extremes.

The M-M M shows that historical deforestation has led to local increases in TXx over extensive parts of North America, Eurasia and South Asia, but also southern South America, eastern Australia and southeastern Africa during present-day (1981-2000) compared to pre-industrial conditions (Fig. 3.1).
Table 3.1: Change in June-July-August TX due to deforestation over North America in CMIP5 models and observations.

<table>
<thead>
<tr>
<th>Model name</th>
<th>JJA  δTX_{def} over North America (°C)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CanESM2</td>
<td>0.77 [0.59, 0.88]</td>
</tr>
<tr>
<td>CCSM4</td>
<td>-0.09 [-0.14, -0.04]</td>
</tr>
<tr>
<td>GFDL-CM3</td>
<td>-0.06 [-0.26, 0.13]</td>
</tr>
<tr>
<td>GFDL-ESM2-G</td>
<td>0.00 [-0.03, 0.04]</td>
</tr>
<tr>
<td>GFDL-ESM2-M</td>
<td>-0.04 [-0.07, -0.00]</td>
</tr>
<tr>
<td>HadGEM2-ES</td>
<td>-0.44 [-0.55, -0.34]</td>
</tr>
<tr>
<td>IPSL-CM5A-LR</td>
<td>0.27 [0.15, 0.40]</td>
</tr>
<tr>
<td>IPSL-CM5A-MR</td>
<td>0.18 [0.07, 0.30]</td>
</tr>
<tr>
<td>MPI-ESM-LR</td>
<td>0.12 [-0.01, 0.27]</td>
</tr>
<tr>
<td>MPI-ESM-MR</td>
<td>0.22 [0.09, 0.36]</td>
</tr>
<tr>
<td>NorESM1-M</td>
<td>-0.17 [-0.29, -0.08]</td>
</tr>
<tr>
<td>Observations</td>
<td>1.16 [0.26, 1.85]</td>
</tr>
</tbody>
</table>

Mean model estimates are computed over grid cells where the deforestation rate by present-day (1981-2000) compared to pre-industrial exceeded 15%. The numbers in brackets indicate the 90% of the spread in the reconstructions for the models, and the interquartile range between individual paired measurement sites for the observations. Models consistent with observations are highlighted in bold.

Model agreement is particularly high over large areas of North America and Eurasia, as indicated by the stippling. In contrast, according to the M-M M only a few regions have experienced a cooling in response to deforestation (mostly southeastern Brazil), besides individual models exhibit low agreement there. The most important deforestation-induced warming of TXx has occurred over North America and Eurasia, where it equals 0.3°C on average over areas that have been at least moderately deforested (encircled in green on Fig. 3.1), and reaches 1°C locally over the Great Plains. The mean warming is more moderate over South Asia (0.1°C), with only the CanESM2 model showing significant changes. Despite the substantial spread between the individual models, for most of them deforestation impacts TXx slightly (but not significantly) more than mean summer temperature.

We also analyse the sensitivities of TXx and mean June-July-August (JJA) TX to local deforestation. Over North America and Eurasia, the M-M M indicates that a diminution of the tree cover by 10% over a model grid cell would lead to a local increase in TXx by 0.2°C, and in JJA TX by 0.08°C (Fig. 3.2 and Table 3.2). These sensitivities are of the same order of magnitude, but a bit lower than those that were observed between 2003
Figure 3.1: Reconstructed local effects of deforestation on TXx for present-day (1981-2000) compared to pre-industrial conditions. The map shows multi-model mean (M-M M) estimates, with the stippling indicating areas where at least three models show changes of the same sign that are significant at the 5% level. The insets show the average changes in mean summer TX (yellow) and TXx (red) due to deforestation (filled bars) and to other forcings (hatched bars) for each of the selected models and the multi-model mean (M-M M), with the black vertical lines indicating 90% of the spread in the reconstructions for the individual models, and the model spread in the case of the M-M M. Results were averaged over the areas of North America, Eurasia and South Asia that have experienced at least 15% of deforestation according to the M-M M (green contours). The same areas are considered in Fig. 3.3, while all the land grid cells within the regions highlighted in black were included in Fig. 3.2.

and 2012 over temperate, boreal and arid areas in a recent satellite-based study (Alkama and Cescatti, 2016) (+0.3-0.6°C in mean JJA TX for 10% of deforestation). If this constitutes further indication that the selected models correctly simulate the sign of the response of summer TX to deforestation over mid-latitudes, it also primarily suggests that CanESM2 best captures the magnitude of this response, even though it is 3-4 times higher than in the other models. This would hence indicate that the results of the M-M M are conservative. However, methodological differences in the employed reconstruction method as well as in the regions used for averaging prevent any
precise quantitative comparison between the mentioned observational results and ours at this stage.

Figure 3.2: Sensitivity of June-July-August (JJA) TX (yellow) and TXx (red) to deforestation over North America and Eurasia. The reconstructed local effects of deforestation are plotted against the deforestation rate, for each of the selected models and the multi-model mean (M-M M). Each dot represents the reconstructed change in one of the temperature indices over one grid cell of these regions (shown in black in Fig. 3.1), averaged over a 20-year period of the full analysis period (i.e. 1861-1880, 1881-1900, etc.). The yellow and red lines show linear regressions without intercept within the data clouds of the corresponding colours (the red dots were plotted over the yellow ones). The values of the sensitivities to 10% of deforestation based on these regressions are shown in Table 3.2.

Extensive deforestation took place early in the industrial period over the northern mid-latitudes, consequently by 1920 the resulting increases in TXx through biogeophysical effects had already reached 0.3°C (∼75% of their present-day values) over the most deforested areas of North America and Eurasia, according to the M-M M (Fig. 3.3). On average over the 1901-1920 period, local deforestation was responsible for the entirety of the warming of TXx over these regions, while other forcings and internal variability had overall led to no changes over North America and to a slight cooling over Eurasia. Our reconstructions show that the deforestation-induced increase in TXx then levelled off over the rest of the 20th century. In the same time, the influence of other forcings became more important, leading to a total
3.1. MAIN

Table 3.2: Sensitivity of June-July-August (JJA) TXand TXx to deforestation over North America and Eurasia.

<table>
<thead>
<tr>
<th>Model</th>
<th>$\delta T X_{def}$ for 10% deforestation ($^\circ$C)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>JJA</td>
</tr>
<tr>
<td>CanESM2</td>
<td>0.25 [0.002]</td>
</tr>
<tr>
<td>IPSL-CM5A-LR</td>
<td>0.11 [0.001]</td>
</tr>
<tr>
<td>IPSL-CM5A-MR</td>
<td>0.10 [0.001]</td>
</tr>
<tr>
<td>MPI-ESM-LR</td>
<td>0.02 [0.001]</td>
</tr>
<tr>
<td>MPI-ESM-MR</td>
<td>0.03 [0.001]</td>
</tr>
<tr>
<td>M-M M</td>
<td>0.08 [0.001]</td>
</tr>
</tbody>
</table>

Values correspond to the coefficients of the linear regressions presented in Fig. 3.2. Standard errors are indicated in brackets.

warming by 1.3$^\circ$C on average over North America and 1$^\circ$C over Eurasia. Although this estimate is very much model-dependent (Fig. 3.1), the M-M M therefore suggests that the relative contribution of the biogeophysical effects of deforestation decreased to $\sim$30% by the end of the 20$^{th}$ century. However, it still remained as high as 50% over North America and 100% over Eurasia on average over the 1961-1980 period. Furthermore, since forest removal was by far the largest contributor to the carbon emissions from historical land-use changes (Houghton, 1999), which accounted for a third of the cumulative total emissions over the 1850-2000 period (IPCC, 2013; Le Quéré et al., 2016), we calculate that the combined biogeophysical and biogeochemical effects of deforestation were responsible for about half of the increase in TXx by 2000 over the considered regions, according to the M-M M (see 3.2).

Because of the large internal climate variability that prevails at regional scale, uncertainties in the observational datasets, as well as possible missing processes in current climate models, the warming contribution of the biogeophysical effects of historical deforestation may be difficult to detect in the observed changes in TXx over these regions, despite the strong modelling evidence we have presented. For example, over North America the selected models neither simulate the warm anomaly in TXx by about 1.5$^\circ$C measured over the 1921-1940 period, corresponding to the Dust Bowl event, nor the slight decrease in TXx over the last half of the 20$^{th}$ century (better known as the "warming hole"). These model weaknesses are also exhibited by the non-selected models (see Fig. B.2), while the inability to represent the "warming hole" is a common characteristic amongst CMIP5 models (Kumar et al., 2013b). Both the Dust Bowl and the warming hole have been partly explained by land-atmosphere feedbacks, resulting from low springtime precipitation or changes in the hydrological cycle, respectively (Schubert et al., 2004; Pan et al., 2004). Yet, climate variability also played a role through anomalous large-scale oceanic and atmospheric conditions (Schubert
CHAPTER 3. HISTORICAL LCC AND HOT EXTREMES

Figure 3.3: Importance of the local effects of deforestation in the historical evolution of TXx over North America and Eurasia. The red and blue lines indicate the multi-model mean estimates of the changes in TXx due to deforestation and to all forcings combined, respectively, on average over the regions highlighted in green in Fig. 3.1. The envelopes in light blue and light red show the spread between the selected models. The contribution of the deforestation-induced local changes in TXx to its total changes are indicated by the green bars in the lower panels. Observations from the Berkeley and HadEX2 datasets over these regions are indicated by the black line and the black line with dots, respectively. The observational coverage of each dataset over the considered regions is indicated between commas. For visualisation purposes, the observational results were vertically shifted so that the 20th-century mean total changes in TXx from models and observations are equal.

et al., 2004; Kumar et al., 2013b). Here, we do not find evidence that the biogeophysical effects of deforestation have significantly contributed to or counteracted these two climate features. However, taking human-induced land degradation due to inadapted agricultural practices into account was found to better explain the magnitude and the location of the Dust Bowl (Cook et al., 2009). Besides, statistically significant correspondences have been observed between the spatial pattern associated to the warming hole and trends in locally-cooling land management practices, namely irrigation and cropland intensification (Mueller et al., 2016). These findings highlight the role of land management on local climate, an aspect that is mostly not considered in current climate models. As for Eurasia, the substantial spread between the observational datasets hinders a robust assessment of the role of deforestation in the observed trend in TXx in this region.

This assessment points at new challenges for the Detection and Attribution community. To our knowledge, the only detection/attribute study
that was able to detect an influence of LCC on daytime hot extremes so far concluded that they had a cooling effect (Christidis et al., 2013). However, we identified that the HadGEM2-ES model with which this result was obtained does not capture the sign of the change in TX due to deforestation during the warm season. This analysis should therefore be repeated with other models that simulate this aspect more realistically. Nevertheless, even if we identified a strong local deforestation-induced temperature signal, this may be difficult to detect in the observations by using the classical, global-based methodologies because these would also include non-local effects of deforestation, which may have counteracting effects on temperature (Winckler et al., 2017). Existing regional-scale detection/attribution tools may not help either because they are more sensitive to internal variability and observational uncertainty. We therefore encourage the development of new methodologies to overcome these issues.

In summary, these results provide a new perspective on the importance of historical deforestation in anthropogenic climate change at regional scale. Contrary to most previous studies which suggested that the biogeophysical effects of historical deforestation had mitigated daytime hot extremes over mid-latitudinal regions (Christidis et al., 2013; Pitman et al., 2012), our observation-constrained analysis of CMIP5 models indeed shows that they have actually led to significant local increases in TXx over many areas in the world. Our analysis indicates that they were responsible for most of the warming of TXx over most-deforested mid-latitudinal regions by as far as 1980. Besides, the contribution of deforestation to this increase still equals \( \sim 50\% \) at present-day once the warming entailed by the associated GHG emissions is also considered.

This analysis also emphasises that non-radiative climate forcings should receive more consideration in comprehensive assessments of past and future temperature changes, especially at the regional scale. Hence, we showed that the local temperature response to deforestation during hot days is dominated by warming non-radiative effects (entailed by decreases in evapotranspirative fraction and roughness) rather than cooling radiative ones (associated to an increase in albedo), in line with recent observational results (Bright et al., 2017). This highlights the limitations of the Radiative Forcing framework that is classically used to compare climate forcings (IPCC, 2013), an issue which had already been mentioned in the context of LCC (Davin et al., 2007).

In conclusion, if it is well-established that the GHG forcing is responsible for most of the observed global warming by present-day (IPCC, 2013), our results shed light on the importance of LCC for the historical evolution of hot extremes at regional scale. This is also relevant for future land-use strategies. Even if a small biogeophysical increase of annual mean temperature has previously been mentioned as a possible consequence of af/reforestation policies that would be primarily designed for carbon dioxide removal in temperate regions (Schwaab et al., 2015; Arora and Montenegro, 2011), our study indeed
suggests that they could locally help reduce the risk of heat extremes. Besides, the mitigation potential of land management practices for this purpose has also been underlined, as there are now multiple pieces of evidence that they have impacts of similar magnitude as LCC on temperature extremes (Davin et al., 2014; Thiery et al., 2017). Current model developments go in the direction of including these aspects, which should therefore be considered in further studies in order to complement the results we have presented here.

3.2 Methods

3.2.1 CMIP5 simulations

We analyse historical ("all-forcings") as well as pre-industrial control simulations from 11 CMIP5 models for which land cover information as well as TX values at daily resolution are available. The ensemble size and the references for each model are indicated in Table B.1. We first compute TXx as well as mean JJA TX over each land grid cell and for each year of the 1861-2000 period, and then compare them to their average values over the first 200 years of the pre-industrial control simulations. After calculation of the reconstructed effects of deforestation, the results from each model were regridded on a common 2.5° X 2.5° grid. The mean of the five selected models (multi-model mean or M-M M) was computed by assigning to each IPSL and MPI model only half of the weight given to CanESM2.

3.2.2 Observational data

The observations from the HadEX2 (Donat et al., 2013) and Berkeley (Rohde et al., 2013) datasets were regridded on the same common grid as the models before the analysis was conducted. We consider only the grid cells for which TXx is available for 90% of the 1901-2000 period, and calculated TXx in the Berkeley dataset only for the years for which at least 90% of the daily TX data is available. The in situ observations used to constrain the models were obtained by comparing surface air temperature measurements over flux towers located over forests and weather stations located over open land (Lee et al., 2011). We consider 33 paired sites in total, that are located in North America between 28 and 56°N and have between 3 and 13 years of overlapping measurement. The average linear distance between forest and open land sites is 28 km. Corrections have been applied in the original publication in order to take the elevation difference (59 m on average) into account.

3.2.3 Local impacts of deforestation on temperature

We reconstruct the local impacts of historical deforestation on mean JJA TX and on TXx by fitting linear regressions between the simulated temporal changes in these variables and those in tree fraction within spatially moving
3.2. METHODS

windows encompassing 5 X 5 model grid cells (also called "big boxes"). This method assumes that LCC constitute a spatially heterogeneous forcing which mostly impacts temperature in each grid cell individually, in contrast to other climate forcings like greenhouse gases (GHG) which affect it similarly in all grid cells from a same big box. Similar methodologies based on this same assumption were already employed to analyse CMIP5 models (Lejeune et al., 2017; Kumar et al., 2013a).

