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ForestPaths

Co-designing holistic forest-based policy pathways for climate change mitigation

D3.4 - Recommendations for considering forest management in IAMs/ESMs

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Key takeaway messages

- Forest management has a large effect on carbon exchange and the surface energy balance and several key aspects should be taken into account in Earth System Models (ESMs) and Integrated Assessment Models (IAMs).
- Forest stand age structure and composition have a large effect on carbon fluxes and biophysical climate variables and therefore should be included in ESM and IAM simulations. The basic components of the data needed to force this at the global scale are available.
- The impact of thinning on within-stand tree size structure has a large effect on the forest carbon sink and biophysical variables highlighting the importance of this management component. It is, however, difficult to parameterise thinning accurately across large scales or going back in time more than a few decades.
- Mass-based timber harvesting may lead to substantial biases in harvested area in process-based models as these typically have biases in woody growth rates. Area-based harvesting is less likely to bias overall ecosystem carbon exchange estimates and may therefore be a relatively simple improvement for forest management representation in IAM and ESM simulations where carbon sink calculations are important.
- If the goal of IAMs is to better match UNFCCC GHGI reporting of LULUCF emissions improved representation of stand age structure, composition and forest management is needed as well as a broader definition of managed forest that counts towards total LULUCF emissions.

Summary

Forests play a key role in the global climate system through biogeochemical processes (notably carbon exchange) and biogeophysical processes (e.g. albedo and evapotranspiration). Forest management, through changes in species composition and age structure influences these processes. Earth System Models (ESMs) and Integrated Assessment Models (IAMs) are tools that are used to study the climate system and their interaction with land cover and, in some cases, land management. The extent to which forest management is taken into account in these models varies widely. Here, we assess the importance of forest management in relation to key climate variables such as carbon exchange and albedo to provide recommendations to IAM and ESM modellers on the relevance of taking forest management into account.

List of abbreviations

AIM	Asia Pacific Integrated Model
CABLE	Community Atmosphere–Biosphere Land Exchange model
CESM	Community Earth System Model
CMIP	Coupled Model Intercomparison Project
COFFEE	COmputable Framework For Energy and the Environment model
CRU-NCEP	Climatic Research Unit National centres for Environmental Prediction
DGVM	Dynamic Global Vegetation Model
DICE	Dynamic Integrated Climate Economy model
EC	European Commission
EC-Earth	European Consortium-Earth
ECOCLIMAP	Database of Land Surface Parameters
EFI	European Forest Institute
ESA-CCI	European Space Agency Climate Change Initiative
ESM	Earth System Model
EU	European Union
FAO	Food and Agriculture Organization of the United Nations
FUND	Climate Framework for Uncertainty, Negotiation and Distribution
GCAM	Global Change Assessment Model
GDP	Gross Domestic Product
GFDL-ESM	Geophysical Fluid Dynamics Laboratory Earth System Model
GR	Grass Only
HILDA	HIstoric Land Dynamics Assessment
HYDE	History database of the Global Environment
IAM	Integrated Assessment Model
IEA	International Energy Agency
IMAGE	Integrated Model to Assess the Global Environment
IPCC	Intergovernmental Panel on Climate Change
LAI	Leaf Area Index
LPJ-GUESS	Lund-Potsdam-Jena General Ecosystem Simulator
LPJmL	Lund-Potsdam-Jena managed Land
LUC	Land Use Change
LULUCF	Land Use, Land-Use Change and Forestry
LUH2	Land Use Harmonisation version 2
LUKE	Natural Resources Institute Finland
LULUCF	Land Use, Land-Use Change and Forestry
MAGNET	Modular Applied GeNeral Equilibrium Tool

MESSAGE-GLOBIOM	Model for Energy Supply Strategy Alternatives and their General Environmental Impact - GLObal BIOsphere Management
MIMOSA	Mathematical Integrated Model for Optimal and Stylised Assessment
MIT	Management with idealised thinning from the Reineke-based approach
MOT	Management with “observed” thinning from the empirically-based harvest
NBP	Net Biosphere Productivity
NFI	National Forest Inventory
NGHGI	National Greenhouse Gas Inventory
NorESM	Norwegian Earth System Model
NOTIMB	timber harvest set to zero
ORCHIDEE	Organising Carbon and Hydrology In Dynamic Ecosystems
PBL	Netherlands Environmental Assessment Agency/Planbureau voor de Leefomgeving
PFT	Plant Functional Type
PNV	Potential Natural Vegetation
RCA4	Rossby Centre regional Atmospheric climate model 4
RCA-GUESS	Rossby Centre regional Atmospheric climate model - General Ecosystem Simulator
REF	reference scenario
REMIND-MAgPIE	REgional Model of Investment and Development - Model of Agricultural Production and its Impact on the Environment
SCM	Simple Climate Model
SSP	Shared Socioeconomic Pathway
TIMER	Targets Image Energy Regional model
UKESM	UK Earth System Model
UKRI	United Kingdom Research and Innovation Council
ULUND	Lund University
UNFCCC	United Nations Framework Convention on Climate Change
USA	United States of America
VISIT	Vegetation Integrative SImulator for Trace gases
WP	Work Package

1 Introduction

Forests play a key role in the global climate system. First and foremost through their role in the global carbon cycle. Circa 54 Pg C circulates through forests each year through the processes of photosynthesis, respiration and combustion (Ma et al., 2015), with a net uptake of 3.5 Pg C yr^{-1} in recent decades (Pan et al., 2024). The cutting and removal of trees due to human activities disrupts the natural process of death and decomposition, with much of the carbon in the harvested biomass rapidly released to the atmosphere. Vice versa, forest growth after harvest, or as an effect of changing climatic circumstances, results in the uptake of carbon from the atmosphere (IPCC, 2019). Historical disturbances, likely primarily harvest, are believed to be responsible for about one quarter of the existing global forest carbon sink (O'Sullivan et al., 2024; T. A. M. Pugh, Lindeskog, et al., 2019). In addition to the carbon cycle, forests affect climate through biogeophysical processes, including changes in albedo, evapotranspiration and roughness (Foley et al., 2003). Changes in forest type can have substantial effects on these variables. Albedo, for instance, is influenced by the structure and leaf type of trees, whilst deciduousness results in the underlying soil or winter snow being much more influential during parts of the year (Foley et al., 2003). Changes in tree cover are known to substantially influence the surface energy budget through changing evapotranspiration and thus the partitioning between sensible and latent heat which strongly affects local surface air temperature (Lawrence et al., 2022).

Earth system models (ESMs) are biophysical models that describe the different components of the earth system such as the atmosphere, the oceans and the biosphere to project changes in climate. ESMs also typically include biogeochemical calculations of how greenhouse gas concentrations in the atmosphere are affected by processes on the land and in the ocean. They are traditionally used to evaluate the impact of greenhouse gas emissions and land-use changes on the global climate (Section 2.1). Land cover is traditionally represented in a fairly simplistic manner, although ongoing model developments have made improvements in this regard in the recent past. Forestry is typically not represented, even though it is shown to have significant impacts both on the dynamics of the carbon cycle as well on biogeophysical processes (Naudts et al., 2016). Here, we will assess whether including or excluding forest management in simulations of forests affects biogeochemical and biogeophysical climate processes that may be relevant to include in ESM simulations and provide recommendations to what extent forest management should be represented (Section 4 and Section 5).

Integrated assessment models (IAMs) are a group of models that describe the interactions between human systems such as the energy and land use systems, and the environment such as the climate and the biosphere, using both economic and biophysical science. These models are used to assess future changes in greenhouse gas (GHG) emissions and dynamics in land use, land-use change and forestry (LULUCF) and can provide insight in potential pathways to limit global warming to 2° or 1.5°. Compared to total anthropogenically caused CO_2 emissions, human actions in the LULUCF sector are responsible for about 14% of annual emissions (IPCC, 2019). As LULUCF emissions are dominated by deforestation, traditionally IAMs have focused on representing LUC dynamics, e.g. from expanding agricultural land use (Section 2.2). However, as mentioned above, forestry has significant effects on the carbon cycle and, both affecting the emissions occurring after forest harvests as well as the carbon sink through forest regrowth. In this deliverable we will assess the question to what extent including or excluding forest management in IAMs affects LULUCF emissions and thereby projections of greenhouse gas emissions, and provide recommendations to what extent forest management should be represented in IAMs.

A key challenge in relation to LULUCF projections by IAMs relates to the mismatch between IAM estimates of emissions and LULUCF emissions as reported by countries to the UNFCCC that are used to agree on climate policy. These greenhouse gas inventories (GHGI) are often very different from IAM estimates as different assumptions on the forest area that is considered anthropogenically managed are used (Grassi et al., 2021a). IAMs usually only consider recently harvested or abandoned lands as anthropogenic, while GHGIs use a much broader definition thereby including emissions or carbon sequestration that would be considered natural in IAMs. As forestry is key to the definition of managed forests, we will assess the role of forest management in the mismatch of LULUCF emissions estimates.

To assess the role of forest management in ESMs and IAMs we use the LPJ-GUESS dynamic global vegetation model and the IMAGE integrated assessment model. LPJ-GUESS is a DGVM which has been widely applied over the last 25 years for studies of the terrestrial biosphere and carbon cycling (Smith et al., 2001, 2014). It is the vegetation component of the EC-Earth ESM (Döscher et al., 2022) and the RCA-GUESS regional climate model (Smith et al., 2011). A detailed representation of forest management has recently been added to LPJ-GUESS, enabling explorations of the impacts of historical changes to forest age alongside current harvest practices such as thinning (Lindeskog et al., 2021; T. Pugh et al., 2024). IMAGE is an IAM that is often used in climate change assessments such as the IPCC to analyse pathways to achieve ambitious climate mitigation goals (van Vuuren et al., 2011, 2017) and has a relatively high detail, process-based representation of the forestry sector. In addition, an evaluation of IMAGE and LPJ-GUESS results is performed using empirical forestry data from national forestry inventories. We further explore biophysical effects of forest management using the RCA-GUESS model. Lastly, we will compare the LULUCF results from this assessment to other regularly used data sources such as the GHGI reported by countries to the UNFCCC and those reported by bookkeeping models which is an often cited source for LULUCF emissions. We focus the investigations on Europe, where substantial empirical data to inform the model set-up is available.

Summarizing, the deliverable aims to answer the following questions:

i. How do different levels of complexity of forest representation affect carbon fluxes?
ii. How do different levels of complexity of forest representation affect climate through biophysical processes?
iii. How do simulated carbon stocks in IMAGE and LPJ-GUESS compare to each other and empirical NFI data?
iv. How do IMAGE and LPJ-GUESS results on LULUCF emissions compare to other data reported by UNFCCC and bookkeeping models.
v. What recommendations can be made to the IAM and ESM modelling community on the representation of forest management in their modelling?

2 Representation of land use, land-use change and forestry in ESMs and IAMs

2.1 ESMs

2.2.1 The impact of forests on climate

Forests affect climate via two main routes: by their influence on the land-atmosphere exchange of greenhouse gases and by their influence on the partitioning of energy incident on the land surface. The exchange of greenhouse gases relevant to forests is principally carbon dioxide, with forests globally being a large net sink of carbon, 70% of which is an uptake in live biomass and 30% in soils and deadwood (Pan et al., 2024). The main influences on energy partitioning can be broken down into (a) the albedo (reflectivity) of the surface to both short and longwave radiation, which affects how much incident radiation is absorbed, (b) the impact of forest on evapotranspiration, which affects the partitioning of energy moving away from the land surface between emission of sensible heat and evaporation of water (latent heat) and (c) the roughness of the land surface, which affects how efficiently connected the land surface is with the overlying atmosphere.

