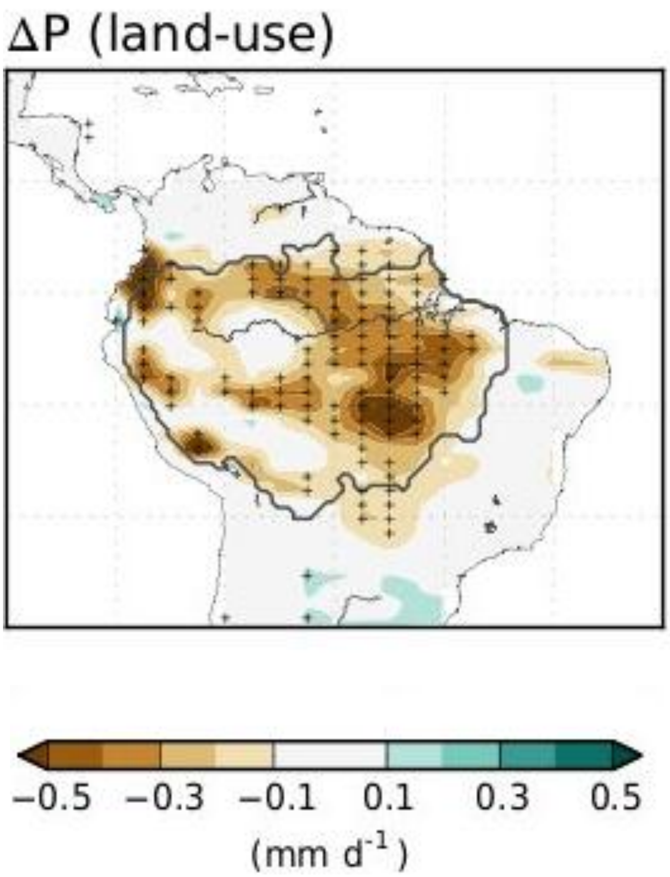
Report on estimated likelihood for irreversible collapse



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Abbreviations and acronyms

AR4/5	IPCC Assessment Report 4/5
CO_2	Carbon dioxide
CASA	NASA Carnegie-Ames-Stanford-Approach project
CDF	Cumulative distribution function
CMIP3/5	Coupled Model Intercomparison Project phase 3/5
CRU	Climatic Research Unit, University of East Anglia UK
DGVM	Dynamics Global Vegetation Model
DJF	December-January-February
ENSO	El Niño-Southern Oscillation
ET	Evapotranspiration
FACE	Free-Air CO_2 Enrichment
FLUXNET	Programme for the coordination of measurements from flux tower sites
GCM	Global Climate Model / General Circulation Model
GHG	Greenhouse Gas
GPCC	Global Precipitation Climatology Centre
HadCM3/(L)C	Hadley Centre Coupled Model version 3/(Low ocean resolution) Carbon cycle version
HadGEM2-ES	Met Office Hadley Centre's Global Environmental Model version 2 Earth System configuration
IAM	Integrated Assessment Model
Inland	Brazilian Integrated Land Surface Processes Model
INPE	Instituto Nacional de Pesquisas Espaciais, Brazilian National Institute for Space Research
IPCC	Intergovernmental Panel on Climate Change
IPSL	Institut Pierre Simon Laplace, France
IPSL-CM5A	Fifth generation climate model of IPSL
ITCZ	Inter-Tropical Convergence Zone
JJA	June-July-August
LAI	Leaf Area Index
LBA	Large Scale Biosphere-Atmosphere Experiment in Amazonia
LUC	Land Use Change
LuccME	INPE's Earth System Science Center Land Use and Cover Change modelling system
LUCID	Land-Use and Climate, IDentification of robust impacts project
LUH	Land Use Harmonization data set
MODIS	NASA Moderate Resolution Imaging Spectroradiometer
MOSES	Met Office Surface Exchange Scheme
NASA	National Aeronautics and Space Administration, US
NPP	Net Primary Productivity
RAINFOR	Amazon Forest Inventory Network
RCP	Representative Concentration Pathway
RD	Runoff and drainage
SAM	South American Monsoon
SON	September-October-November
SRES	Special Report on Emissions Scenarios
SSP	Shared Socioeconomic Pathways
SST	Sea Surface Temperature
TRIFFID	Met Office vegetation dynamics model

Executive Summary

The Amazon forest, like many other forests across the globe, is subject to increasing pressure from multiple anthropogenic and natural sources, including deforestation, extreme climate events and climate change, and fire. There has been rising concern over the future viability of the Amazon forest system, together with a growing recognition of the ecosystem services that it provides. This has prompted research into the potential nature of environmental change and response of the Amazon forest, within the context of other pressures.

The Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report (AR4) placed *medium confidence* on the statement that “Replacement of tropical forest by savannas is expected in eastern Amazonia…due to synergistic effects of both land-use and climate changes” (Chapter 13, Working Group II, Magrin et al. 2007). At that time, the studies investigating dieback of the Amazon were limited in number. No comprehensive assessment of likelihood was available and results were relatively isolated. As more model data has become available, it has become possible to put earlier results into the context of other projections of change.

Here, we present an assessment of the likelihood of Amazon forest collapse. It is based on current best understanding of how anthropogenically-driven change in the Earth system may evolve and interact with the Amazon forest, drawing on novel AMAZALERT work and the wider body of Amazon research.

This report presents a range of different types of information relating to the likelihood of Amazon dieback. Current climate-vegetation models do not have the sophistication and accuracy required to produce a fully quantitative probabilistic assessment for such an event and so this assessment relies on semi-quantitative and qualitative results based on the available imperfect set of model simulations. A range of simulated forest responses are given, but also ranges of the drivers of forest change. The latter has value, as while not directly quantifying forest change, they may be more reliably simulated than the final forest response. An expert elicitation was also carried out as an alternative view on risk. Therefore this report presents different levels of information, both quantitative and qualitative, which overall give a qualitative picture of risk. This can be updated as knowledge increases and more information becomes available and moreover, it can be used to help identify and prioritize further scientific developments.

Dieback of the Amazon

One of the most well-known potential impacts of a changing global climate is the catastrophic dieback of the Amazon forest, as simulated first (White et al. 1999) in a Dynamic Global Vegetation Model (DGVM) and then by the Met Office Hadley Centre’s HadCM3LC coupled climate carbon cycle model (Cox et al. 2000) over a decade ago. In addition, the existence of forest/savanna bistable states in tropical South America has been proposed as possible (Oyama and Nobre 2003, Staver et al. 2011, Hoffmann et al. 2012). Dieback of the Amazon forest would be high impact, but it is highly uncertain. Subsequent investigation has found the Cox et al. (2000) result to be atypical in the context of other complex models (Global Climate Models (GCMs)/DGVMs), including an ensemble of versions of the same model and the next generation Met Office Hadley Centre model HadGEM2-ES (Good et al. 2013).

In this report, dieback likelihood is explored in terms of both transient (initial response) and committed vegetation response to climate change, which represents the potential long term change in the forest that is yet to be realised due to lags in processes within the Earth system (Figure ES1). The difference between transient and 'committed' changes found by Huntingford et al. (2013) and Boulton et al. (in prep.) demonstrate lags in forest response to climate change, with potentially greater losses to be realised beyond the transient response. It implies a degree of 'temporary resilience'. This could provide an opportunity for rapid mitigation action to reduce the likelihood of dieback. This depends on the timescales of forest response to climate change. It may be that model simulated time scales are biased due to missing mortality processes such as drought or fire. Temporary resilience may thus depend on the return period of extreme drought/fire seasons.

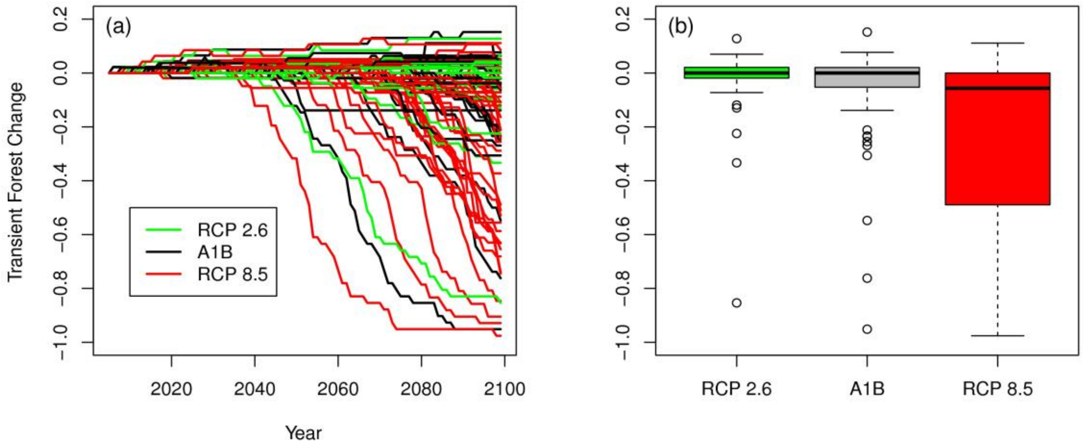


Figure ES1. Changes in number of grid boxes containing Amazon forest (broadleaf tree fraction > 0.4 within the region 40°W-70°W, 15°S-5°N) in a 'perturbed parameter' ensemble of the coupled climate-carbon cycle model HadCM3C. (a) Time series of transient changes for each individual member of the ensemble. (b) Box and whisker plots for each scenario showing the median, inter-quartile range and minimum and maximum values (excluding outliers, black circles).

Modelling drivers of critical change

Global change: Different 'pathways' allow alternative scenarios of emissions to be explored, most recently through CMIP5 (Coupled Model Intercomparison Project phase 5). However, owing to great uncertainty in the terrestrial carbon cycle feedback, there is likewise great uncertainty in the transformation of emissions into atmospheric concentrations, something that has not received much attention to date.

Carbon dioxide (CO_2): CO_2 fertilization confers significant benefits to Amazon forest carbon uptake and increased carbon storage in the models, but this process is a key uncertainty marked by a lack of understanding of how this operates in tropical vegetation and in conjunction with other nutrient and radiation availability. The planned Amazon FACE (Free-Air CO_2 Enrichment) experiments could increase understanding and reduce uncertainty in this area.

Temperature: Temperature increase is a common feature of climate projections, and considered alone has a negative effect on forest health. However, poorly-represented temperature dependency of respiration and photosynthesis is likely to make most if not all models too sensitive to high temperatures. Ongoing observational work, including through AMAZALERT, should help to develop better model representation of this process.

Drought and dry season characteristics: Droughts such as 2005 and 2010 as well as imposed drought experiments have demonstrated that the forest is sensitive to these conditions. The mechanisms of response to drought appear to be different than in current models, which is in part due to missing processes such as direct drought- and fire-driven mortality.

Observations suggest that in the southern part of Amazonia at least, the dry season may be lengthening. This is known to be important to the forest health in terms of water stress and fire incidence. Although there is still a wide range in projections of precipitation over Amazonia, the latest multi-model ensemble (CMIP5) displays greater agreement in projections for a deepening and lengthening of the dry season in the future. This could be related to differential heating of the northern and southern hemispheres, with dry season rainfall negatively associated with tropical north Atlantic SSTs.

It may be possible to reduce uncertainty in rainfall change using observation-based constrained projections. Although there is uncertainty in the magnitude and even the direction of change in annual rainfall, results presented in this report support the tendency of the GCMs towards a strengthened Amazon dry season. The 'diagnostic' projections and the observed past trends indicate that the model democracy approach (ensemble mean) would likely underestimate the amplitude of the projected Amazon dry season lengthening, which may have implications for forest viability. Further analyses are needed to shed light on the spatial detail of constrained projections to evaluate whether the regions affected are vulnerable or not.

There are missing or partially represented processes in models, and hence uncertainty is wider than that encompassed by CMIP and other ensembles. Furthermore, there is inaccurate representation of other processes such as drought phenology and the onset of the wet season, as well as a widespread dry bias in the ensemble model climatology, which requires further model development to address.

Land use: Land use (LU) and climate change interaction is still poorly understood, but improved scenarios of land use provide the opportunity to investigate the combined effects. One of a suite of new LU scenarios (to 2050) developed within AMAZALERT has been used to assess the effects of the new scenario in the Amazon basin relative to the standard CMIP5 simulation. The new experiments used a standard CMIP5 scenario (up to 2050) of greenhouse gas concentrations and LU outside the Amazon basin, but imposed the new LU within the basin. Results suggest a modification to the hydrological cycle, with significant reductions in both evapotranspiration and precipitation in the new LU experiment relative to the CMIP5 simulation (Figure ES2). Effects of these LU-induced climate changes on the remaining land cover could be tested in a DGVM.

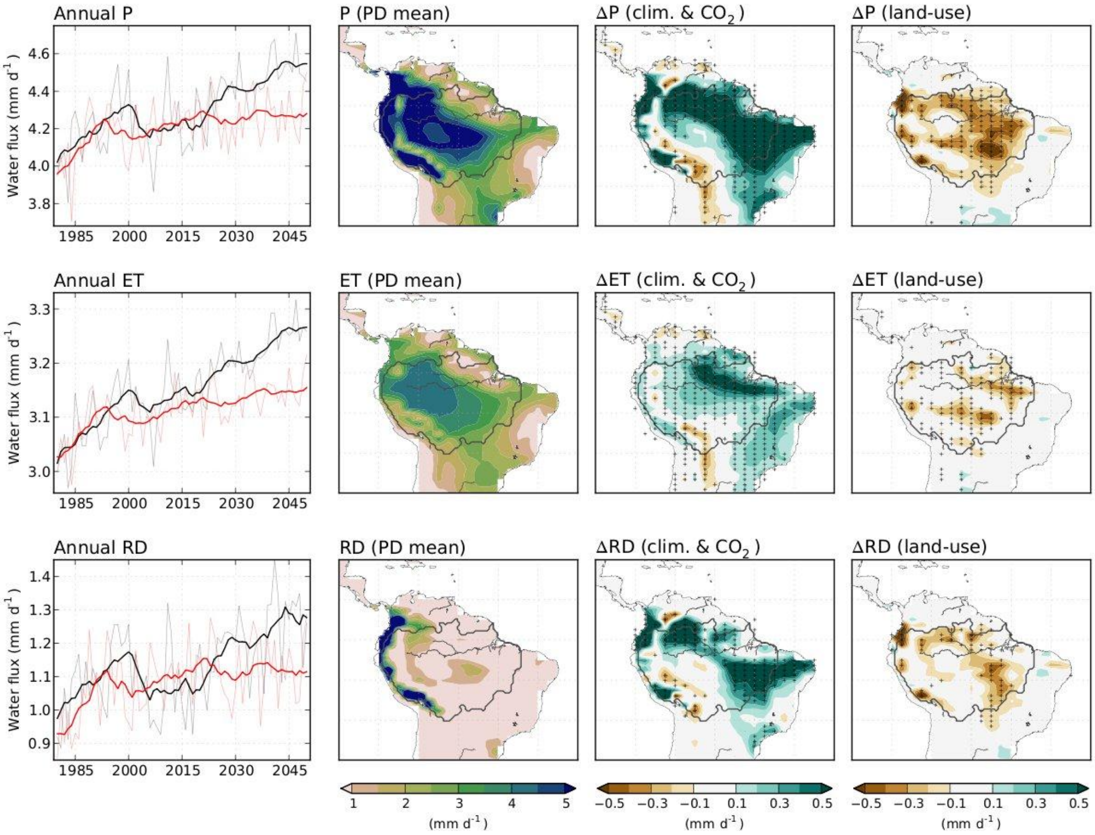


Figure ES2. Amazon basin-average times-series of annual precipitation (top), evapotranspiration (middle) and runoff/drainage (bottom), from standard CMIP5 simulations (black) and including a new scenario of Amazon LU (red). The ensemble and 5-year moving average is indicated as thick lines. The maps illustrate, for each variable, the present-day (1980-1995) climatology (centre-left), and the long term change driven by greenhouse gases (centre-right) and land-use (right). Marks indicate the anomalies that are statistically significant ($p < 0.05$).

Fire: Fire is a critical process that is still missing in most complex models, in particular so-called land-use fires that involve the combination of a climate-induced high fire risk, forest fragmentation and human drivers of deforestation and pasture formation. Recent improvements to INPE's Inland model include a new scheme for estimating the impacts of fires on vegetation dynamics. It estimates that the impacts of climate change in Amazonia increase when effects of land use changes and fire are considered. The most important changes will potentially occur in the east/north-east and south of the Amazon, with an increase in surface temperature, and decrease in precipitation and evapotranspiration. Dry season length is expected to increase, and a reduction of upper-canopy biomass and increase in lower-canopy biomass is related to an increase of the biomass in grasses and a replacement of tropical forest by seasonal forest and/or savanna.

Observed and modelled indicators of change

Indicators of forest health developed from observed relationships that can also be modelled provide a crucial link in the investigation of the forest response to projected future change and in assessing the future viability of the forest.

Research highlighted here presents a framework for achieving this, and provides a worked example. However, this approach is designed to allow indicators to be updated as improvements are made. An essential part of this work lies in gaining more in-depth knowledge of observational products, how these relate to forest health, and then understanding how to obtain or develop comparable indicators in the models. Utilizing information obtained during real-world events that are stressful for the forest provides a test case for determining what kind of information we can get from the models about how the forest responds to such an event. Finally, by relating model projections of change in indicators to quantities that are observable, it is more likely to motivate action.

Subjective probability of Amazon collapse

An expert elicitation was carried out to estimate the likelihood of critical change in the Amazon consistent with current scientific knowledge. The aim was to provide an alternative view on likelihood combining different sources of information from the literature. This was done because Amazonian critical change may involve processes that are not all captured by or are biased in current GCMs (e.g. fire, drought mortality), and have no analogue in historical change. An elicitation from a range of experts helps provide a balanced view of current knowledge. Such an assessment involves subjective choices, because of the various assumptions underlying each scientific study. From this, the probability of Amazon critical change is generally viewed by the respondents as greater than very low. Significant value is robustly seen in mitigation of climate change. Estimated probabilities are notably lower for the low global warming pathway than the high. However, a wide spread of probabilities was reported. Comparing our results with the original Kriegler et al. (2009) study suggests a small decrease in mean estimated probability of dieback.