In practical terms, to derive the changes in Txx due to local deforestation over a given land grid cell $i$ ($\delta T_{Xx}^{def}(i)$), we consider a big box of a size of 5 X 5 grid cells centered over $i$. Within this big box, for every year the total changes in Txx ($\delta T_{Xx}$) for each land grid cell are modelled by linear regression using four spatial predictors: the deforestation rate experienced by the grid cells between the pre-industrial period and the year of interest ($defrate$), their latitude ($lat$), longitude ($lon$) and elevation ($elev$), such that:

$$\delta T_{Xx} = \beta_0 + \beta_1 \times defrate + \beta_2 \times lat + \beta_3 \times lon + \beta_4 \times elev.$$  \hspace{1cm} (3.1)

$defrate$, $lat$, $lon$ and $elev$ are here vectors containing up to 25 values, while the $\beta$ coefficients are specific to each year and each particular big box. $\delta T_{Xx}^{def}(i)$ is then obtained by scaling the results of this local regression with the deforestation rate experienced over $i$ (compared to pre-industrial):

$$\delta T_{Xx}^{def}(i) = \beta_1 \times defrate(i).$$  \hspace{1cm} (3.2)

We apply the same method to simulate changes in mean JJA TX. Previous studies based on similar methodologies employed another approach to separate the grid cells within each big box in two bins. They indeed used an ad hoc threshold corresponding to a critical change in either crop (Kumar et al., 2013a) or tree fraction (Lejeune et al., 2017). The suitability of the threshold-based method to investigate the local impacts of historical LCC on seasonal mean albedo, surface heat fluxes and surface air temperature was previously demonstrated (Lejeune et al., 2017), showing that it gives similar results to the more commonly used factorial experiment method (i.e. the difference between a model experiment in which the land-cover forcing is applied and a control one). Here we apply the regression-based reconstruction method over each land grid cell for which the corresponding big box contains at least 15 land grid cells, which is an advantage compared to the threshold-based approach that could only be applied to grid cells where the intensity of historical LCC exceeded the specified ad hoc threshold. We chose to use three spatial predictors (latitude, longitude, and elevation) in addition to the deforestation rate experienced by the grid cells, because we found that this limits the reconstruction of false deforestation signals or artefacts, which are in reality due to natural climatic gradients within the big boxes and not related to variations in the LCC forcing. This can however make our estimates of the local impacts of deforestation slightly conservative.
3.2.4 Uncertainties about the reconstructions

Uncertainties about the reconstructions are computed by applying the regression to each ensemble simulation of a given model. Besides, for each ensemble simulation and each big box a jackknife resampling is also conducted: Alternatively, and as many times as there are land grid cells with non-missing values in the big box, the values from one grid cell are systematically left out before the regression is computed again based on this new sample. We thus obtain between 16 and 26 estimates of $\delta T X_{x_{\text{def}}}^J$ and $\delta T X_{x_{\text{def}}}^{J,A}$ for each land grid cell of each ensemble simulation. We then retain the median of these estimates, which increases the robustness of our results by eliminating strong dependences on single model grid cells (Efron, 1982).

3.2.5 Biogeochemical effects of deforestation

Global assessments based on bookkeeping methods concluded that land-use change was responsible for 33% of the cumulative carbon emissions over the 1861-2000 period (Le Quéré et al., 2016; Houghton, 1999). Since it was also estimated that the net land-to-atmosphere carbon flux due to deforestation was as important as the net balance between emissions from all types of land disturbances and forest regrowth over the 1850-1990 period (Houghton, 1999), and responsible for 85% of it in the 1990s (Houghton, 2003), we calculate that at least 28% of the cumulative carbon emissions over the analysis period were due to deforestation. Because the other forcings included in CMIP5 overall have a cooling effect (aerosols, volcanic emissions, Taylor et al., 2012; IPCC, 2013), this means that the biogeochemical effects of deforestation make up for at least $\sim$30% of the total present-day warming compared to the pre-industrial period.

3.3 Acknowledgments

We acknowledge partial support from the European Union through the projects FP7 EMBRACE (grant agreement No 282672), H2020 CRESCENDO (grant agreement No 641816) and ERC DROUGHT-HEAT. We thank very much Xuhui Lee and colleagues for making the observational data available. We also acknowledge the World Climate Research Programme’s Working Group on Coupled Modeling, which is responsible for CMIP, and we thank the climate modelling groups who took part in this project for producing and making available their model output. For CMIP the U.S. Department of Energy’s Program for Climate Model Diagnosis and Intercomparison provides coordinating support and led development of software infrastructure in partnership with the Global Organization for Earth System Science Portals. Besides, we are very grateful to Urs Beyerle for his management of the CMIP5 database at ETH. Finally, we also thank Chris
Jones, Vivek Avora, Ingo Bethke and Dave Lawrence for providing additional data from CMIP5 simulations.
Influence of Amazonian deforestation on the future evolution of regional surface fluxes, circulation, surface temperature and precipitation

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Abstract The extent of the Amazon rainforest is projected to drastically decrease in future decades because of land-use changes. Previous climate modelling studies have found that the biogeophysical effects of future Amazonian deforestation will likely increase surface temperatures and reduce precipitation locally. However, the magnitude of these changes and the potential existence of tipping points in the underlying relationships is still highly uncertain. Using a Regional Climate Model at a resolution of about 50 km over the South American continent, we perform four ERA-interim-driven simulations with prescribed land cover maps corresponding to present-day

⁰This publication was slightly changed from its original version by adapting abbreviations and spelling in order to ensure consistency throughout this thesis.
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vegetation, two deforestation scenarios for the twenty-first century, and a totally-deforested Amazon case. In response to projected land cover changes for 2100, we find an annual mean surface temperature increase of 0.5°C over the Amazonian region and an annual mean decrease in rainfall of 0.17 mm/day compared to present-day conditions. These estimates reach 0.8°C and 0.22 mm/day in the total-deforestation case. We also compare our results to those from 28 previous (regional and global) climate modelling experiments. We show that the historical development of climate models did not modify the median estimate of the Amazonian climate sensitivity to deforestation, but led to a reduction of its uncertainty. Our results suggest that the biogeophysical effects of deforestation alone are unlikely to lead to a tipping point in the evolution of the regional climate under present-day climate conditions. However, the conducted synthesis of the literature reveals that this behaviour may be model-dependent, and the greenhouse gas-induced climate forcing and biogeochemical feedbacks should also be taken into account to fully assess the future climate of this region.

4.1 Introduction

Recent international environmental summits have recognized the importance of forests in acting as a carbon sink for the climate system, and therefore advocated international efforts to curb deforestation (UNFCCC, 15th Conference of the Parties, 2009). However, replacement of forests by agricultural land or urban environments has other climatic consequences. Deforestation indeed perturbs not only carbon fluxes, but also energy and water fluxes between forests and the atmosphere, because it modifies the physical characteristics of the land surface, such as its albedo, evapotranspiration, and roughness (Bonan, 2008a). Pongratz et al. (2010) and de Noblet-Ducoudré et al. (2012) have shown that for historical land-cover changes (LCC), these biogeophysical climatic impacts could have been regionally as strong or even stronger than the biogeochemical ones (i.e. those related to the associated carbon emissions to the atmosphere).

Thus, biogeophysical effects have to be taken into account in order to fully assess future climate changes, especially in regions where anthropogenic modifications of land cover are expected to be large in the future. Amazonia is one of them: Deforestation has intensely taken place there since the 1970s (Fearnside, 2005), with a gross deforestation rate as high as \(~25,000\) km² yr⁻¹ in the 1990s (Achard et al., 2002); the forest is now still shrinking, and the pressure for more agricultural land is likely to continue. Observations show that in Amazonia, pastures have a higher albedo than forests, but lower roughness lengths and evapotranspiration rates (Jipp et al., 1998; von Randow et al., 2004). Consequently, while the deforestation-induced increase in albedo tends to cool the surface by decreasing net solar radiation amount, the decreases in evapotranspiration and roughness length have
a warming effect. Less evapotranspiration indeed means a lower latent heat flux, which is compensated by a higher sensible heat flux and tends to increase the near-surface temperature. Additionally, a lower roughness length leads to a reduced turbulent transport of heat to the atmosphere, hence to heat accumulation close to the surface. In spite of these opposite effects, modelling studies overall agree that deforestation in Amazonia locally leads to temperature increases, even if the spread between models is large (d’Almeida et al., 2007). In the same way, a decrease in precipitation over the Amazonian basin was generally modelled in response to local deforestation. A first explanation for this result is that the local input of water to the atmosphere through evapotranspiration is lowered, which reduces precipitation recycling within the Amazonian basin (Eltahir and Bras, 1993). Besides, some modelling studies found that atmospheric moisture input in the basin would be reduced due to deforestation, thereby amplifying the diminution of precipitation. However, this response of large-scale circulation and its impact on moisture convergence is debated in the literature (Marengo, 2006).

The first modelling studies investigating the biogeophysical impacts of future Amazonian deforestation used Global Circulation models (GCMs) with relatively coarse resolutions (from 1.8 to 7.5°, e.g. Dickinson and Henderson-Sellers, 1988; Lean and Warrilow, 1989; Nobre et al., 1991). They performed similar idealised experiments in which they replaced the Amazonian forest by grassland, but the spread in the magnitude of the simulated climate impacts is high. Many studies were realised by the same modelling centers, which successively published follow-up studies in which they used the same model but implementing revised parameterisations and/or increased resolution, in order to improve the representation of both current and post-deforestation climates.

In the late 2000s, similar modelling studies using mesoscale-resolution Regional Climate Models (RCMs) (∼0.2-0.5°) have been published (e.g. Moore et al., 2007; Ramos da Silva et al., 2008; Walker et al., 2009). Their higher resolution presents several advantages. Firstly, the spatial variability of climate conditions is better represented than in large grid cells. Secondly, it allows to resolve explicitly some of the biggest mesoscale phenomena that bring an important part of precipitation over this region (Greco et al., 1990), which is not well assessed by the parameterisation schemes of lower-resolution GCMs (Dai, 2006). Lastly, increased resolution makes the implementation of more complex and more finely-resolved land cover maps as surface conditions possible. These represent realistic scenarios of future land covers based on the current land settlement and on various economic assumptions. However, because of the increase in computational demand, the RCM experiments conducted by Moore et al. (2007), Ramos da Silva et al. (2008) and Walker et al. (2009) were limited to two months or one year, and may thus be affected by spin-up effects. Those three studies provided a limited estimation of interannual variability, in running each experiment several times but forced by bound-
ary conditions corresponding to observations from four or five different years. Besides, they used a domain restricted to the Amazonian region, and forced by lateral boundary conditions based on current observations. Hence, noticing that RCM studies generally simulated a smaller response of precipitation to deforestation, Medvigy et al. (2011) questioned the ability of RCMs to fully assess the climate response to future LCC over Amazonia, because they might miss feedbacks involving non-local, atmospheric or oceanic processes. Even if no systematic comparison of GCMs and RCMs has been carried out to confirm this conjecture, the latter are by design more suitable to finely investigate the local to regional changes in surface fluxes and their impacts on climate, than to study the whole climate response to deforestation.

In the 2000s, several studies also started to investigate whether the deforestation-induced evolution in climate conditions over Amazonia would exhibit nonlinear effects. In spite of ongoing deforestation, observations indeed do not provide clear evidence for a decrease in precipitation yet (d’Almeida et al., 2007). However, it has sometimes been suggested that beyond a certain threshold, the lower evapotranspiration rates of grassland would lead to a major decrease in precipitation recycling, which could considerably weaken the hydrological cycle in this region (d’Almeida et al., 2007; Avissar et al., 2002). Following this hypothesis, a tipping point could then be reached, after which a dramatic and strongly nonlinear decrease of precipitation would lead to permanent drier conditions and potentially to perturbations of the local ecosystems.

Here we use an RCM to assess the biogeophysical effects of possible scenarios of LCC on the South American climate. To investigate possible tipping points and the linearity of the these changes, we prescribe different levels of Amazonian deforestation corresponding to the current vegetation distribution, two scenarios for the 21st century, and a total deforestation case. We aim to reduce the above-mentioned limitations of previous RCM studies by running our simulations over a multidecadal period, and for a simulation domain encompassing the whole South America. Besides, since the good representation of land surface processes and their feedbacks with the atmosphere is an important requirement for the good representation of climate (Bonan, 2008a; Koster et al., 2010; Seneviratne et al., 2010; Davin et al., 2011), we use a state-of-the-art Land Surface Model (LSM). To assess uncertainties about the modelled regional climate response to Amazonian deforestation, we then compare our results to previously published similar RCM and GCM experiments. We also investigate whether more recent studies using latest model versions tend to reach a consensus on the magnitude of the mean deforestation-driven climate changes for the Amazonian region. Our methodology is described more extensively in Section 4.2. In Section 4.3, we evaluate the ability of the employed model to represent the current climate over South America, and present the results of our simulations. In Section 4.4, we finally conduct a comparative analysis of over 25 similar deforestation
experiments and describe its results.

4.2 Methods and Data

4.2.1 Model Description

We use the climate model COSMO-CLM\(^2\) (Davin et al., 2011; Davin and Seneviratne, 2012), which consists of the atmospheric component of the COSMO-CLM RCM (version COSMO4.8-CLM11) coupled to the version 3.5 of the Community Land Model (CLM3.5) for the simulation of land surface processes.

The COSMO-CLM RCM is widely used for climate studies and for weather forecasting purposes; an extensive description of the model is available at http://www.clm-community.eu. In this study, we use 32 vertical layers to represent the 23 first kilometers of the atmosphere, with a higher density of levels next to the surface. Vertical turbulent mixing is parameterised according to a level 2.5 closure using Turbulent Kinetic Energy as a prognostic variable (Mellor and Yamada, 1974, 1982). We use the mass flux scheme of Tiedtke (1989) for parameterisation of subgrid moist convection and a four-category 1-moment cloud-ice scheme including cloud water and rainwater, snow and ice for large-scale precipitation.

CLM3.5 is a state-of-the-art third-generation LSM. It uses 10 vertical levels to model areas covered by both soils (up to a depth of 3.5 m) and lakes. This model can represent five subgrid land cover types: vegetation, lake, glacier, wetland and urban area, each one occupying a determined fraction of each grid cell. The portion covered by vegetation is further divided into fractions of each Plant Functional Type (PFT). Each PFT represents a particular plant type, defined in the model by various optical, morphological and physiological parameters and is a separate column for energy and water calculations. Over Amazonia, the most abundant PFTs are broadleaf evergreen tropical tree, broadleaf deciduous tropical tree, grasses (C3 and C4), and crops.