There is now ample evidence that shows that human impacts on forests, through historical land-use changes (i.e. land abandonment or establishment of new forest) and clearcut harvest activity have substantially modified the size of the carbon sink that forests provide, accounting for around 25% of the uptake globally (Kondo et al., 2018; O'Sullivan et al., 2024; T. A. M. Pugh, Arneth, et al., 2019). This occurs because the distribution of stand ages in global forests has been overall shifted towards younger forest. Compared to older forests, younger forests tend to grow faster and that growth is less compensated by carbon losses due to tree death. So, a forest which is unnaturally young because of past human activity will tend towards a net carbon uptake (although it may be a source in the years directly following a disturbance). This means that accurate calculations of the land carbon sink require realistic reconstructions of forest age. Whilst ESM simulations in the latest round of the Coupled Model Intercomparison Project (CMIP6) (Eyring et al., 2016) do not currently capture these stand age effects well (or at all), datasets now exist with which to improve this situation (Besnard et al., 2021; Poulter et al., 2019; Pucher et al., 2022). What is less clear is the extent to which more subtle forest management actions such as thinning and species choice have affected these carbon fluxes, but the existing evidence suggests that the influence is large (Vilén et al., 2016). Some studies with the ORCHIDEE model have included the impacts of these actions at a continental scale (Luyssaert et al., 2018; Naudts et al., 2016), but large-scale assessments which isolate their impacts on carbon fluxes are currently lacking.

Many ESM experiments have established a strong effect of landcover type on surface energy partitioning. Stylised deforestation experiments show regional changes in temperature of the order of as much as several degrees and global changes in the range of 0.5-1°C as a result of large-scale deforestation (Brovkin et al., 2009; Davin and de Noblet-Doucoudré, 2010). More realistic land-use change scenarios have been found to produce impacts in the range of 0.1-1.0° in regional mean temperatures, depending on the level of tree cover change (Boysen et al., 2020; De Noblet-Ducoudré et al., 2012) (de Noblet-Doucoudré et al., 2012; Brovkin et al., 2013; Boysen et al., 2020). However these studies on deforestation or land-use change do not constitute realistic forest management interventions. ESM studies of the impact of realistic forest management interventions on surface energy exchange have so far only been carried out by a version of the ORCHIDEE land surface model within the IPSL ESM (Luyssaert et al., 2018; Naudts et al., 2016). Naudts et al. 2016 explored the effect of forest management since 1750 on carbon fluxes and biophysics in Europe, including species conversion and harvest. They found that the biophysical effect of forest management (species composition change and harvest) was of similar magnitude to that from the quite substantial level of afforestation that also occurred over this period, consistent with a previous observational study (Luyssaert et al., 2014). They found a 1% decrease in albedo across Europe as a result of afforestation, associated with an increase in summer temperatures of 0.12°C. The albedo increased in northern Europe, however, as a result of forest management reducing the age of forests and opening up the canopy, allowing a larger effect of the more reflective forest floor. This harvest effect overrode the change towards more coniferous species which were also favoured by management and which tends to lead to lower albedo. Whilst Naudts et al. found that changes in evapotranspiration and sensible heat tended to offset each other in terms of their effect on surface temperature, they found that the reduced evapotranspiration led to a drier atmosphere which lowered atmospheric emissivity and, in turn, led to a 0.08°C summer warming across the continent. Locally, the changes in summer temperature due to species conversion could be up to ca. 0.5°C. Given the uncertainties in modelling the biophysical impacts of changes in the land surface (Boysen et al., 2020), results from a single model do not allow to draw unequivocal conclusions, but there are thus strong indications of a relevant effect of forest management on surface temperatures at local and continental scales.

2.2.2 Simulation of forests in ESMs

Representation of forest in ESMs falls into three broad classes: (1) Prescribed land cover type maps which tell the land surface model what forest type is found in a location. Photosynthesis, respiration and energy budget partitioning are represented, but forest structure and dynamics are not resolved and the area of landcover types does not respond to climate. This is the most common approach found in CMIP6 ESMs. (2) Dynamic vegetation models in which the area of different landcover types can be influenced by climate. For instance, forest cover can advance or retreat on biome edges, assuming these movements are not constrained by other land-uses. Only a handful of CMIP6 models included dynamic vegetation in their simulations (Egerer et al., 2025). (3) Demographic vegetation models which represent how forest dynamics affect forest structure and how both of these influence carbon cycling and biophysical processes. To the best of our knowledge only two CMIP6 ESMs, EC-Earth and GFDL-ESM, included demographic vegetation models. There are several more ESMs, however, for which a demographic vegetation component exists, but was not used in CMIP6, or for which a demographic vegetation component is under development. These include ORCHIDEE, UKESM, CABLE, CESM and NorESM (Eckes Shephard et al., under review).

In order to explore the biophysical and full biogeochemical impacts of forest management and disturbances, a demographic vegetation model is necessary. However, it is also necessary to have sufficient input information or sub-models to enable that demographic model to generate a realistic forest structure. Key to this is the information on the history of the forest and broader land system. Currently land-use change data in ESMs is provided by the Land Use Harmonisation version 2 (LUH2) process (Hurtt et al., 2020). This land-use data is based on the HYDE land-use change dataset for the historical period (Klein Goldewijk et al., 2017) and smoothly connects it with the land-use outputs of IAMs to provide a consistent past-to-future timeseries. Land-use change data provides some information on forest structure, but only in areas where there has been substantial re/afforestation. A key further innovation in LUH2 is the addition of forest harvest information, based on national wood harvest statistics, which is provided in terms of forest area harvested or biomass removed per year. In principle, this should allow for much more realistic forest structures in areas where forests are strongly managed, such as Europe where tree death is overwhelmingly by harvest (Schelhaas et al., 2018; Suvanto et al., 2025). In practice, LUH2 can help a demographic vegetation model obtain realistic forest stand age structures, as verified by an independent dataset, in the United States of America and Russia, but strongly deviates elsewhere, particularly in Europe where it results in the majority of forest being younger than 30 years (T. A. M. Pugh et al., 2024a).

The other major component which impacts forest demography, and thus its impact on climate, is natural disturbances. Stand-replacing disturbances are a natural part of forest dynamics worldwide and include events such as fires, windthrow, landslides and large biotic outbreaks (Frolking et al., 2009; Pickett & White, 1985; T. A. M. Pugh, Arneth, et al., 2019; Seidl et al., 2014). They are, however, rarely represented explicitly in ESMs. A subset of ESMs include fire models, but there have only been a handful of studies considering other types of disturbances conducted with offline versions of the land component of ESMs (Chen et al., 2018; Kautz et al., 2018; Lagergren et al., 2012, 2025; Marie et al., 2023; T. A. M. Pugh et al., 2024b). The only large-scale study to date that combines land-use change, forest harvest and disturbances to assess their effect on forest age structure suggests that for large regions of the world's forests it is necessary to have a good representation of natural disturbances in addition to forest management (T. A. M. Pugh et al., 2024b). However, this is not the case for Europe and much of the USA.

2.2 IAMs

2.2.1 General description and types of IAMs

Integrated assessment models (IAMs) aim to represent the interaction between the economy, society, and the environment to support environmental policymaking. They typically include a description of human activity (such as energy and agriculture), direct drivers of environmental change (e.g., emissions, land use, and resource use), environmental change processes (like the carbon cycle, climate change, and pollution), resulting impacts (e.g., consequences for crop yields), and response options (e.g., diet change or investments in yields). The most common use of IAMs is in the field of climate mitigation, through the generation of scenarios representing climate action (from no action to the 1.5°C goal) under a broad range of assumptions about future socio-economic, institutional, and technological developments.

A broad range of IAMs exists, differing in their core topic, level of detail, type of representation, relationships with various disciplines (leaning towards economics or engineering), solution concept (optimization versus simulation), and temporal and spatial system boundaries (particularly global versus national scope). A set of IAMs, such as DICE, MIMOSA, and FUND, are primarily focused on optimizing the costs and benefits of climate policies, often with little detail in the representation of the processes involved. Another class comprises the so-called process IAMs, like REMIND-MAgPIE, MESSAGE-GLOBIOM, IMAGE, AIM, GCAM, and COFFEE, which typically include a considerably more detailed representation of energy and land use processes. An overview of many IAMs can be found here: https://www.iamcdocumentation.eu/IAMC_wiki.

IAMs are also used in other fields, such as exploring how to meet biodiversity goals, adapt to climate change, and ensure food or water security. Regarding land use, IAMs primarily focus on land-based mitigation, food production, and biodiversity protection. This means that several critical themes can be found in the literature, such as the relationships between agricultural policies, climate mitigation, and hunger, or between ambitious biodiversity goals and land use in climate policies (e.g., reforestation).

Land cover and land use form important elements of most IAMs, given their roles in climate change (as a cause, solution, and impact sector) and biodiversity loss. Some IAMs, such as MESSAGE-GLOBIOM, REMIND-MAgPIE, and IMAGE, have detailed agriculture-food systems, while others have a simplified land representation as an integral part of the overall model. The land use component of IAMs describes how land is used to meet the demand for producing food, fibers, timber, and energy, as well as providing space for shelter and nature. The representation of these processes can be at either the regional or gridded scale.

The land use categories specified by IAMs typically include cropland, pasture, built-up area, forests, and other land. Cropland and pasture follow the definitions of the FAO, describing the physical cropland area and the grazing area as reported in FAO statistics. It should be noted that these categories do not always align with remote sensing products that allow for mixed land cover of cropland and other vegetation (Doelman & Stehfest, 2022). This discrepancy needs to be accounted for when coupling IAM land-use data to ESMs or DGVMs. Built-up area in most IAMs is described for the present day, but only a few models project future built-up areas. The description of all other land cover classes is based on biome distribution maps, either static or dynamic, distinguishing vegetation into at least forest and non-forest natural vegetation that can potentially be converted to agriculture, as well as other lands. Within forests, models distinguish between managed forests and natural forests. However, the area of managed forest in IAMs is generally lower than that reported under UNFCCC reporting (Grassi et al., 2021b; Nabuurs et al., 2023).

2.2.2 Greenhouse gas emissions from agriculture, land use, land use change and forestry

IAMs calculate both CO_2 emissions from land-use change and non-CO_2 emissions from agricultural activities. We will discuss this briefly below. The IAM methods to calculate mitigation for non- CO_2 and CO_2 emissions, including afforestation, are also described in Roe et al. 2021.

2.2.2.1 CO_2 emissions from land.

IAMs use a wide range of approaches to estimate CO_2 emissions caused by land use and land cover change. The models typically include both anthropogenic and natural CO_2 flows related to land. Conceptually, they align with the approach used in bookkeeping models (e.g (Hansis et al., 2015)), defining anthropogenic emissions only in cases of land use changes and sometimes additional forest management. The overall approach involves estimating the difference in equilibrium carbon stocks caused by the land use and land cover change from time step to time step taking into account stylized growth curves. The exact approach depends on internal assumptions and whether the IAM includes or is informed by a land carbon-cycle model. Key differences across IAMs are:

- Which carbon pools are considered? For instance, some IAMs provide carbon fluxes based only on changes in living biomass carbon pools, thereby ignoring changes in the dead biomass, litter, and soil organic carbon pools, while others provide comprehensive estimates.