Caution is required in interpreting these results. Dieback probability is highly uncertain and involves many subjective choices. This is just one method of summarising our current understanding of this system and what this understanding lacks. Reported probabilities are generally higher than might be directly inferred from some GCM-based analyses. This is consistent with the idea that the full uncertainty is widened, e.g. by missing processes such as the response of fire to climate change. There may also be bias through the self-selection of experts towards those with more concern over the future of the forest.

Notes and recommendations

With more models and increased modelling capability, it has now become possible to determine how representative the early dieback result was of other model projections. The new data describe a range of uncertainty in projections of change and hence permit an assessment of probability, albeit in a qualitative manner.

In the context of climate-vegetation modelling, it has emerged that the large regional drying and warming behind the dieback reported in Cox et al. (2000, 2004) is not typical of current models. Huntingford et al. (2013) forced a single land-surface model by climate patterns from 22 GCMs. They find that of the 22 climate patterns, only one (from HadCM3) causes committed – or potential – ‘major biome loss’. This is consistent with probability somewhere between 0 and 15% (95% confidence interval assuming models are independent and equally likely; the range is a result of the small sample of models). The changes seen in the Cox et al. (2000) study are atypical even of an ensemble of different versions of the same model. As reported here, around 30% of that ensemble shows committed ‘dieback’ (at least 25% forest loss) under the high (RCP8.5) emissions scenario. The probability of climate-driven dieback by the end of the century is systematically lower than the probability of committed loss.

Thus, results from current climate-vegetation models, taken at face value, imply that the probability of climate-driven dieback occurring by the end of the century is significantly less than the probability of it not occurring. However, missing processes and biases (known and potential) in these models are such that dieback is much harder to rule out than implied by these models alone. There are key uncertain processes, such as fire, CO_2 fertilization and regional rainfall dynamics, which could lead to substantial changes in model projections in the future. Thus the probability of dieback is contentious, as illustrated by the range of assessments from the expert elicitation, but should not be regarded as very low. Further, the interactions between climate variability and change and land use change, particularly through fire, are likely to increase the probability of biome change, especially in regions such as the south and east of Amazonia that are already particularly vulnerable to these drivers of change.

Any assessment of likelihood is a snapshot in time, and should be updated as understanding and capability increases. To facilitate a targeted approach to this, this report has highlighted throughout the areas that most require improvements to reduce uncertainty and to advance future assessments of likelihood of collapse. These make clear the need for continued improvements in model representation of processes on the basis of greater understanding developed through observations and targeted field experimentation, which in turn requires more and sustained observational campaigns of Amazonia. In addition, further developments in the modelling of multiple and interacting drivers of change will provide important insight.

1. Introduction

The prospect of large-scale collapse of the Amazon forest ecosystem by the end of the century was raised through model experimentation over a decade ago as a plausible yet highly uncertain high-impact outcome of climate change. Monitoring systems have provided visible evidence of how continuing deforestation contributes directly to forest loss and degradation. Concern over the future of a forest subject to multiple pressures, together with a growing recognition of the ecosystem services provided by the Amazon, has prompted further research into the potential nature of environmental change and response of the forest. The irreversible collapse of the forest can be regarded as a critical transition and an important question is if anthropogenic forcing, whether that is direct, indirect, or some combination of the two, is likely to tip the system into another state.

In some model experiments (White et al. 1999, Cox et al. 2000, Salazar et al. 2007, Sitch et al. 2008, Salazar et al. 2010) the Amazon basin exhibits 'tipping point' behaviour, which marks the transition of a critical threshold into a qualitatively new environmental regime characterized by alternative land cover. This change in state may be irreversible or effectively so within the time scales of interest. The possibility of bistability in climate-vegetation states in tropical South America has been raised, where one equilibrium state corresponds to the current tropical forest vegetation that covers much of the basin, and the other corresponds to much sparser vegetation cover or savanna (Oyama and Nobre 2003, Staver et al. 2011, Hoffmann et al. 2012). With a complex combination of forcing agents acting upon Amazonia, it is not a trivial scientific question to determine the likelihood of reaching a critical threshold at which point the current state could switch (perhaps abruptly) to a second state.

The ecosystems of Amazonia are subject to two major driving forces of change: one is the regional climate response to global climate change (Nobre and Borma 2009), and the other is direct land use change and associated processes such as biomass burning and forest fragmentation. The effects of deforestation on the regional climate system could bring about changes significant enough to affect the viability of the remaining forest (Sampaio et al. 2007) in the absence of additional climate change. Hence it is possible that either of the principal drivers of change could lead the Amazon towards and perhaps beyond a critical threshold (Lenton et al. 2008), but it is more likely that a combination of these will determine the future of the tropical forest biome in this region. Where deforestation and global warming act synergistically, this could make drastic biome change in Amazonia more likely. In unusually dry conditions, as exemplified during the recent severe droughts of 2005 and 2010, there are not only direct impacts of high temperatures and water stress on the trees, but an elevated incidence of fire. Fire is not only more prevalent in drought conditions but it is closely related to human activities (such as pasture and previous deforestation). It has been proposed as the prime agent of change that could bring about significant biome change in Amazonia (Hutyra et al. 2005, Aragão et al. 2007, Hoffmann et al. 2012).

The loss of the Amazon forest and its associated ecosystem services has the potential to have a great impact on society both local, such as through effects on basin hydrology and river flow (Marengo et al. 2008a, b, Tomasella et al. 2013) and remote to the region, such as through feedbacks on the global carbon cycle (e.g. Cox et al. 2000). Hence there is a requirement for an assessment of the likelihood and the predictability of this transition. Further, given the likely negative implications of reaching that tipping point, information about the trajectory and proximity of a tipping point along with knowledge of how human activity affects these attributes could form an important input into decision making.

The Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report (AR4) placed *medium confidence* on the statement that "Replacement of tropical forest by savannas is expected in eastern Amazonia…due to synergistic effects of both land-use and climate changes" (Chapter 13, Working Group II, Magrin et al. 2007). At that time, the studies investigating dieback of the Amazon were limited in number. No comprehensive assessment of likelihood was available and results were relatively isolated. A study by Kriegler et al. (2009), based on work carried out in 2006, combined and summarized some of the available information through the subjective assessment of probabilities based on expert opinion. Higher estimates of probability of dieback were generally expressed for higher emissions pathways, although the ranges of probability estimates were very wide, reflecting large uncertainty in the dieback outcome. Since then, as more model data has become available, it has become possible to put earlier results into the context of other projections of change.

Here we present an assessment of the likelihood for the collapse of the Amazon forest to occur, towards supporting decision makers in taking action required to avoid such an outcome, and managing and adapting to changes as well as informing further scientific development. It is based on current best understanding of how anthropogenically-driven change in the Earth system may evolve and interact with the Amazon forest, drawing on the body of Amazon research and novel AMAZALERT work.

This report presents a range of different types of information relating to the likelihood of Amazon dieback. Assessing this likelihood involves many subjective choices, because of the various assumptions underlying each scientific study. Current climate-vegetation models lack the sophistication and accuracy required to produce a fully quantitative probabilistic assessment for such an event. Therefore this report presents different levels and types of information, both quantitative and qualitative, which overall give a qualitative picture of risk. This includes semi-quantitative and qualitative results based on the available imperfect set of model simulations. A range of simulated forest responses are given, but also ranges of the drivers of forest change. The latter has value, as while not directly quantifying forest change, they may be more reliably simulated than the final forest response. Some real-world observations are also discussed, covering forest sensitivity and regional climate trends and the development of comparable observational/modelled indicators of forest health. An expert elicitation was also carried out as an alternative view on risk. Therefore this report presents different levels of information, both quantitative and qualitative, which overall give a qualitative picture of risk. This can be updated as knowledge increases and more information becomes available and moreover, it can be used to help identify and prioritize further scientific developments.

2. Dieback of the Amazon

In this section, we introduce some of the work that prompted investigation into Amazon dieback and how this was simulated to occur, put this into the context of other modelling studies, and consider the Amazon as a possible Earth system tipping element.

Simulated Amazon forest dieback

One of the most well-known potential impacts of a changing global climate is the catastrophic dieback of the Amazon forest, as simulated first (White et al. 1999) in a Dynamic Global Vegetation Model (DGVM) and then by the Met Office Hadley Centre's HadCM3LC model (Cox et al. 2000, 2004) over a decade ago. In pioneering work, a climate model was coupled to a carbon cycle model including vegetation dynamics, which allowed investigation of how the oceanic and terrestrial ecosystems may respond to increased concentrations of greenhouse gases and climate change, and permitted biophysical and biochemical feedbacks. Notably, direct anthropogenic land use change and fire were not represented in this model. In the Amazon region, climate change and feedbacks drove rapid dieback of the forest, with almost complete loss of trees by the end of the 21st century (Figure 1). The regional signature of global climate change over Amazonia was characterized by severe warming and drying, and these climate effects on photosynthesis and respiration drove tree mortality (refer to Box 1).

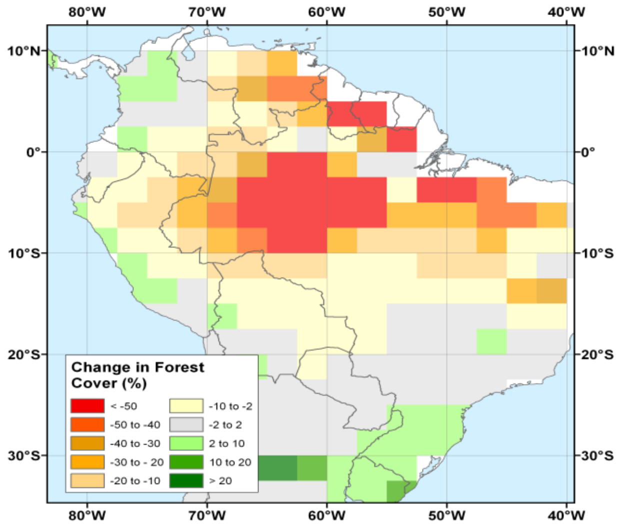


Figure 1. Percentage change in forest cover by late 21st century compared with pre-industrial conditions, as modelled using Hadley Centre coupled climate-carbon model HadCM3LC with a ‘business as usual’ greenhouse gas concentration scenario. Red colours indicate a reduction in forest cover. It demonstrates the ‘dieback’ of the forest resulting from simulated warmer and drier climate in the future, and carbon cycle feedbacks. After Cox et al. (2000).

Box 1: Dieback as a balance between productivity and mortality

In several Global Climate Models (GCMs) including the Met Office Hadley Centre models, which run with TRIFFID vegetation dynamics, mortality is not modelled explicitly, but is rather driven by changing productivity. For example, under drought conditions, declining productivity is simulated, which then feeds into litter flux, but explicit drought-driven mortality is not represented. Comparison with observations indicates that models lacking a drought mortality mechanism respond incorrectly to imposed drought conditions (Powell et al. 2013). In addition, there is no representation of fire-driven mortality, which is thought to be a critical process in the wider northern South America Amazon to savanna region (e.g. Aragão et al. 2007, Staver et al. 2011).

There were a number of reasons behind this result, which combined to give the high impact response in the Amazon region. First, global climate change produced more rapid warming of tropical north Atlantic sea surface temperatures (SSTs) and tropical east Pacific. Precipitation over the Amazon is sensitive to SST anomalies in both of these regions: warmer than average SSTs are associated with drought or rainfall deficit in parts of the Amazon. However, it is not just the chain of events simulated by this model: global climate change to regional climate change. In addition to the radiative effect of carbon dioxide (CO_2) in the atmosphere as a greenhouse gas, it can also exert direct physiological forcing on the vegetation. Betts et al. (2004) found that because of increased water use efficiency of plants under increased atmospheric CO_2 concentrations, less water was recycled back into the atmosphere via evapotranspiration, and hence less was available to fall again as rain. But CO_2 also has a fertilizing effect on plants, and at least initially, the combination of this effect and the increased water use efficiency mitigating the effects of declining rainfall caused forest productivity to increase. However, in the model, the negative effects of regional climate change eventually overrode the positive CO_2 effects on the forest and strong declines in productivity ensued. Feedbacks on the regional and global climate followed. Loss of tree cover reduces latent heat loss through evapotranspiration, acting both to increase temperatures and reduce available rainfall. Higher surface albedo could also suppress convection and moisture convergence. Together, these regional feedbacks were found to contribute approximately 25% of the rainfall decline. A further feedback occurred through the global carbon cycle. Loss of trees is a loss of an important carbon sink, as well as becoming a net source of carbon. Both of these elements mean that the ratio of carbon in the atmosphere to that in store increases, although the greatest release of carbon to the atmosphere with warming comes from the global soils. This further enhances global to regional climate change. Cox et al. (2000) found that total global carbon cycle feedbacks significantly enhanced climate change over the 21st century. Global mean temperature increases were 1.5K greater than those projected by the standard (non-carbon cycle) version of the model.

A number of interacting factors came together in this model simulation to produce the extreme dieback of the Amazon forest, some of which worked against each other in terms of effect on forest health, and some of which reinforced and enhanced the reduction in forest productivity. However, once forest decline had begun, feedbacks on the climate – either directly through land surface interactions or via the global carbon cycle – tended to promote warmer drier conditions and further forest loss.

This and the preceding DGVM study were very important in the field of Amazon research as they opened up the possibility of this high-impact consequence of climate change, quite apart from any direct deforestation. This startling potential prospect has been among the motivations for investigating it further, using a variety of existing and emerging tools and models, and using observations to enhance understanding and measure and monitor change.

Subsequent modelling of dieback in complex models

The authors in the studies above were careful to point out that while this result could be regarded as plausible, it was also highly uncertain. Uncertainties are inherent in model projections of change and there are established ways of addressing some of these. On climate change time scales, uncertainties are generally understood to arise from the future emissions pathway, dependent on a range of socio-economic factors, how those emissions translate into concentrations in the atmosphere, and also in model structure and process representation. While we do not know how emissions will evolve, we can examine the effects of forcing GCMs according to different emissions/concentration scenarios such as SRES (IPCC Special Report on Emissions Scenarios, Nakićenović et al. 2000) or RCP (Representative Concentration Pathways, van Vuuren et al. 2011a). Furthermore, multi-model ensembles provide an important opportunity to explore the range of outcomes that different model formulations bring. Another source of uncertainty in GCM projections is in parameter settings. In 'perturbed physics ensembles' (Murphy et al. 2004, Lambert et al. 2013), parameters are perturbed within their plausible, expert-defined ranges. So, even within a single model structure, there can be a range of outcomes depending on the parameter combinations.

The Coupled Model Intercomparison Project (CMIP) has provided a process for bringing together simulations from modelling groups around the world into coordinated and comparable multi-model ensembles. The third version of the programme, CMIP3, fed into the IPCC's Fourth Assessment Report (IPCC, 2007) and the recently completed CMIP5 has formed the basis of the Fifth Assessment Report (IPCC, 2013). HadCM3LC, which gave us the dieback results, was a version of HadCM3, one of the CMIP3 generation of models, and an important step was to put this result into the context of the other CMIP3 models. These

GCMs were not able to explicitly model changing vegetation, but other means have been used to assess the potential future of the forest using the CMIP data.

Certain climate characteristics and changes have been highlighted as important to the future of the Amazon forest: higher temperatures and reduced moisture. In HadCM3, there is strong warming and drying over Amazonia, which is more pronounced in the carbon cycle and vegetation feedbacks version of the model (HadCM3LC). Warming is a feature common to the CMIP3 ensemble, but HadCM3 is known to have high climate sensitivity: in other words, to respond to a given forcing with a greater temperature increase than in many other models. Over the basin as a whole, rainfall response in the CMIP3 ensemble exhibits a large spread that spans zero, meaning that some models project drier conditions while others indicate a wetter future. These results suggest that the broad pattern of climate changes simulated by HadCM3 were at the extreme end of the CMIP3 ensemble, and that in the key variable precipitation, there is large uncertainty in both the magnitude and the direction of change.

As outlined in AMAZALERT Deliverable 3.1, the broad patterns of climate change projected by the CMIP5 ensemble are similar to those of CMIP3, and show that impacts tend to increase under higher concentration scenarios. Temperature is projected to rise over South America, with regional maximum warming occurring over Amazonia. The changes in rainfall projected by the ensemble are mixed over the Amazon basin, and vary by season. However, there is generally more agreement on drying in the eastern basin, particularly in the June to November period, with wetter conditions projected by the majority of models in the western basin particularly in December to May. But as in CMIP3, there is a spread in the model projections that spans zero, and over the Amazon basin itself, there is no clear scenario dependency apart from an increase in spread of response in RCP8.5 over 4.5 and 2.6. The newer generation Hadley Centre model HadGEM2-ES is similarly placed within the CMIP5 ensemble as HadCM3 was within CMIP3, with relatively greater warming and drying than much of the ensemble, although the projected changes in precipitation are not as extreme as with HadCM3 (Good et al. 2013). However, a strong warming and drying signal in HadGEM2-ES does not correspond to Amazon dieback. In idealized experiments where CO_2 concentrations increase by 1% per year over 140 years, the familiar dieback of the Amazon occurs in HadCM3LC while minimal loss takes place in HadGEM2-ES (Good et al. 2013). In the RCPs, changes in forest extent are dominated by direct anthropogenic land use change (Betts et al. 2013). The sources of the discrepancy are investigated by Good et al. (2013), who find that differences between dry season characteristics play an important role, as well as model climatology, projections of regional climate, and forest response to climate and CO_2. In another large model ensemble of versions of HadSM3 (slab ocean), the standard deviation of Amazon basin NPP changes under doubled CO_2 climate was around the same or – in north-eastern parts of the basin – even more than the average change, indicating a highly uncertain response, even in this single model (Hemming et al. 2013). More discussion of modelled environmental drivers of forest health, including seasonal characteristics, follows in Section 3.