CLM3.5 has been evaluated at the global scale by Oleson et al. (2008), and in the context of COSMO-CLM\(^2\) by Davin et al. (2011), Davin and Seneviratne (2012) and Lorenz et al. (2012). Over South America, CLM3.5 showed a good representation of hydrological processes in comparison to other land surface models, for example in simulating the water table depth in Amazonia (Fan and Miguez-Macho, 2010). However, it still exhibits some biases, for example an overestimated latent heat flux compared to observations (Lawrence et al., 2011). It has also been reported that ground evaporation in CLM3 and CLM3.5 tends to overly compensate changes in plant transpiration when leaf area index diminishes (Lawrence and Chase, 2007; Lorenz et al., 2013), which may lead to a lower sensitivity of evapotranspiration to deforestation than in reality.
4.2.2 Description of the experiments

![Map showing the domain used for the simulation (black line), the area used for averaging over the Amazonian region (red line) and the transect used for the cross-sections shown on Fig. 4.5 (blue line). Colours show the cumulated percentage of trees in each grid cell in the control simulation.](image1)

![Zooms on the Amazonian basin showing the cumulated percentages of trees in the DEF_50% (b), DEF_A2 (c) and the DEF_TOT (d) experiments](image2)

Figure 4.1: a Map showing the domain used for the simulation (black line), the area used for averaging over the Amazonian region (red line) and the transect used for the cross-sections shown on Fig. 4.5 (blue line). Colours show the cumulated percentage of trees in each grid cell in the control simulation. b, c, d Zooms on the Amazonian basin showing the cumulated percentages of trees in the DEF_50% (b), DEF_A2 (c) and the DEF_TOT (d) experiments.

All simulations were performed over the domain used for the COrdinated Regional climate Downscaling EXperiment (CORDEX) intercomparison (Fig. 4.1a), which covers the whole of South America with a horizontal resolution of 0.44° (Solman et al., 2013). Each simulation was run over the time period 1979-2010 with a time step of 150 seconds, the first 8 years being used as spinup time, while the next 24 years were analysed in this study. For both atmospheric lateral boundary conditions and sea surface temperatures, we used the ERA-Interim reanalysis (Dee et al., 2011). The greenhouse gas concentrations were prescribed to those observed during the period covered by the reanalysis data, while a seasonal cycle of aerosols was also prescribed.
We performed four simulations with COSMO-CLM$^2$, differing only in terms of their vegetation characteristics, as summarized in Table 4.1. The vegetation map of the control simulation (CTL) is the standard vegetation map of CLM3.5 (Lawrence and Chase, 2007). It is primarily based on a separation of land cover types between bare soil, forested, and herbaceous areas following MODIS satellite data from 2001 (Hansen et al., 2003), while the crop fraction is adapted from Ramankutty and Foley (1999). The DEF_A2 experiment was conducted using a land cover map for the year 2100, developed by the IMAGE 2.2 land-use change model (IMAGE team, 2001), following the A2 storyline (Nakicenovic et al., 2000). Due to the assumptions of strong population growth and of regionalization of the future world economy, it predicts high deforestation rates in the tropics. Another experiment is forced by a land cover map which reflects an intermediate level of these modifications. This latter experiment is hereafter referred to as DEF_50%, as it was obtained by linear interpolation, halfway between the percentages of each PFT in the control and the DEF_A2 case, for each grid cell. A last experiment (DEF_TOT) was conducted with a land cover map in which percentages of all types of trees were set up to 0, for each grid cell within -20$^\circ$S to 20$^\circ$N, and 80 to 40$^\circ$W (i.e. tropical South America, roughly). The percentages of other PFTs were defined by extrapolation of the linear trend between the control and DEF_A2 scenarios in each grid cell, so that for all PFTs (trees included), the rate of change between the DEF_A2 and DEF_TOT maps was the same as between the control and DEF_A2 scenarios. These three maps hence describe a “linear evolution” of deforestation, which enables us to study possible nonlinear effects of deforestation on climate.

For each simulation, the average amounts of trees, grasslands and crops in the Amazonian region (14$^\circ$S-2$^\circ$N, 72-45$^\circ$W, see red box in Fig. 1a) are given in Table 4.1. Fig. 4.1 shows the cumulated percentages of the 8 PFTs belonging to the tree class, for each of the four experiments. We only show a zoom over Amazonia for the DEF_50%, DEF_A2 and DEF_tot experiments, as this is where the most important LCC occur.
Table 4.1: Characteristics of the vegetation maps in the different experiments: state of the land cover they represent, source of the data of vegetation cover or method to obtain them, and fraction of grid cells occupied by grasslands, croplands and trees. Given percentages are averages over the Amazonian region, which is defined as follows: from 14°S to 2°N, and from 72° to 45°W, here and thereafter (see also red box in Fig. 4.1a)

<table>
<thead>
<tr>
<th>Simulation</th>
<th>CTL</th>
<th>DEF_50%</th>
<th>DEF_A2</th>
<th>DEF_TOT</th>
</tr>
</thead>
<tbody>
<tr>
<td>State of land cover map</td>
<td>Current vegetation</td>
<td>Intermediate state between control and DEF_A2</td>
<td>2100 vegetation map according to the A2 scenario (Nakicenovic et al., 2000)</td>
<td>total deforestation in tropical South America</td>
</tr>
<tr>
<td>Data source for the land cover map</td>
<td>Lawrence and Chase (2007)</td>
<td>Linear interpolation between the two other maps</td>
<td>IMAGE model (IMAGE team, 2001)</td>
<td>Suppression of trees and linear extrapolation for other PFTs</td>
</tr>
<tr>
<td>Fraction of grid cells occupied by grasslands</td>
<td>30%</td>
<td>21%</td>
<td>11%</td>
<td>11%</td>
</tr>
<tr>
<td>Fraction of grid cells occupied by croplands</td>
<td>3%</td>
<td>35%</td>
<td>66%</td>
<td>89%</td>
</tr>
<tr>
<td>Fraction of grid cells occupied by trees</td>
<td>65%</td>
<td>44%</td>
<td>22%</td>
<td>0</td>
</tr>
</tbody>
</table>
4.3 Results

4.3.1 Model evaluation

We evaluate the ability of COSMO-CLM\textsuperscript{2} to represent current climate by comparing the simulated 2-m temperature and precipitation fields in the control simulation with observations from the CRU dataset (Mitchell and Jones, 2005) over the 1986-1995 period (Fig. 4.2). Biases in 2-m temperature are limited over Amazonia; however there is a substantial cold bias over the Andes (1 to 4°C), while surface temperature is partially overestimated by 1-3°C on a roughly North-South strip stretching from the Guianas to northern Patagonia. This bias reaches a maximum in September, October and November (SON, not shown). It is likely linked to an important underestimation of precipitation amounts east of the Andes chain, and is highest over the Guianas, the mouth of the Amazon river and the foothills of the Andes where it can locally reach 5 mm/day (Fig. 4.2b). This means that almost all precipitation is suppressed in these regions, which likely influences the sensitivity of the simulated climate to deforestation. This quite important bias is not an isolated problem, as most of the climate models evaluated in the framework of the IPCC 4\textsuperscript{th} and 5\textsuperscript{th} assessment reports exhibited the same tendency to underestimate rainfall over this region (Joetzer et al., 2013; Yin et al., 2013; Randall et al., 2007). Interestingly, COSMO-CLM\textsuperscript{2} presents biases of similar magnitude and over the same regions as the mean of an ensemble of recent versions of 7 RCMs run over the same domain, with the same resolution and also forced with ERA-Interim reanalysis data (cf. Solman et al., 2013). Hence, the deforestation experiments presented in this study were conducted with a model presenting the average performance and biases of state-of-the-art RCMs. Even if the characteristic rainfall features of South America, like the maxima over Amazonia, the Intertropical Convergence Zone and the South Atlantic Convergence Zone are correctly captured by the model (not shown), the shortcomings of the model should be kept in mind while analysing the results of our simulations.

4.3.2 Regional effects of deforestation on surface fluxes, circulation, surface temperature and precipitation

Evolution of surface temperature with deforestation and its link to surface energy fluxes

The changes in annual mean 2-m temperature in the deforestation experiments compared to CTL (Fig. 4.3a, c and e) indicate a warming over deforested areas, which matches well the deforestation pattern (see Fig. 4.1). The average increase in 2-m temperature over the Amazonian region increases with the extent of deforestation, reaching 0.29°C in DEF_50%, 0.53°C in DEF_A2 and 0.78°C in DEF_TOT (Table 4.2). In DEF_A2, the warming becomes statistically significant at the 5% level over extensive areas. This
Figure 4.2: Differences in annual mean 2-m temperature (a, in °C) and precipitation (b, in mm/day) between the control simulation and observations (CRU), for the period 1987-1995.

Evolution scales well with the amount of deforestation, i.e. changes in surface temperature are proportional to changes in the area covered by trees (Table 4.2). This, as well as the good match between the pattern of the warming and that of deforestation, indicates that the surface temperature response is determined by changes in surface properties. Among these properties, the albedo, the emissivity, the root depth, the leaf area index and the roughness length of the vegetation, are all modified through the prescribed extent of deforestation.

The albedo increases linearly with the amount of trees that is replaced by crops and grasslands (Table 4.2). Cloud feedbacks modify incoming shortwave radiation by no more than 1 W/m² (0.5%), while their impact on incoming longwave radiation is close to scale with the prescribed amount of deforestation in our simulations (Table 4.2). This is also the case for outgoing longwave radiation, which is modified by changes in ground temperature and in emissivity. Consequently, changes in net radiation (both shortwave and longwave) also closely follow such a linear evolution on average over the Amazonian basin. We find that this decrease in net incoming radiation almost exclusively translates into a linear diminution of the latent heat flux on both regional (Table 4.2) and local scales (not shown), while the sensible heat flux is modified by less than 0.5 W/m² (1.6%). This decrease of the latent heat flux results firstly from the reduction in vegetation cover, which diminishes both interception and transpiration. Secondly, due to reduced precipitation amounts, the soil moisture content decreases, which means that less water is
4.3. RESULTS

Figure 4.3: Deforestation-induced annual mean anomalies in 2-m temperature (a, c, e, in °C) and precipitation (b, d, f, in mm/day) in the DEF_50% (a, b), DEF_A2 (c, d) and DEF_TOT (e, f) simulations compared to CTL, for the period 1987-2010. Changes that are different from 0 at the 5% significance level after evaluation with a two-tailed t-test are marked by stippling.
available for evapotranspiration. Thirdly, grasses have shallower roots than
trees, and can therefore not access water stored deeply. Overall, the effect of
the decrease in latent heat flux dominates over that of the albedo increase,

hence leading to the simulated warming, consistently with most previous
studies (e.g. Davin and Noblet-Ducoudré, 2010 and other studies reported in
Table 4.3). The good scaling of variations in surface energy fluxes with the
prescribed amount of deforestation results in the fact that, in our simulations,
2-m air temperature is also proportional to the extent of deforestation. This
is not a self-evident result, as physical processes relating surface temperature
and energy fluxes are not expected to be all linear.

The analysis of the mean seasonal cycle of 2-m temperature over the
Amazon region confirms the close link between surface energy fluxes, in par-
ticular the latent heat flux, and air surface temperature. Figure 4.4a indeed
reveals that the surface warming occurs all year round, but also that the
maximum anomalies occur at the end of the dry season, i.e. the time of
the year when soil moisture levels are at their lowest point. Von Randow
et al. (2004) observed that, during the dry season, evapotranspiration is
sustained in forested areas but not over pastures, because trees have deeper
roots than grasses, which enable them to access water stored more deeply.
This behaviour is captured by the model, the deforestation-induced decrease
in evapotranspiration being largest at the end of the dry season (not shown).
These interactions between land surface processes and the hydrological cycle
explain the amplification of the warming at that time of the year.

In addition to the local effect of the surface energy budget, surface temper-

ature is also affected by the circulation of warm or cold air masses. However,
the fact that changes in surface temperature scale with the extent of defor-
estation, as well as the good match between the patterns of deforestation
and the resulting warming, indicate that changes in surface temperature are
mostly driven by local effects. Nevertheless, part of the effect of deforestation-
induced circulation changes on air temperature may be missing in our simu-
lations, since we used an RCM with prescribed boundary conditions.

Evolution of precipitation with deforestation

On average over the Amazonian region, deforestation leads to a decrease in
annual mean precipitation, although there are regional differences (Fig. 4.3b,
d and f). On the one hand, west of the 55°W meridian, the Amazon basin
is dominated by a decrease in annual mean precipitation in response to de-
forestation. On the other hand, the eastern edge of the rainforest and the
Guianas experience a slight increase in precipitation, although deforestation
also occurs there. Anomalies are statistically significant for specific seasons,
particularly in DJF (not shown). This dipole pattern is found for all defor-
estation experiments, and increases with the extent of deforestation, which
suggests that this is not due to random noise (Fig. 3).

The mean seasonal cycle of precipitation in Fig. 4.4b shows that the most
Table 4.2: Average values over the Amazonian region for several climatic variables (left column), and their corresponding changes in deforestation experiments. From top to bottom percentage of trees compared to CTL, 2-m temperature, albedo, downward and upward shortwave radiation at the surface, downward and upward longwave radiation at the surface, net radiation at the surface, latent heat flux, sensible heat flux, precipitation, evapotranspiration and precipitation minus evapotranspiration. Temperature is given in °C, energy fluxes in in W/m², and water fluxes in mm/day.

<table>
<thead>
<tr>
<th></th>
<th>CTL</th>
<th>DEF_50%</th>
<th>DEF_A2</th>
<th>DEF_TOT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trees</td>
<td>100%</td>
<td>66%</td>
<td>33%</td>
<td>0</td>
</tr>
<tr>
<td>T2m</td>
<td>26.42</td>
<td>+0.29</td>
<td>+0.53</td>
<td>+0.78</td>
</tr>
<tr>
<td>albedo</td>
<td>0.145</td>
<td>+0.011</td>
<td>+0.022</td>
<td>+0.034</td>
</tr>
<tr>
<td>SW down</td>
<td>189.6</td>
<td>-0.6</td>
<td>-0.3</td>
<td>+1.0</td>
</tr>
<tr>
<td>SW up</td>
<td>27.5</td>
<td>+2.0</td>
<td>+4.1</td>
<td>+6.7</td>
</tr>
<tr>
<td>LW down</td>
<td>410.1</td>
<td>+1.1</td>
<td>+2.1</td>
<td>+2.8</td>
</tr>
<tr>
<td>LW up</td>
<td>456.1</td>
<td>+2.8</td>
<td>+5.4</td>
<td>+7.9</td>
</tr>
<tr>
<td>Rn</td>
<td>116.1</td>
<td>-4.2</td>
<td>-7.7</td>
<td>-10.8</td>
</tr>
<tr>
<td>LH</td>
<td>83.9</td>
<td>-3.9</td>
<td>-7.6</td>
<td>-11.5</td>
</tr>
<tr>
<td>SH</td>
<td>30.6</td>
<td>+0.5</td>
<td>-0.4</td>
<td>+0.14</td>
</tr>
<tr>
<td>P</td>
<td>4.15</td>
<td>-0.11</td>
<td>-0.17</td>
<td>-0.22</td>
</tr>
<tr>
<td>E</td>
<td>2.9</td>
<td>-0.13</td>
<td>-0.26</td>
<td>-0.4</td>
</tr>
<tr>
<td>P-E</td>
<td>1.25</td>
<td>+0.02</td>
<td>+0.09</td>
<td>+0.18</td>
</tr>
</tbody>
</table>

An important decrease in precipitation occurs in the middle of the dry season, because this is the season when evapotranspiration is most reduced (June, July, August and September). Although the simulated reduction in annual mean rainfall remains small, these seasonal differences in the climate changes induced by deforestation, especially the higher impact during the dry season, are of importance for local ecosystems. It was indeed observed that they experienced lasting negative effects after the extremely severe dry seasons of years 2005 and 2010 (Samanta et al., 2010; Xu et al., 2011).