- How carbon emissions are distributed over time? Most IAMs assume the difference in carbon stocks is emitted following a response curve that depends on the land use activity that triggers the emission or uptake (e.g., deforestation or land abandonment) or on the pool itself (e.g., soil carbon equilibration). However, a few models assume immediate release of the carbon to the atmosphere, especially if considering only biomass.
- Whether carbon densities are fixed or change because of environmental conditions (such as atmospheric CO_2 and climate)? Most IAMs rely on fixed carbon densities (similar to most bookkeeping models), in which case the difference in carbon stocks used to estimate emissions is caused only by land use and land cover change. However, a few IAMs include transiently changing carbon densities informed by a vegetation model. In these cases, additional steps are required to exclude the natural response and isolate the carbon flux that is consistent with the bookkeeping approach. This can be done, for instance, by using a cut-off period after the conversion has occurred.
- Forest management. The carbon stocks in forests can also be influenced by forest management. The level of detail with which IAMs represent forest management varies significantly. Many models allow for afforestation, often assuming some form of active management. However, some models include even more detailed management categories.

Table 1: overview of land use and forest management representation in five global process-based integrated assessment models.

	AIM	GCAM	GLOBIOM	IMAGE	MAgPIE
Calculation level	17 regions and 30'x30' grid	32 energy regions; 384 land use regions	37 regions and 30'x30' grid	26 regions + 5'x5' grid	12-16 regions, up to 2000 spatial units, downscaling to 30'x30' grid
Demand detail	7 crop types and 3 animal products;	24 crops: 7 animal commodities; Forest products, biomass for energy	18 crops, 8 animal products, finished & semi-finished forest products, biomass for energy	16 crop types and 5 animal product types, 5 bioenergy commodities; 4 wood products	16 food/feed crop types, 2 bioenergy crop types, 5 animal product types, 2 wood product types
Land use classes	Crop, intensive pasture, range-land, unmanaged forest, managed forest, natural land, build-up area and others.	Crops, Cellulosic biomass, Forest (managed and unmanaged), Pasture ; Grass, Shrubs, Desert (fixed), Rock/Ice/Tundra (fixed), Urban (fixed)	Cropland, grassland, short rot. plantations, managed forests, unmanaged forests, other natural vegetation land, urban (fixed), Rock/other (fixed)	Crop, intensive pasture, extensive pasture, managed forest; unmanaged forest, natural vegetation (14 biomes), built-up area, rock/other (fixed)	Crops, 2nd generation bioenergy crops, pasture and rangeland, timber plantations, re/afforestation, primary forest, secondary forest, other natural land, urban land
Forest management types	managed or unmanaged.	Managed and unmanaged, tree crops (softwood, hardwood)	short rotation plantations, managed forests	Clearcut, selective cut, forest plantations	Timber plantations with clear-cut after a certain rotation length. Selective harvest from natural forests.
Land-use change related CO2	Stock change with fixed densities based on DGVM VISIT. Instantaneous except sequestration (regrowth curve based on DGVM).	Stock change with fixed densities. Instantaneous for above ground sources of CO_2 except afforestation (regrowth curve), but below ground gets emitted with a decay rate.	Stock change with fixed densities. Instantaneous except afforestation (regrowth curve).	LPJml calculates all stocks and flows, for natural vegetation dynamics, and land use transitions. After a transition, net flux assumed anthropogenic for a number of years, then natural.	Carbon stocks based on LPJml (input data) are used to calculate annual emissions. Emissions include both direct anthropogenic and indirect natural / environmental effects.
CO2 stocks included	biomass	biomass and soil	biomass	all	all

2.2.3 Linkage with other climate research communities

2.2.3.1 From IAMs to climate models.

ESMs and DGVM require patterns of land use and land cover change to simulate carbon fluxes caused by these perturbations in an internally consistent manner. The Land-use Harmonization process version 2 (LUH2) connects historical land-use reconstructions with future projections from IAMs in a format suitable for ESMs (Hurtt et al., 2020). This harmonization produces land use patterns, identifies underlying land use transitions, provides key agricultural management information, and predicts resulting secondary lands. The historical reconstruction seamlessly extends into the future based on land-use changes projected in IAM scenarios. The latest iteration also includes detailed information on multiple crop and pasture types, along with associated management practices such as irrigation and fertilizer use. The harmonization process applies definitions used in the historic land use dataset HYDE (Klein Goldewijk et al., 2017). Challenges can arise from differences in definitions between human and natural land use/cover. For example, many ESMs use a land cover approach based on remote sensing whilst others use dynamic vegetation models based on plant functional types. IAMs, on the other hand, provide information on land use. Additionally, Simple Climate Models (SCMs) are used in the IPCC, calibrated to outcomes from complex climate models to evaluate a broader range of scenarios. SCMs have a simplified carbon cycle representation and therefore rely on land use CO_2 emissions estimated by IAMs as input. As part of the process, IAM data is adjusted to be consistent with historical emissions used in complex models. By design, this ensures that the land use CO_2 emissions provided as input to SCMs align with bookkeeping emissions. The overall consistency of the land carbon cycle—between prescribed anthropogenic fluxes and their natural responses—depends on each SCM's specific configuration.

2.2.3.2 From IAMs to UNFCCC.

As described above, IAMs define land-use-related CO_2 emissions directly based on land use/land cover change, excluding natural processes such as CO_2 fertilization from this category. This means that the IAM estimates are aligned with emission inventories, which typically use a bookkeeping approach. The UNFCCC, however, uses a different definition in which the net uptake of CO_2 in managed forests can be accounted for as an additional sink. The difference between these definitions results in substantial differences in the calculated fluxes. Recently, both Grassi et al. and Gidden et al. used methods (either using IMAGE/LPJmI or a simple climate model) to calculate land use emission data that is consistent with the bookkeeping models and the national inventory conventions. In mitigation scenarios, the difference between the two estimates decreases over time as the CO_2 stored in forests starts to reach equilibrium with atmospheric CO_2. As a result, the conversion has a strong impact on annual emissions and carbon budgets, but only a small influence on, for instance, the net zero year.

3 Methods

3.1 Model descriptions

3.1.1 LPJ-GUESS

LPJ-GUESS is a dynamic global vegetation model which has been widely applied over the last 25 years for studies of the terrestrial biosphere and carbon cycling (Smith et al., 2001, 2014). It is the vegetation component of the EC-Earth ESM (Döscher et al., 2022) and the RCA-GUESS regional climate model (Smith et al., 2011). LPJ-GUESS includes detailed representations of forest, grassland, croplands, pasture, peatlands and arctic vegetation, as well as the land-use changes between them (Bayer et al., 2017; Lindeskog et al., 2013). In this description we focus on those components of the model most relevant to the simulation of forests in Europe.

LPJ-GUESS simulates vegetation and soils as a series of pools of carbon and nitrogen, whose sizes are governed by the fluxes between them and between the pools and the atmosphere. The processes of photosynthesis and respiration, along with updates of hydrology, are carried out on a daily timestep, whilst vegetation growth and mortality are assessed annually. The basic processes of photosynthesis, respiration, carbon allocation and vegetation dynamics are described in Smith et al. (2014). These processes are forced by externally-provided boundary conditions of climate, atmospheric CO_2 mixing ratio, nitrogen deposition and soil type. This information is provided in grid cells, whose size is primarily determined by the spatial scale of the boundary conditions provided. Large-scale simulations are typically run at 0.5° x 0.5°. Within a grid cell, the basic unit of an LPJ-GUESS simulation is the 0.1 ha patch. Within patches, age cohorts of different plant functional types (PFTs) compete for light, water and nitrogen. In the European version of LPJ-GUESS, vegetation is represented by 24 plant functional types, 20 of which are directly parameterised based on major tree species (Hickler et al., 2012; Lindeskog et al., 2021). Vegetation structure is vertically resolved, such that taller vegetation shades the vegetation underneath. Because the processes of vegetation establishment and mortality have a strong stochastic component, multiple replicate patches are typically simulated to provide a realistic representation of the range of trajectories that patches might take. Replicate patches are forced by the same external boundary conditions of climate, soil type, atmospheric CO_2 mixing ratio and nitrogen deposition.

Like other dynamic vegetation models, LPJ-GUESS is able to simulate a best estimate of potential natural vegetation, i.e. the vegetation that would exist in the absence of human influence, based on the processes of establishment, competition and mortality (e.g. (Hickler et al., 2012; Smith et al., 2014)). However, LPJ-GUESS also contains a detailed description of forest management, including clearcut harvest, thinning and species selection (Lindeskog et al., 2021). Clearcut harvest can be set based on a fixed rotation period for a particular forest type or prescribed based on observations (D3.1; (T. Pugh et al., 2024)). Thinning can be prescribed at fixed intervals, or dynamically based on Reineke's self-thinning rule, such that thinning in applied before self-thinning (i.e. natural competition mortality) is activated (Lindeskog et al., 2021). This Reineke-based approach can be considered to represent an optimal rate of wood extraction that minimises losses of trees due to natural mortality (self-thinning). A recent development is to use harvest probabilities based on national forest inventory data from eleven European countries (Suvanto et al., in prep.; (T. Pugh et al., 2024)). This harvest probability approach approximates actual harvest practices as observed over the period ca. 2000-2020, providing the best available estimate of the impact of actual harvest practices. In order to capture the impact of past harvest and disturbances on forest structure, the distribution of stand ages can be prescribed by initialising the appropriate area of different forest types in different years. For example, in order to have 5% coverage of a 50-year-old spruce stand in 2010 in a grid cell, a spruce stand equivalent to 5% of the grid cell area would be initialised in 1960 (following a clearing of whatever vegetation was previously on that part of the grid cell). These forest management decisions influence both forest albedo and roughness length by altering vegetation composition and tree size distribution. The albedo of a forest stand is determined by the mix of PFTs, each with distinct albedo values for direct and diffuse radiation. Snow cover is excluded from our albedo calculations, as the focus is solely on changes in vegetation-driven albedo. Roughness length is influenced by stand density and average tree height, following the parameterization described by (Raupach, 1994).

3.1.2 RCA-GUESS

The regional vegetation-atmosphere Earth system model RCA-GUESS (Smith et al., 2011) couples LPJ-GUESS with the Rossby Center Atmospheric model (RCA4) (Samuelsson et al., 2015). LPJ-GUESS provides the vegetation component of the land surface scheme, affecting the relative coverage of trees and low vegetation, along with the leaf area of the vegetation. These components in turn affect the albedo and surface energy fluxes. RCA-GUESS has been applied in multiple regions around the world (Smith et al., 2011; Wu et al., 2017; Zhang et al., 2014). Previously simulations have focused on simulating natural vegetation. We updated the version of LPJ-GUESS within RCA-GUESS to include the detailed description of forest management applied in offline simulations (Lindeskog et al., 2021), providing the capability to explore the effects of forest management actions within a regional Earth system model.

3.1.3 IMAGE

IMAGE 3.4 is an integrated assessment modelling framework that simulates the interactions between human activities and the environment (Stehfest et al., 2014) to explore long-term global environmental change and policy options in the areas of climate, land, and sustainable development. IMAGE consists of various sub-models describing land use, agricultural economy, the energy system, natural vegetation, hydrology, and the climate system. Socioeconomic processes are modelled at the level of 26 regions. Most environmental processes are modelled on the grid-level at 30 or 5 arc-minutes resolution with upscaling and downscaling functions used to couple the different resolutions. Data exchange between sub-models takes place either through hard-coupling with an annual exchange of data or soft-coupling using an iterative approach of scenario data exchange. For this deliverable, the land use and carbon cycle components of the IMAGE model framework are most relevant, which are discussed in the next paragraphs.