In some recent work carried out in a collaboration between Exeter University and AMAZALERT researchers, further understanding on the risk of dieback through declining productivity has been gained through an analysis of a perturbed parameter coupled climate-carbon cycle model ensemble, HadCM3C (Boulton et al. in prep.). This was based on the HadCM3C model structure that simulates Amazon dieback in its standard form. Both atmospheric and land-surface parameters were perturbed (Lambert et al. 2013). Each model version is run under three emissions scenarios (SRES A1B, RCP 2.6 and RCP 8.5) to 2100.

Dieback likelihood is explored in terms of both transient and committed vegetation response. The transient response is determined by the change in forest coverage at the end of the 21st century. The committed response (Jones et al. 2009) is the eventual change in forest coverage that would occur if the forest was allowed to adjust fully to the climate conditions at the end of the 21st century. The transient and committed changes are different because of lags in forest response to climate changes. These represent the potential long term change in the forest which is yet to be realized due to lags in the vegetation. A prediction of the committed response is made by a novel use of the Good et al. (2011) dry-season resilience (DSR) technique.

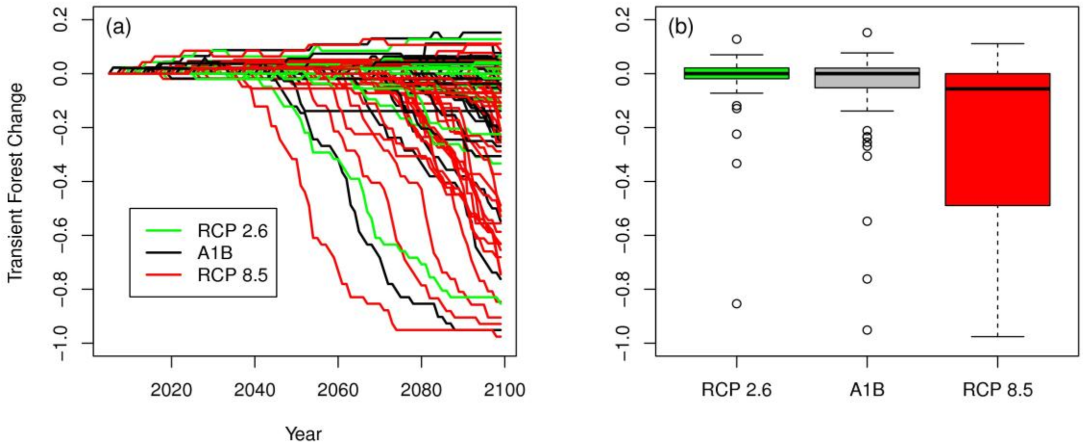


Figure 2. Transient changes in number of grid boxes containing Amazon forest (BL fraction > 0.4 within the region 40°W-70°W, 15°S-5°N) in the HadCM3C perturbed parameter ensemble. (a) Time series of this transient changes for each member of the ensemble. (b) Box and whisker plots for each scenario showing the median, inter-quartile range and minimum and maximum values (excluding outliers, black circles).

There is a large spread in the transient responses of the forest by 2100 (Figure 2), with uncertainty increasing as the emission scenarios get stronger. The general picture from this ensemble of HadCM3 versions is broadly consistent with estimates based on CMIP3 (SRES) climate changes. And the large dieback seen in the standard version of HadCM3 is not typical of other CMIP3 models (Huntingford et al. 2013). The mean response of the forest for both RCP 2.6 and A1B scenarios is for the forest to remain unchanged, with a greater tendency for dieback seen in A1B. RCP 8.5 has a mean response of slight forest loss but a lot more of a spread in results. The dieback observed in the standard configuration of HadCM3 of ~60% (Cox et al. 2000) appears to simulate dieback that is higher than the typical response when the parameters are perturbed.

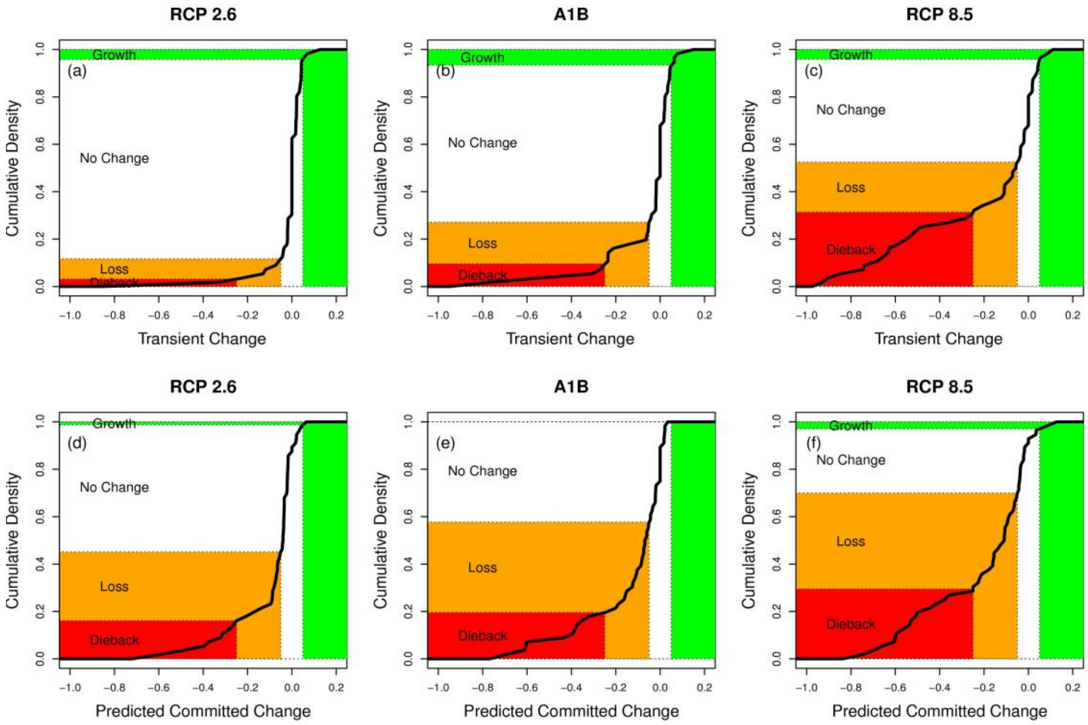


Figure 3. Summary CDFs of the Amazon rainforest fractional changes in grid boxes deemed forest for ensemble members of HadCM3C. Transient responses observed by 2100 for scenarios (a) RCP 2.6, (b) A1B and (c) RCP 8.5 are shown above predicted committed responses using the DSR method for (d) RCP 2.6, (e) A1B and (f) RCP 8.5. Coloured regions show proportion of models which show 'Dieback' (red, <-25%), 'Loss' (orange, >-25%<-5%), 'No Change' (white, >-5% <5%) and 'Growth' (green, >5%).

The transient response and the prediction of committed loss for each scenario can be compared using cumulative distribution function (CDF) plots (Figure 3). The predictions suggest that especially under RCP 2.6 and A1B scenarios, there is high forest loss that is potentially yet to be realized in the transient response. This is also true of RCP 8.5, but the difference between the transient and predicted committed responses is less than in the other scenarios. As well as uncertainty increasing as emissions scenarios get stronger, it also increases from the transient response to the predicted committed response. Interestingly, although proportions are greater in the higher scenarios, over 40% of the ensemble members show at least predicted committed 'loss' (> 5%) under RCP 2.6, which is an aggressive mitigation scenario in which radiative forcing peaks and declines before 2100.

As well as fully coupled models, offline vegetation models provide an important way to investigate the potential effects on the Amazon forest of the range of projected climate changes. By using the GCM output to drive offline vegetation models, forest change can be modelled explicitly. In addition, in combination with observation-driven modelling, DGVMs are highly valuable in developing understanding and modelling of key vegetation processes that can in time be brought into fully coupled models.

Effects on the forest of uncertainty in climate model projections can be explored by forcing a single DGVM with data from a range of GCMs; DGVM model uncertainty can be sampled by combining a single GCM with more than one DGVM. Under the ongoing Inter-Sectoral Impacts Model Intercomparison Project (ISI-MIP; Warszawski et al. 2013), there is scope to more easily sample uncertainty in both DGVMs and GCMs. Existing studies give a range of results for the Amazon forest. Some allow the possibility of loss of forest, to a greater or lesser extent, with reductions in rainfall or lengthening dry season proposed as driving the reduction in vegetation carbon or transition in biome in parts of the Amazon (Sitch et al. 2008, Salazar et al. 2007, Cook et al. 2012) while a recent study (Huntingford et al. 2013) finds evidence for resilience of tropical forests to CO_2-induced climate change. The latter study presents tropical biomass projections by MOSES-TRIFFID driven by data based on 22 CMIP3 models. It finds that the HadCM3-driven dieback by 2100 is unique in the context of other models, although several others begin to lose vegetation carbon towards the end of the 21st century. However, it also puts these in the context of other available model runs using versions of HadCM3C (see above) and a DGVM intercomparison, and finds that the largest uncertainties in future Amazon vegetation carbon come from the plant processes as represented by the different DGVMs. Another study suggests that the uncertainty associated with CO_2 effects is greater than that associated with precipitation change (Rammig et al. 2010). In a systematic comparison of vegetation sensitivity to different environmental drivers, Galbraith et al. (2010) found that different DGVMs can produce dieback for different reasons. The effect of modifying DVGM parameter settings within a single model has been investigated (Poulter et al. 2010) and some recent work has placed emphasis on the importance of dynamic and demographic processes (carbon residence time), finding that this dominates over productivity in the uncertainty of vegetation response to climate and CO_2 changes (Friend et al. 2014). Evidently, significant uncertainties remain in the modelling of vegetation processes as well as in the regional climate changes.

Critical transitions in simple models

While complex models provide the most sophisticated means for making projections of climate and ecosystem response in an interacting Earth system, simple models form an important tool in investigating important processes and system behaviour. Stripping out complexity confers a number of benefits. First, potentially important drivers of change can be tested in clean experiments that isolate particular elements of interest. Secondly, because of their relative simplicity, model equations and parameters are much more transparent and readily understandable and further, changes are easier to make. Finally, as they are significantly less computationally expensive to run, there is scope to perform many more simulations. This gives the freedom to experiment within a greater portion of uncertainty space, permitting exploration of conditions under which tipping point behaviour or low probability high impact outcomes may be realized. Thus, simple models may be regarded as a useful part of a toolbox for assessing likelihood.

Stability of the rainforest has never before been investigated with a simple model containing both atmosphere and vegetation dynamics, and the novel work presented here has been undertaken for AMAZALERT. The soil-vegetation-atmosphere model developed here is zero dimensional (one grid point with one level for soil, vegetation, and atmosphere). Vegetation dynamics roughly follow the CASA model (http://geo.arc.nasa.gov/sge/casa/bearth.html), and include fire (Hirota et al. 2010). As a single point model, influence of spatially varying characteristics such as land use change on the surroundings cannot be studied. The inflow of moisture from the ocean is imposed according to season and made stochastic. The strength of such a model is that the sensitivity toward changes in ambient state parameters and in model parameters can be easily investigated, allowing feedbacks and tipping points to emerge.

Experiments with this simple model reveal that moisture stress is more important than temperature stress, and the evolution of the soil moisture content appears to be a central parameter for determining the fate of the vegetation. The vegetation flourishes as long as the soil moisture is sufficient to maintain maximum transpiration. As it drops below this level, vegetation wilting and mortality becomes more important. In addition, this model uses soil "wetness" as a proxy to estimate the vulnerability of the litter to fire. It is found that precipitation is of secondary importance, since the vegetation will not suffer as long as the soil moisture remains abundant.

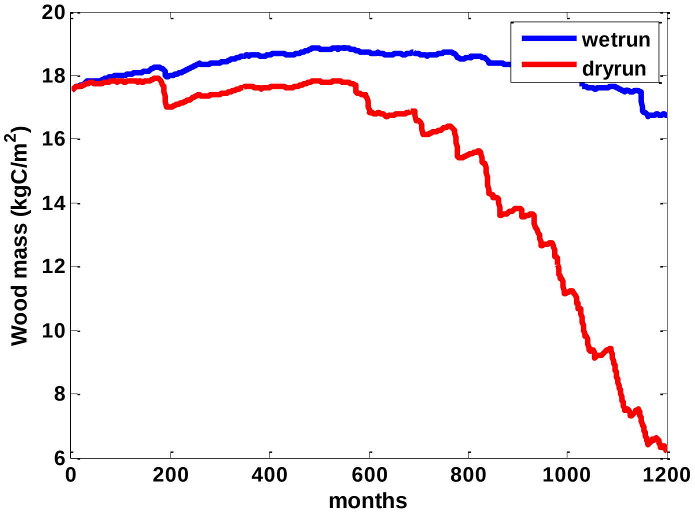


Figure 4. A simple experiment showing the sensitivity of tipping point occurrence to the inflow of moisture from the Atlantic. For the "wet run", the initial lateral moisture inflow is 1200 mm year^{-1} (corresponding to about 1600 mm year^{-1} of precipitation, a bit less than current observed totals); For the "dry run" the inflow is 4/5 of the wet run. The inflow gradually drops by one half over 100 years for both runs.

The forest appears very robust with respect to a decrease in moisture inflow from the ocean. This is caused by the strong moisture recycling, which can keep the average precipitation far above the amount of incoming moisture. Under sufficiently dry conditions, tipping points for the forest emerge. According to the simulations, the average lateral moisture inflow would have to be halved before a serious stress on the vegetation would occur (Figure 4). Such estimates are, however, sensitive to assumptions concerning the typical soil moisture levels where enhanced tree mortality (e.g. through fire) would begin.

Simple sensitivity experiments have been carried out with rising temperatures and CO_2 levels, assuming that maximum transpiration drops linearly over 100 years due to CO_2-induced stomatal closure. This would lead to an additional decrease in the recirculation of the moisture, undermining the robustness of the inland forest. Unfortunately, the magnitude of such adverse effects is hard to estimate on the basis of current data and understanding within the tropics.

The Amazon forest: an Earth system tipping element

Evidence from the past tells us that parts of the Earth system are capable of large nonlinear change, sometimes on relatively short time scales (McNeall et al. 2011). Simple and complex model simulations described above have opened the possibility – albeit highly uncertain – of the Amazon forest as being a 'tipping element' in the Earth system (Lenton et al. 2008) that could transition to an alternative, non-tropical forest, state. The tipping point in question here is the point at which a (small) perturbation results in the collapse of the tropical forest system. Once the system has passed this point a central concern is whether this transition is irreversible. A collapse of the forest system can be regarded as irreversible if recovery times are very long (effective irreversibility), if feedbacks in the system maintain the new state, or if it enters into an alternative stable state. The likelihood of large impacts to natural and socio-economic systems resulting from such a transition provides motivation for seeking early warning of an approaching tipping point that could trigger policy response to mitigate the underlying causes or the associated risk.

Recent work on a number of Earth system tipping points has identified generic signals of tipping behaviour and indicated that early warning is possible (Lenton 2011). In applying the analysis to the Amazon forest in the HadCM3C model, in which the tipping point – dieback – occurs, it is found that the expected early warning signals are not present in tree cover, vegetation carbon or net primary productivity (Boulton et al. 2013). The absence of these signals leads the authors to propose that a more Amazon system-specific approach is required, and make the suggestion that the key process of fire, which is missing from most complex models, could be critical in creating forest/savanna alternative stable states (Aragão et al. 2007 Staver et al. 2011).

What does this mean for an assessment of likelihood?

- Dieback of the Amazon forest is high impact but highly uncertain. As such it is worthy of likelihood assessment
  - Savanna/seasonal forest - tropical forest bistability has been proposed as possible in tropical South America
  - The Cox et al. (2000) HadCM3LC result was atypical in the context of other GCMs/DGVMs, including an ensemble of versions of the same model and the next generation Met Office Hadley Centre model HadGEM2-ES
- There is still a wide range in regional climate response to global climate change in the CMIP5 ensemble
  - Missing or poorly-represented processes increase the uncertainty over the range encompassed by the CMIP5 or other ensembles
- There remain large uncertainties in how the forest may respond to climate changes and greenhouse gases
  - There is the potential to narrow uncertainty in particular by constraining carbon residence time/mortality
  - Current simplified forest characteristics in models are likely to miss complexity in response. For example, species structure may change, which may add resilience to changing climate, but with negative effects on biodiversity (Butt et al. 2008)
- Lags in forest response to climate change could potentially result in greater losses beyond the transient response
  - The difference between transient and 'committed' changes found by Huntingford et al. (2013) and Boulton et al. (in prep.) implies a degree of 'temporary resilience'. It could provide an opportunity for rapid mitigation action to reduce the likelihood of dieback, but depends on the time scales of forest response to climate change
  - It may be that model simulated time scales are biased due to missing mortality processes such as drought or fire. Temporary resilience may thus depend on the return period of extreme drought/fire seasons
  - It may be useful to define a level of impact (e.g. % total forest area loss) and a time scale for dieback, given that vegetation has the potential to keep changing after successful climate mitigation
- GCMs, DGVMs, simple models and observations should all form part of a toolbox for assessing likelihood of dieback

  - Observations are fundamental for developing system understanding, for monitoring, and are essential to model development
  - Complex modelling provides a way of representing system interactions that may not evolve in linear ways, and exploring potential futures
  - Simple models can isolate elements of interest and are relatively easy to modify in response to new information
- It is desirable to be able to give early warning of tipping behaviour if it is early enough to permit action to reduce likelihood
  - Generic indicators are not promising for the Amazon, and therefore more system-specific indicators are sought

3. Modelling drivers of critical change

Model investigation of forest change described above have indicated in general terms that moisture levels play a critical role in forest change, and highlight the importance of drought and dry season length on forest health. In addition to changes in climate, CO_2 has an important direct effect on the forest and surface hydrology. So, in this section these environmental drivers of critical change are examined more closely, and in addition it introduces a crucial direct driver of change: deforestation, and how this interacts with the forest and regional climate.