The average diminution in mean precipitation over the Amazonian region becomes more important as deforestation progresses (Figs. 4.3 and 4.4). These changes correspond to decreases of 2.7%, 4.1% and 5.3% of mean precipitation. It is interesting to note that the mean rainfall change in DEF_50% corresponds to half of that in DEF_TOT, although the amount of deforestation is three times lower. Thus, in our simulations the mean precipitation decrease curbs as deforestation progresses without reaching a tipping point, i.e a threshold after which it would drastically decrease in a strongly non-linear way. To explain this result, we can separate the different contributions to precipitation within the Amazonian region into the local water input to the atmosphere through evapotranspiration, and the atmospheric moisture
convergence into the region. We assume here that the atmospheric moisture content remains constant in all experiments, which is equivalent to considering that moisture convergence equals the difference between precipitation and evapotranspiration (hereafter referred to as P-E). This assumption is often made for climatic timescales, and we indeed found that changes in P-E and atmospheric moisture convergence are very similar. As discussed in the previous section, average changes in evapotranspiration within the Amazonian basin are proportional to the amount of deforestation. However, this is not the case for changes in P-E, as it increases by 1.6% in DEF_50%, 7.2% in DEF_A2 and 14.4% in DEF_TOT compared to CTL. This nonlinear evolution explains the tendency of the mean precipitation decrease to slightly curb as deforestation progresses.

Mechanisms underlying the regional variations in the precipitation response

Figure 4.5 displays a cross-section showing the changes in the annual mean of several variables in DEF_TOT compared to CTL, along a West-East transect across the Amazonian basin (shown in blue on Fig. 1(a)). The other deforestation experiments exhibit similar changes qualitatively, but of lower magnitude (not shown). The main feature we aim to understand in this section is the East-West dipole pattern characterising the change in precipitation (2nd panel). The spatial pattern of changes in evapotranspiration (3rd panel) reflects relatively well the local deforestation rates (lower panel). Besides,
Figure 4.5: Longitudinal cross-sections showing annual mean changes in several variables in the DEF_TOT simulation compared to CTL, along the transect drawn on Fig. 4.1. Values are averaged latitudinally over a 12°-wide band. Upper panel changes in vertical (filled contours) and zonal wind velocities (contour lines) with altitude. Contour lines are drawn every 0.1 m/s, and dashed lines indicate an increase in mean wind speed in the westward direction. 2nd, 3rd and 4th panels mean changes in precipitation (P), evapotranspiration (E) and in precipitation minus evapotranspiration (P-E), in mm/day. 5th panel changes in the sum of latent and sensible heat fluxes. Lower panel absolute amount of trees in CTL, in % of the grid cells.

over this same area the trees that are removed in the deforestation simulations mostly belong to the PFT broadleaf evergreen tropical tree, whose transpiration rates are similar to those of grasslands, contrary to the western part of the transect where most of the trees belong to the PFT broadleaf deciduous tropical tree, for which transpiration rates are higher. Amazonia has been shown to be a region of major precipitation recycling (e.g. van der Ent et al., 2010), where water is made available for precipitation locally and
downwind through sustained evapotranspiration rates. In the western part of the Amazonian region, this mechanism is dampened because of the reduction in evapotranspiration. As moisture is mostly transported westward by westerlies over Amazonia (Fig. 4.6a), this drives the decrease in precipitation over the western part of the transect.

Unlike evapotranspiration, P-E increases over the deforested region (4th panel), which is related to changes in the atmospheric circulation. Deforestation induces a decrease in roughness length due to the replacement of trees by short vegetation. This reduces surface friction, and leads to an increase in wind speed in the lower atmosphere (upper panel in Fig. 4.5). Hence, the moisture transport from the ocean to the Amazonian region is increased by deforestation in our experiments (Fig. 4.6b).

We find that vertical velocity is decreased over the western part of the transect in our deforestation experiments (upper panel in Fig. 4.5), which indicates that deforestation induces subsidence over this region. This is mainly related to changes in surface heat fluxes: Over deforested areas, the albedo-induced decrease in surface net radiation lowers the overall amount of energy transmitted into the atmosphere. This means that less energy is available for convection, following the mechanism described by Eltahir (1996). However, this diminution of net radiation is maximal west of the 55°W meridian, whereas east of 50°W changes are roughly zero (5th panel in Fig. 4.5). Consequently, large-scale subsidence occurs over the western part of the transect. The surplus of moisture transport induced by the reduced surface friction is then mostly contributing to the increase in precipitation east of ∼55°W, while its transport further west is dampened by the subsiding motion (as shown by the reduced horizontal wind velocities from ∼2 to 6 km over the eastern part of the transect). This results in the creation of the dipole pattern. Furthermore, the peak in the rainfall increase (at ∼53°W) coincides with a local diminution of the sensible heat flux (not shown), which is due to the albedo-driven decrease in net radiation, while the latent heat flux remains almost constant. Interestingly, in their two-month simulations of both partial and total deforestation, Ramos da Silva et al. (2008) observed a similar dipole pattern in the response of precipitation to deforestation, which was due to similar mechanisms.

To sum up, the spatial variations in the response of precipitation to deforestation are determined by both local effects (surface energy and water fluxes) and changes in regional atmospheric circulation. We, however, acknowledge that the use of an RCM may dampen possible circulation changes at large scale due to the prescribed lateral boundary conditions. This may in particular affect the changes in large-scale subsidence or convection which determine the simulated dipole pattern of precipitation. Since the response of moisture convergence also induces some non-linearity in the evolution of mean precipitation with deforestation in our experiments, it is hence interesting to compare our results to those of other similar previously published
4.4. COMPARISON WITH EARLIER MODELLING STUDIES

Our modelling results are compared here with results from 28 previously published deforestation experiments. Of these, 23 were performed with GCMs and are listed in Table 4.3, while the five others were conducted with RCMs and are listed in Table 4.4. In all studies the control simulation represents the current vegetation state, and the domain used for the computation of the reported average values covers an area whose size is comparable to that of the Amazonian rainforest, and is centred over the deforested area. Furthermore, all experiments were conducted during at least one year, and with greenhouse gas concentrations fixed to present-day values. We compare the annual mean changes in surface temperature and precipitation obtained in these experiments against the percentage of deforestation they assumed in the Amazonian region (Fig. 4.7, see the Appendix C for a detailed description of the methodology).

These numerous reported experiments differ in many aspects, which are thus likely to induce spread between the obtained results. They were conducted with different models, employing different resolutions, different surface schemes, different simulation lengths, different representations of the land cover, etc. Their range of responses can thus be used to assess the current uncertainty in the regional climate response to deforestation, and whether some types of models exhibit a systematic tendency in their results (e.g. RCMs compared to GCMs, or latest model versions against older ones).

Figure 4.6: Atmospheric moisture transport at 850hPa in CTL (a), and difference between DEF_TOT and CTL (b). Vector scale (upper-right corner of the maps) is 0.1 (kg H$_2$O/kg air)(m/s) for a, and 0.01 (kg H$_2$O/kg air)(m/s) for b.

4.4 Comparison with earlier modelling studies
CHAPTER 4. AMAZONIA

Legend

- RCM experiments
- This study
- "oldest" GCM studies
- "newest" GCM studies

Figure 4.7: Changes in annual mean surface temperature (a), precipitation (b), evaporation (c), and P-E (d) against percentage of deforestation, as simulated in this study and previous ones. Big light blue dots represent the results from the "oldest" GCM studies, and small dark blue ones those from the "newest" GCM studies (see Table 4.3). Small markers stand for the results from our study (black) or from two other series of RCM experiments (red), surface temperature changes are only available for one study, see Table 4.4). The 0% level of deforestation refers to present-day land cover (complete methodology is available in the Appendix C). The vertical bars show the range between the first and ninth deciles for the "oldest" (light blue bar) and the "newest" studies (black blue bar). The horizontal black lines inside each bar indicate the median for each category of models, while the numbers above or below the bars indicate how many models are included in each category.
4.4. COMPARISON WITH EARLIER MODELLING STUDIES

4.4.1 Uncertainties in the effect of total deforestation and the influence of GCM development

Most of the GCM studies reported on Fig. 4.7 (blue dots on the right of each graph) agree that complete deforestation over Amazonia would induce an increase in surface temperature (median = 1.3°C) and a decrease in precipitation (median = -0.74mm/day) regionally (Fig. 4.7a, b), even if there is an important spread within the simulated changes. To assess whether the historical development of climate modelling has led to a change in the mean or the spread of the estimated regional changes, we differentiate between the 12 "newest" and the 11 "oldest" GCM studies considered here. This separation is partly based on the publication date, but because five groups of studies have been performed with different versions of the same models, we retained only the experiments which employed the latest version of these models among the "newest" studies (see Table 4.3 for the exact listing for each category).

For surface temperature, a non-parametric Wilcoxon test gives us 90% confidence that the medians of the estimates for the "newest" and "oldest" studies are not statistically different. The spread between the estimates of the "newest" studies is smaller than between those of the "oldest" studies, as highlighted by the range between the first and ninth deciles of each category (3.1°C for the oldest studies, 1.8°C for the newest) and confirmed by a Student's t-test and a non-parametric Wilcoxon test (Fig. C.1). We note that this conclusion does not hold if we only consider the criterion of the publication date (see Fig. C.1). However, the two GCM studies simulating the strongest increases in surface temperature (Polcher and Laval, 1994a; Dickinson and Henderson-Sellers, 1988), as well as two of the three studies simulating the strongest decreases (Manzi and Planton, 1996; Voldoire and Royer, 2004), have been followed by studies giving results closer to the median of all GCMs after inclusion of model improvements in the newest version of the respective GCMs (Polcher and Laval, 1994b; Hahmann and Dickinson, 1997; Voldoire and Royer, 2005).

Regarding precipitation, a non-parametric Wilcoxon test reveals that the medians of the estimates for the "newest" and "oldest" studies are also not statistically different (p-value = 0.88). The spread between the first and the ninth deciles is lower for the "newest" (1.1mm/day) than for the "oldest" studies (1.6mm/day). These conclusions are confirmed by a Student's t-test and a Wilcoxon test, and still hold if we only consider the criterion of the publication date (see Fig. C.1). Furthermore, the only study simulating an increase in precipitation (Polcher and Laval, 1994a), the two studies simulating the weakest decreases (Dickinson and Henderson-Sellers, 1988; Manzi, 1993), as well as four out of the six studies simulating the most extreme decreases in rainfall (Nobre et al., 1991; Henderson-Sellers et al., 1993; Dickinson and Kennedy, 1992; Lean and Warrilow, 1989) have been followed by studies using improved model versions and giving results closer to the model median (Polcher and Laval, 1994b; Hahmann and Dickinson, 1997; Voldoire
This reduction in the spread of estimated temperature and precipitation changes can be partly related to a small reduction in the spread of the simulated changes in evapotranspiration (0.93 mm/day for the "newest" studies, against 1.05 mm/day for the "oldest" ones, see also Fig. 4.7c). There is strong agreement among the reported GCM studies that deforestation will entail a reduction in evapotranspiration, with a median decrease of ~0.6 mm/day for both "oldest" and "newest" studies. Even more striking is the reduction in the spread of the changes in moisture convergence, which is more than three times more important (from 1.25 for the "oldest" studies to 0.82 mm/day for the "newest" ones, see also Fig. 4.7d). The better agreement in the newest GCMs concerning the magnitude of the mean precipitation decrease is therefore mostly due to a closest agreement in terms of moisture convergence and circulation changes following deforestation. This result is confirmed by a Student’s t-test and a Wilcoxon test. That said, even the "newest" studies do not agree on the sign of the change in moisture convergence, and both "oldest" and "newest" studies indicate a median decrease in P-E which is not statistically different.

Overall, these results suggest that improvements in climate models have reduced the range of responses to Amazonian deforestation, and thus indicate that the most extreme estimates (increase of temperature by more than 2.5°C or decrease of temperature, decrease of precipitation by more than 1.5 mm/day or increase of precipitation) are very unlikely. However, the sign of the changes in moisture convergence, which induce some nonlinearity in the precipitation response in our experiments, still remains uncertain.
### Table 4.3: Characteristics of the GCM studies used for the comparison in Fig. 4.7:

reference for the studies, employed model and land surface scheme, resolution of the model, presence of a dipole pattern in the response of rainfall to deforestation (if we notice a dipole pattern, we firstly mention over which region of the Amazonian basin there is an increase in rainfall and then where the associated decrease is located), deforestation-induced mean change in surface temperature and precipitation over the Amazonian region, methodology for the SSTs (prescribed or computed by an ocean mixed layer model interacting with the atmospheric model), and category to which the studies pertain ("O" for "oldest" or "N" for "newest"). "na" means that no information was reported.