IMAGE-LandManagement determines the area and location of irrigated and rainfed cropland on a 5 arc-minute geographical grid required to fulfil the demand for production of 16 crop categories. The historical locations and areas of cropland and grazing land are based on the HYDE database (Klein Goldewijk et al., 2017) which is based on regional FAOSTAT data (FAOSTAT, 2020). For each region in each time step crop production is calculated using gridded potential yields from LPJmL, locations of cropland in the previous time step and a regional management factor (calibrated to historical yields from FAO and future yield trends according to MAGNET). If production is higher than demand, cropland is abandoned at the least productive locations. If production is lower than demand, cropland is expanded following empirically-based statistical suitability layers derived from ESA-CCI land-use change data (Cengic et al., 2023). IMAGE-

LandManagement also calculates livestock production for five categories taking into account variations between regions in feed composition, feed efficiency, genetic animal productivity and age at slaughter (Bouwman et al., 2005; Lassaletta et al., 2019) and subsequently calculating grazing land requirements.

The dynamic global vegetation model LPJmL is an integral part of IMAGE (Müller et al., 2016) and simulates crop yields, grassland productivity, vegetation dynamics, and carbon and water cycles on a 30 arc-minute geographic grid. LPJmL is based on the concept of multiple plant functional types (PFTs) categorized according to biophysical characteristics. Both natural and crop PFTs are represented. LPJmL also includes a full hydrological model with a river routing module that calculates river discharge, with lakes and reservoirs as additional water stores. The effects of climate change are dynamically included in LPJmL as spatial-explicit data on changing temperature and precipitation drive the model, affecting many key processes such as crop yields, water availability, crop water use efficiency and forest growth (Jägermeyr et al., 2021; Schaphoff et al., 2018).

IMAGE-LandManagement includes a spatial-explicit representation of the forestry sector, including forest management. Projections of timber demand are modelled at the level of 26 world regions for saw logs, paper/pulp wood and fuelwood. The demand for saw logs and paper/pulp wood is based on a simple empirical relation with population and GDP (Doelman et al., 2018), while fuelwood is projected by the energy model TIMER based on projections of traditional fuel use in households and other sectors (Daioglou et al., 2012). Trade is not explicitly modelled so only the demand for timber that needs to be produced in each region is projected. On the wood production side, IMAGE represents four management systems: clear cut, selective cut (conventional or reduced impact logging) and wood plantations (Arets et al., 2011). Globally, the harvested area shares in 2020 are approximately 40%, 45% and 15%, for clear cut, selective cut and wood plantations, respectively. For Europe, around 25% is harvested from wood plantations and 75% in clear-cut systems. For each management system, biome-specific rotation cycles are defined. Harvest first takes place in wood plantations where the rotation cycle is completed, subsequently in clear-cut and selective cut systems that are at the end of their rotation cycle with regional production shares, and lastly in pristine forests. Harvesting continues until the regional timber demand is met or when no more forests are available where harvest is allowed. Harvests in the different systems are defined by specific cutting rates (i.e. defining the share of trees that is cut down) and biomass removal fractions (i.e. share of each biomass category (trees, branches, leaves, roots) that are used to fulfil timber demand) based on literature review (Arets et al., 2011). Harvest in clearcut and wood plantation systems assumes 100% cutting rates with removal of all stems and branches in most regions, and the rest of the biomass left on the land accounting for losses and/or for environmental reasons. In selective logging systems, cutting rates differ substantially depending on regional characteristics: in high-income regions such as the USA and China the rates are typically high at 50%, while in low-income regions such as Western Africa rates are low at 10%. Also the biomass removal fractions differ, where medium to low cutting rates with low biomass removal fractions represent selective logging with high levels of damage to the overall vegetation, while cutting rates with high biomass removal fractions represent reduced-impact logging. For example in Western Africa, only 18% of the stems that are felled in selective logging systems are assumed to be effectively harvested and used to fulfill timber demand, while in Western Europe 100% of stems and 80% of branches are used to fulfil demand. The information on share of tree cover cut down and fractions of takeaway is sent to LPJmL to inform dynamics in the DGVM, while information on harvested biomass is sent back to IMAGE-LandManagement to inform the amount of demand that is fulfilled. Conventional clear-cut and selective cut logging is represented by natural vegetation growth in LPJmL (Schaphoff et al., 2018), while wood plantations are a separate plant functional type representing planted and managed trees (Braakhekke et al., 2019).

3.2 Simulation setup

3.2.1 LPJ-GUESS

LPJ-GUESS was run at 0.5° x 0.5° resolution for the countries of Spain, France, Switzerland, Belgium, Netherlands, Germany, Czech Republic, Poland, Sweden and Finland. These countries were chosen because they represent a transect across the different major forest types in Europe and national forest inventory data was available to inform the set-up. The simulation set-up is the same as that described in (T. Pugh et al., 2024) and so is only briefly described here. Only forest was simulated with the forest area per grid cell set according to the HILDA v2.0 dataset (Fuchs et al., 2015). Simulations began with a 500-year spin-up phase starting in the year 1401 and using repeated climate and atmospheric forcing (see below) starting from bare ground to provide a first initialisation of vegetation and soil pools. Following the spin-up, a simulation phase following transient climate was initiated from the year 1901. Stand age was initialised based on the European forest age 1870-2010 dataset of (Pucher et al., 2022). From 1801-1870 an area equivalent to the 1870 forest area was gradually converted from the potential natural vegetation land cover to managed forest land cover to allow a representation of forests older than 140 years in 2010. Clearcut harvest and disturbances prior to 2010 were accounted for based on this stand-age initialisation process. Therefore, as soon as a forest stand was established following the age distribution input, further clearcutting or stand-replacing disturbance before 2010 was disallowed. Clearcut harvest from 2011-2023, as well as stand-replacing disturbances of fire, windthrow and bark beetle outbreaks, were specified based on satellite observations (T. Pugh et al., 2024; Viano-Soto & Senf, 2023). Non-stand-replacing harvests were specified following the empirically harvest scheme based on national forest inventory data (Section 3.1.1). Forest species composition was initialised based on observations from the NFI in each grid cell. In total, 27 stand types were specified including both monospecific and mixed species stands, to represent the variety of tree species combinations found in the simulation domain.

In order to explore how different levels of complexity of forest representation affect carbon fluxes and biophysical climate, we carried out four simulations with different levels of forest management complexity. We also carried out a grass-only simulation to contextualise our results versus those in the most common relevant ESM experiments, which involve deforestation. The simulations were:

- Grass only (GR)
- Potential natural vegetation (PNV)
- Management without thinning (MNT)
- Management with idealised thinning from the Reineke-based approach (MIT)
- Management with “observed” thinning from the empirically-based harvest (MOT)

All three management simulations include initialisation of forest age and composition to hit the base year of 2010; from 2011 onwards, clearcuts and stand-replacing disturbances are forced based on satellite observations. The PNV simulation contains no representation of management at all. We make our comparisons using the means for the years 2011-2023. Comparing MNT with PNV isolates the effect of age structure (primarily past clearcuts and land-use changes) and composition. Comparing MIT with MNT isolates the effect of idealised thinning. Comparing MOT with MNT isolates the effect of “observed” thinning. We consider MOT as our best estimate of the real state and dynamics of the forest.

The best estimate simulation here with LPJ-GUESS still contains many uncertainties. One of the chief uncertainties among these is how forest stands have been managed during the period between their establishment and the period for which our observational harvest data is valid (ca. 2000-2020). We have assumed here that the recent historical harvest regime has been applied throughout the whole period. Given that stand management plans are by their nature long-term, this is likely a fairly reasonable assumption. But it is also a highly uncertain one. Our best estimate “MOT” simulation should therefore not be considered as the truth, but rather the differences between this and simpler assumptions reflect the size of effects that can be expected from a more realistic representation of forest management.

3.2.2 RCA-GUESS

We made two simulations with RCA-GUESS. One simulation was based on potential natural vegetation, comparable to the PNV simulation with offline LPJ-GUESS (Section 3.1.1). The second simulation used the forest disturbance map of Viana-Soto and Senf (2023; ForestPaths Deliverable 2.1) to replicate the effect of clearcut harvests and disturbances on European forest structure. The disturbance map from 1985-2023 was converted into an annual probability of disturbance for each model grid cell which was applied to the forest vegetation within RCA-GUESS. The PNV simulation specified natural disturbances based on (T. A. M. Pugh et al., 2024b) and included no clearcut harvest. The simulations were run from 1979-2010 for a domain covering the European continent. The spin-up took place in two stages. First, we used climate variables of observation-based CRU-NCEP (Viovy, 2018) data to force LPJ-GUESS in uncoupled mode and spin it up for a duration of 500 years with a 30 year detrended climate based on the period 1901-1930. This was followed by a period with transient climate from1901 until 1979. The disturbance return period was set to be 300 years for every grid cell at this stage of the experiment. RCA4 went through a separate spin-up with a duration of only a few months (Wramneby et al., 2010) forced by ERA-Interim data (Gustafson, 2022) and with landcover input from the ECOCLIMAP map (Masson et al., 2003). Afterwards, the coupled model was run for 30 years to equilibrate. RCA4 climate output of this run was then detrended and used as forcing data for LPJ-GUESS for the second spin-up stage, at which point the disturbance scenarios were introduced. After the second spin-up, LPJ-GUESS vegetation was in equilibrium with the RCA4 spin-up climate and was run in coupled mode.

3.2.3 IMAGE

For IMAGE, two simulations are used for the analysis in this deliverable. Both are based on a default baseline scenario run, with a historical simulation period from 1970 to 2020 and future projection period from 2020 to 2100.

For the historical period, land use for cropland and grassland is calibrated to the HYDE 3.4 database (Klein Goldewijk et al., 2017) which is a spatially explicit historical database based on

FAO statistics and additional country-level information. For forestry, regional demands for saw logs and paper/pulp wood are derived from FAO (FAOSTAT, 2022). Fuelwood demand is taken from IEA in terms of energy content and converted to volumetric wood demand using constants for higher heating value and volume of wood per dry matter content. The total area and spatial distribution of managed forests are not calibrated but an endogenous result of the model.

For the projection period, the baseline scenario is an updated SSP2 scenario with middle-of-the-road projections for GDP and population (Riahi et al., 2017). These drivers are key determinants of projected food demand which determines expansion or subtraction of agricultural land, as well as projected timber and fuelwood demand.

In this analysis, we assess the default reference scenario (REF) and a counterfactual scenario where timber harvest is set to zero both (NOTIMB) during the historical as well as the scenario period. The goal of the simulation setup is to assess the role of forestry in land-use change dynamics, CO_2 emissions and carbon sequestration. Changes in the historical period allows us to make a comparison to observed empirical data to validate the model setup.