Effects of CO_2 on the forest

As described in the context of biome change in Section 2, CO_2 has both indirect radiative and direct physiological effects on terrestrial ecosystems. An important greenhouse gas, it exerts influence over global climate change and therefore on the regional climate response. As outlined above, climate changes are uncertain, but warming and more especially drying tends to have a detrimental effect on forest productivity. However, increased atmospheric concentration of CO_2 enhances plant productivity through fertilisation where nutrients are not a limiting factor. It has even been suggested that this effect may be large enough to force a transition of some tropical savannalands (focus on Africa) to a high biomass/woody plant state (Higgins and Scheiter 2012). In addition, because of greater water use efficiency, evapotranspiration is reduced, which may increase resilience of the forest to local drying of the climate. That said, as noted in Section 2, the recycling of water is a very important process in the Amazon basin, and a reduction in evapotranspiration may have knock-on effects on precipitation elsewhere in the basin. In HadCM3LC the negative effects of climate change began to dominate the positive effects of CO_2 and dieback was the result (Betts et al. 2004).

Integrated Assessment Models (IAMs) are designed to represent interactions between driving agents of climate change, including environmental, social and economic factors (van Vuuren et al. 2011b). Part of their function is to convert greenhouse gas emissions scenarios into scenarios of greenhouse gas concentrations that are used as input into climate models. However, there are uncertainties in IAMs associated with the simplified representations of the climate system and carbon cycle, and the climate feedback on the global carbon cycle is recognized as a key source of this uncertainty (van Vuuren et al. 2011b). The traditional approach to sampling uncertainty in the evolution of CO_2 in the atmosphere and hence the effects on the Amazon forest has been to follow different concentration scenarios, but recent work has suggested that the uncertainty in the terrestrial carbon cycle feedback on the global carbon cycle within one emissions scenario may be greater than that described by the full range of SRES scenarios (Booth et al. 2012a).

At the regional scale, complex interactions between CO_2 and Amazon vegetation are both insufficiently understood and potentially of critical importance. At present, the simulated positive effects of CO_2 on Amazon productivity mitigate to some extent negative effects of regional climate changes (Huntingford et al. 2013). A number of researchers have identified the size and stability of the forest response to CO_2 as a key determinant of risk of loss (e.g. Rammig et al. 2010, Cook et al. 2012, Cox et al. 2013). This has implications for climate policy and the mix of greenhouse gases (Rammig et al. 2010, Cox et al. 2013): all are not equal in terms of effect on vegetation. CO_2 is known to have directly beneficial effects on plants, but the magnitude and stability of this association is not well known for the tropics and in conjunction with other nutrient and radiation availability. Part of the reason for the large uncertainty is the lack of suitable observational data. In free-air CO_2 enrichment (FACE) experiments that have been carried out over the past couple of decades, the response of forest to enhanced CO_2 concentrations can be measured. However, to date these have been limited to the extratropics in forests very different in character to the Amazon. But firm plans are now in place to conduct the first FACE-type experiment in the tropics, and will be set up in the heart of the Amazon, north of Manaus (Tollefson 2013). This will provide a tremendous opportunity to enhance understanding of this process.

Temperature

Temperature has influence over Net Primary Productivity (NPP) through both direct and indirect mechanisms. Its direct effects are on respiration and through physiological controls on photosynthesis while indirect effects on rates of photosynthesis occur via temperature control on leaf-to-air vapour pressure difference. As temperature rises, evaporative demand increases and stomatal conductance decreases to limit moisture loss, which also has the effect of reducing CO_2 uptake (Lloyd and Farquhar 2008, Galbraith et al. 2010). 21st century temperature increases over Amazonia are common to all GCM projections and when considered in isolation, have a negative effect on the biomass in the region (Huntingford et al. 2013). However, close inspection of the effects of increasing temperatures on Amazon vegetation carbon simulated by three DGVMs reveals that while both direct and indirect influences contribute to a reduction in vegetation carbon, the relative importance of these mechanisms in each is very different (Galbraith et al. 2010). This study also argues that observational data is required to develop more sophisticated understanding and model representation of respiration sensitivity to temperature. Plants are thought to acclimate long-term to higher temperatures (Atkin et al. 2005, Smith and Dukes 2013) and where this is not taken into account, it is suggested that respiration and photosynthesis in some if not all models is too sensitive to very hot conditions.

Drought and dry season characteristics

Severe droughts in recent years have demonstrated how hotter, drier environmental conditions can damage the forest and associated ecosystem services (Phillips et al. 2009, Lewis et al. 2011, Marengo et al. 2008, 2011, Potter et al. 2011, Tomasella et al. 2013) in both the short term and over prolonged time periods. Observational evidence has shown that enhanced mortality rates (Phillips et al. 2010) or declines in canopy structure and moisture (Saatchi et al. 2013) can persist for years after the meteorological event has come to an end. Long-term throughfall exclusion experiments (Meir et al. 2009) provide a more controlled manner of investigating the effects of deficient moisture on the forest. In a similar way to the lags in mortality in observed drought events, the forest in these imposed drought conditions display resilience initially, followed by heightened tree mortality after a few years, with the larger trees worst affected (da Costa et al. 2010). In a climate regime that is marked by repeated strong droughts, there is the potential for longer-term alteration of forest composition and biodiversity (Meir et al. 2009, Butt et al. 2008). In the past few years, droughts have been interspersed by extreme wet conditions, and it is suggested that the net result of carbon neutrality in wet years and carbon losses from reduced photosynthesis and increased fire in the dry years may be a move towards the Amazon as a carbon source if these extremes continue (Gatti et al. 2014).

Drought in the Amazon is related to variations in SSTs and pressure in the surrounding oceans (Andreoli et al. 2012). It has long been recognized that on interannual time scales, the El Niño-Southern Oscillation (ENSO) phenomenon is one of the major climate modes that affects Amazonia, and El Niño events have been linked to rainfall deficits and resultant low river levels as well as enhanced fire occurrence over the observational record (e.g. Ronchail et al. 2002, Marengo 2004, Marengo et al. 2008a) and in palaeo records (Meggers 1994). The drought of 2010, although it began during an El Niño event, was also subject to the influence of higher than normal sea surface temperatures in the tropical North Atlantic, which have previously been associated with drought events that occurred during non-El Niño years such as 1964, 1980 and 2005 (Marengo et al. 2011, Cox et al. 2008).

Moisture availability and temperature have been used to define climatic envelopes for tropical forest, which enables the future of the forest to be examined under future climate regimes to be related to tropical forest distrbution. Malhi et al. (2009) used the Maximum Climatological Water Deficit (MCWD) measure, based on the balance between precipitation and evapotranspiration, to define “rainforest”, “seasonal forest” and “savanna”, and found that under climate change, conditions in the eastern Amazon move become more appropriate for seasonal forest rather than rainforest. A later study defined a tropical forest climate envelope (constrained by temperature and precipitation) for tropical forest, based on the empirical relationship between forest cover and evapotranspiration, and used this to explore the maximum potential tree cover response to future climate simulated by the CMIP3 ensemble (Zeng et al. 2013). This work indicated a reduction in tropical forest cover according to this measure, particularly in the transition zones between forest and savanna. Based on these models, it suggested with medium confidence that the eastern Amazon could shrink by 5% or more under end-of-the-century climate compared to present-day (2000–2009) conditions (Zeng et al. 2013).

Considering the precipitation regime, as well as total water supply, the strength and duration of the dry season are thought to be important for the long-term future of the Amazon basin (Malhi et al. 2009, Marengo et al. 2011). The dry season in Amazonia is normally defined as the number of consecutive months with maximum monthly rainfall of 100 mm (Sombroek 2001), as below that level, evapotranspiration is assumed to exceed incoming precipitation and the forest is hence in water deficit (Aragão et al. 2007).

In order to identify possible changes in the dry season length, Marengo et al. (2011) applied this definition to observed (GPCC) monthly data from 1951 to 2010. Figure 5 shows a Hovmoller diagram with the distribution of monthly rainfall in southern Amazonia. The 100 mm month^{-1} isohyets are shown by the bold black line. They found that during the 1950s and 1960s, the dry season was longer, suggesting a late demise of the dry season and possibly a late onset of the rainy season. In the mid 1970s, during the climate shift, the dry season was shorter. Since the 1990s, there has been a tendency for a late demise of the dry season. Moreover, during the last 5 years, the dry seasons have become longer, with early onset and late demises, exemplified by the conditions in 2010 (Marengo et al. 2011).

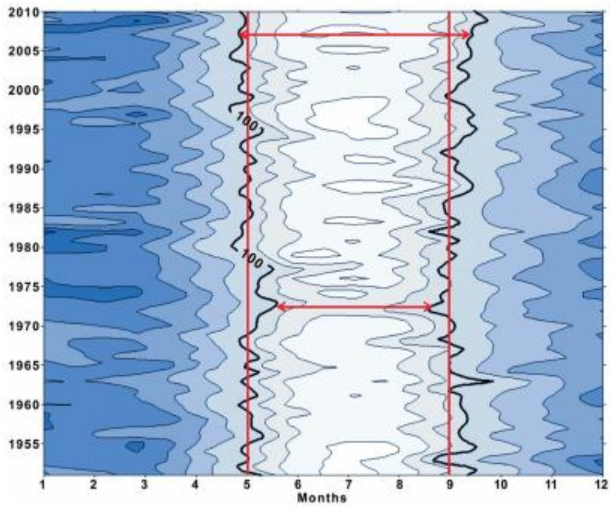


Figure 5. Hovmoller diagram of monthly rainfall from 1951 to 2010 for southern Amazonia. Units are in mm month^{-1}. The 100 mm month^{-1} isohyet is marked in bold and is an indicator of dry months, after Sombroek (2001). Source: Marengo et al. (2011)

Previous studies have suggested that the wet season onset in the Amazon is initiated by increased evapotranspiration (Li and Fu 2004, Li et al. 2006) as a result of the rainforest's response to a seasonal increase of solar radiation (Myneni et al. 2007), or due to changes of cross-equatorial atmospheric moisture transport could influence convection and thus the wet season onset (Marengo et al. 2001, Rao et al. 1996). These findings have additional support from another study (Fu et al. 2013), in which the dry-season length has been observed to increase over southern Amazonia since 1979, primarily owing to a delay of its ending dates, and is accompanied by a prolonged fire season. These changes cannot be simply linked to the interannual variability of the tropical Pacific and Atlantic Oceans.

Recent modelling studies have been influenced by the need to examine changes more appropriate to the Amazon, and have also found evidence for increases in the length (Kitoh et al. 2011) or intensity (Cook et al. 2012) of the dry season in certain regions. As reported in AMAZALERT Deliverable 3.1, although there is a large spread in CMIP5 projections of annual rainfall, there is greater agreement for reductions in rainfall during the dry season, particularly in the eastern basin. There is a stronger agreement for this outcome in the CMIP5 models than CMIP3, as well as reduced agreement for wetter conditions during the rainy season (Joetzjer et al. 2013). Lengthening and deepening of the dry season is found to be related to a northward shift of the ITCZ associated with greater north Atlantic warming and an El Niño-type pattern in the tropical Pacific. High uncertainty remains with respect to evapotranspiration and moisture convergence (Joetzjer et al. 2013) – those processes that are set out above as important in wet season onset. Fu et al. (2013), too, find that important processes controlling the length or cessation of the dry season are inadequately represented by the CMIP5 models and significantly underestimate variability in these characteristics. Hence future changes in these characteristics could also be underestimated.

In some new AMAZALERT research, the modelled rainfall regime of the Amazon has been confronted with observations in order to try to constrain future changes. To provide an emerging constraint on Amazon rainfall projections, the Amazon basin-wide mean precipitation was examined using observations and a large ensemble of simulations from 35 GCMs carried out in the context of the CMIP5 (Boisier et al., in prep.-1).

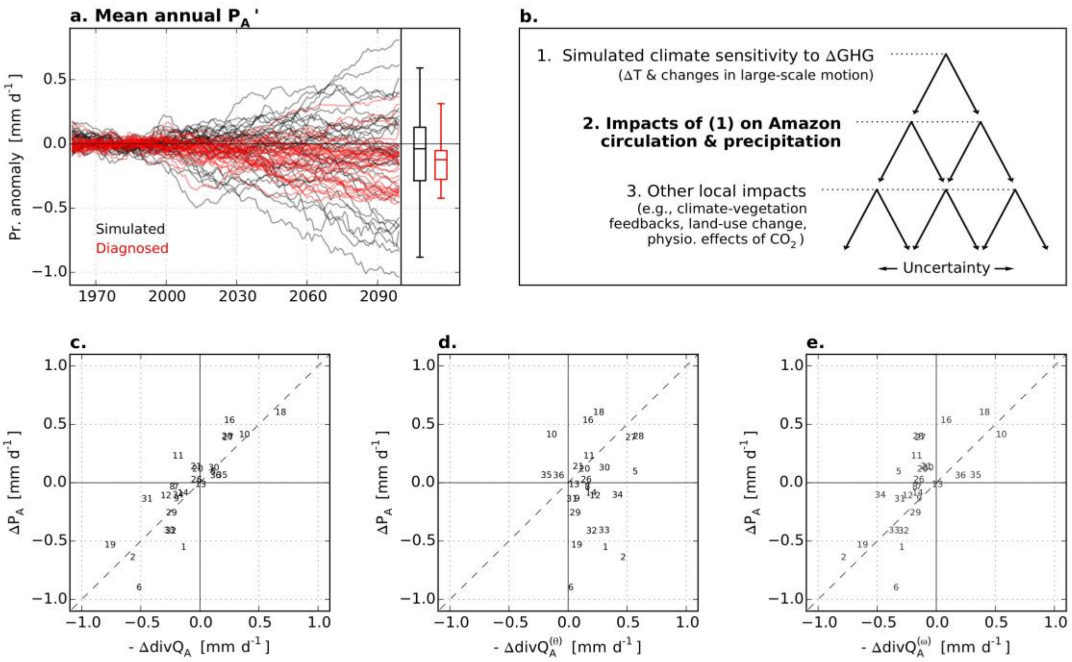


Figure 6. (a) Annual mean precipitation anomalies (relative to 1960-1999) simulated by 36 CMIP5 GCMs (black lines) and diagnosed using observations (red lines) on average over the Amazon basin. Time-series are smoothed with an 11-yr running mean filter. Box-whisker plots show the statistics (median, lower/upper quartiles and extremes) of the precipitation anomalies for each ensemble member at the end of 21st century (2060-2099). (b) Qualitative outline of uncertainty propagation for the long-term Amazon precipitation change simulated by climate models. (c) Simulated change (2060-2099 minus 1960-1999) in the annual basin-average precipitation plotted against the corresponding change in water vapour flux divergence (*-1) over the Amazon basin. Numbers indicate the results of the various GCMs assessed. (d) As in (c), but for the thermodynamic water vapour flux divergence component. (e) As in (c), but for the dynamic water vapour flux divergence component.

The annual rainfall simulated in Amazonia by the CMIP5 GCMs shows a negative trend in the ensemble mean towards the end of the 21st century, but embedded in a very large spread (Figure 6a). Qualitatively, the uncertainty in the modelled long-term precipitation changes in the Amazon can be attributed to different processes simulated in GCMs that operate at different spatial scales (Figure 6b). To look at the role of different sources of uncertainty in the model projections, we compare for each GCM the rainfall anomalies at the end of the 21st century, and the corresponding change in moisture flux divergence. A very close inter-model relationship is observed between the changes in those two variables: decreases in precipitation correspond to increases in divergence (Figure 6c)Figure 6, indicating a dominant role for atmospheric processes over land-surface ones in the control of the Amazon rainfall changes. The weak effects of surface processes in the long-term evolution of Amazon precipitation that could result from land-use changes is not surprising given the small perturbations in Amazon forest area prescribed in the CMIP5 simulations (Brovkin et al. 2013).

A deeper examination of the flux divergence term suggests a major dynamic influence in the long-term evolution of Amazon precipitation (Figure 6e) over the thermodynamic component of this term (Figure 6d). On this basis, we attempt to build a relationship between observed present-day precipitation and large-scale circulation to constrain the model projections, in a similar approach to that adopted in a variety of climate assessment studies (e.g. Shiogama et al. 2011, Cox et al. 2013). This method is based on linear regression models of Amazon precipitation as a function of sea-level pressure of different tropical and subtropical regions, representing the large-scale circulation. The regression models were calibrated with observations and the method evaluated by using present-day GCM data. Finally, the calibrated models were driven by CMIP5 modelled sea-level pressure, 1960-2099, to derive constrained 'diagnostic' projections of Amazon annual precipitation (Figure 7).

Compared to the direct GCM outputs (Figure 6a), the diagnostic long term Amazon precipitation changes show a lower spread within the individual estimations, and an ensemble-mean negative trend of larger amplitude. In line with observed historical precipitation trends and independent reports of recent changes in the South American Monsoon (SAM) regime (e.g. Fu et al. 2013), these results show a likely strengthening of the SAM seasonal cycle, with a longer and more intense dry season (Figure 7). This signature also supports the leading seasonal pattern of precipitation changes simulated by GCMs, although the ‘model democracy’ view of the latter underestimates the amplitude of the projected SAM changes. Yet these observation-constrained changes in the SAM remain moderate compared to extreme scenarios projected by some GCMs.