<table>
<thead>
<tr>
<th>Reference</th>
<th>Model/Land surface scheme</th>
<th>Resolution</th>
<th>dipole pattern</th>
<th>∆T</th>
<th>∆P</th>
<th>SSTs</th>
<th>Category</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dickinson and Henderson-Sellers (1988)&lt;sup&gt;a&lt;/sup&gt;</td>
<td>CCMOB/BATS</td>
<td>4.5° x 7.5°</td>
<td>E/W</td>
<td>+3</td>
<td>0</td>
<td>fixed</td>
<td>O</td>
</tr>
<tr>
<td>Lean and Warrilow (1989)</td>
<td>UKMO</td>
<td>2.5° x 3.75°</td>
<td>na</td>
<td>+2.4</td>
<td>-1.34</td>
<td>fixed</td>
<td>O</td>
</tr>
<tr>
<td>Nobre et al. (1991)</td>
<td>NMC/SIB</td>
<td>1.8° x 2.8°</td>
<td>NO</td>
<td>+2.5</td>
<td>-1.76</td>
<td>fixed</td>
<td>O</td>
</tr>
<tr>
<td>Dickinson and Kennedy (1992)</td>
<td>CCM1/BATS1e</td>
<td>4.5° x 7.5°</td>
<td>na</td>
<td>+0.6</td>
<td>-1.4</td>
<td>interactive</td>
<td>O</td>
</tr>
<tr>
<td>Henderson-Sellers et al. (1993)</td>
<td>CCM1/BATS1e</td>
<td>4.5° x 7.5°</td>
<td>NO</td>
<td>+0.6</td>
<td>-1.61</td>
<td>interactive</td>
<td>O</td>
</tr>
<tr>
<td>Manzi (1993)&lt;sup&gt;b&lt;/sup&gt;</td>
<td>EMERAUDE/ISBA</td>
<td>2.8° x 2.8°</td>
<td>na</td>
<td>+1.3</td>
<td>-0.04</td>
<td>fixed</td>
<td>O</td>
</tr>
<tr>
<td>Lean and Rowntree (1993)</td>
<td>UKMO</td>
<td>2.5° x 3.75°</td>
<td>NO</td>
<td>+1.5</td>
<td>-0.5</td>
<td>fixed</td>
<td>O</td>
</tr>
<tr>
<td>Dirmeyer and Shukla (1994)</td>
<td>NMC/SSIB</td>
<td>4.5° x 7.5°</td>
<td>NE/SW</td>
<td>+2</td>
<td>-0.28</td>
<td>fixed</td>
<td>N</td>
</tr>
<tr>
<td>Polcher and Laval (1994a)</td>
<td>LMD3/SECHIBA</td>
<td>2.0° x 5.0°</td>
<td>SW/NE</td>
<td>+3.8</td>
<td>1.08</td>
<td>fixed</td>
<td>O</td>
</tr>
<tr>
<td>Polcher and Laval (1994b)</td>
<td>LMD3/SECHIBA</td>
<td>2.0° x 5.0°</td>
<td>na</td>
<td>-0.11</td>
<td>-0.51</td>
<td>fixed</td>
<td>N</td>
</tr>
<tr>
<td>Sud et al. (1996)</td>
<td>GLA/SSIB</td>
<td>4.0° x 5.0°</td>
<td>SE/NW</td>
<td>+2</td>
<td>-1.48</td>
<td>fixed</td>
<td>N</td>
</tr>
<tr>
<td>Zhang et al. (1996)</td>
<td>CCM1/BATS1e</td>
<td>4.5° x 7.5°</td>
<td>NO&lt;sup&gt;c&lt;/sup&gt;</td>
<td>+0.3</td>
<td>-1.10</td>
<td>interactive</td>
<td>O</td>
</tr>
<tr>
<td>Manzi and Planton (1996)</td>
<td>EMERAUDE/ISBA</td>
<td>2.8° x 2.8°</td>
<td>W/E</td>
<td>-0.5</td>
<td>-0.04</td>
<td>fixed</td>
<td>O</td>
</tr>
<tr>
<td>Lean and Rowntree (1997)</td>
<td>UKMO</td>
<td>2.5° x 3.75°</td>
<td>NO</td>
<td>+2.3</td>
<td>-0.27</td>
<td>fixed</td>
<td>N</td>
</tr>
<tr>
<td>Hahmann and Dickinson (1997)</td>
<td>RCCM2/BATS1e</td>
<td>2.8° x 2.8°</td>
<td>E/W</td>
<td>+1</td>
<td>-0.99</td>
<td>fixed</td>
<td>N</td>
</tr>
<tr>
<td>Costa and Foley (2000)</td>
<td>GENESIS/IBIS</td>
<td>4.5° x 7.5°</td>
<td>S/N</td>
<td>+1.4</td>
<td>-0.73</td>
<td>interactive</td>
<td>N</td>
</tr>
<tr>
<td>Gedney and Valdes (2000)</td>
<td>ECMWF</td>
<td>3° x 3°</td>
<td>NO</td>
<td>+1.3</td>
<td>-0.79</td>
<td>fixed</td>
<td>N</td>
</tr>
<tr>
<td>Kleidon and Heimann (2000)</td>
<td>ECHAM</td>
<td>5.6° x 5.6°</td>
<td>E/W</td>
<td>+2.5</td>
<td>-0.38</td>
<td>fixed</td>
<td>N</td>
</tr>
<tr>
<td>Voldoire and Royer (2004)</td>
<td>ARPEGE/ISBA&lt;sup&gt;d&lt;/sup&gt;</td>
<td>2.8° x 2.8°</td>
<td>na</td>
<td>-0.1</td>
<td>-0.40</td>
<td>fixed</td>
<td>O</td>
</tr>
<tr>
<td>Voldoire and Royer (2005)&lt;sup&gt;e&lt;/sup&gt;</td>
<td>ARPEGE/ISBA&lt;sup&gt;d&lt;/sup&gt;</td>
<td>2.8° x 2.8°</td>
<td>NO</td>
<td>+0.6</td>
<td>-0.72</td>
<td>interactive</td>
<td>N</td>
</tr>
<tr>
<td>Ramos da Silva et al. (2008)</td>
<td>GISS</td>
<td>4° X 5°</td>
<td>NO</td>
<td>+0.8</td>
<td>-1.24</td>
<td>fixed</td>
<td>N</td>
</tr>
<tr>
<td>Nobre et al. (2009)&lt;sup&gt;f&lt;/sup&gt;</td>
<td>CPTEC/SSIB</td>
<td>1.85° X 1.85°</td>
<td>E/W</td>
<td>na</td>
<td>-3.3</td>
<td>interactive</td>
<td>N</td>
</tr>
<tr>
<td>Medvigy et al. (2011)</td>
<td>OLAM</td>
<td>~25 km over South America, ~200 km otherwise</td>
<td>SE/NW</td>
<td>na</td>
<td>-0.17</td>
<td>fixed</td>
<td>N</td>
</tr>
</tbody>
</table>

<sup>a</sup> Values were obtained from Henderson-Sellers et al. (1993)

<sup>b</sup> Values are given as reported in Lean and Rowntree (1997)

<sup>c</sup> Based on the results of McGuffie et al. (1995)

<sup>d</sup> ARPEGE is the improved version of the EMERAUDE model

<sup>e</sup> We consider the simulations run with the coupled ocean-atmosphere GCM using the corrected roughness length

<sup>f</sup> We consider the simulations run with the coupled ocean-atmosphere GCM rather than the atmospheric GCM, because the current climate it represents is closer to observations
4.4.2 Evolution of the climate impacts with the extent of deforestation according to RCM experiments

Fig. 4.7 shows the evolution of the biogeoophysical effect of deforestation as a function of the deforestation rate in different RCM experiments (black and red dots). The results reported in the left part of each graph (left in white) were obtained in response to percentages of deforestation lower or equal to the estimate of the A2 scenario for 2100 used in this study, and therefore represent changes which could occur during the 21st century.

Our results and those from Correia et al. (2008) agree that the biogeophysical effects of Amazonian deforestation would induce an increase in annual mean surface temperature on average over Amazonia. This warming is limited to 0.6°C during the twenty-first century, and to 0.8°C in case of total deforestation. Yet, Correia et al. (2008) found that the increase of surface temperature with the extent of deforestation departs from the linear behaviour observed in our simulations (Fig. 4.7a).

We report three RCM studies which give estimates of changes in precipitation following deforestation, including ours. They agree on the fact that deforestation would not entail an increase in mean precipitation over Amazonia. They suggest a decrease in mean rainfall ranging from 0 to 0.85 mm/day by 2100, and from 0.2 to 1.3 mm/day in response to total deforestation (∼5-10%, excluding Correia et al. (2008) where relative changes were not available, see also Fig. C.2). The shape of the evolution of mean precipitation with the extent of deforestation is model-dependent (Fig. 4.7b): It curbs in our simulations, it is linear in Correia et al. (2008), while it remains rather insensitive until the threshold of 55% is reached in Walker et al. (2009), after which it declines more quickly. Contrary to our simulations, Correia et al. (2008) find a decrease in moisture convergence following deforestation, but this response exhibits a nonlinear behaviour as well (Fig. 4.7d).

Note, however, that the mentioned tipping point might be more likely to occur in the context of enhanced greenhouse gas forcing (Malhi et al., 2008; Cox et al., 2004), for which some (but not all) GCMs project an increase of drought conditions in the Amazon (e.g. Seneviratne et al., 2012; Orlowsky and Seneviratne, 2012, 2013). Besides, the global warming signal, not considered in these studies, will likely dominate the changes in surface temperature over the Amazonian basin during the twenty-first century (Costa and Foley, 2000). Furthermore, the limited number of RCM experiments reported here prevents us from drawing clear conclusions at this stage. Together with the possibly lacking representation of large-scale circulation feedbacks in RCMs, this highlights the need for a comparison of the large available number of GCM studies to better assess uncertainties about the climate response to deforestation, as presented in Section 4.4.1.
Table 4.4: Characteristics of the RCM experiments used for the comparison in Fig. 4.7: reference for the studies, percentage(s) of deforestation in the performed experiment(s), employed resolution, simulation domain, simulation time and boundary conditions, presence of a dipole pattern in the response of rainfall to deforestation, and deforestation-induced mean change in surface temperature and precipitation over the Amazonian region. If we notice a dipole pattern, we firstly precise over which region of the Amazonian basin there is an increase in rainfall, and then where the associated decrease is located.

<table>
<thead>
<tr>
<th>Reference</th>
<th>Percentage of deforestation</th>
<th>Resolution</th>
<th>Simulation domain</th>
<th>Simulation time (boundary conditions)</th>
<th>Dipole pattern</th>
<th>ΔT</th>
<th>ΔP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Moore et al. (2007)</td>
<td>12</td>
<td>∼20 km</td>
<td>Amazon basin</td>
<td>5 X 12 months (1997-2001)</td>
<td>NO</td>
<td>na</td>
<td>0</td>
</tr>
<tr>
<td>Moore et al. (2007)</td>
<td>100</td>
<td>∼20 km</td>
<td>Amazon basin</td>
<td>5 X 12 months (1997-2001)</td>
<td>NO</td>
<td>na</td>
<td>-0.41</td>
</tr>
<tr>
<td>Walker et al. (2009)</td>
<td>55</td>
<td>∼20 km</td>
<td>Amazon basin</td>
<td>5 X 12 months (1997-2001)</td>
<td>SE/NW</td>
<td>na</td>
<td>+0.03</td>
</tr>
<tr>
<td>Correia et al. (2008)</td>
<td>23</td>
<td>∼40 km</td>
<td>South America</td>
<td>12 months (2000)</td>
<td>NE/SW</td>
<td>+0.4</td>
<td>-0.27</td>
</tr>
<tr>
<td>Correia et al. (2008)</td>
<td>100</td>
<td>∼40 km</td>
<td>South America</td>
<td>12 months (2000)</td>
<td>NO</td>
<td>+0.8</td>
<td>-1.29</td>
</tr>
<tr>
<td>This study</td>
<td>33</td>
<td>0.44°</td>
<td>South America</td>
<td>24 years (1987-2010)</td>
<td>E/W</td>
<td>0.36</td>
<td>-0.11</td>
</tr>
<tr>
<td>This study</td>
<td>66</td>
<td>0.44°</td>
<td>South America</td>
<td>24 years (1987-2010)</td>
<td>E/W</td>
<td>0.61</td>
<td>-0.17</td>
</tr>
<tr>
<td>This study</td>
<td>100</td>
<td>0.44°</td>
<td>South America</td>
<td>24 years (1987-2010)</td>
<td>E/W</td>
<td>0.75</td>
<td>-0.22</td>
</tr>
</tbody>
</table>

* Spin-up time excluded
* Simulation of Moore et al. (2007) and Walker et al. (2009) only differ in terms of vegetation maps, and are hence considered as only one experiment in Fig. 4.7
* The different 12-month periods were simulated in different runs
* Values are adapted from the Figure 3 of Walker et al. (2009)
4.4.3 Impacts of missing large-scale feedbacks in RCMs on their estimation of the climate response to deforestation

The three RCM experiments of total deforestation (including ours) reported in Fig. 4.7b simulate decreases in rainfall over Amazonia. Compared to GCM estimates, these decreases are approximately equal to the 25\textsuperscript{th} and 75\textsuperscript{th} percentiles of the range of GCM studies. When seen in terms of relative changes, our RCM experiment and that of Moore et al. (2007) (values were not available for Correia et al., 2008) are even closer to the median of GCM studies (Fig. C.2). Although RCMs and GCMs differ in terms of their representation of large-scale atmospheric feedbacks, which might lead to differences in the simulated sensitivity to deforestation, this analysis does not support the hypothesis of a systematically different sensitivity to Amazonian deforestation in RCM studies compared to GCM studies because 1) existing RCM estimates lie within the range of GCM estimates and 2) there is still too few RCM studies available to statistically identify systematic differences between RCM and GCM estimates. This contradicts the earlier suggestion by Medvigy et al (2011) who noted, based on a smaller number of RCM and GCM studies, that RCMs generally simulate a smaller response of precipitation to deforestation compared to GCMs. We note however that a direct comparison between a GCM and a RCM including the same physical parameterisations would be necessary to strictly disentangle the possible role of missing large-scale feedbacks in RCMs.

As for oceanic feedbacks, only six from the reported GCM studies implemented an ocean mixed layer. They simulated a median decrease in rainfall almost twice higher (-1.36 mm/day) than the median of all GCM studies, but a twice-lower median surface warming (+0.6\degree C). In particular, Nobre et al. (2009) ran simulations both with and without an interactive ocean, and found a 60\% higher rainfall reduction in the first configuration than in the second one. However, with the same protocol but a different model Voldoire and Royer (2005) came to the opposite conclusion, which shows that the importance of oceanic feedbacks remains very uncertain. Still, the inability to take these feedbacks into account constitutes a limitation of RCMs.

4.4.4 Regional variations in the impact of deforestation on rainfall within the Amazonian basin

We already mentioned that, similarly to our experiments, Ramos da Silva et al. (2008) found that changes in precipitation induced by deforestation are not monotonic over Amazonia, but rather follow a dipole pattern closely linked to the response of surface energy fluxes. This pattern is reinforced for higher percentages of deforestation, but may be partly due to the prescribed atmospheric boundary conditions. In Tables 4.3 and 4.4, we make an inventory of other modelling studies that found such a pattern in the
response of rainfall to deforestation – in a qualitative way – and precise its orientation. We estimate that a bimodal pattern is simulated in 12 of the 23 experiments for which maps of the deforestation-induced changes in precipitation are shown (including 10 GCM experiments), while for four studies (including three GCM ones), its orientation is the same as in our experiments. This shows that even if we expect precipitation to decrease on average over Amazonia in response to deforestation, about half of the studies that provide information on the spatial pattern of these changes indicate that there should be high geographical variability in these trends within the Amazonian basin. This is of particular importance if one wants to study the impacts of these deforestation-induced changes in precipitation on local ecosystems. It also highlights the importance of using mesoscale resolutions and state-of-the-art land surface schemes for that purpose. These are required to finely represent the forthcoming deforestation pattern and resulting climatic changes, as well as the mechanisms underlying them through a correct description of surface energy fluxes.

4.5 Conclusion

Using a RCM coupled to a state-of-the-art land surface model (COSMO-CLM\(^2\)), we ran four simulations of 32 years each at a resolution of 50 km over South America. Each run differed only in terms of the prescribed land cover maps, in order to investigate the biogeophysical effects of possible future deforestation on the Amazonian climate. A control experiment was run using a land-cover map representative of present-day vegetation distribution. Two deforestation experiments were forced by maps reproducing two scenarios of LCC of different intensity that may both occur before the end of the twenty-first century, while another one considered a totally deforested Amazon. We find that COSMO-CLM\(^2\) shows non-negligible biases, but its performance over this region is very similar to that of other state-of-the-art RCMs.

Results show that by year 2100, prescribed LCC would induce a surface temperature increase of 0.5°C on average over the Amazonian region, compared to present conditions. The warming is higher over areas experiencing the strongest rates of deforestation, where it can reach +2°C at the end of the dry season, because shallow-rooted grasses cannot take up water in the deep soil water reservoirs. The hydrological cycle is also perturbed by these LCC. On average over the Amazonian basin, we find an average decrease in precipitation of 0.17 mm/day. This diminution in precipitation is highest during the summer and winter seasons. In our total deforestation simulation, the LCC-induced annual mean surface warming reaches 0.8°C, while the decrease in precipitation is as high as 0.22 mm/day. While we find that surface temperature increases linearly as deforestation progresses, this is not the case for precipitation, because of the nonlinear response of moisture convergence into the Amazonian region. Besides, the mean decrease in precipitation hides
the fact that there is a redistribution in rainfall amounts within the region, with central and western Amazon getting drier and eastern Amazon getting wetter. This results from regional variations in the changes of surface energy and water fluxes, which lead to a reorganisation of the large-scale circulation.