4 Forest management effects on CO_2 fluxes

4.1 LPJ-GUESS

Within LPJ-GUESS, the influence of forest management on biomass is stark. A standard potential natural vegetation (PNV) approach leads to ca. 100% overestimations in biomass in many locations compared to the simulation with the most realistic description of current management (MOT) (

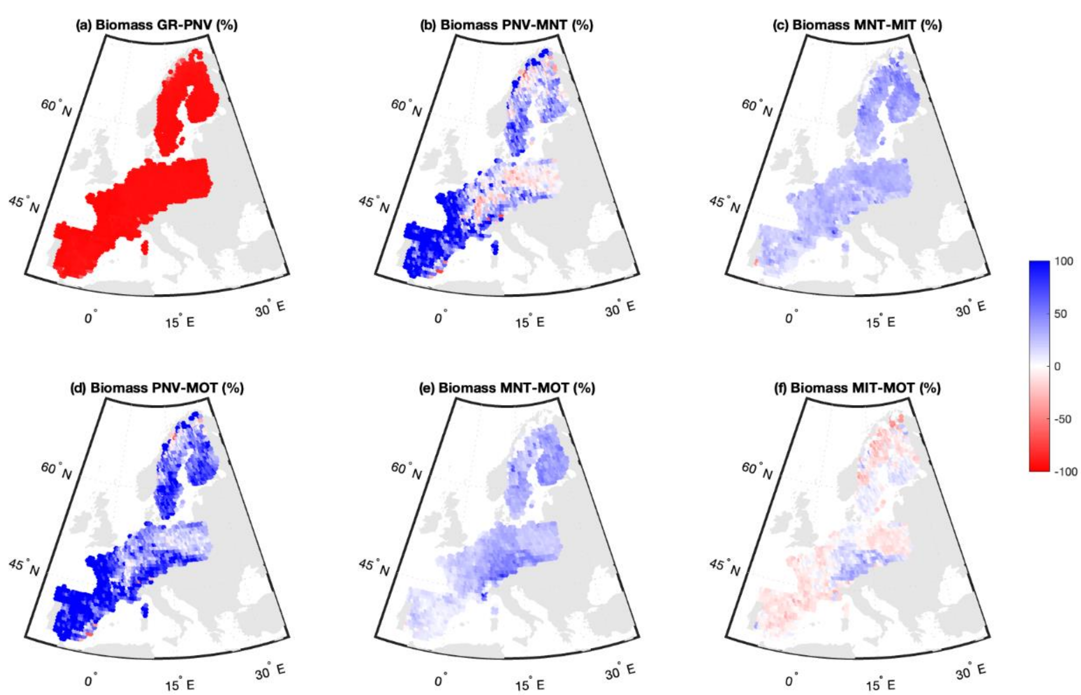

Figure 1d). The inclusion of information on historical stand age structure and composition (MNT) very substantially reduces this overestimation, but biomass remains consistently higher by a factor of 10-50% across the simulation domain compared to the MOT simulation (

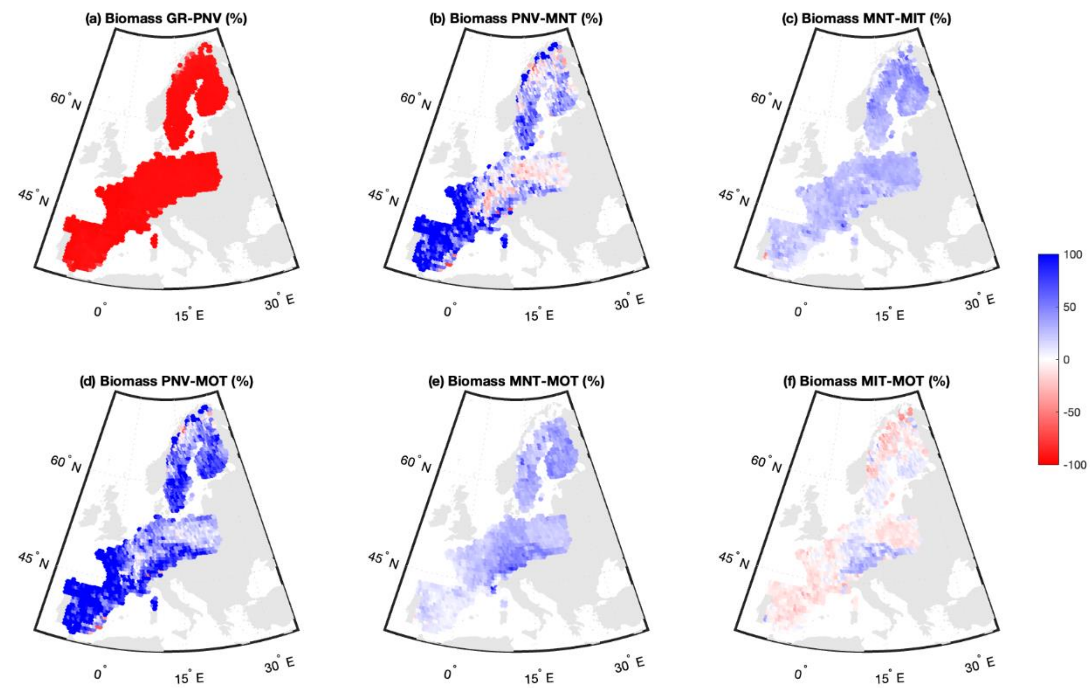

Figure 1e). This means that, even with a realistic stand age structure, thinning remains a crucial process to represent in order to properly simulate the effects of forest management on biomass. Comparing the two approaches to thinning, a simple Reineke-based approach (as in MIT) and a more complex empirically-based approach (as in MOT), the general effect on biomass was similar (*cf.* Figure 1c and 1e), but there were substantial regional differences (Figure 1f).

Whilst biomass stocks are a key determinant of how much carbon is stored out of the atmosphere, the net biospheric carbon exchange (net biospheric productivity, NBP) is a much more direct measure of the current impact that forests are having on changes in atmospheric carbon concentration. Differencing NBP between the different levels of management complexity reveals changes that are of the same order as between having forest or grassland (Figure 2). The effect of including forest age structure and composition (MNT) versus a potential natural forest (PNV) gives local changes approaching +/-0.3 kg C m^{-2} yr^{-1}, i.e. of a similar magnitude to total woody productivity (*cf.* Figure 2a and 2b). For the most part, these changes are giving a stronger sink, but in some regions such as south-west France and north-western Spain the opposite (*i.e.* a weaker sink or a source) can be found, which is likely a legacy of disturbances and intensive harvesting prior to 2011 (Figure 2b). The total effect of including observed age structure and composition is to take the mean sink across the whole simulation domain during 2011-2020 from 32.0 to 50.6 MtC yr^{-1}. The effect of thinning (shown by comparisons of MNT with either MIT or MOT simulations) is equally pronounced but unidirectional, providing a uniform reduction in sink across the whole domain, equivalent to a change from 50.6 to 20.9 MtC yr^{-1} in the case of MOT (Figure 2c,e). The empirically-based thinning approach (MOT) results in a stronger sink for much of Europe compared to the idealised approach (MIT) (Figure 2f), reflecting that thinning intensity in the real world is below an idealised maximum due to the multiple different objectives with which owners manage their forests.

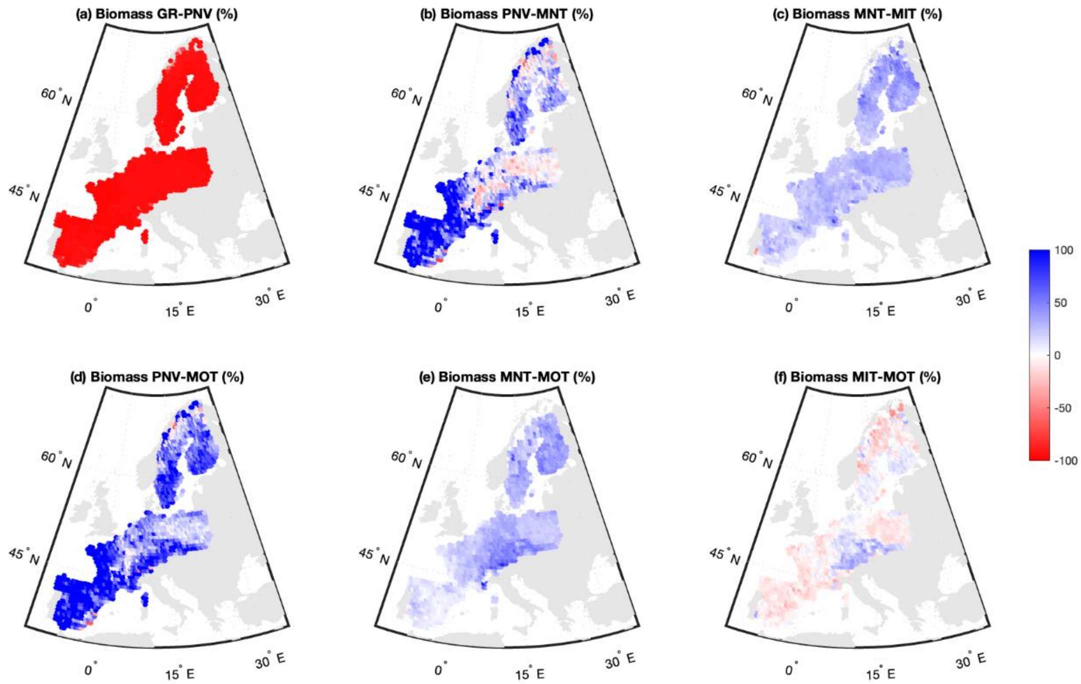

Figure 1: Relative difference in biomass (%) between different representations of forest averaged over 2011-2023, as simulated by LPJ-GUESS. (a) Difference between grass only (GR) and potential natural vegetation (PNV), i.e. the effect of deforestation. (b) Difference between potential natural vegetation and management without thinning (MNT), i.e. the effect of stand age structure and actual composition. (c) Difference between simulations without and with (MIT) idealised thinning. (d) Difference between potential natural vegetation and the most detailed representation of forest management including empirically-based thinning (MOT). (e) Difference between management without thinning and empirically-based thinning, i.e. the comparator to panel c with empirical instead of idealised thinning. (f) Difference between idealised thinning and empirically-based thinning. Differences are relativised according to values from the MOT simulation, apart from panel a which is relativised by PNV values. Blue values mean that the first simulation has a higher biomass than the second.

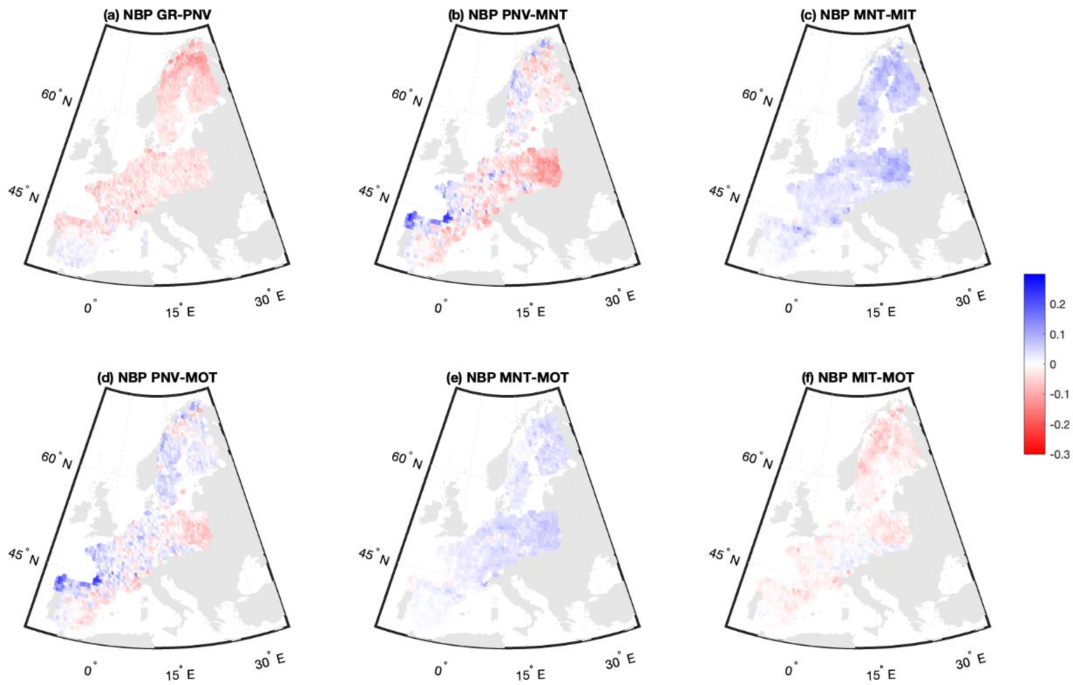

Figure 2: Difference in net biospheric productivity (NBP; kg C m^{-2} yr^{-1}) between different representations of forest averaged over 2011-2023, as simulated by LPJ-GUESS. NBP is defined as positive for a carbon uptake, therefore blue values here mean that the first simulation has a stronger carbon uptake than the second.