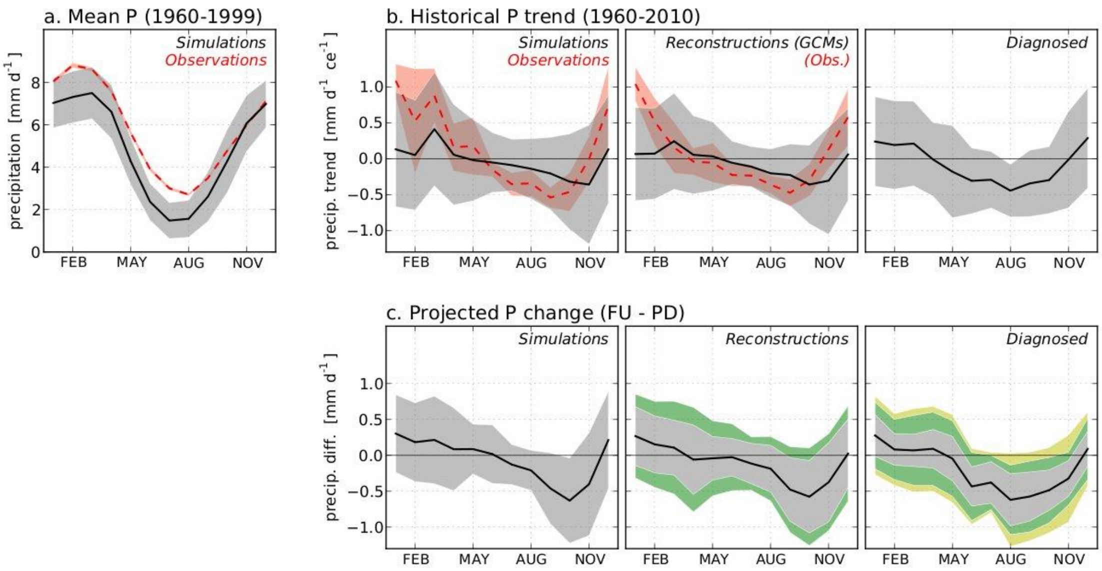


Figure 7. (a) Monthly mean present-day climatology (1960-1999) of Amazon precipitation, (b) PA trends from 1960 to 2010 and (c) long term precipitation change (between the ends of the 20th and 21st century). Thick lines and shading intervals indicate the ensemble mean (μ) ± 1 standard deviation (σ) of the corresponding metric of precipitation, based on GCM (black) or observational (red-dashed) data. 'Reconstructions' refer to regression models predictions in which both the input data used to calibrate the models and that used to force them are of the same origin (from GCMs or observational datasets). 'Diagnosed' refer to precipitation metrics predicted by regression models calibrated with observations and forced with large-scale motion indicators simulated by GCMs. Light grey shades in the diagnosed precipitation metrics indicate the contribution to the overall σ associated with uncertainty in observations.

A subject of intense interest, given its near-global reach, is whether and how ENSO characteristics and its teleconnections may change in the future under global warming. It has proved difficult to form conclusions about future ENSO frequency and intensity (Collins et al. 2010), although a recent study has focused on the extreme El Niño events, such as in 1997/98, in the CMIP3 and CMIP5 ensembles plus a perturbed physics ensemble, and reports a doubling in the frequency of these events under global warming (Cai et al. 2014), which would have implications for the impacts of these events, such as drought in Amazonia. Of additional interest for this region is any variability or trends in the meridional gradient in the tropical Atlantic. An important driver of the HadCM3LC regional climate change and dieback was the rapid warming of the tropical north Atlantic SSTs, which have influence over the position of the ITCZ and moisture inflow over Amazonia. Cox et al. (2008) find that the inclusion of aerosols in a climate model (HadCM3LC) is essential to its ability to capture the observed multidecadal variability in the tropical Atlantic gradient, and that projected decreases in aerosol load in the future lead to enhanced warming of the northern tropical Atlantic relative to the south. This strengthening of the TAG is associated with more frequent severe, 2005-like drought in the future. Booth et al. (2012b) argue that the omission or partial representation of indirect aerosol effects in the previous generation of climate models has meant that their role in influencing Atlantic variability has been overlooked.

Land use change

Recent model intercomparison studies, such as those resulting from the LUCID (Land-Use and Climate, IDentification of robust impacts project) initiative, have shown very little climate impacts of land-use (LU) changes within the Amazon basin (Brovkin et al. 2013). The scenarios of LU that are used are behind the weak effects of land-cover changes simulated in Amazonia by the state-of-the-art GCMs (i.e. the CMIP5 generation), which are in most cases very optimistic and do not reflect the present-day rates of deforestation (see AMAZALERT deliverable D3.1). The lack of realistic land-cover forcings for the Amazon responds both to deficient characterizations of regional (country-level) socioeconomic processes driving changes in LU in large-scale land-cover datasets, and to inadequate interpretations of those datasets when adapted in land-surface models (de Noblet-Ducoudré et al., 2012).

Under AMAZALERT, new scenarios of land use change have been developed (Aguiar et al. in prep.) using the LuccME modelling framework (available at http://www.terrame.org/luccme). These describe three contrasting scenarios of change that sample low to high environmental and social development futures, aligned with the IPCC Shared Socioeconomic Pathways (SSPs). These regional LU scenarios should be more appropriate to perform regional-scale analyses than the LU scenarios used in the simulations of CMIP5.

The most severe LU scenario projected to 2050 by LuccME (Scenario C, hereafter LuccMEc) was used in a modelling experiment to evaluate the potential biophysical and biochemical impacts in Amazonia (Boisier et al. in prep.-2). A set of simulations was performed with the medium resolution configuration (1.25° × 2.5°) of the IPSL-CM5A GCM, following the same protocol used in historical simulations and future projections in CMIP5 (i.e., fully-coupled transient runs, including natural and anthropogenic forcings). The set of simulations (three ensemble runs) covers the period 1980-2050 following the pessimistic pathways both of fossil-fuel emission (and hence concentration of GHGs, RCP8.5) and of land-use in Amazonia (Table 1). The standard LU scenario used in the historical and RCP8.5 simulations of CMIP5, based on the land-use harmonization (LUH) dataset (Hurtt et al. 2010), was prescribed outside the Amazon basin. Thus, the experience done with LuccME (S2) only differs from the equivalent one done for CMIP5 (S1) by the land-cover prescribed in the Amazon basin area.

Table 1. Set of IPSL-CM5A simulations used to evaluate biophysical and biochemical impacts of LU

Sim. reference	GHGs & aerosols	Land cover (Amazonia)	# runs
S1 (CMIP5)	1850-2005 (HIST) 2006-2100 (RCP 8.5)	1850-2005 (LUH-HYDE) 2006-2100 (LUH-MESSAGE)	3
S2 (AMAZALERT)	1980-2005 (HIST) 2006-2050 (RCP 8.5)	1980-2010 (PRODES-Killen) 2011-2050 (LuccMEc)	3

Figure 8 illustrates the change from 1980 to 2050 in fractional area covered by trees, as prescribed in IPSL-CM5A in both simulations (S1 and S2). As mentioned above, the LU scenario adapted in IPSL-CM5A from the LUH-MESSAGE dataset shows little deforestation within the Amazon area. The perturbations are also constrained to the southernmost boundary of the Amazon rainforest, in areas partially covered by trees (savanna-like). In contrast, the prescribed LU forcing based on LuccMEc shows extensive areas across the basin with substantial decreases in forest fraction (> 10%, absolute) and hotspots of deforestation with more than 50% of tree cover loss. Given the weak land-cover perturbation prescribed in S1, we use the differences between S2 and S1 to evaluate the effect of LU. It should be noted, however, that the resulting differences in a given variable between the two simulations do not measure the net effect of the LU described by LuccMEc, but should be a very close indicator of it.

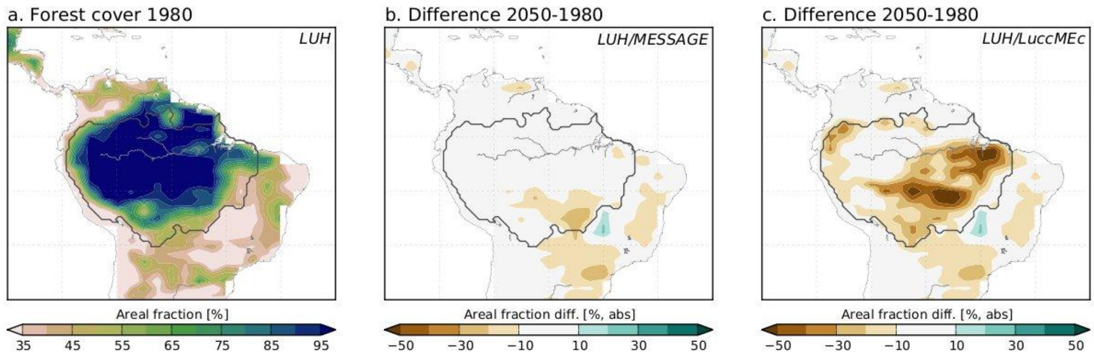


Figure 8. Forest cover in 1980 (a) and changes from 1980 to 2050, as prescribed in IPSL-CM5A for simulations S1 (b) and S2(c).

As a basin average, the IPSL model simulates a positive annual precipitation trend in response to the standard RCP8.5 forcing (Figure 9). This particular regional signature of climate change places this model towards one end of the CMIP5 ensemble range, the mean of which indicates a small trend towards drier conditions (Figure 6), and results from large precipitation increases (> 200 mm yr^{-1}) in the north-eastern part of South America. In line with the changes in precipitation, the model projects basin-wide increases both in evapotranspiration (ET) and in surface runoff and drainage (RD), with spatially coherent changes in the three variables.

The ‘LU-induced effect’, computed as the mean difference between S2 and S1 at the end of the period simulated (2035-2050), shows the effect of the new LU scenario over the standard forcing, and is illustrated for each component of the surface water budget on the right hand panels of Figure 9. Although the S2 simulations still show basin-average increases in precipitation, ET and RD, the relative effect of the new LU is for statistically significant decreases in these quantities in many areas of the basin. This finding is consistent with previous modelling work that suggested that large-scale deforestation could bring about reductions in precipitation (Sampaio et al. 2007) and also some observational evidence (Spracklen et al. 2012). The amplitudes of the changes are generally lower than but of the same order as those induced by the GHG forcing. Hence, on average across the Amazon, the hydrological impacts of large-scale climate change (GHGs), as simulated by the IPSL model, are significantly dampened by the LU effects.

It is noteworthy that, in terms of water flux, the LU-induced precipitation changes are larger in amplitude than those of ET. This feature indicates that mechanisms other than moisture recycling may play a major role in controlling the Amazon precipitation response to LU, as has been reported in earlier model-based assessments of Amazon deforestation (see d'Almeida et al., 2007, and references therein). Alternatively, there could be a role for the convergence feedback that may amplify an effect driven by moisture recycling (Chadwick and Good 2013).

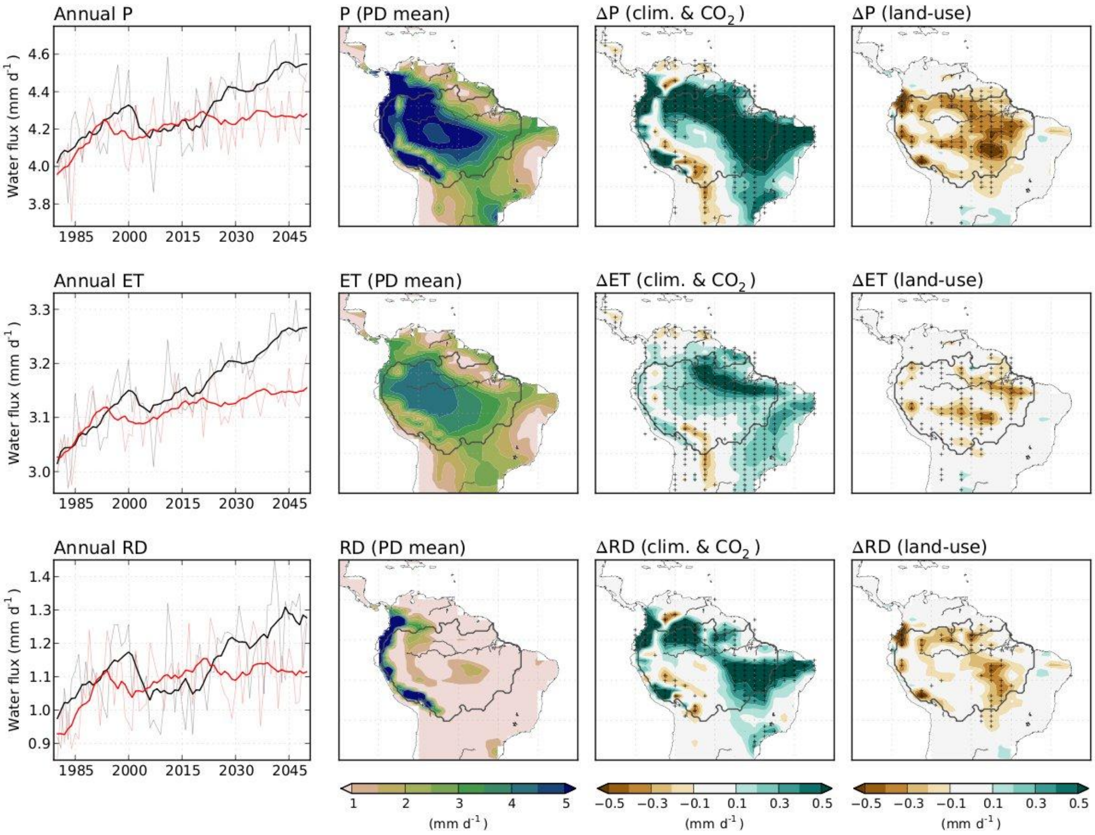


Figure 9. Amazon basin-average times-series of annual precipitation (top), evapotranspiration (middle) and runoff/drainage (bottom), from simulations S1 (black) and S2 (red). The ensemble and 5-yr moving average is indicated as thick lines. The maps illustrate, for each variable, the present-day (1980-1995) climatology (centre-left), and the long term change driven by GHGs (centre-right) and land-use (right). Marks indicate the anomalies that are statistically significant ($p < 0.05$).

Some regions without – or with small – land-cover perturbations, such as in the northernmost part of the basin (Figure 8), show significant LU-induced changes in precipitation (Figure 9). Such exported impacts of LU are of particular interest regarding the natural response of vegetation and potential feedbacks with climate (Sampaio et al., 2007). However these processes are however not accounted for in the model assessed here, which does not include dynamic vegetation.

Seasonal LU-induced precipitation anomalies are illustrated in Figure 10. The model shows mostly decreases in rainfall with variations from season to season roughly following the South American monsoon cycle (not shown). That is, larger impacts occur towards the south during the austral summer (DJF) and towards the north of the basin in winter (JJA). Statistically significant changes in precipitation are highlighted in Figure 10, as well as those located in areas with small changes in tree cover from 1980 to 2050 (see red marks). In most seasons, the robust precipitation response to LU and the exported (remote) effects occur near the hotspots of deforestation. A clear exception is observed in JJA, when the model simulates an extensive region north of the Amazon river with substantial precipitation decreases despite the very low deforestation prescribed in this area (Figure 8). Further analyses are required to shed light on the processes leading to these anomalies; reduced water flux advection from the south could be a good candidate.

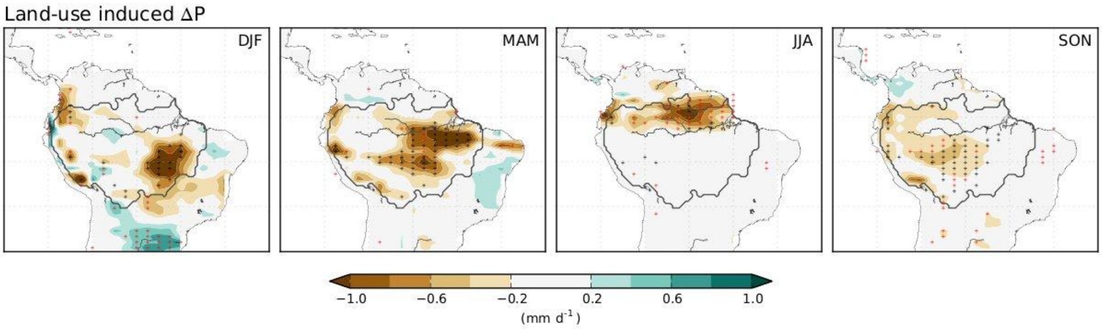


Figure 10. Land-use induced precipitation changes in DJF, MAM, JJA and SON. Marks indicate the anomalies that are statistically significant ($p < 0.05$). Red marks highlights statistically significant changes over areas with small change in tree cover from 1980 to 2050 (less than 5%, absolute).

Fire and interacting drivers of change

The preceding description of drought in Amazonia includes several references to enhanced fire occurrence during drought episodes. There is seasonality in fire occurrence in Amazonia, as meteorological conditions during the dry season are more favourable for fire, and therefore when a dry season is longer or more intense than normal, higher numbers of fires are detected. Although it is difficult to compare the absolute number of fires detected by satellites (Cardoso et al. 2005), in 2004/2005, the number of NOAA12 satellite fire detections was substantially higher than in the previous years 2000-2003. Also, the changes in the south (7°S – 18°S) of the region were more intense than in the north (6°N – 7°S), consistent with the spatial patterns of the drought in those years (Marengo et al 2008b).

Fire is a process that is currently missing from most complex models, but has the potential to exert considerable influence over biome distribution. Staver et al. (2011) argue that a large portion of the wider Amazon region could support alternative stable of forest or savanna, and are at risk of a switch in biome. Changes brought by encroachment of fire into forest regions could be perpetuated through fire-vegetation feedbacks and result in a shift to the alternative stable state. The incorporation of fire into complex models will be an important step in understanding how fire may affect land cover, and further, in coupled modelling, should allow the operation and investigation of feedbacks.

Recent improvements made at INPE to the Brazilian Integrated Land Surface Processes Model (Inland, http://www.ccst.inpe.br/inland) include the implementation of a new scheme for estimating the impacts of fires on vegetation dynamics. The current version of the fire model for Inland is derived from previous work of Arora and Boer (2005) (hereafter AB2005), and estimates fire potential from fuel and moisture conditions, assuming random presence of ignition sources. The current fire modelling for Inland is concentrated on the simulation of fire probability and its effects as a disturbance to the vegetation dynamics. Presence of fuel was modelled as in AB2005, which determines that a minimum of 200 gC m^{-2} of plant biomass is required to sustain a fire.