We then analysed the results from 28 previously published deforestation experiments conducted with a GCM or an RCM. Overall, the set of studies we looked at suggests that deforestation within the twenty-first century, independently of the effects of greenhouse gas forcing on climate, will lead to an increase in annual mean surface temperature by no more than 0.6°C on average over the Amazonian region, while a median estimate for the warming following total deforestation is 1.3°C. However, the estimates for the decrease in average precipitation by 2100 range from 0 to -0.85 mm/day (~-5-10%), whereas a median estimate in case of total deforestation reaches -0.75 mm/day. In our simulations, we find that the average changes in surface temperature and precipitation over the Amazonian region lie within the range of those obtained by other studies investigating the effects of comparable scenarios of deforestation. This comparative analysis also reveals that historical developments in modelling have decreased the uncertainty in the simulated climate response to total deforestation by GCMs. Hence, studies using the most recent version of a model generally simulate changes that are closer to the median of the whole sample of GCM studies than those using older versions of the same model. This emphasises the further needs for model improvements in order to better assess the effects of LCC on the climate system. RCMs may fail to fully capture the large-scale circulation feedbacks induced by LCC, but contrary to what has been previously suggested, and even if only a few RCM studies investigating the effect of total deforestation have been conducted, the reported RCM experiments do not systematically show a lower sensitivity to Amazonian deforestation than GCM studies. However, this might have been the case if all GCM experiments had accounted for oceanic feedbacks, which were shown to amplify the response to deforestation in some studies, but cannot be taken into account in an RCM.

The dipole pattern in the precipitation response to deforestation was already obtained in previous studies, emphasising that deforestation will likely entail regional differences in the trends in rainfall within the Amazonian basin. The shape of the evolution of precipitation with deforestation is model-dependent, but only one out of three studies suggests that a tipping point after which mean rainfall amounts would nonlinearly decline will be reached, though with limited impacts. It is important to note that these estimates do not consider concomitant effects of enhanced greenhouse gas forcing, nor possible interactions and amplifications between greenhouse-gas and deforestation-induced effects. Besides, the large-scale feedbacks following deforestation may be incompletely represented in these RCM studies. Nonetheless, although this needs to be confirmed by further model simulations, our RCM experiments as well as the conducted survey of the literature
suggest that recent climate models simulate a more consistent biogeophysical response to Amazonian deforestation than earlier climate models, and that extreme scenarios related to the presence of tipping points from biogeophysical effects alone in the absence of greenhouse gas forcing are rather unlikely.

4.6 Acknowledgements

This study was partially supported by the EU-FP7 EMBRACE project. Computing time was provided by the Swiss National Supercomputing Centre (CSCS). We are particularly thankful to Anne Roches for technical support and Lukas Gudmundsson for his advice regarding statistics, as well as Silvina Solman for helpful discussions.
Conclusions and outlook

5.1 Concluding summary

The aim of this thesis was to contribute to reduce the uncertainties about the biogeophysical effects of past and possible future land-cover changes on regional climate. In particular, I looked into the impacts of the land-cover changes that occurred during the industrial period over the northern mid-latitudes, as well as those of possible future scenarios of deforestation over Amazonia. To achieve this goal, I firstly relied on the analysis of climate simulations ran with climate models containing a state-of-the-art land surface component. All along this thesis, particular care was taken to compare the conclusions from various models, so as to better assess the robustness of their findings as well as remaining uncertainties. Likewise, when this was possible these results were confronted with observational evidence of the local impacts of deforestation on near-surface climate, in order to evaluate their representation in climate models and estimate which of them simulated the most realistic changes. I summarise here the main outcomes from these investigations, which I believe can help better understand the role played by land-cover changes in the climate system.
5.1.1 Local climate impacts of land-cover changes in the northern mid-latitudes during the industrial period

In Chapter 2, I looked at the climate impacts of LCC which occurred over the northern mid-latitudes during the industrial period. For that purpose, a statistical method introduced by Kumar et al. (2013a) to reconstruct the local climate impacts of LCC in simulations including all climate forcings was adapted and further developed. The first extensive multi-model evaluation of this reconstruction method was conducted by applying it to historical simulations from the LUCID model intercomparison project. For the 6 analysed LUCID models I could demonstrate that over the grid cells which experienced a substantial decrease in tree cover, the reconstruction method is able to capture the sign and the seasonal cycle of the local impacts of LCC on albedo, latent heat flux and surface air temperature shown by the traditionally used factorial experiment approach. However, it tends to underestimate them, which was interpreted as a consequence of their partially non-local nature.

I then also applied the reconstruction method to historical all-forcing simulations run by eleven models from the CMIP5 model intercomparison project, and compared their results to those of the LUCID models. I was thus able to confirm some results from the previous LUCID studies. Hence, I found a high model agreement on an albedo increase due to LCC during the industrial period. This is especially true in winter because the reduction in tree cover diminished the snow-masking effect, consequently all models simulated a cooling effect of LCC in this season. Also, these results showed a high model spread about the changes in evapotranspiration in summer and spring, indicating the absence of a consistent response of the surface energy partitioning between latent and sensible heat fluxes following deforestation. However, in contrast with the LUCID results it was concluded that most models simulated a local warming effect of LCC in summer.

Besides, these model results were compared with in situ measurements of the local effect of deforestation on surface air temperature over North America. Particularly, I focused on the ability of models to reproduce the observed specific signature of deforestation on the diurnal cycle of temperature, i.e. an increase during daytime but a decrease during nighttime. This evaluation, which is to my knowledge new, showed that none of the analysed models are able to fully reproduce this behaviour. However, in contrast to the LUCID models some of those that took part in the more recent CMIP5 project were able to capture the daytime warming effect during the warm season, overall suggesting positive effects of recent model developments.

In Chapter 3, I base on these results to conduct a global analysis of how deforestation influenced the evolution of daytime hot extremes through
biogeophysical effects during the industrial period. To do so, the reconstruction method was extended in order to apply it at global scale. After having extracted the impacts of deforestation on temperature in historical CMIP5 simulations, I selected five models which were able to reproduce its observed daytime warming effect over North America during summer, i.e. the season during which extremely hot days occur. Using this model subset, we showed that since the mid-19th century deforestation has enhanced the intensity of daytime hot extremes over many areas in the world, and especially in northern mid-latitudes. This conclusion contrasts with those of most previous studies on the topic, but has a particular weight since it for the first time results from an observation-constrained investigation. It is however consistent with previous findings that the historical LCC and GHG forcings have been of comparable importance for the evolution of climate conditions over regions that have experienced important anthropogenic changes in vegetation. Besides, it shows that the impact of deforestation gets even more important during hot extremes compared to climatological conditions.

The findings of Chapters 2 and 3 have several implications. Firstly, the suitability of the reconstruction method to study the local LCC impacts on land surface properties as well as energy fluxes and temperature at the land-atmosphere interface offers new possibilities for the research community. This technique is indeed less computationally-intensive than the factorial experiment approach, and also allows to consider possible interactions between LCC and other forcings which are simultaneously imposed on the climate system. Since it focuses on the local impacts of LCC on climate, I argue that its results are moreover more comparable to observations. However, one of its downside is that it misses the non-local impacts of LCC on climate, an aspect which is less well-understood because of the high confounding effects of interannual variability. Then, other independent and more extensive observational datasets need to be used to improve the robustness of the primary evaluation conducted in Chapter 2 and the observation-constrained analysis presented in Chapter 3, as well as to extend their spatial coverage. Further investigation is also required to understand the mechanisms underlying the local effects of LCC revealed by observations, and to evaluate their representation in climate models. Finally, the conclusion that historical deforestation increased the risk of heat extremes over mid-latitudes hints that appropriate land-use planning strategies involving afforestation efforts may help mitigate the impacts of global warming at the regional scale. Even if the presented results offer interesting perspectives on this aspect, more work still needs to be done to assess how they could be realistically translated into policies, and how effective these would be.
5.1.2 Regional climate impacts of possible future deforestation in Amazonia

In Chapter 4, the regional climate consequences of various scenarios of deforestation in the Amazon basin were investigated using the RCM COSMO-CLM coupled to the third-generation land surface model CLM. It was able to reasonably simulate the present-day climate over South America, despite a slight overestimation of surface temperature and a dry bias which is a recurrent feature among climate models in this region. In total, I ran one control simulation and three perturbed experiments reflecting different levels of deforestation. Present-day reanalysis data were used as boundary conditions, which means that I focused on the biogeophysical impacts of future land-cover changes on climate, without considering the consequences of global warming driven by greenhouse gas emissions.

In response to the projected LCC for 2100, the results showed an increase in surface air temperature by 0.5°C and a decrease in rainfall by 0.17 mm/d on average over the Amazonian basin compared to present-day conditions. In the total deforestation scenario, these estimates increase up to 0.8°C and 0.22 mm/d. It was found that the increase in temperature is locally almost proportional to the imposed changes in land-cover. It is driven by both the lower evapotranspiration rates of short vegetation types compared to forests in that region, and reinforced by the overall decrease in soil moisture due to reduced precipitation, two effects which are maximal in the dry season. In contrast, the precipitation response exhibits a dipole pattern within the Amazonian region: it diminishes over its western part where precipitation recycling is mostly affected by reduced evapotranspiration, but increases over its eastern part because of an enhanced moisture input from the Atlantic Ocean.

A comparison of these results with those from 28 previous climate modelling experiments revealed that most of them agree on a regional mean precipitation decrease and surface temperature increase in response to the biogeophysical effects of Amazonian deforestation. I also showed that more recent studies found on average similar climate sensitivities to full deforestation over this region to older ones (+1.3°C and -0.8mm/d), but with reduced uncertainties. Yet, it remains unclear whether a possible reorganisation of the large-scale circulation following such an extreme scenario would amplify or dampen the evapotranspiration-induced diminution in rainfall. Even if I am not able to address this problem with the employed RCM, the conducted meta-analysis suggests that GCMs do not simulate systematically higher changes in the water cycle than RCMs. However, some indication is found that it is the case when oceanic feedbacks are taken into account. Overall, based on the current literature it appears rather unlikely that the biogeophysical effects of future deforestation alone would lead to extreme
decreases of precipitation related to the presence of tipping points during the 21st century. This conclusion is of importance given that their possible occurrence had often been mentioned in the literature, and has since then been supported by the more extensive meta-analysis from Spracklen and Garcia-Carreras (2015).

However, a number of challenges remain to be accomplished to reinforce the robustness and extend the scope of these results. First, they need to be interpreted and re-evaluated in view of the projected global warming driven by the greenhouse gas forcing. Then, model development efforts are required to alleviate the usual biases of climate models over South America, in particular their underestimation of rainfall over Amazonia, because they may affect the conclusions of deforestation studies in this region. Ideally, such investigations should also be conducted by considering the large-scale response of the coupled ocean-atmosphere system, whose feedbacks on the impact of LCC remain largely uncertain. Besides, increases in resolution would also be needed to permit the representation of the mesoscale circulations driven by the highly heterogeneous land cover pattern in deforested areas, since these were observed to significantly affect the water cycle locally. More generally, the highlighted deforestation-driven climate changes need to be translated in terms of local-scale impacts for the ecosystems and the native societies, in order to facilitate their preservation.

5.2 Outlook

Based on the results and conclusions of this thesis, I list here some suggestions for future research topics, some of which are already under investigation:

**Extension of the evaluation of the effect of deforestation on climate:**

The observational dataset from Lee et al. (2011) used for comparison with the reconstructed impacts of historical deforestation on surface air temperature from climate simulations in Chapters 2 and 3 is limited to 33 sites scattered in North America, which besides include at most 13 years of measurements. Therefore, this evaluation effort needs to be repeated by making use of more observations of the effect of LCC on climate. To do so, more measurement sites could be considered, for example by making use of the newly released FLUXNET2015 dataset. Besides, more data sources such as the satellite-based studies of Li et al. (2015) and Alkama and Cescatti (2016) could be included in such an analysis. Furthermore, the consideration of various climate variables such as albedo or surface energy fluxes at subdaily resolution would be needed to better understand the mechanisms underlying the deforestation-induced climatic changes, especially those on the diurnal cycle of surface air temperature. Finally, ideally this effort would need
to be repeated for different types of land-cover transitions, in order to better reflect their multiplicity.

**Comparison of the local and non-local impacts of LCC:** In Chapters 2 and 3, even if I focused on the climate impacts of LCC at local scale in order to be able to compare their representation in climate models with observational evidence, more efforts also need to be done to understand what are the effects of land-use decisions over areas where the land cover is not perturbed. For this purpose, a joint analysis of climate simulations by both the reconstruction and the factorial experiment methods could be realised. The results of these two methods could thus be compared in order to assess the relative importance of the local and non-local impacts of a given scenario of LCC, and the mechanisms underlying them.

**Climate mitigation potential of afforestation policies over mid-latitudes:** The results from Chapter 3 showing that historical deforestation played an important role in the amplification of daytime hot extremes over the northern mid-latitudes suggest that future afforestation policies may help mitigate their projected future increase in these regions. However, several investigations would be required to evaluate the usefulness of such policies as well as to properly design them. First, one would need to confirm that the daytime warming effect of deforestation observed under current climate conditions would still exist in a warmer world. The findings from Teuling et al. (2010) suggesting that it is reinforced during heatwaves compared to mean climate conditions go in that sense. However, future changes in plant transpiration due to increased water-use efficiency in the presence of higher CO$_2$ concentrations may for example alter this conclusion. Thus, appropriately designing land-use decisions would require to consider their regional mitigation potential under future climate conditions, to assess if they may lead to climatic changes over remote regions, but also to take into account the possible limits on their spatial extent exerted by potentially opposing interests from the agricultural, tourism or energy sectors.

**Climate impact of Amazonian deforestation with the new COSMO-CLM$^2$ version:** Similarly to many climate models, the version of COSMO-CLM$^2$ employed in Chapter 4 exhibited a pronounced dry bias over the Amazonian region, as well as a slight overestimation of near-surface temperature. This may have affected the results of the investigation of the impacts of Amazonian deforestation on the future climate of this region. The recent coupling of the COSMO-CLM atmospheric model with the more recent version 4.0 of CLM through the OASIS software provides the opportunity to evaluate whether the improvements in the representation of soil moisture dynamics compared to CLM 3.5 modify the conclusions drawn in Chapter 4. Some runs have already
been conducted over South America with this new model, which also included a few revisions of some atmospheric parameters. The first years of simulation show an improved representation of background climate conditions over South America. This affects the simulated impacts of possible future LCC over this region, suggesting an even higher temperature increase over deforested areas, but a lower rainfall decrease because of an enhanced moisture input from the ocean. The significance of these results needs to be confirmed for extended simulations, but already show that alleviating the climate model biases over this region will help understand the evolution of its future climate under the pressure of deforestation.