4.2 IMAGE

Forestry has a substantial impact on the carbon flux in the IMAGE model. A comparison between the default REF and counterfactual NOTIMB case clearly shows differences in patterns (Figure 3 to Figure 5): notably in the US, Europe and China more negative fluxes are shown, typically from harvest events, as well as positive fluxes from forest regrowth. Aggregated to regional and global scale (Table 2 and Table 3), the IMAGE model finds that including timber harvest results in a reduction in NBP ranging from 272-323 MtC per year in the 10-year periods from 1990-2020. The largest share of this effect occurs in temperate regions with large forestry sectors, most notably Northern America and the USA. For Europe, the effect of timber harvests is a reduced NBP in a range from 42-53 MtC per year, which is substantial compared to the global total, which is explained because of the relatively high harvest rates in Europe compared to other world regions.

The large negative effect of timber harvest on carbon in forest ecosystems uptake illustrates that forestry plays a significant role in the carbon cycle and substantially increases net LULUCF emissions in the IMAGE implementation. The strong negative effect of timber harvest on total biomass stock however is not in line with NFI observations (see Section 4.3) and therefore requires additional scrutiny into the IMAGE forest management representation. It does underscore the importance of a realistic representation of forest management for representation of the carbon cycle, as also found in the analysis with the LPJ-GUESS model (Section 4.1).

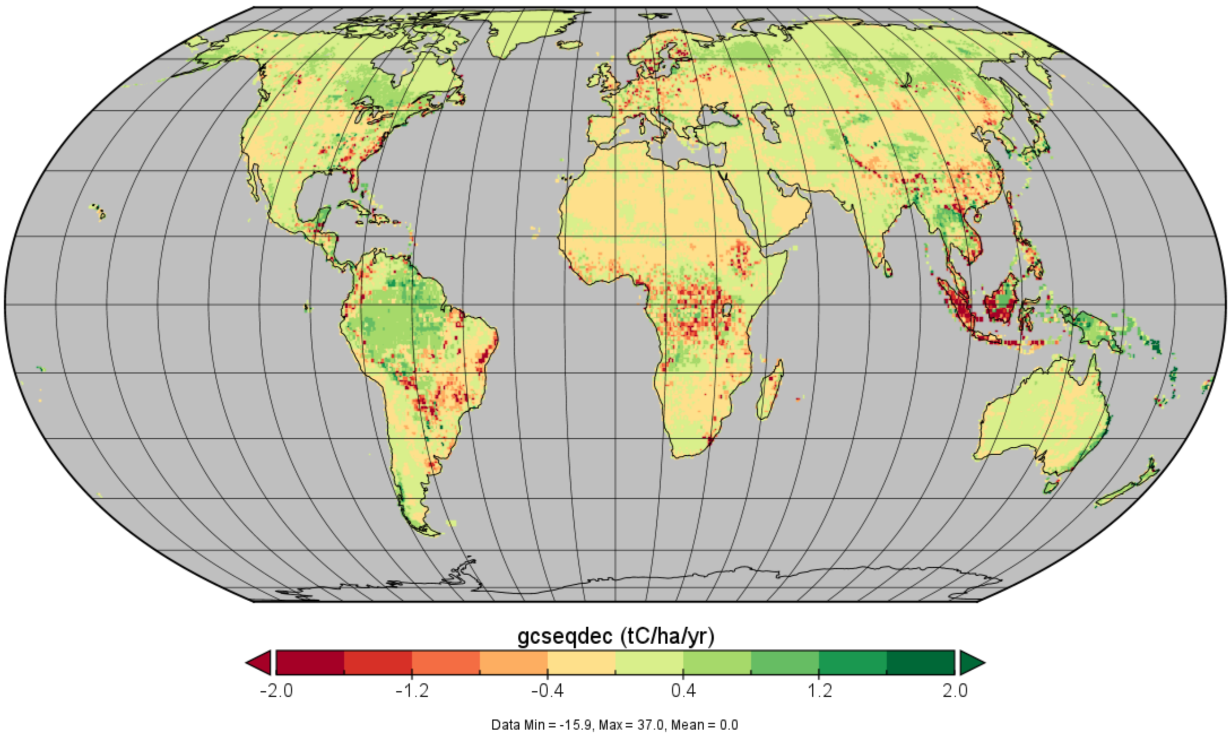

Figure 3: 10-year average annual carbon flux per half-degree grid cell in tonnes C per hectare for the 2011-2020 period as simulated with IMAGE for the REF default case, i.e. including timber harvest.

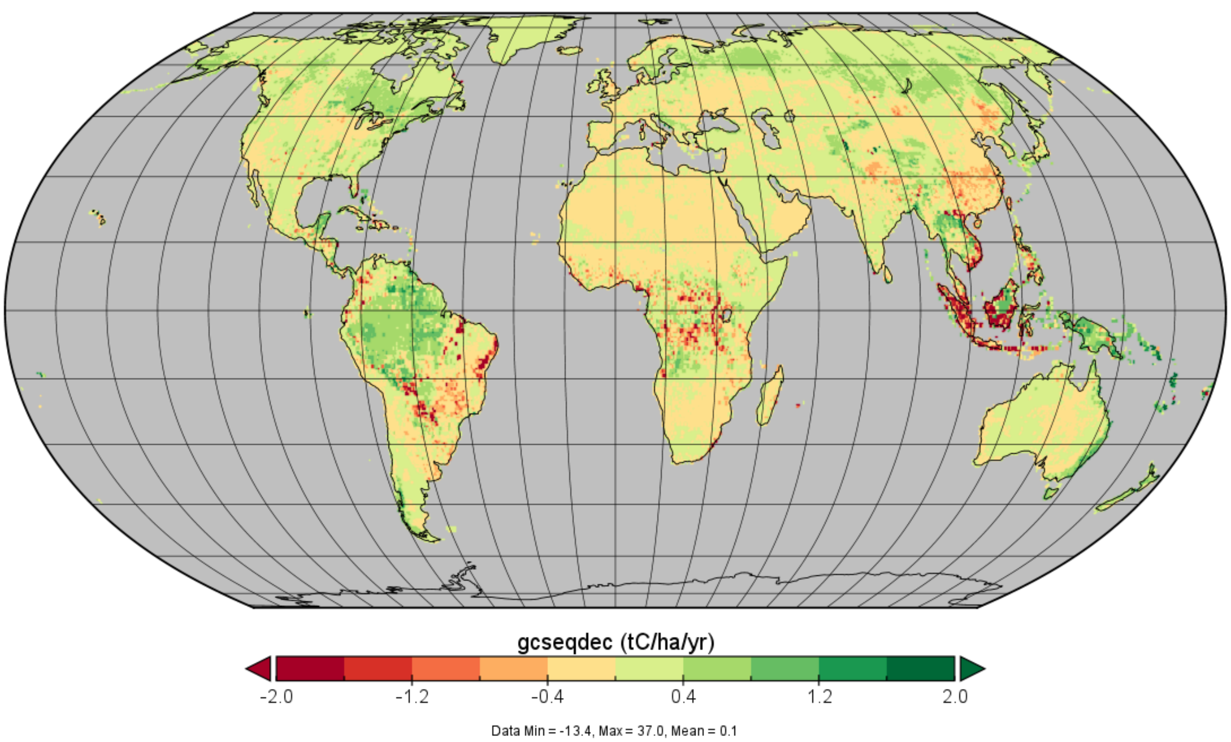

Figure 4: 10-year average annual carbon flux per half-degree grid cell in tonnes C per hectare for the 2010-2020 period as simulated with IMAGE for the NOTIMB counterfactual case, i.e. excluding timber harvest.

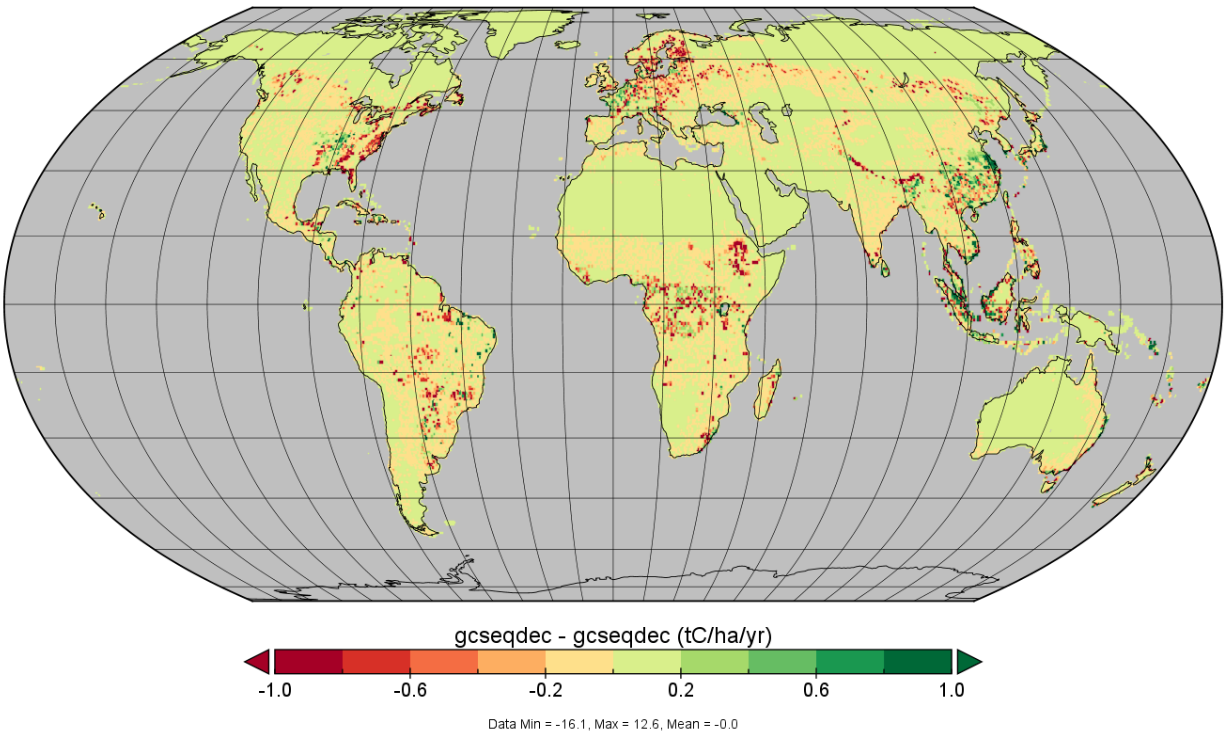

Figure 5: difference between REF and NOTIMB in 10-year average annual carbon flux per half-degree grid cell in tonnes C per hectare for the 2011-2020 period as simulated with IMAGE.