In the Inland implementation, plant biomass is considered the sum of stem and leaf biomass from all vegetation types over land. Flammability is also modelled as described in AB2005, where flammability increases exponentially as soil moisture at the root zone approaches the wilting point. In Inland, we calculate flammability based on the moisture at the model's first soil layer, where most of roots are located. Our approach to represent ignitions sources differed from AB2005 as we assume that lightning and other process that trigger fires are simply random. Final fire occurrence probability is calculated by multiplying these three estimates, as in AB2005.

To account for fire disturbance, we propagate the fire occurrence probability estimation into the calculation of vegetation dynamics. That is done by assuming that the fraction of the vegetation affect by fires is proportional to the fire probability. As other disturbances considered in Inland, fires affect biomass, leaf area index (LAI), and total ecosystem aboveground NPP. These variables, in turn, modify the fractional cover of forest and herbaceous canopies.

Fire occurrence in Amazonia is closely tied both to direct human action and to the climate (e.g. Cardoso et al. 2003, Aragão et al. 2008) and these drivers of change acting in combination could increase the likelihood of a high-impact outcome, even where projected climate changes alone are sufficient to bring this about. Forests that are subject to direct fragmentation or are in a more vulnerable state from changes in dry season characteristics, drought or previous fire occurrence, are more susceptible to further damage from fire when it does occur, making a shift to a different forest or vegetation type more likely (Malhi et al. 2009). Aragão et al. (2007) found that in the drought of 2005, five times the area of forest was burnt through ‘leakage fires’ in the Brazilian state of Acre than directly deforested, and suggest that fire leakage could be a major agent of biome change in a climate regime marked by frequent drought. Increases in temperature projected by CMIP5 and the stronger signal for a longer and deeper dry season described above would increase the meteorological fire danger, particularly in the eastern basin. Where this enhanced fire danger intersects with human activity (deforestation), which is also projected to be greatest in the southern and eastern basin, there is greater risk of forest loss through fire (Golding and Betts 2008).

From the application of Inland, we estimate that the impacts of climate change in Amazonia increase when effects of land use changes and fire are considered. The most important changes will potentially occur in the east/north-east and south of the Amazon, with an increase in surface temperature, and decrease in precipitation and evapotranspiration. Dry season length is expected to increase, and a reduction of upper-canopy biomass and increase in lower-canopy biomass is related to an increase of the biomass in grasses and a replacement of tropical forest by seasonal forest and/or savanna (Figure 11). The effects of fire and land use cover change and climate changes, resulting in warmer and possibly drier climates, are important to the future of biome distribution in Amazonia. The vulnerability of Amazon rainforest to more frequent and severe droughts, either through a direct effect on tree mortality or through an indirect effect, via increased probability of vegetation fires, is important to understand the potential for an Amazon forest dieback and its implications for the global carbon cycle and future climate (Cardoso et al. in prep., Sampaio et al. in prep.).

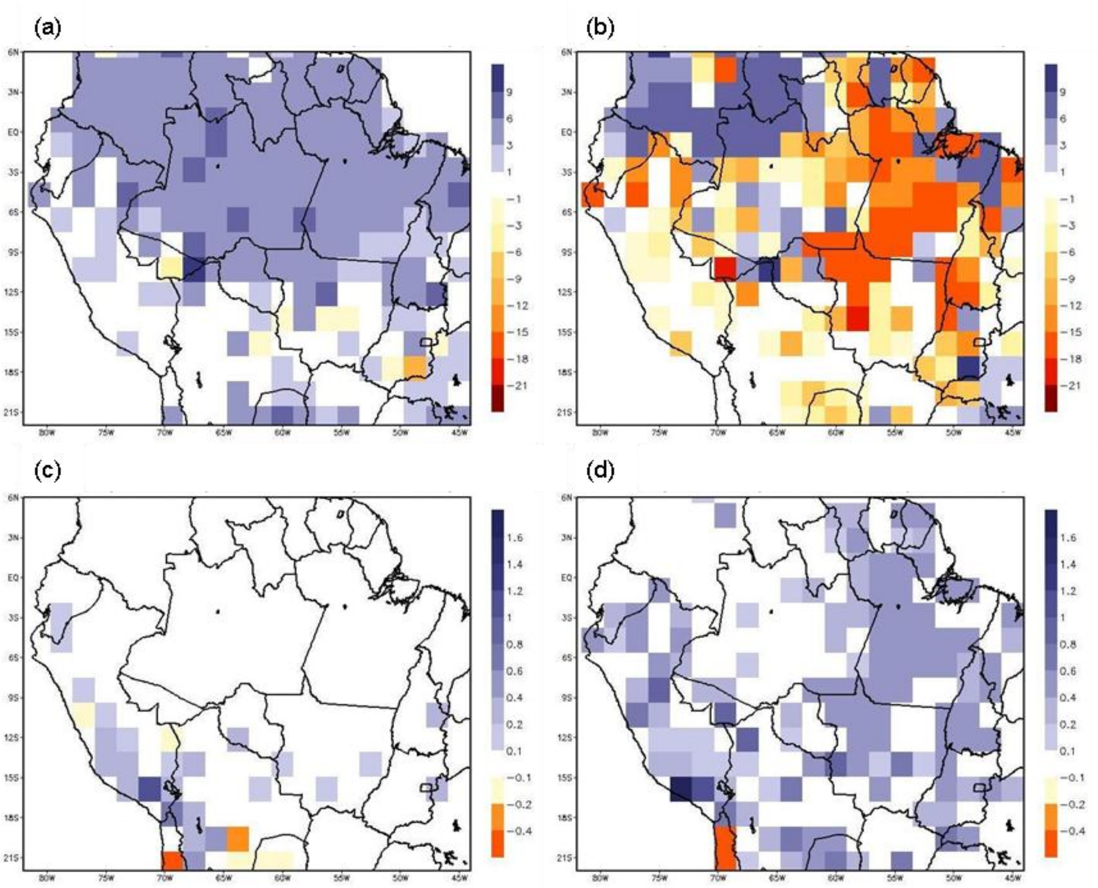


Figure 11. Biomass anomalies (kgC m^{-2}) of the upper canopy (a and b) and biomass anomalies of the lower canopy (c and d) for 2065-2070, as simulated by INPE's Inland model: (a) and (c) the model was run under RCP4.5 greenhouse gas concentration, (b) and (d) the model was forced by the same configuration but also considering the effects of deforestation and forest fire.

What does this mean for an assessment of likelihood?

- There is large uncertainty in the transformation of emissions into atmospheric concentrations, which IAMS provide as the input into climate models, owing to great uncertainty in the terrestrial carbon cycle feedback, and has not received much attention to date
- CO_2 fertilization confers significant benefits on Amazon forest carbon uptake and increased carbon storage in the models, but this process is a key uncertainty marked by a lack of understanding of how this operates in tropical vegetation and in conjunction with other nutrient and radiation availability
  - The planned Amazon FACE experiments could reduce uncertainty
- Poorly-represented temperature dependency of respiration, photosynthesis and turnover is likely to make most if not all models too sensitive to high temperatures
  - Ongoing observational work should help to develop better model representation of this process
- The forest is observed to be sensitive to drought, as demonstrated by droughts such as 2005 and 2010 as well as in imposed drought experiments

  - The mechanisms of response to drought appear to be different than in current models, which is in part due to missing processes such as direct drought- and fire-driven mortality.
- The dry season may be lengthening
  - CMIP5 displays greater agreement in projections for a deepening and lengthening of the dry season in the future
  - This could be related to differential heating of the northern and southern hemispheres, with dry season rainfall negatively associated with tropical north Atlantic SSTs
  - Models appear to be inadequate to represent processes behind changes in onset of the wet season
- Aerosols may play an important role in Atlantic SSTs and hence on dry season rainfall. The current generation of models that fully represent aerosol processes will provide more opportunities to investigate this further
- It may be possible to reduce uncertainty in rainfall change using observation-based constrained projections
  - The results presented here support the tendency of the GCMs towards a strengthened Amazon dry season
  - The 'diagnostic' projections and the observed past trends indicate that the model democracy approach (ensemble mean) would likely underestimate the amplitude of the projected Amazon dry season lengthening, which may have implications for forest viability
  - Further analyses are needed to shed light on the spatial detail of constrained projections to evaluate whether the regions affected are vulnerable or not
- Land use and climate change interaction is still poorly understood, but improved scenarios of land use provide the opportunity to investigate the combined effects
  - Results suggest a modification to the hydrological cycle, with significant reductions in both ET and precipitation in the new LU experiment relative to the standard
  - Effects of these LU-induced climate changes on the remaining land cover could be tested in a DGVM
- Droughts favour the occurrence of fires in Amazonia
- Fire is a critical process that is still missing in most complex models, in particular so-called land-use fires that involve the combination of a climate-induced high fire risk, forest fragmentation and human drivers of deforestation and pasture formation.
- Recent improvements to INPE's Inland model include a new scheme for estimating the impacts of fires on vegetation dynamics
  - It estimates that the impacts of climate change in Amazonia increase when effects of land use changes and fire are considered
  - The most important changes will potentially occur in the east/north-east and south of the Amazon, with an increase in surface temperature, and decrease in precipitation and evapotranspiration
  - Dry season length is expected to increase as well as a reduction of upper-canopy biomass related to an increase of the biomass in grasses and a replacement of tropical forest by seasonal forest and/or savanna

4. Monitoring and measuring the forest

Observations lie at the heart of addressing limitations in our knowledge and modelling of Amazon processes as well as being necessary for ongoing monitoring of forest health and response to policy decisions. Indicators of forest health developed from observed relationships that can also be modelled provide a crucial link in the investigation of the forest response to projected future change and in assessing the future viability of the forest.

A major challenge in the region is the availability of suitable observations. Even the globally best directly measured variables (surface air temperature, precipitation) are generally relatively sparse, particularly when going back a few years, which has implications for process understanding and long term trends and variability. Good quality gridded datasets do exist for certain variables but uncertainty in 'observations' must be considered. Observations of forest properties are even more limited, and rely on programmes such as FLUXNET (coordination of measurements from flux tower sites, http://fluxnet.ornl.gov/), the LBA (Large Scale Biosphere-Atmosphere Experiment in Amazonia, https://daac.ornl.gov/LBA/lba.shtml) and RAINFOR (the Amazon Forest Inventory Network, http://www.rainfor.org/en). Improvements in understanding of forest processes, sensitivities and response to stressors are essential and a challenge is to maintain and extend these programmes, and promote long-term campaigns. As noted in Section 3, there have been positive developments in this area regarding the implementation of FACE-based experiments in Amazonia. The satellite era has brought opportunities through great improvements in the spatial and temporal resolution of observations over Amazonia. However, there are important caveats in the use of satellite data associated with the fact that products are derived as opposed to being directly observed quantities. Satellite products should be regarded as useful when the process behind their production is understood and they have been validated with ground-based observations to determine how they may be used.

For AMAZALERT, work has been done towards addressing the requirement for meeting models with observations for understanding and assessing likelihood of future change. This work is carried out within a risk framework that is aimed at being flexible and responsive to changes in observational data availability, and improvements in observed and modelled indicators of forest health. As a prototype study it is designed to demonstrate the application of this methodology to critical thresholds in the Amazon region.

It begins with the hypothesis that we are able to characterize an extreme event using meteorological and vegetation observations and use these characteristics to identify similar events in climate model simulations of past climate and projections of future climate. We choose indicators that are available as both observed quantities in the real world and simulated diagnostics in models to enable a direct comparison, notwithstanding the model biases that might exist. Once indicators are chosen we can identify these events in the observational record, current and future projections and our goal ultimately would be to use their characteristics to inform an early warning system.

Indicators

Observed data and metrics chosen

The meteorological variables chosen here as indicators are precipitation and temperature due to the comparative ease with which these are available as gridded observed datasets over a relatively long period, and the validation which is given to these variables as model parameters. However, drivers of extreme events are not thought to be limited to these, and other indicators such as radiation will also be important, and an avenue for future work. Here gridded monthly observations from the CRU (Climate Research Unit, University of East Anglia) temperature and precipitation datasets (CRU, 2014) were used for the period 1901-2009, with horizontal resolution of 0.5° latitude/longitude (Harris et al. 2013). Others such as cloud cover and radiation were considered but more work needs to be done on deriving comparable model diagnostics which would also require validation against observational datasets.

As an indictor of forest health, we use NPP. NPP is defined as the difference between the amount of CO_2 taken in by plants during photosynthesis and the amount released during respiration (NASA MOD17 2014a). Other indicators of vegetation health, preferable due to their greater availability in observed datasets (e.g. Fraction of Absorbed Photosynthetically Active Radiation and Leaf Area Index, Zhu et al. 2013), were not available directly as output from the models. However, diagnosing these indicators, from some models at least, is a future possibility. We look at monthly in addition to annual mean data as plants response to climate variability and extremes is important as well as mean changes (Reyer et al., 2013). Observed NPP from the NASA MODIS satellite was used for the period 2000-2012 (monthly-NASA MOD17 2014b; annual-NASA MOD17 2014c). Although monthly data is available, it is not an official NASA product, and it is recommended to be used only for trends and general comparisons rather than in a quantitative fashion (Kevin Ward, NASA, and Chris Jones, Met Office Hadley Centre, pers. comm.), and our understanding of the MODIS NPP calculation concludes the annual NPP is the more accurate measure (Running et al. 1999).

Saleska et al. (2007) indicates that the Amazon rainforest appeared to be greener, hence healthier, during the 2005 drought, and suggested this may be due to increased availability of sunlight when water was not limited (such as for deep rooted trees). However, other studies showed that higher tree mortality was seen in ground observations (Phillips et al. 2009), and others indicated that this ‘greening’ was an irreproducible feature of an atmosphere corrupted version of the data (Samanta et al. 2010). More recently, Morton et al. (2014) suggests the ‘greening’ could be a feature of how satellites image the Amazon region, and how much the forest changes in the dry season may be overestimated because of seasonal differences in the angles of satellite observation and solar radiation. To what extent the NPP MODIS data could be affected by this is not obvious as it is derived from several products including analysed model fields and ancillary data in addition to remotely sensed products.

To enable us to capture the characteristics of a particular ‘extreme’ event, various metrics were trialled using the observed data, which would enable the 2005 drought to be identified as an extreme meteorological event using these indicators. Annual rainfall of the region chosen did not indicate 2005 as a year with particularly low amount. Here we used the lowest total rainfall of June, July and August, although many alternatives are used in other studies (e.g. (Maximum) Cumulative Water Deficit, Aragão et al. 2007, Malhi et al. 2009).

Use of observations to link known event with indicators

Results are shown from a region of the eastern Amazon, chosen as the region has been used in previous observational and modelling studies (e.g. Malhi et al. 2009). The 2005 drought was noted for severe effects in the south and west of the region which spread to the east (e.g. Chen et al. 2009)

Monthly time series for 2001-2009 (the period covered by the monthly MODIS NPP data), Figure 12, illustrates how 2005 might be characterized by these indicators. Temperature (Figure 12a) in the first half of 2005 particularly, was high compared to the rest of the period. For 2005 June precipitation in this region seemed particularly reduced compared to other years (Figure 12b). NPP (Figure 12c, given caveats over the interpretation of the monthly data), indicates that 2005 was a year with lower productivity, especially in the May to September period. So, for the eastern Amazon region 2005 is drier, warmer, and has reduced productivity over other years in the first decade of the 21st century.

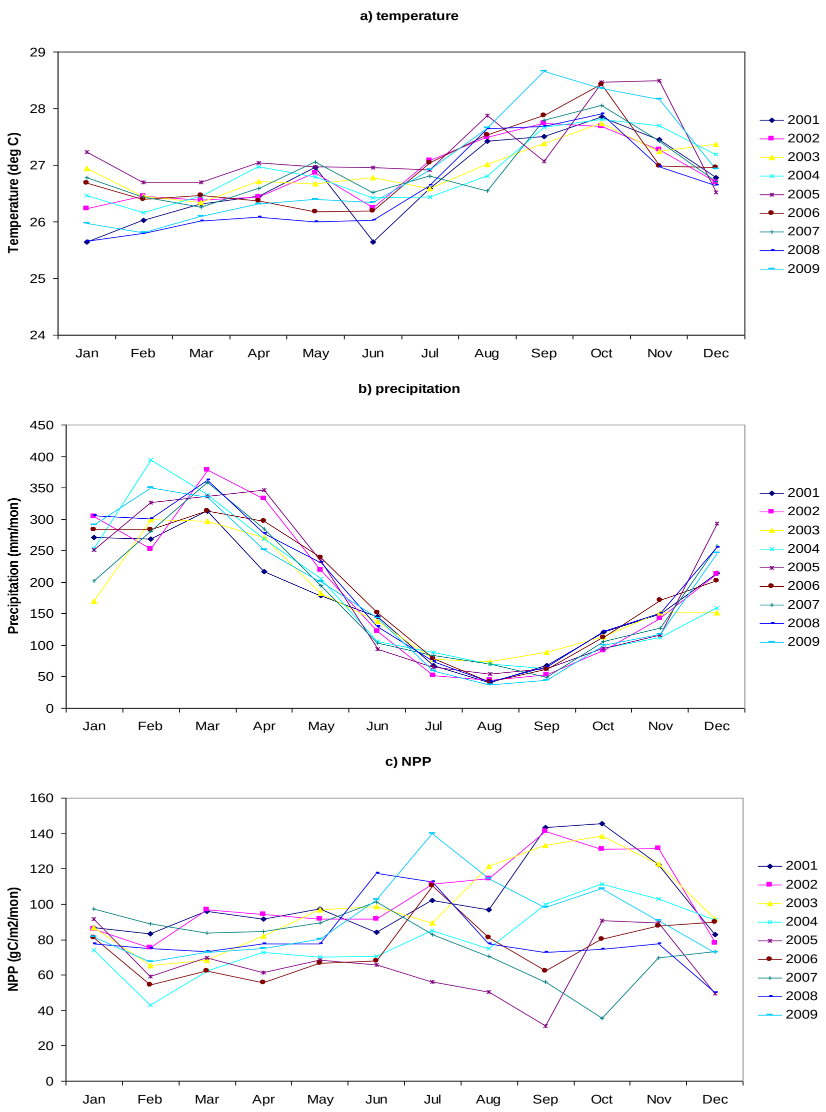


Figure 12. Seasonal cycle of observed indicators in the eastern Amazon region for individual years in the first decade of the 21^{st} century a) CRU temperature b) CRU precipitation c) MODIS NPP

Model data

We use those CMIP5 datasets (CMIP5, 2014), provided for the IPCC AR5 report, with the chosen indicators available for the entire periods chosen at the time of retrieval. For the study described here we present findings for each model individually, and do not attempt to create ensemble mean statistics or regrid models to any ‘standard’ resolution. Hence results presented reflect absolute data from each model with only temporal accumulation or meaning, and spatial meaning over the chosen region. In addition we do not attempt to rank models as being more or less realistic than others, as determined by accuracy of representation of historical climate or any other method.