**Future Amazonian deforestation and global warming:** The future evolution of climate conditions over the Amazonian region will not only be determined by the extent of deforestation, but also by global warming. If there is a high spread among CMIP5 models concerning its consequences for climate in this region, the observation-constrained analysis of Boisier et al. (2015) projects a strengthening of the dry season in response to business-as-usual scenarios for the increase in greenhouse gas emissions. This would then reinforce the deforestation-induced climate changes; if I concluded that the biogeophysical effects of deforestation alone are rather unlikely to lead to extreme precipitation decreases related to the presence of tipping points, this conclusion may therefore well be altered because of the added effect of global warming. To re-evaluate its validity, climate simulations should thus be conducted that take into account the possible synergistic effects of deforestation and global warming. Ideally, they should be run by various climate models using the same protocol in order to assess the robustness of their results. Furthermore, such analyses could be combined with observational constraints similar to those described by Boisier et al. (2015), to bring out the most realistic future outcome of the Amazonian climate.
Appendix to Chapter 2
Figure A.1: Changes in crop fraction between the pre-industrial (1862-1891) and the present-day (1975-2004) periods in the dataset of Hurtt et al. (2011). The North America (30-60°N, 230-310°E), Eurasia (40-60°N, 20-100°E) and South Asia (5-35°N, 65-115°E) domains used for computing regional averages are outlined in black.
Figure A.2: Left For each LUCID model, mean fraction of each land cover type over high-LCC grid cells in Eurasia in the 1870 vegetation maps (corresponding to pre-industrial conditions). Right Difference in the rate of change in land cover fraction between the vegetation maps of 1870 and those of 1992 (representative of present-day conditions), between high- and low-LCC grid cells. A negative value for the tree bar means for example that the tree fraction has decreased more over high-than over low-LCC grid cells between the pre-industrial and present-day periods.

Figure A.3: As in Fig.A.2, but for CMIP5 models.
Figure A.4: Left For each LUCID model, mean fraction of each land cover type over high-LCC grid cells in South Asia in the 1870 vegetation maps (corresponding to pre-industrial conditions). Right Difference in the rate of change in land cover fraction between the vegetation maps of 1870 and those of 1992 (representative of present-day conditions), between high- and low-LCC grid cells. A negative value for the tree bar means for example that the tree fraction has decreased more over high-than over low-LCC grid cells between the pre-industrial and present-day periods.

Figure A.5: As in Fig.A.4, but for CMIP5 models.
Figure A.6: Comparison of the regional mean LCC impacts on albedo (top), latent heat flux (middle) and daily mean temperature (bottom) in Eurasia in LUCID models according to the reconstruction and factorial experiments methods. The numbers on the left hand-side of each panel indicate the slopes of the regression line between the seasonal mean impacts diagnosed by the reconstruction versus the factorial experiments method, as well as the associated correlation coefficients. Dots indicate that results are statistically significant from zero in the case of the factorial experiments method, and statistically significant from zero and the noise estimates in the case of the reconstruction method (at the 5% level, estimated with two-tailed t-tests considering the spread between ensemble members).
Figure A.7: As in Fig.A.6, but for South Asia.
Figure A.8: Signal-to-noise ratios for seasonal mean albedo, latent heat flux and daily mean temperature over Eurasia in LUCID models. Small dots stand for individual grid cells, while big dots represent the domain-averaged signal-to-noise ratios.
Figure A.9: As in Fig.A.8, but for South Asia.
Figure A.10: Comparison of the LCC impacts on seasonal mean albedo in North America in LUCID models according to the reconstruction and factorial experiments methods, for different thresholds used to discriminate between high- and low-LCC grid cells. The numbers on the left hand-side of each panel indicate the slopes of the regression line between the impacts diagnosed by the reconstruction and the factorial experiments method, as well as the associated correlation coefficients.
Figure A.11: As in Fig.A.10, but for latent heat flux.
Figure A.12: As in Fig.A.10, but for seasonal mean temperature.
Figure A.13: Signal-to-noise ratios as a function of the threshold used to differentiate between high- and low-LCC grid cells, when the differentiation between both categories of grid cells is based on the decrease in tree fraction (left), or on the increase in crop fraction (right). Here for the ARPEGE, CCAM and CCSM models, next page for ECHAM5, IPSL and SPEEDY (from top to bottom). Each black dot indicates the average ratio for one variable (mean temperature, albedo, LH, Tmin or Tmax) during one season and over one of the three domains (North America, Eurasia or South Asia). The red dots stand for the median of these ratios, while the red figures indicate the amount of them which are lower than 1.
Figure A.14: As in Fig. A.13, but the signal-to-noise ratios are plotted as a function of the size of the bigger box and the differentiation between high- and low-LCC grid cells is based on the decrease in tree fraction. "KUMAR" indicates the algorithm using a varying bigger box approach that we employed for our analysis.
Figure A.15: As in Fig. A.6, but for North America, and the discrimination between high- and low-LCC grid cells is made depending on whether the increase in crop fraction was lower or at least of 15%.
Figure A.16: As in Fig. A.15, but for Eurasia.
Figure A.17: As in Fig. A.15, but for South Asia.
Figure A.18: Reconstructed impacts of LCC on seasonal mean albedo (top), latent heat flux (middle) and temperature (bottom) over Eurasia in LUCID (left) and CMIP5 (right) models. The different colors refer to different seasonal averages. The number of ensemble simulations included in the analysis is indicated in black. LCC impacts are calculated based on the decrease in tree cover (threshold = -15). In the case of CMIP5, the multi-model mean (M-M M) was computed by giving to the two models of the IPSL family and the two models from the MPI family only half a weight, while models including the CLM land surface model (CCSM4, CESM1-CAM5, CESM1-FASTCHEM and NorESM1-M) were given a quarter of a weight each. Dots indicate that results are significantly different at the 5% level from zero as well as from the noise estimates computed for each ensemble member (according to a two-tailed t-test).
Figure A.19: As in Fig. A.18, but for South Asia.
Figure A.20: Reconstructed LCC impacts on albedo in DJF, for each model.
Figure A.21: As in Fig. A.20, but for JJA.
Figure A.22: Reconstructed LCC impacts on latent heat flux in DJF, for each model. Units are W/m².
Figure A.23: As in A.22, but for JJA.
Figure A.24: Seasonal cycle of the LCC impact on daily maximum (red) and minimum (blue) temperatures for 6 LUCID models and 11 CMIP5 models over Eurasia.
Figure A.25: As in Fig. A.24, but for South Asia.
Appendix to Chapter 3
Table B.1: List of the CMIP5 models analysed Chapter 3 with corresponding references and number of historical "all-forcings" simulations

<table>
<thead>
<tr>
<th>Model name</th>
<th>Reference</th>
<th>Ensemble size</th>
</tr>
</thead>
<tbody>
<tr>
<td>CanESM2</td>
<td>Arora et al. (2011)</td>
<td>5</td>
</tr>
<tr>
<td>CCSM4</td>
<td>Gent et al. (2011)</td>
<td>2</td>
</tr>
<tr>
<td>GFDL-CM3</td>
<td><a href="http://www.gfdl.noaa.gov">http://www.gfdl.noaa.gov</a></td>
<td>5</td>
</tr>
<tr>
<td>GFDL-ESM2-G</td>
<td><a href="http://www.gfdl.noaa.gov">http://www.gfdl.noaa.gov</a></td>
<td>1</td>
</tr>
<tr>
<td>GFDL-ESM2-M</td>
<td><a href="http://www.gfdl.noaa.gov">http://www.gfdl.noaa.gov</a></td>
<td>1</td>
</tr>
<tr>
<td>HadGEM2-ES</td>
<td>Collins et al. (2008)</td>
<td>4</td>
</tr>
<tr>
<td>IPSL-CM5A-LR</td>
<td><a href="http://icm.ipsl.fr">http://icm.ipsl.fr</a>, Dufresne et al. (2013)</td>
<td>6</td>
</tr>
<tr>
<td>MPI-ESM-LR</td>
<td>Raddatz et al. (2007); Marsland et al. (2003)</td>
<td>3</td>
</tr>
<tr>
<td>MPI-ESM-MR</td>
<td>Raddatz et al. (2007); Marsland et al. (2003)</td>
<td>3</td>
</tr>
<tr>
<td>NorESM1-M</td>
<td>Bentsen et al. (2013)</td>
<td>3</td>
</tr>
</tbody>
</table>
Figure B.1: Comparison of the local effects of deforestation from the reconstruction and factorial experiment method. The bars show the average changes in mean summer TX (yellow) and TXx (red) due to deforestation (filled bars) and to other forcings (hatched bars) according to both methods, for the selected models for which factorial experiments are available. The black vertical lines indicate 90% of the spread in the reconstruction for the reconstruction method, or the spread between ensemble simulations for the factorial experiment one. In the case of IPSL-CM5A-LR, the factorial experiments exclude the LCC forcing, therefore the lines show the spread in the effect of other forcings than deforestation. The numbers indicate the ensemble size of historical (all-forcings) and factorial experiments, for each model. Results were averaged over the areas of North America, Eurasia and South Asia that have experienced at least 15% of deforestation according to the M-M M (encircled in green in Fig. 3.1).
Figure B.2: Local effects of deforestation in the historical evolution of TXx over North America and Eurasia, according to the non-selected models. The red and blue lines indicate the multi-model mean estimates of the changes in TXx due to deforestation and to all forcings combined, respectively, on average over the regions highlighted in green in Fig. 3.1. The envelopes in light blue and light red show the spread between the non-selected models (CCSM4, GFDL-CM3, GFDL-ESM2G, GFDL-ESM2M, HadGEM2-ES, NorESM1-M). The contribution of the deforestation-induced local changes in TXx to its total changes are indicated by the green bars in the lower panels. Observations from the Berkeley and HadEX2 datasets over these regions are indicated by the black line and the black line with dots, respectively. The observational coverage of each dataset over the considered regions is indicated between commas. For visualisation purposes, the observational results were vertically shifted so that the 20th-century mean total changes in TXx from models and observations are equal.
C.1 Methodology for the comparison between modelling studies

Nobre et al. (2009) showed with their deforestation experiments that the mean changes in precipitation are in first-order approximation determined by the extent of deforestation, even if the geometry of the deforestation pattern also plays a role. For this reason, on Fig. 4.7 we plotted the changes in surface temperature and in precipitation reported in the studies listed in Tables 4.3 and 4.4 against the percentage of deforestation implemented in the corresponding simulations. We defined this percentage of deforestation as the surface fraction of the rainforest which is removed on average over the Amazonian region, compared to the vegetation distribution of roughly year 2000. In the two following paragraphs, we present how the percentage of deforestation was calculated for each of the reported experiments.

C.1.1 Calculation of the percentage of deforestation in the experiments of partial deforestation

Our control simulation, that of Moore et al. (2007) and Walker et al. (2009), as well as the PROVEG scenario of Correia et al. (2008) use land cover maps representative of the vegetation distribution of the late 1990s or the early 2000s. Thus, the land cover map implemented in our control simulation is based on data from the Moderate-Resolution Imaging Spectroradiometer
project (MODIS) that were collected in 2000/2001 (Hansen et al., 2003), that of the control experiment of Moore et al. (2007) and Walker et al. (2009) was derived from satellite observations conducted in 2004 by the Instituto Nacional de Pesquisas Espaciais (INPE), while that used for the PROVEG scenario of Correia et al. (2008) is based on observations collected in 1997. We therefore consider that there is zero % of deforestation in these three vegetation maps, and these are used as baseline scenarios to calculate the percentage of deforestation in the corresponding deforestation experiments, following a methodology explained below and summarized in Table C.1.

The percentage of deforestation $p$ in our deforestation experiments is calculated as follows: $p = (1 - f_{def}/f_{ctl}) \times 100$, where $f_{ctl}$ represents the average fraction of the grid cells of the Amazonian region (as defined on Fig. 4.1) that is occupied by trees in our control experiment, and $f_{def}$ corresponds to the same fraction in the deforestation experiments. Walker et al. (2009) report in their Figure 3 the percentages of deforestation implemented in their simulations and those of Moore et al. (2007). Unlike us, they attributed a percentage of deforestation of 17% to their control scenario, because they considered that the zero-percent level corresponds to a pre-deforestation state. We consistently adapted the percentages of deforestation they report to the scale of deforestation that we used.

The land cover map used by Correia et al. (2008) for their CEN2033 experiment was produced by Soares-Filho et al. (2006), who assessed that it represents a decline of forests by 23% as compared to 2001 (information available at http://www.csr.ufmg.br/simamazonia/) We therefore attributed a percentage of deforestation of 23% to this experiment.
Table C.1: Methodology for the estimation of the percentages of deforestation in each RCM deforestation experiment.

<table>
<thead>
<tr>
<th>Reference</th>
<th>Description of the experiment in the original publication</th>
<th>Percentage of deforestation</th>
<th>Method of estimation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Moore et al. (2007)</td>
<td>Business-as-Usual complete deforestation</td>
<td>12%</td>
<td>Adapted from the Fig. 3 of Walker et al. (2009)</td>
</tr>
<tr>
<td>Walker et al. (2009)</td>
<td>complete deforestation except over Protected Areas</td>
<td>55%</td>
<td>Adapted from their Fig. 3</td>
</tr>
<tr>
<td>Correia et al. (2008)</td>
<td>CEN2033</td>
<td>23%</td>
<td>value given at <a href="http://www.csr.ufmg.br/simamazonia/total">www.csr.ufmg.br/simamazonia/total</a> deforestation</td>
</tr>
<tr>
<td></td>
<td>DESFLOR</td>
<td>100%</td>
<td></td>
</tr>
<tr>
<td>This study</td>
<td>DEF_50%</td>
<td>33%</td>
<td>fraction of trees over the Amazonian region as compared to the control</td>
</tr>
<tr>
<td></td>
<td>DEF_A2</td>
<td>66%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>DEF_TOT</td>
<td>100%</td>
<td></td>
</tr>
</tbody>
</table>
C.1.2 Validity of the comparison between recent and old control vegetation maps

We equally assigned a percentage of deforestation of 100% to the reported total deforestation experiments which were conducted with GCMs (listed in Table 4.3) or with RCMs (listed in Table 4.4), because they all implemented a vegetation map in which the whole Amazonian forest is replaced by patures or grasslands. Unlike the land cover maps used in the RCM control experiments, which represent the vegetation distribution of the late 1990s or the early 2000s, most of those used in the GCM control simulations represent the state of the land cover as it was observed between the early 1970s and the early 1980s. Since intense deforestation started in the early 1970s in Amazonia, and Soares-Filho et al. (2006) estimated that the cumulated deforested area amounted to 837,180 km$^2$ in 2001 (i.e. $\sim$13% of the original extent of the forest, see their Supplementary Material), one may argue that these GCM experiments cannot be directly compared to those conducted with RCMs. Yet, we believe that the concerned GCMs can hardly capture such changes. Hence, they are made up of grid cells covering a surface of 65,000 to 420,000 km$^2$, and most of them only represent the dominant vegetation type in each grid cell. As deforestation is scattered within Amazonia, and is characterized by a fragmentation of the forest following the so-called ‘fishbone pattern’ rather than by its large-scale replacement, we do not expect the land cover maps representing the vegetation distribution of years 1970 and 2000 in these coarsely-resolved GCMs to be substantially different. Eventually, this should thus have a negligible influence on the comparison we conducted. Our finding that RCM studies do not not systematically show a lower climate sensitivity to total deforestation than GCM studies, underlined in Section 4.4.3, tends to support this argument.

Unlike the other GCM studies, Medvigy et al. (2011) used a mesoscale resolution (25 km) over South America, but the land cover map they used in their control experiment is based on satellite imagery data from 1992-1993, therefore the comparison between their total deforestation experiment and those conducted with RCMs remains meaningful.