Table 2: 10-year average annual total carbon fluxes for Europe and for the world with positive values implying emissions and negative values sequestration in megtatonnes carbon for three time periods: 1991-2000, 2001-2010 and 2011-2020 for the REF and NOTIMB case in IMAGE.

MtC/yr	**1991-2000**		**2001-2010**		**2011-2020**	
	REF	**NOTIMB**	**REF**	**NOTIMB**	**REF**	**NOTIMB**
Europe	67	25	41	-8	22	-32
World	315	4	30	-243	-552	-875

Table 3: differences between the REF and NOTIMB case in IMAGE for 10-year average annual total carbon fluxes for Europe and for the world in megatonnes carbon for three time periods: 1991-2000, 2001-2010 and 2011-2020.

MtC/yr difference due to timber harvest	1991-2000	2001-2010	2011-2020
Europe	-41	-49	-53
World	-310	-272	-323

4.3 Comparison of LPJ-GUESS and IMAGE to NFI data

Detailed spatially resolved observations to evaluate the effect of forest management are rare. Here a comparison is made of aboveground forest biomass stocks in a selection of European countries from the IMAGE and LPJ-GUESS models to NFI data broadly representative of the year 2010 (Figure 6 and Figure 7). For IMAGE, the default REF case and the counterfactual NOTIMB case are assessed for the historical year 2010. For LPJ-GUESS the MOT (observed thinning) and potential natural vegetation (PNV) simulations are used also for the historical year 2010. The REF and MOT scenarios both represent the best estimate simulation for each of IMAGE and LPJ-GUESS respectively, whilst NOTIMB and PNV simulations both represent worlds without harvest or harvest legacies. In both IMAGE simulations and in the LPJ-GUESS MOT simulation forest biomass is broadly underestimated compared to the NFI results, except for the Nordic and southern France regions. In the LPJ-GUESS PNV simulation there is much more biomass simulated than found in observations of the present day, except in central Europe. The patterns in the biases for the REF and MOT simulations are surprisingly similar, but arise for different reasons.

For IMAGE, the low biomass in the NOTIMB simulation (which has no harvest) indicates either that woody growth rate (here defined as conceptually the same as the forestry term "gross annual increment", but referring to total annual wood growth in carbon terms) is too low or that the natural mortality rate of vegetation is too high, meaning that for central and southern Europe biomass stocks are substantially underestimated despite the real forest having a relatively young age structure compared to a natural forest (T. A. M. Pugh et al., 2024c; Vilén et al., 2012). Large biases in forest growth rates are common in DGVMs (Eckes-Shephard et al., under review), which are typically evaluated against primary productivity and biomass observations, rather than woody growth rate. It is clear that timber harvesting increases the mismatch between observed NFI data and IMAGE aboveground forest carbon stocks, with the default case REF having a lower mean difference to the NFI data (-3.3 kg C m^{-2}) compared to the counterfactual NOTIMB case (-1.2) (Figure 6). The default implementation in IMAGE leads to an overestimation of grid cells with close to zero aboveground carbon stocks (Figure 7), which is due to the model implementation where all vegetation carbon stocks in a 30 arc-minute grid cell can be harvested in one timestep. This is probably an overly crude representation of harvesting regimes leading to an underestimation of vegetation carbon stocks.

Unlike IMAGE, the MOT simulation from LPJ-GUESS includes detailed historical information on stand age structure and species composition. This leads to a substantially lower biomass than generated in a PNV simulation, which is the closest comparator to the NOTIMB simulation by IMAGE. That LPJ-GUESS with stand age structure lowering the average age of the forest, along with a full representation of harvest, simulates a similar set of biomass biases compared to the IMAGE REF simulation suggests that the underestimation of woody growth in LPJ-GUESS is less marked than that in IMAGE. This is likely related to the calibration process against growth rate observations of individual major tree species in Europe that has been performed for LPJ-GUESS within the ForestPaths project (T. Pugh et al., 2024). Previous evaluation of LPJ-GUESS within the ForestPaths project, however, has shown that the current version of LPJ-GUESS still has a substantial growth bias in central Europe (T. Pugh et al., 2024).

Although the biases in woody growth are marked, this does not necessarily mean that the net carbon exchange from the system is also heavily biased. Lower growth rates result in less biomass. If harvest rate is defined on an area or probability basis, then less biomass means lower harvest fluxes, meaning that overall the net exchange of carbon can remain representative of the effect of management actions applied. If harvest is applied on a mass basis, however, then a low biomass level will result in too much area being harvested and an overly negative effect on NBP. Overall, there is clearly an imperative for more work to focus on benchmarking and calibrating woody growth dynamics in vegetation models used for large-scale assessments in order to reduce biases as much as possible. However, given that it remains difficult to eliminate all growth biases in process-based models, a practical recommendation would be to apply area-based harvesting in ESM simulations, as well as in IAM simulations where NBP assessments are an important part of the study.

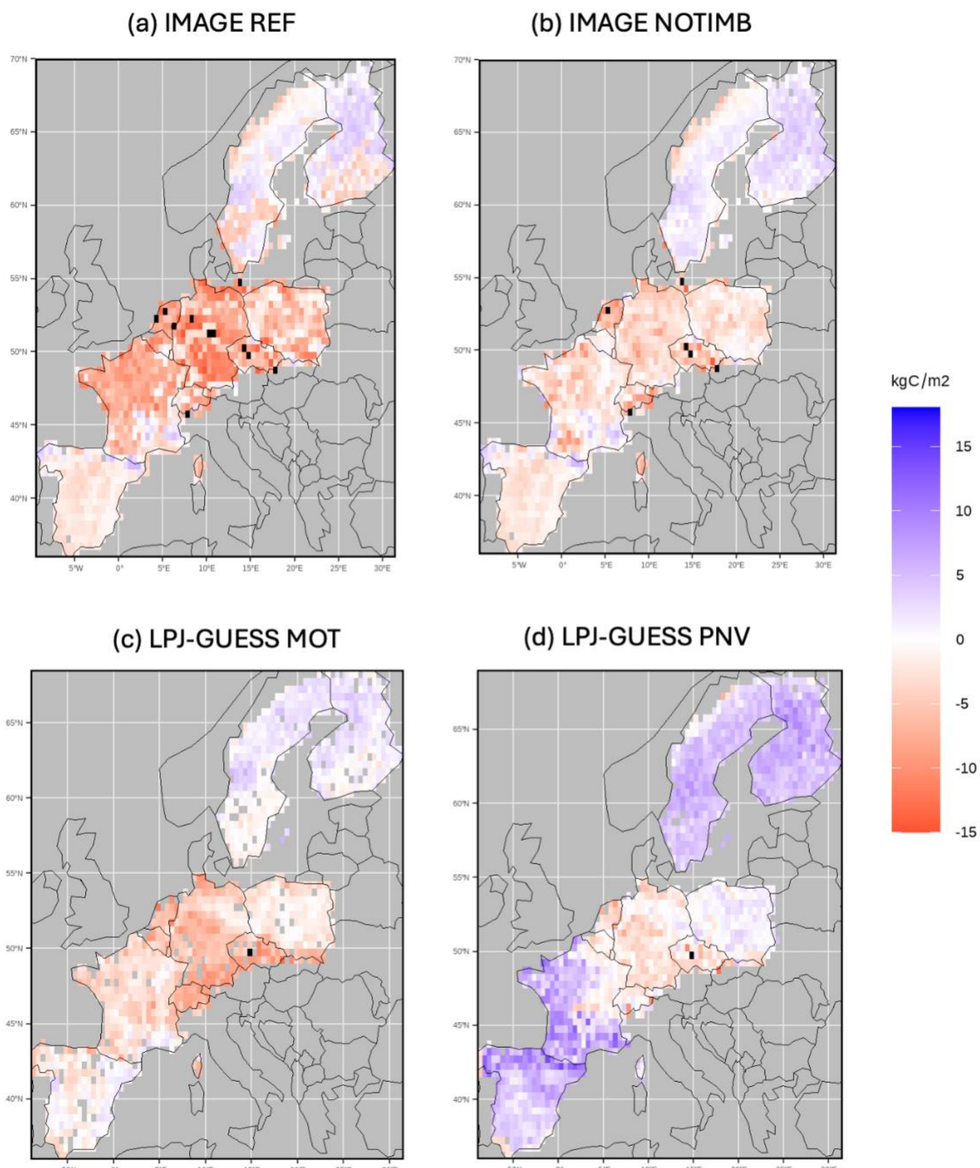

Figure 6: Spatially explicit comparison of aboveground biomass (kg C m^{-2}) between NFI data for the year 2010 and IMAGE and LPJ-GUESS results for the historical period in 2010 for REF and NOTIMB (IMAGE) and for MOT and PNV (LPJ-GUESS).

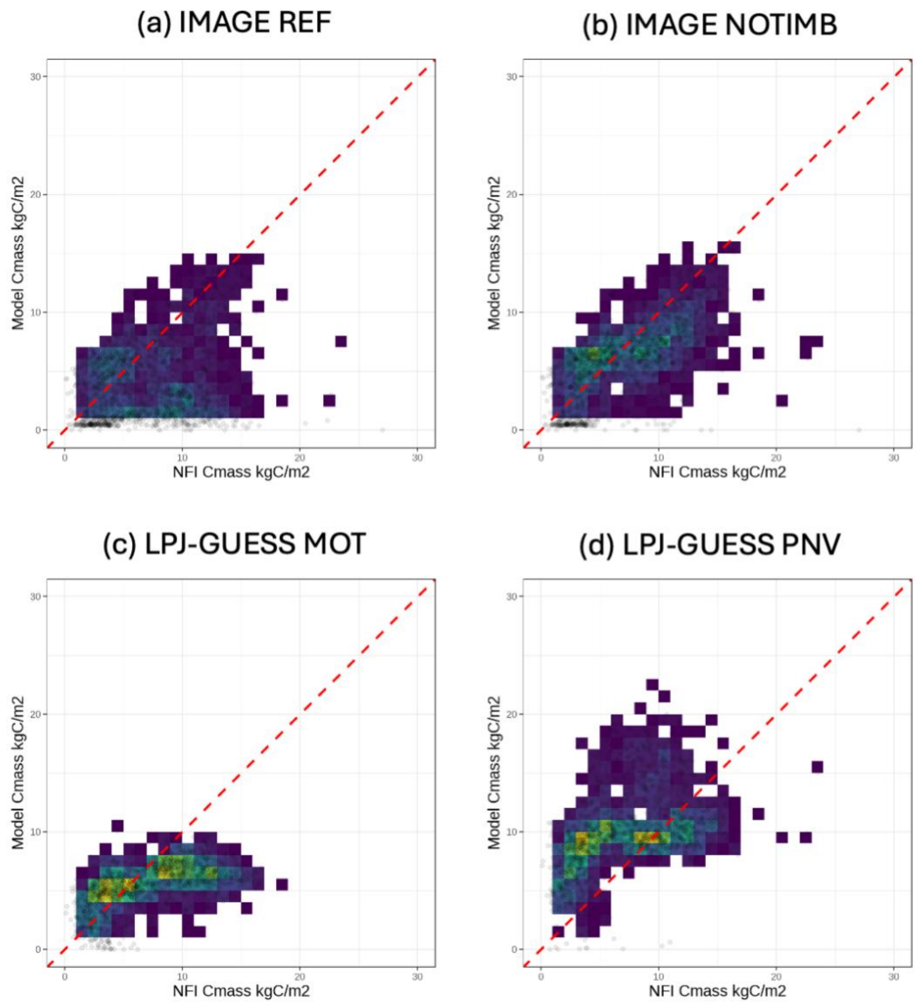

Figure 7: Scatter plot with the comparison of aboveground biomass (kgC/m²) between NFI data for the year 2010 and IMAGE and LPJ-GUESS results for the historical period in 2010 for REF and NOTIMB (IMAGE) and MOT (LPJ-GUESS). Brighter colours indicate a higher density of pixels with those values.