Figure 13 shows the annual cycle for CMIP5 models covering the same ‘baseline’ historical period for the eastern Amazon region as the observations in Figure 12. The ‘dry year’ is 2005 for the observations and the driest year from 2001-2009 for models. ‘Other years’ shows the multi-year mean monthly values from the rest of the years in that range. For precipitation, most models reproduce the annual cycle but tend to be drier than observations, particularly in the rainy season. Observations show a steeper transition from wet to dry, between April and June, in the drought year, 2005.

For temperature, the seasonal cycle is captured in the models, although with increased amplitude. We note that the ‘dry year’ cycle may be expected to be less smooth, as the ‘other years’ cycles are mean values. The dry year is slightly warmer, especially at the beginning of year. For NPP, the monthly averages from observations fall within the wide spread shown by the models, and the dry year, 2005, coincided with reduced NPP over the region. However, the clear seasonal cycles seen in the models for this period are not evident in the observations.

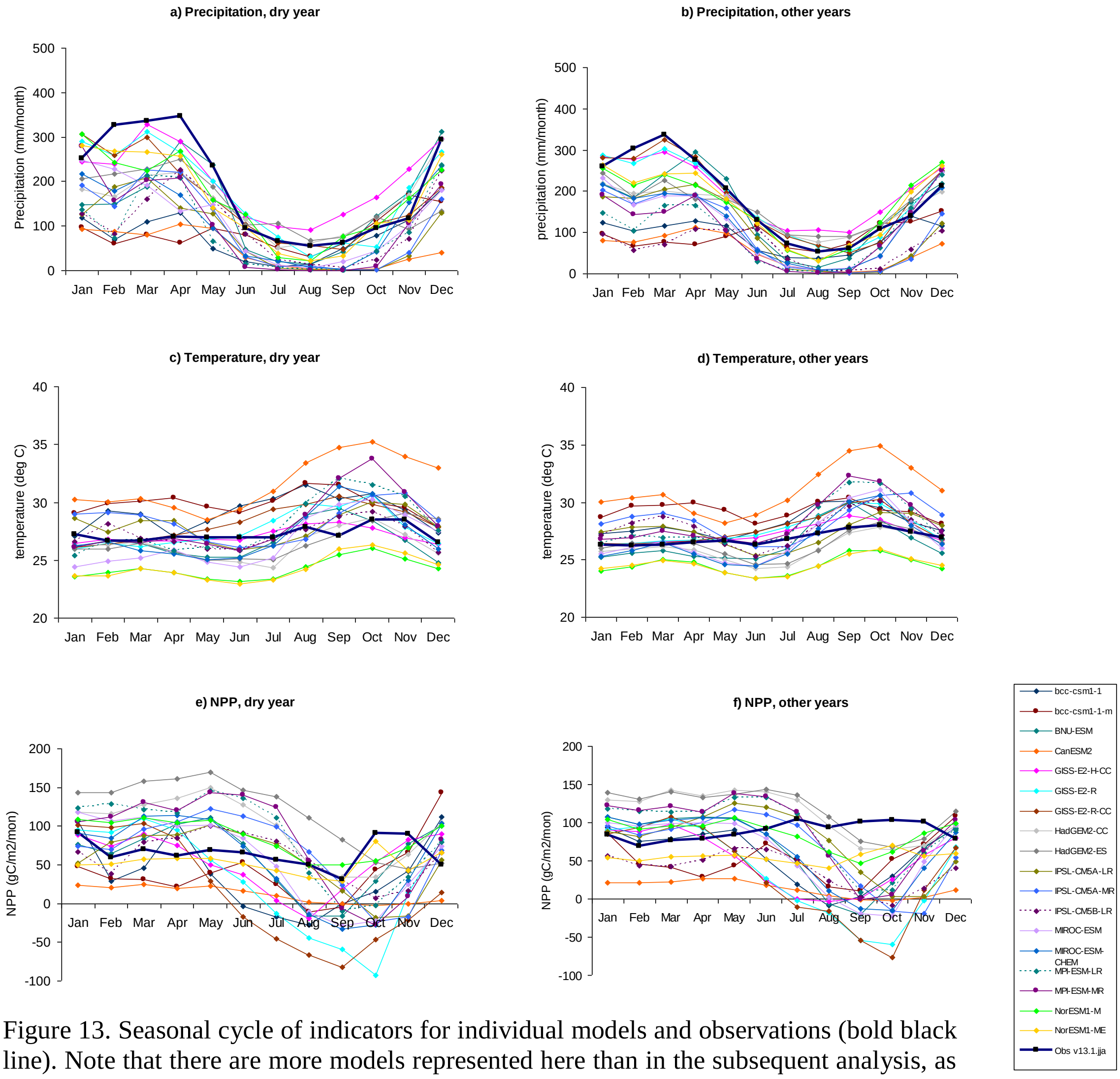


Figure 13. Seasonal cycle of indicators for individual models and observations (bold black line). Note that there are more models represented here than in the subsequent analysis, as only nine years’ of data were needed.

The monthly NPP is more difficult to compare as the NASA MODIS values are indicative of trend rather than absolute value, but we can see a reduction in a ‘dry year’ is not so marked in model fields. It is possible that temperature differences are not as important a driver as precipitation for NPP (see e.g. Figure 1 of Schloss et al. 1999). As these observations do not show 2005 as substantially warmer than other years in this region, hence we assume temperature is not a primary driver of the reduced NPP in this year and region. However, this does not mean that thresholds do not exist in the temperature climate regime (e.g. Cowling et al. 2006).

Observed events

Relationship between observed events and forest health/climate indicators

With the JJA total precipitation metric, a minimum, although by a small margin, is seen in 2005 (Figure 14, blue line). The annual and JJA total NPP derived from the monthly values also show a minimum (green circles and crosses respectively). The annual MODIS NPP values are also shown on Figure 14 (green squares) and, as expected, show a discrepancy from the annual values derived from monthly data, but the minima in 2005 is still clear. Hence we choose to use the occurrence of the 2005 level JJA precipitation as a threshold to identify where an event of the severity of 2005 might have occurred in the historical period in observations and models, with evidence that it was an event where forest health was affected (e.g. Phillips et al. 2009). Although we do not have historical observations of NPP for the entire twentieth century, we look at the relationship between the vegetation indicator (as proxy of forest health) and meteorological indicators in the historical model period, although with no particular causal mechanism identified.

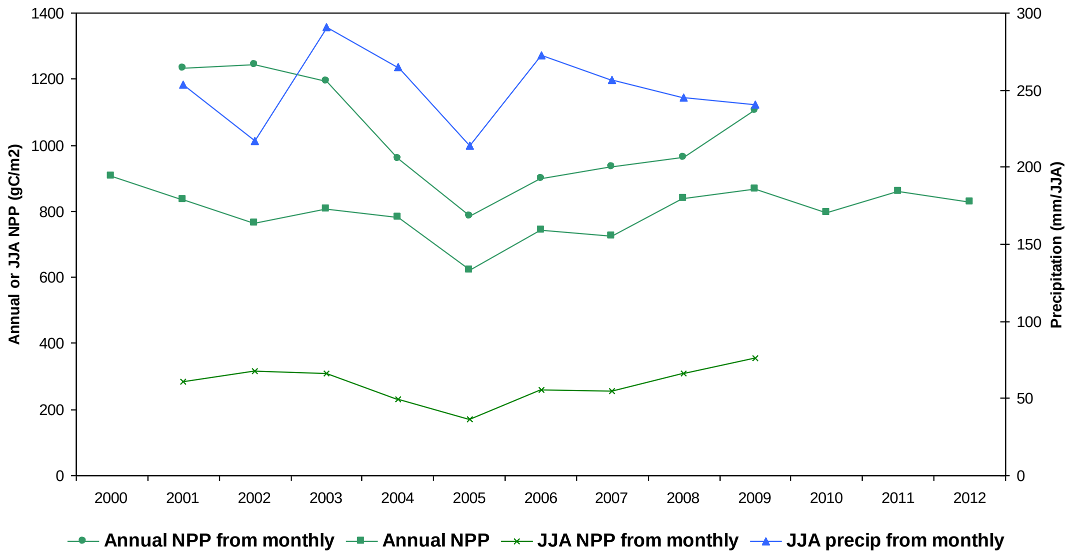
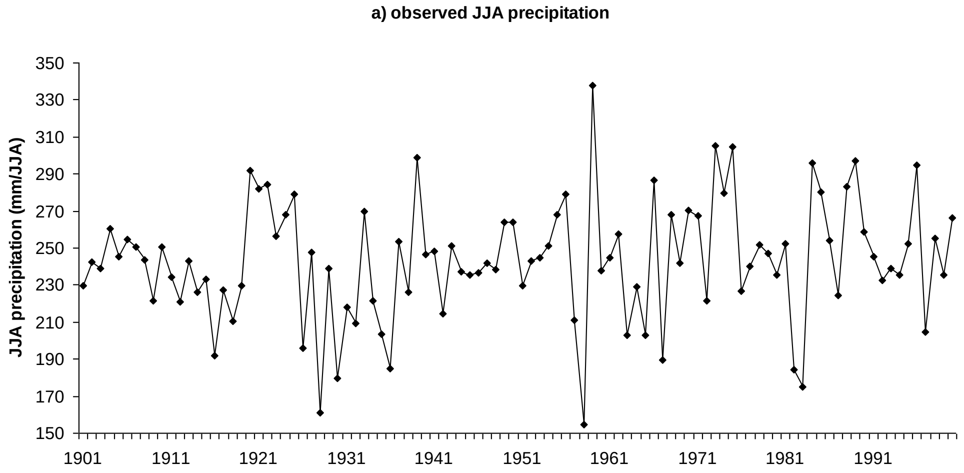


Figure 14. Precipitation (mm/JJA, blue) and NPP (gC m^{-2} annual (green dots) and JJA total (green crosses)) derived from monthly NASA MODIS and NPP (gC m^{-2} annual, green squares) from annual NASA MODIS data.

Application of 2005 threshold value

The 2005 value of JJA precipitation (214 mm/JJA) occurs at the 16th percentile in the 1901-2000 observed dataset (time series shown in Figure 15a). For this dataset, it means that values lower than the 2005 value were observed 16 times in the 1901-2000 period. To apply the same value as a threshold to each model, they would first need to be bias corrected, as their absolute values are, to varying degrees, biased from observed. Time series of absolute values from the historical period clearly show differences between models and observations (Figure 15b).



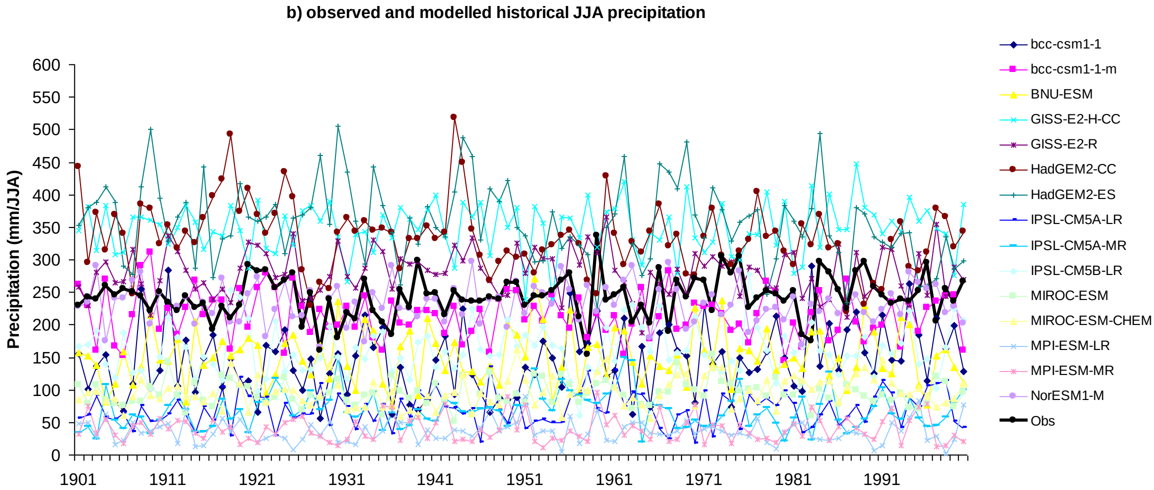


Figure 15. a) Time series of observed total JJA precipitation over the 20th century b) Time series of total JJA precipitation for the 20th century for observations and CMIP5 models

There are many methods used for bias correction (e.g. Hawkins et al. 2012); one often implemented method is to use only the 'delta', that is the change in future from historical data seen in individual models or to use a change factor which also accounts for any difference in variance.

Here, as a first step we take the equivalently ranked value from each modelled distribution of JJA precipitation and use that as our modelled 'observed 2005 equivalent' threshold. In this way we do not bias correct the model data, although further work exploring this would be instructive. It should be noted that as the series is non-stationary the occurrences at or below a particular threshold may be more or less frequent at the end of the period to the beginning. That is not explored further here, but it has been demonstrated that NPP in the Amazon region has increased in the last two decades of the 20th century (Nemani et al. 2003).

Modelled events

Indicator thresholds in CMIP5 20th century historical runs and 21st century projections - precipitation

The distributions of JJA precipitation for observations and individual models for the historical period (Figure 16, black lines) were first compared using a Kolmogorov-Smirnov test to estimate the probability that two samples have the same distribution (removing the mean value and normalising by the variance). Three models (indicated with italics in Table 2) failed the 5% significance level, but are included here for completeness. The future model distributions are shown (Figure 16, red lines) and for most, but not all, models indicate a shift to drier conditions.

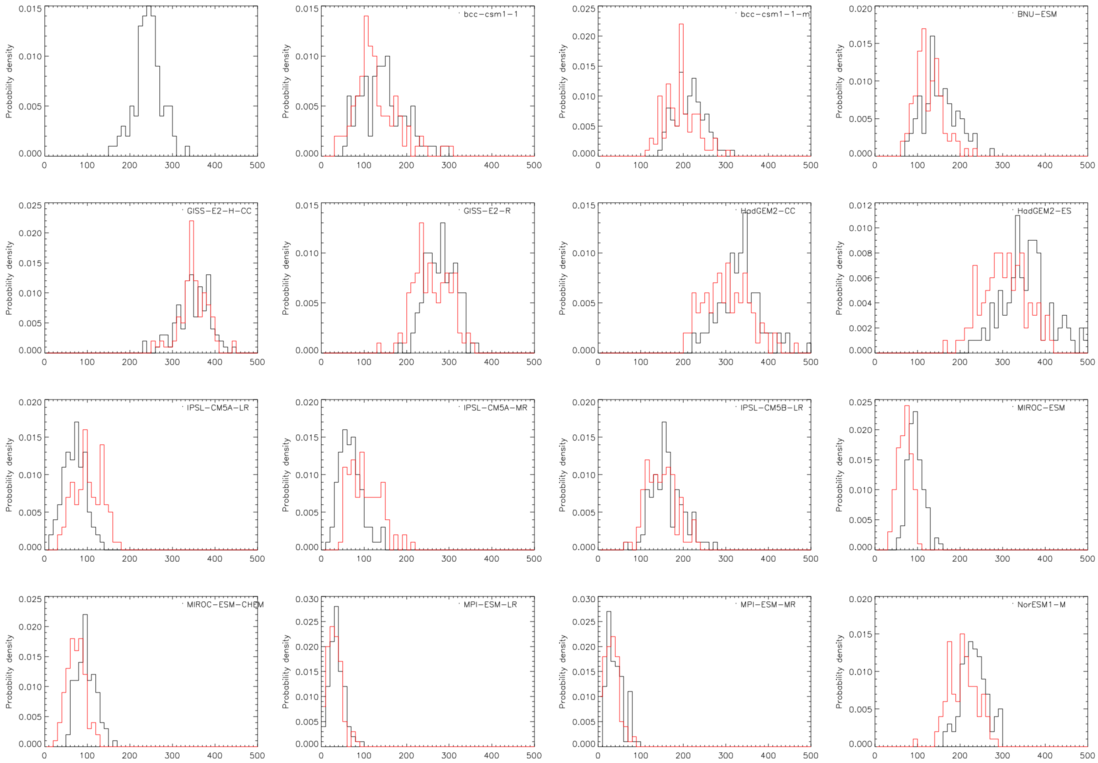


Figure 16. Distributions of JJA precipitation (mm) for observations and all models for baseline (black) and future (red – model data only)

Having obtained a threshold value for each model (indicated in Table 2, column 2), then the occurrence of events which exceeded (that is, with amounts of precipitation which fell below) this threshold was determined in future model projections (column 3). We use this to see if there is any change, in future projections, in the frequency of occurrence of events below the threshold. For this indicator, in all but three models, the number of times the threshold was equalled or lower values occurred increased.