C.1.3 Validity of the comparison between experiments of Amazonian versus tropical deforestation

In their total deforestation experiments, a few of the reported GCM studies use vegetation maps in which tropical forests are replaced by grasslands in both Amazonia and Indonesia (Henderson-Sellers et al., 1993), or in the whole tropical belt (Polcher and Laval, 1994a,b; Sud et al., 1996; Zhang et al., 1996; Voldoire and Royer, 2004, 2005). The literature dedicated to the investigation of remote effects of tropical deforestation suggests that these experiments can still be compared to those which implemented Amazonian deforestation only, and that the significant climatic changes simulated over
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the Amazonian region are almost exclusively due to local land cover changes. Hence, in their modelling study Avissar and Werth (2005) found only limited, likely non-significant impacts of deforestation occurring in Central Africa and Southeast Asia on the Amazonian climate. Moreover, another fact that gives us confidence in the validity of this comparison is that the seven GCM studies that implemented deforestation in other tropical regions than Amazonia do not simulate systematically different mean changes in surface temperature and precipitation, compared to the other reported GCM studies. The changes in surface temperature they found indeed range from -0.11 to +3.8°C (median = 0.6°C), while for precipitation they range from -1.61 to +1.08 mm/d (median = -0.74 mm/d). For comparison purposes, we recall that the simulated changes in surface temperature for the whole set of 28 studies range from -0.5 to 3.8°C with a median value of +1.3°C, while for precipitation they range from -3.3 to +1.08 mm/d, with a median value of -0.74 mm/d.

C.2 Complementary Analysis

C.2.1 Estimate of the spread within the results from different studies

To assess whether the spread between the estimates of the changes in surface temperature and precipitation is statistically different within the "oldest" or the "newest" studies (see section 4.4.1), we use three different methods. Firstly, we compare the ranges between the first and ninth deciles of the simulated changes within each category of studies. Secondly, we perform two two-tailed Student’s t-tests to test the null hypothesis that the mean of each category is different from 0, which gives us 95%-confidence intervals for the distribution of the simulated changes in surface temperature and precipitation in each category of studies. Eventually, we perform two two-tailed Wilcoxon tests to test the same null hypothesis, but without implicitly assuming that the simulated changes are normally distributed within each category. For both t-tests and Wilcoxon tests, we compare the spreads of the computed 95%-confidence intervals for "oldest" and "newest" studies.

All of these three estimates agree that the spread between the estimates of the changes in surface temperature is smaller within the "newest" than within the "oldest" studies (Fig. C.1, left part). For precipitation, only the Student’s t-test shows less conclusive results.

C.3 Discrimination between GCM studies using only the criterion of the publication date

To assess whether our conclusions regarding the influence of the historical development in modelling on the simulated results are sensitive to the method
Figure C.1: Effects of the historical development in modelling on the evolution of the uncertainty about the mean surface temperature (top) and precipitation (bottom) changes over Amazonia following total deforestation, using different methods. *Left* Estimates from oldest (light blue dots) and newest GCMs (dark blue dots) and range between the first and ninth deciles of each category, as shown on Fig. 4.7. Other estimates of the spread are calculated with a t-test (two vertical bars in the middle) and a Wilcoxon test (two vertical bars on the right), used to test the hypothesis whether the mean (or median) of the two categories of models were different from 0. The computed 95%-confidence intervals are shown here. Numbers indicate the number of studies considered in each category. *Right* Same as the left part, but models are discriminated in two categories according to the sole criterion of the publication date.
chosen to distinguish between "oldest" and "newest" studies (Section 4.4.1), we conducted the same analysis but applying the sole criterion of the publication date to discriminate between the two categories of studies. As discussed in Chapter 4, the results from this supplementary analysis show that the spread in the deforestation-induced changes in precipitation is still reduced within the new studies compared to the old ones (see the right parts of Fig. C.1). This is indicated by all of the three spread estimates we used. However, regarding surface temperature the ranges between the first and ninth deciles of both "oldest" and "newest" studies are similar when considering the sole criterion of the publication date. This shows that the reduction in the spread within the "newest" studies compared to the "oldest" ones, as presented in Fig. 4.7, comes from the closest agreement between the latest studies of each series of experiments realised with the same GCMs. Besides, the mean of the "newest" studies is lower than that of the "oldest" studies when one only considers the criterion of the publication date.

C.4 Uncertainties in the effect of total deforestation and influence of GCM development on the relative changes in precipitation

Similarly to the analysis conducted in the Section 4.4.1, we investigated whether the historical developments in modelling had an influence on the simulated relative changes in precipitation induced by total deforestation. These were calculated as percentages of the annual mean rainfall amounts simulated in the control simulation, on average over the Amazonian region. The values for these relative changes in precipitation were reported in only 9 of the "oldest" studies listed in Table 4.3, and 11 of the "newest" ones. Both of these two categories show very close median relative changes in precipitation: -14% for the oldest studies and -15.6% for the newest ones (Fig. C.2). A Wilcoxon-test gives us 60% confidence that these two medians are not statistically different. The spread between the first and ninth deciles of the "newest" studies is reduced compared to that of the "oldest" ones (from 28.2 to 23%, Fig. C.2). This conclusion is confirmed by a Student’s t-test and a Wilcoxon test (Fig. C.3). If we consider the sole criterion of the publication date, the range between the first and ninth deciles of each category of studies is similar, but both the t-test and the Wilcoxon test indicate a reduced spread for the "newest" studies (Fig. C.3).
Figure C.2: Relative changes in annual mean precipitation against percentage of deforestation, as simulated in this study and reported in previous ones. Big light blue dots represent the results from the "oldest" GCM studies, and the small black blue dots those from the "newest" GCM studies. Small markers stand for the results from our study (in black) or from the RCM study of Correia et al. (2008) (in red). The 0% level of deforestation refers to present-day land cover. The vertical bars show the range between the first and ninth deciles for the "oldest" (light blue bar) and the "newest" studies (black blue bar). The horizontal black lines inside each bar indicate the median for each category of models, while the numbers below the bars indicate how many models were included in each category.
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Figure C.3: Same as Fig. C.1, but for relative changes in annual mean precipitation.
Supplementary Analysis: Decomposition of the LCC impacts on the Surface Energy Balance during hot days

The analyses presented in Chapter 3 pointed out some differences in the representation of the historical LCC impacts on summer mean and extreme values of daily maximum temperature (Tmax) amongst CMIP5 models. Only 5 out of the eleven analysed models simulated a warming in response to historical deforestation over the northern mid-latitudes, in line with observations (e.g. Lee et al., 2011; Zhang et al., 2014 and Li et al., 2015), while the others showed no effect or rather a cooling. Here I conduct an investigation about the mechanisms underlying these differences, by isolating the contributions from the various components of the Surface Energy Balance (SEB) to the overall change in temperature.

D.1 Methodology

Starting from Eq. 1.5 and without using the simplifications made between Eqs. 1.3 and 1.4 (see Chapter 1), the SEB can be written as:

$$
\epsilon \sigma T_s^4 = SW_d - SW_u + LW_d - LH - SH - R, \quad (D.1)
$$
where \( \epsilon \) is the emissivity, \( \sigma \) is the Stefan-Boltzmann constant, \( T_s \) is the surface skin temperature (in K), \( SW_d \) and \( SW_u \) are respectively the downward and upward shortwave radiative fluxes, \( LW_d \) is the downward longwave radiative flux, \( LH \) and \( SH \) are the turbulent fluxes of latent and sensible heat, and \( R \) is a residual term including both the ground heat flux and variations in heat storage in the soil.

I use a surface energy decomposition method to investigate the processes responsible for the LCC-induced reconstructed changes in temperature, as was introduced by Juang et al. (2007) and further developed by Luyssaert et al. (2014). It aims to isolate the contributions of direct changes in surface energy fluxes arising from the modifications of the biogeophysical properties of the land surface (e.g. albedo, evapotranspiration) and indirect contributions resulting from atmospheric feedbacks (e.g. involving cloud-radiative processes).

I consider changes in the SEB between a pre-industrial (PI, 1862-1891) and a present-day (PD, 1975-2004) period, similarly as in Chapter 2. The surface temperature change between PI and PD can then be decomposed by calculating the full derivative of Eq. D.1. Neglecting the (typically small) higher-order terms, and approximating the land surface as a blackbody (with \( \epsilon \) being constantly equal to 1), it can thus be expressed as:

\[
\Delta T_s = \frac{1}{4\sigma T_s^3} \times (\Delta SW_d - \Delta SW_u + \Delta LW_d - \Delta LH - \Delta SH - \Delta R).
\]  

I reconstruct the changes in each of the components of this equation induced by LCC by using a threshold-based reconstruction method, as in Chapter 2. I separate high- and low-LCC grid cells based on a 15\% threshold in the decrease in tree cover. The LCC-driven surface temperature change and the respective contributions from each of the surface energy fluxes are hence given by:

\[
\delta T_s = \frac{1}{4\sigma T_s^3} \times (\delta SW_d - \delta SW_u + \delta LW_d - \delta LH - \delta SH + \text{Err}),
\]  

where \( \text{Err} \) is an error term representing the mismatch between the added reconstructed contributions of the terms on the right-hand side with the reconstructed changes in \( T_s \), which arises from both the uncertainties in the reconstruction and the omission of the ground heat flux and variations in soil heat storage. I apply the reconstruction method to daily mean values of surface energy fluxes in North America (30-60\(^\circ\)N, 230-310\(^\circ\)E), for four models for which they were available at daily resolution over the whole study period: CanESM2, IPSL-CM5A-LR, IPSL-CM5A-MR and GFDL-CM3. Since I focus on the mechanisms underlying temperature changes during daytime hot extremes, before that the Tmax values were sorted by increasing order and separated into bins representative of various quantiles: between the 50\(^{th}\) and
D.2. RESULTS

The results of this analysis suggest important differences in the mechanisms underlying the LCC-induced historical changes in temperature among the investigated models, even between those which show a similar impact on Tmax, i.e. CanESM2, IPSL-CM5A-LR and IPSL-CM5A-MR (Fig. D.1). Strikingly, while CanESM2 exhibits the most important changes in Tmax during daytime hot extremes (see also Chapter 3), these cannot be explained by the very low daily mean variations of the components of the SEB that I reconstruct in this model. This suggests either a compensation of the LCC-driven changes during daytime and nighttime, or a decoupling between the land surface and the lower atmospheric layers. In contrast, in the two IPSL models I find positive changes in Ts by $\sim 0.4^\circ$C during the hottest days (hotter than the 90th percentile). These are mostly driven by reductions in LH, as well as a significant contribution of enhanced solar forcing during the very hot days in IPSL-CM5A-MR. These changes are partly counteracted by an increase in $SW_u$ driven by the higher albedo values of agricultural areas, as well as an increase in SH. Note that the contribution of the error term is not negligible in IPSL-CM5A-LR. The reconstructed changes in daily mean $T_s$ match well those in Tmax, which suggests that the described processes may qualitatively be well representative of what happens during daytime in these two models. Finally, the GFDL-CM3 model shows low increases in daily mean $T_s$ during hot days (above Q75 of the distribution of daily Tmax values). These are driven by a decreased SH and an increase in $LW_d$, while the albedo-induced increase in $SW_u$ goes in the opposite direction and the contributions of LH and $SW_d$ do not show consistent changes. The changes in daily mean $T_s$ cannot explain the LCC-driven decrease in Tmax found in this model, and since it was found to simulate an increase in daily minimum temperature following deforestation they are probably more representative of nighttime processes.

In summary, the results from the decomposition of the Surface Energy Balance highlight some crucial differences amongst models regarding how
they represent variations in the Surface Energy Balance in response to deforestation. More work is needed to better understand these differences, in particular this analysis highlights that subdaily data of the surface fluxes from both models and observations are needed in order to evaluate whether models are able to simulate well the observed specific impact of deforestation on the diurnal variations of temperature, as well as the mechanisms underlying it.
D.2. RESULTS

Figure D.1: Over North America and for the CanESM2, IPSL-CM5A-LR, IPSL-CM5A-MR and GFDL-CM3 models, reconstructed contributions of the LCC-driven daily mean changes in the various components of the Surface Energy Balance to the historical change in surface temperature ($T_s$), for different bins of quantiles of the distribution of $T_{max}$. Reconstructed changes in $T_s$ are estimated from changes in outgoing longwave emission and indicated by red lines, while the contributions from the latent heat flux (LH), sensible heat flux (SH), upward shortwave radiation (SWu), downward shortwave radiation (SWd), downward longwave radiation (LWd) as well as the error term are shown with coloured bars. The black dots stand for the LCC impacts on $T_{max}$. The surface energy fluxes and $T_{max}$ values are averaged for each grid cell and for each bin of quantiles, before I apply a threshold-based reconstruction method as in Chapter 2 (using a threshold value of 15%). Results are then spatially averaged over all high-LCC grid cells in North America.
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Before putting a full stop to this thesis, I owe quite some thankyous to a fair amount of people who helped to make it become real, each in their own way.

The first acknowledgments obviously go to my PhD supervisor tandem, Sonia and Edouard. It all started when I was looking for a topic for my master thesis, and they immediately encouraged my curiosity and gave me the opportunity to spend all these years at ETH. Sonia, by offering me this PhD position you set the frame for this thesis, but then you also often pushed me to enlarge it, in order to articulate my thoughts within a broader context. When you were challenging my results as well as their potential implications, I believe that I have learnt how to understand and communicate them better, always keeping the "big picture" in the background. Edouard, your day-to-day support and your contagious enthusiasm about the topics of land-cover changes were here to ensure that I was staying on tracks, while your ability to decide what was is important and what is not was crucial to help me draw something meaningful within the frame. Even if I’m still not fully respecting your "80% perfect" rule, I believe you managed to get me under 100%. So many thanks to both of you for teaching me all that, while respecting my personal choices before, during and after my PhD.

Another round of thankyous go to the co-authors who took the time to give me comments on my papers. Thank you Benoît for being one of the first supporters of this Amazon study. Thank you Lukas for unveiling some of the meaning of statistics, their use and misuse by climate scientists. Thank you Johannes for these inspiring conversations, hopefully the future will tell us whether local or non-local effects matter most.

I also want to thank Victor for accepting and taking the time to evaluate my thesis.

A collective thank you goes to all my colleagues from the Landclim group. I will not drop names since the group has got so big that I could almost fill
in this page with them while still forgetting some of them, but I have really appreciated the good vibes you have been sending around. It was stimulating to work with such passionate persons publishing so many interesting studies – and not only because that meant more cake.

And now of course I want to thank my family, my closest supporters all the way long through the past 27 years. Especially Papa, Maman, Lucile and Robin, your verve, your wit and your unconditional encouragements are priceless, I cannot repeat it enough.

I also have the chance to be indebted to many friends for a big bunch of funny moments, kind attentions, cheering chats and intense discussions. To the whole Saint-Lô team first, it has been more than ten years now, that makes up to 1000 kilometers but when the big day had come this became not more than a night ride in the car for you, so thanks for keeping the spirit alive. And to all my Zürich friends, those who left and those who stayed, those who can speak Swiss German and those who cannot, those who showed the way by rushing through their PhDs and those who taught me to step back, those who shared their playlists, those I still live with despite the legal cases, those who always invite for dinner, those who can sail, those who can work with wood, those who go to Büxe and those who prefer Klubi, those who come from Estonia, those who will become Swiss and those who will emigrate again. Thanks for being here and teaching me what I could not study.

Quentin, April 2017
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