Table 2. Absolute values of '16th percentile' JJA total precipitation and the exceedance of that threshold value in future for models (italics indicate those models which when compared to the observed distribution, failed the Kolmogorov-Smirnov test)

Data source	**Absolute value of '16th percentile' total JJA precipitation (mm/JJA) in baseline**	**No. of times this threshold Reached or exceeded in future**
Observations	*214.7	No data
bcc-csm1-1	92.4	22
bcc-csm1-1-m	178.4	38
BNU-ESM	109.2	33
GISS-E2-H-CC	311.1	9
GISS-E2-R	244.1	41
HadGEM2-CC	284.3	40
HadGEM2-ES	299.1	48
IPSL-CM5A-LR	41.9	3
IPSL-CM5A-MR	43.0	0
IPSL-CM5B-LR	128.2	33
MIROC-ESM	*78.2*	*71*
MIROC-ESM-CHEM	74.4	53
MPI-ESM-LR	*21.1*	*30*
MPI-ESM-MR	*21.4*	*30*
NorESM1-M	203.9	43

* 2005 value

Indicator thresholds in CMIP5 20th century historical runs and 21st century projections - NPP

As described above, there is evidence that both annual and JJA total NPP is correlated to JJA precipitation, that JJA NPP is low when JJA precipitation is low, as exemplified in the drought of 2005. As there is no long gridded observed record of NPP for the twentieth century, the same ranking of events to detect a threshold performed for the JJA precipitation climate indicator cannot be done for a NPP vegetation indicator. Instead, we looked at model NPP for the historical period, and found the total JJA NPP for the model year of the threshold 16th percentile JJA precipitation. This was done for each model and taken as the historical threshold JJA NPP value; hence we were able to calculate how the threshold exceedance of this value changed in future.

Distributions of NPP values for each model are shown in Figure 17 for the historical period (black) and future (red). There is a good deal of variation in changes in the distributions – some (such as BNU-ESM) show little change, while others show a shift to lower (e.g. bcc-csm1-1) or higher (e.g. IPSL-CM5A-LR) values. This is reflected in the changes in number of times values do not reach the threshold. Table 3 gives number of times NPP is lower than the threshold value in the historical and future period, and indicates no consistent trend across models.

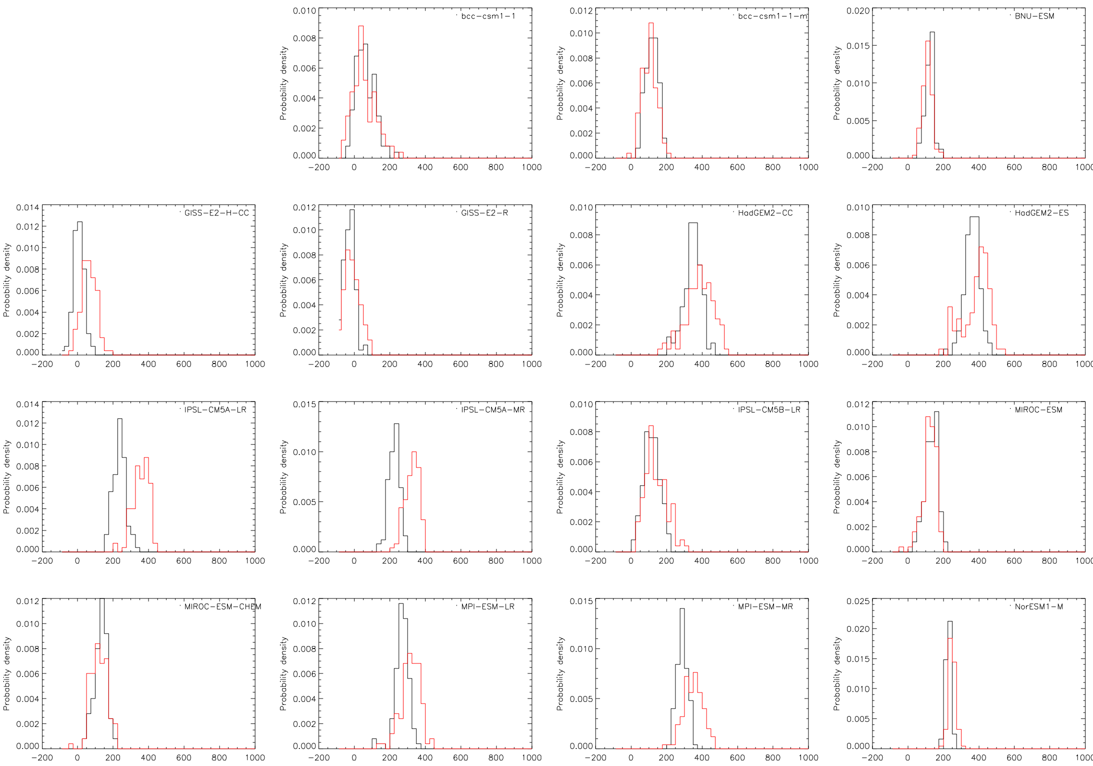


Figure 17. Distribution of historical (black) and future (red) JJA NPP (gC m^{-2}) for individual models

Table 3. Threshold exceedance for JJA NPP at year of '2005 equivalent' in each model

Data source	**NPP threshold: absolute value of NPP (gC m^{-2} for JJA) for year of JJA precipitation threshold value**	**No. of times this threshold reached or exceeded in historical period**	**No. of times this threshold reached or exceeded in future period**
Observations	*172.2	No data	No data
bcc-csm1-1	-1.6	9	20
bcc-csm1-1-m	67.5	8	21
BNU-ESM	100.1	20	35
GISS-E2-H-CC	-1.0	42	7
GISS-E2-R	-30.0	51	41
HadGEM2-CC	263.0	8	9
HadGEM2-ES	343.1	34	27
IPSL-CM5A-LR	240.7	60	2
IPSL-CM5A-MR	237.3	67	2
IPSL-CM5B-LR	87.6	31	18
MIROC-ESM	*157.4*	*73*	*79*
MIROC-ESM-CHEM	159.3	71	77
MPI-ESM-LR	*216.5*	*8*	*5*
MPI-ESM-MR	*242.5*	*8*	*2*
NorESM1-M	225.8	46	10

* 2005 value from monthly NASA MODIS data, which is likely to be an over-estimate

The lack of a consistent signal could be indicative of many issues. It could point to the indicator needing refinement – it could be that the JJA precipitation metric is not adequate in capturing characteristics of an extreme drought event in this region. Alternative metrics could be examined to determine if another better represents how NPP responds to periods of drought. It has been shown that there are other drivers such as radiation which are important

(Running et al. 2004) and so the correlation between precipitation and NPP may not be as straightforward as assumed here. In models, the parameterization of NPP in each model is likely to differ, and an investigation into what parameterization schemes are used in each is needed to interpret projected future changes. There are also known deficiencies in modelled vegetation schemes. For instance Smith and Dukes (2013) highlight 'missing' processes in carbon exchange responses in plants such as the way individual plants 'acclimate' to new climate regimes.

Observed and modelled indicators of change

This work employs a risk framework to Under a risk framework methodology, information contained within observed extreme events, known to put stress upon the forest, is utilized to try to identify thresholds in regional meteorological and vegetation indicators. These are then used to identify similar events in both observed data and modelled historical/future projections.

In this prototype study, the 2005 drought is taken as an event with severe impacts on the forest. Using this, we identified initial indicators of forest health (NPP) and associated climate regime (here, temperature and precipitation) for a region in the Amazon. We have begun to develop means to assess where thresholds and transitions in these indicators may exist, thresholds which are particularly associated with the health of the forest vegetation. In this study, there is not a consistent shift in NPP threshold in all models under climate change – this could be due to one or a combination of several factors.

However, this work is intended to provide a framework that can be updated with improved indicators. Future work includes consideration of alternative precipitation metrics such as cumulative water deficit (Aragão et al. 2007, Malhi et al. 2009), and bias correction to the model fields (Hawkins et al. 2012). Ongoing work, including that within AMAZALERT, will help to inform better vegetation indicators and possibilities exist to derive diagnostics equivalent to observed fields from model data available. The important point is to formulate indicators that can be represented within models as well as in observations. This approach also provides a test case for determining what kind of information we can get from the models about how the forest responds to an event, such as a drought, corresponding to a measureable, stressful, real-world episode.

A future goal is for thresholds such as these, together with other indicators, to be utilized within a multi-hazard framework to develop early warning systems relating climate variability and change to changes in forest health in the region. By relating model projections of change in indicators to quantities that are observable, it is more likely to motivate action.

What does this mean for an assessment of likelihood?

- Indicators of forest health developed from observed relationships that can also be modelled provide a crucial link in the investigation of the forest response to projected future change and in assessing the future viability of the forest
- This framework is flexible to allow implementation of improved indicators. An essential part of this work lies in gaining more in-depth knowledge of observational products, how these relate to forest health, and then understanding how to obtain or develop comparable indicators in the models
- Developing suitable indicators allows an assessment of position with respect to a more vulnerable state, which would form part of an early warning system, and the monitoring and modelling of response to policy decisions

5. Subjective probability of Amazon collapse

An expert elicitation was carried out to estimate the likelihood of critical change in the Amazon consistent with current scientific knowledge. The aim was to provide an alternative view on likelihood combining different sources of information from the literature. This was done because Amazonian critical change may involve processes that are not all captured by or are biased in current GCMs (e.g. fire, drought mortality), and have no analogue in historical change. An elicitation from a range of experts helps provide a balanced view of current knowledge. Such an assessment involves subjective choices, because of the various assumptions underlying each scientific study. This is especially true for the case of critical changes (such as in the Amazon). Critical change may involve processes that are not all captured by current GCMs, or indeed relevant to historical change. An elicitation from a range of experts helps provide a balanced view of current knowledge.

The Amazon part of the elicitation questionnaire designed by Kriegler et al. (2009, survey originally performed in 2006) was repeated. The exact text as created by Kriegler et al. was used, to allow comparability between the two studies. A range of experts agreed to take part from AMAZALERT and the wider community, some of whom participated in the original Kriegler study.

The elicitation asks experts to give feedback in terms of imprecise probabilities. This recognizes that the probability of critical change consistent with current knowledge is not known precisely. The meaning of imprecise probability intervals is explained in the questionnaire in terms of betting odds:

> "Assume you have stated that the probability of Amazon dieback for a given temperature scenario lies somewhere between a lower bound of 0.2 and an upper bound of 0.6. Your statement about the lower probability means that you are committed to buy a bet paying you $1 if dieback occurs and nothing if it remains intact for any price below 20 cent (*supremum* buying price). Your statement about the upper probability means that you are committed to issue such a bet if someone is willing to pay you more than 60 cent (*infimum* selling price). This price range reflects the interval of probability values that are plausible within the limits of your ambiguity about your belief." (Kriegler et al. 2009)

Consistent with the original study, participants were told that Amazon rainforest dieback referred to a greater than 50% loss of the area of forest that currently exists and that they should assume land use changes would account for no more than 20% loss over the time. This meant that they were providing information on their beliefs that at least 30% of the Amazon rainforest would be lost due to changes in climate only. Probabilities were requested for each of three future 'corridors' of global warming, shown in Figure 18.

The results are shown in Figure 18a-c), along with the results of Kriegler et al. in Figure 18d-f). The experts gave a range of different answers, emphasising the difficulty in quantifying probability. However, some broad themes emerge.

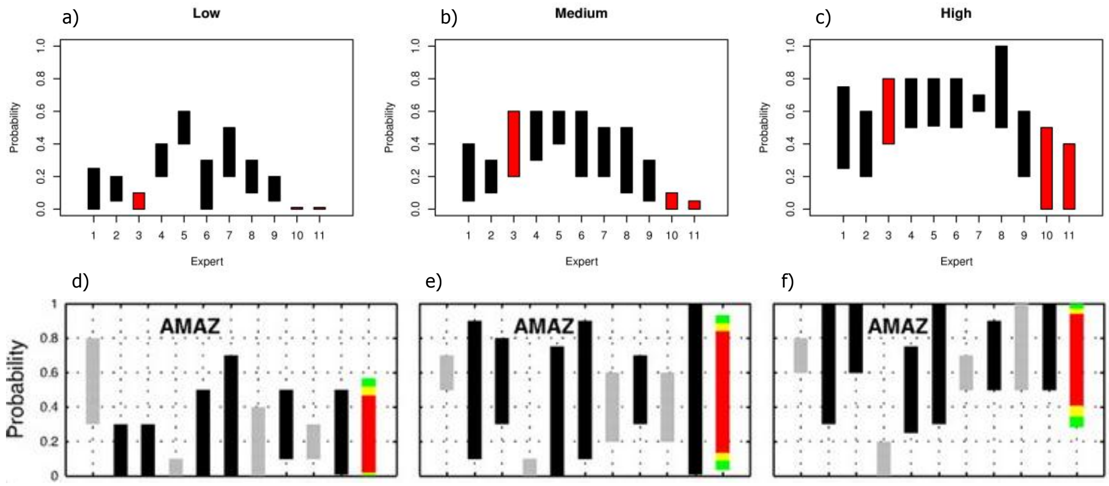


Figure 18. Results from expert elicitation on probability of Amazon rainforest dieback. Experts were asked for their views on the lower and upper probability bounds of dieback under (a) low, (b) middle and (c) high future warming scenarios. These results are compared to those found by Kriegler et al. (2009) when the elicitation was originally carried out in 2006 (d-f). Experts participating in both elicitations are shown in red in (a-c)

First, the probability of Amazon critical change was not generally viewed as very low. Even under the medium temperature corridor, most experts believe the probability of critical change is greater than about 5%. For the high temperature corridor this figure rises to about 20%. This is broadly consistent with the original Kriegler study.

However, significant value is seen in mitigation of climate change. Mean estimated probabilities are around 3 times lower for the low temperature corridor than for the high temperature corridor.

Comparing our results with the original Kriegler study suggests a small decrease in mean estimated probability. Indeed 6 of 11 experts who expressed an opinion believed that the probability was lower than that understood in 2006, with 5 choosing 'no change'. The Huntingford et al. (2013) study was highlighted as one of the reasons for this change.

Overall, however, the difference between our study and that of Kriegler is relatively small: the key messages identified above apply to both studies.

What does this mean for an assessment of likelihood?

- Caution is required in interpreting these results. Dieback probability is highly uncertain and involves many subjective choices. They are just one method of summarising our current (lack of) understanding of this system
- Reported probabilities are generally higher than might be directly inferred from some GCM-based analyses (e.g. Huntingford et al. 2013, Malhi et al. 2009).
  - This is consistent with the idea that the full uncertainty is inflated e.g. by missing processes such as deforestation and the response of fire to climate change.
  - Also, the elicitation considers a longer time horizon than in most GCM studies
  - The voluntary participation of experts could potentially self-select towards those who have greater concern over the future of the forest and therefore introduce bias in the results (which is also acknowledged in Kriegler et al. 2009).

6. Final remarks and recommendations

In making an assessment of likelihood, it is necessary to bring together many layers of information. Each layer may be of a different type, and associated with different levels of uncertainty. Quantitative likelihood assessment is thus not possible given the varied nature of the available information. In this report, model results have been put in perspective via semi-quantitative and qualitative assessments of the possible effects of missing processes, other uncertainties or potential biases in the above models. This includes understanding of key processes as observed, and whether they might be reliably simulated. This work contributes to AMAZALERT objectives of improving the understanding and modelling of complex interactions, which includes understanding how these are modelled and where improvements should be made. In addition, it provides important background material towards the overriding AMAZALERT aim to develop a blueprint for an early warning system, in terms of our current levels of knowledge and the need to build flexibility into such a blueprint to enable future system understanding to be assimilated.

With more models and increased modelling capability, it has now become possible to determine how representative the early dieback result was of other model projections. The new data describe a range of uncertainty in projections of change and hence permit an assessment of probability, albeit in a qualitative manner.

In the context of climate-vegetation modelling, it has emerged that the large regional drying and warming behind the dieback reported in Cox et al. (2000, 2004) is not typical of current models. Huntingford et al. (2013) forced a single land-surface model by climate patterns from 22 GCMs. They find that of the 22 climate patterns, only one (from HadCM3) causes committed – or potential – ‘major biome loss’. This is consistent with probability somewhere between 0 and 15% (95% confidence interval assuming models are independent and equally likely; the range is a result of the small sample of models). The changes seen in the Cox et al. (2000) study are atypical even of an ensemble of different versions of the same model. As reported here, around 30% of that ensemble shows committed ‘dieback’ (at least 25% forest loss) under the high (RCP8.5) emissions scenario. The probability of climate-driven dieback by the end of the century is systematically lower than the probability of committed loss.

Thus, results from current climate-vegetation models, taken at face value, imply that the probability of climate-driven dieback occurring by the end of the century is significantly less than the probability of it not occurring. However, missing processes and biases (known and potential) in these models are such that dieback is much harder to rule out than implied by these models alone. There are key uncertain processes, such as fire, CO_2 fertilization and regional rainfall dynamics, which could lead to substantial changes in model projections in the future. Thus the probability of dieback is contentious, as illustrated by the range of assessments from the expert elicitation, but should not be regarded as very low. Further, the interactions between climate variability and change and land use change, particularly through fire, are likely to increase the probability of biome change, especially in regions such as the south and east of Amazonia that are already particularly vulnerable to these drivers of change.

Some themes have come across strongly when drawing together the body of research presented here. One of these is the range of uncertainty that stretches right from the emissions pathway to the response of the forest to drivers of change. Another is the constant and great need for more observations and for these to be brought together with modelling work. This will enable growth in understanding and in representation of key processes for the Amazon and should lead to a reduction in some elements of uncertainty described in this report. Defining better indicators of forest health is a goal in itself as well as working towards developing comparable indicators in models, which would provide an important tool for both monitoring the forest and modelling its future viability. A third theme is the necessity to recognize and much better understand the complexity of the Amazon system, and the multiple and interacting drivers of change that are acting on the region that may combine to have much greater impacts than any one element acting alone.

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