4.4 Comparison of IMAGE carbon fluxes to NGHGI data and bookkeeping models

The land-based carbon fluxes that are counted towards the UNFCCC accounting of GHG emissions, i.e. LULUCF emissions, differ a lot between various estimates. A key reason for this is the amount of forest land that is considered managed and is therefore taken into account in the reporting (Grassi et al., 2021b; Nabuurs et al., 2023). Here, we compare IMAGE results for the REF and NOTIMB simulations following different accounting rules to emissions reported by countries to UNFCCC in their Greenhouse Gas Inventories (i.e. GHGI) for the 2011-2020 period. In addition, we cross-check with three estimates based on bookkeeping models, another often cited source of LULUCF emission estimates (Friedlingstein et al., 2025). For IMAGE, three accounting rules are considered: 1) total land, i.e. all carbon fluxes are taken into account on both managed and unmanaged land (both forest and non-forest), 2) default managed land, i.e. the default IMAGE approach where only forest lands that have been harvested in the past 75 years are taken into account as well as any area where agriculture has been abandoned in the past 75 years, and 3) observed managed forest, where all carbon fluxes in locations that are considered managed forests according to a remote-sensing-based dataset are taken into account (Lesiv et al., 2022). We assess the differences at the Global and the European scale (Figure 8 and Figure 9).

Concerning the global scale results (Figure 8), a large difference can be observed between the UNFCCC GHGI data on the one hand, and the bookkeeping and the IMAGE default approach on the other hand. This is a direct result of the fact that many forests that are a carbon sink which is considered natural in the bookkeeping models and the IMAGE default approach, are reported as part of LULUCF emissions in the countries GHGI data. This also explains the alignment between the global total land carbon flux from IMAGE and the GHGI data that both include a substantial share of the natural carbon sink. Only taking into account IMAGE carbon fluxes in locations with observed managed forest and other land makes LULUCF a modest net source of CO_2 emissions as it excludes a large share of the natural sink, but still emissions are substantially lower than the default IMAGE approach which considers a smaller managed land area. Excluding forest harvests (i.e. NOTIMB results) leads to lower LULUCF emissions as it increases the carbon sink for the IMAGE accounting methods 1 and 3. This is in line with the observations in section 4.2 that the IMAGE forest management representation probably has an overly strong negative effect on the carbon sink capacity of the biosphere. In the default managed forest approach of IMAGE (method 2), emissions in fact slightly increase in the NOTIMB case. This is caused by the IMAGE definition of managed forest that is only considered managed if it has recently been harvested, which logically results in a much smaller area if no timber harvests are implemented and consequently a smaller forest area with forest sink capacity.

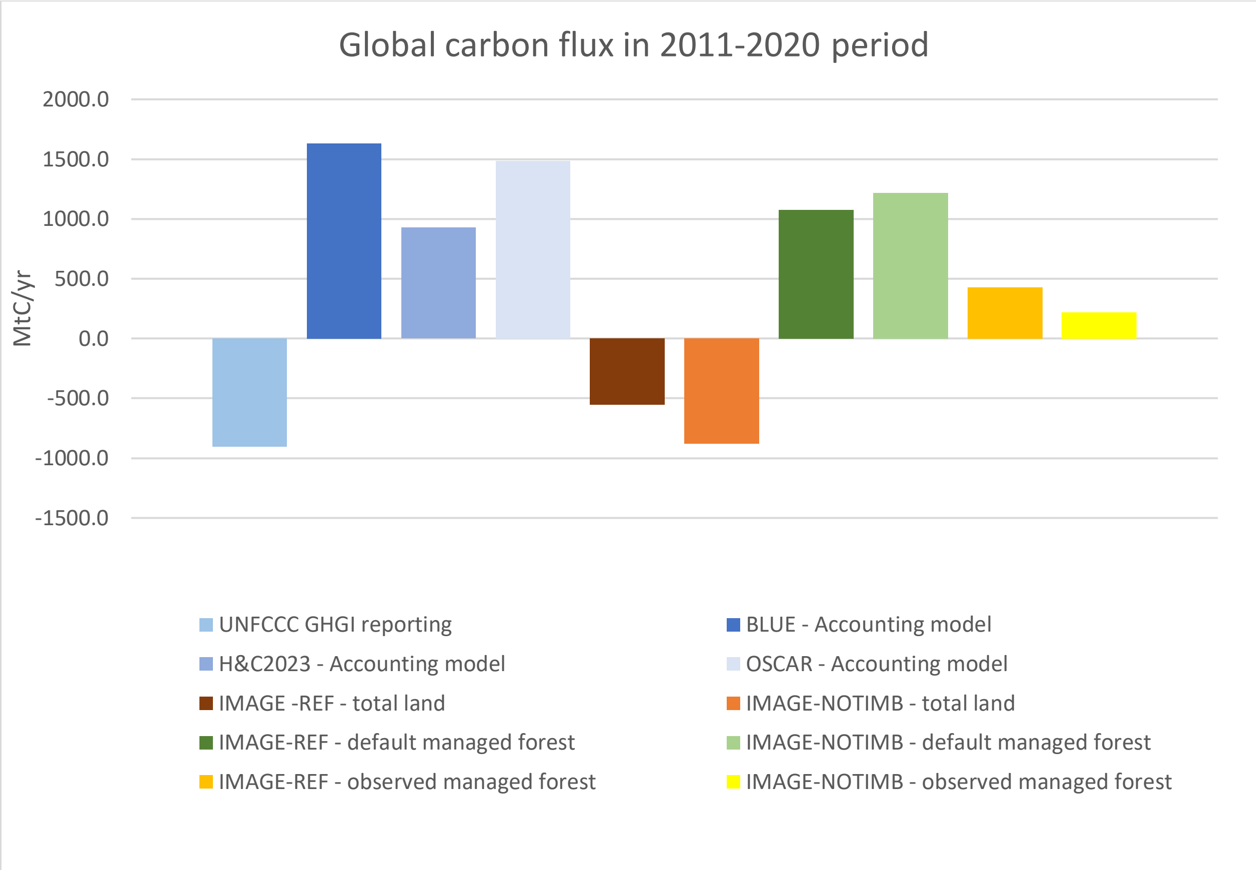

Figure 8: Carbon fluxes at the global scale for the 2011-2020 period according to UNFCCC's GHGIs, three bookkeeping models, and the two IMAGE simulations following three different accounting approaches: 1) total forest, i.e. both natural and managed forests, 2) default IMAGE managed forest as endogenously calculated, and 3) observed managed forest following Lesiv et al. (2022).

At the European scale (Figure 9), the situation looks very different: the UNFCCC GHGI data and the BLUE and H&C bookkeeping models align much better, related to the fact that most European forests are considered to be managed The IMAGE-NOTIMB simulations for total land and observed managed forest (methods 1 and 3) show substantial carbon sequestration for Europe, although still the carbon removals are smaller than those reported to UNFCCC, indicating the underestimation of the European forest carbon sink in LPJmL. The LULUCF emissions according to the IMAGE-REF case for the total land approach, as well as both default approaches find a significant LULUCF emission source in Europe, highlighting the overly negative effect of timber harvesting on the European carbon sink.

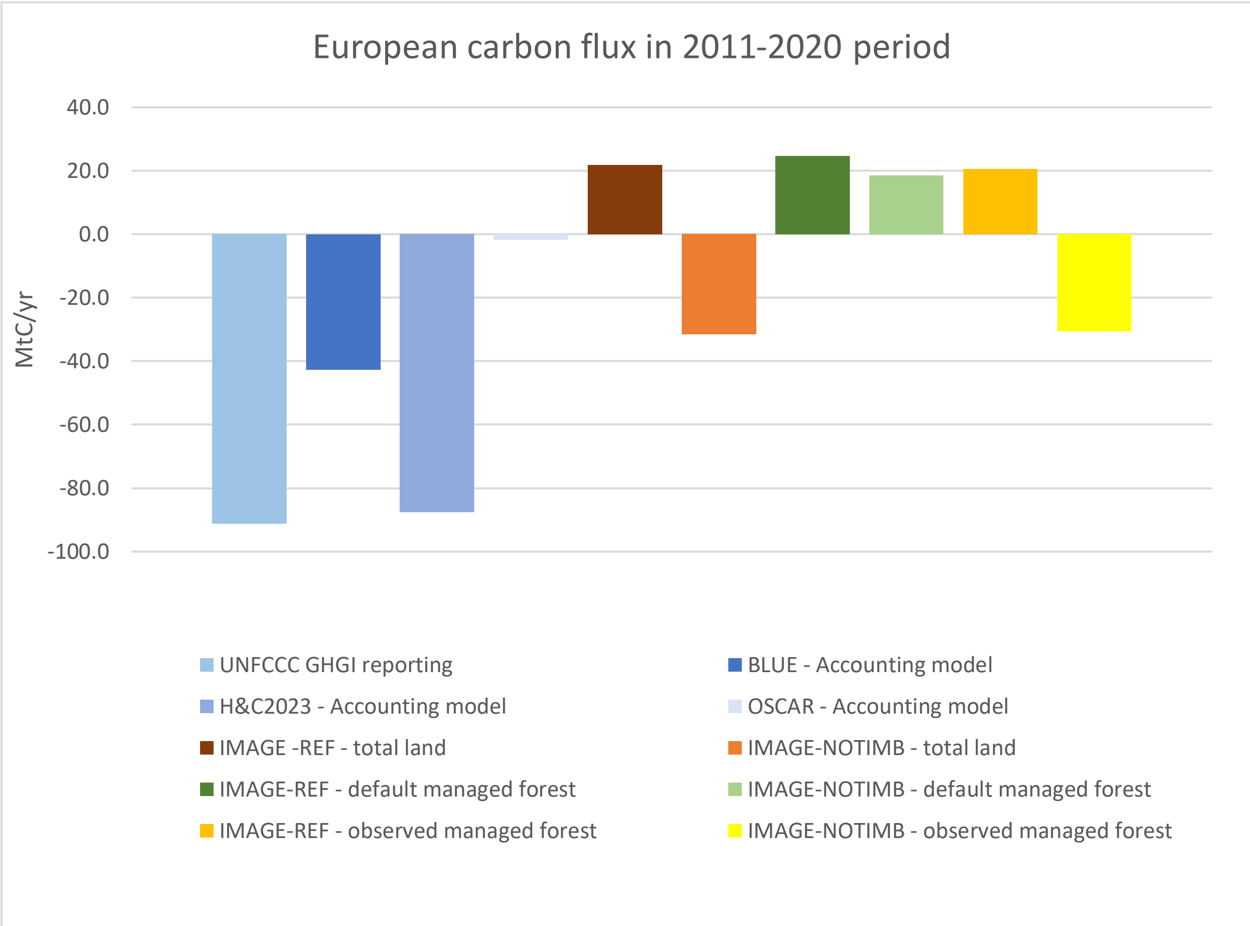

Figure 9: Carbon fluxes at the European scale for the 2011-2020 period according to UNFCCC's GHGIs, three bookkeeping models, and the two IMAGE simulations following three different accounting approaches: 1) total forest, i.e. both natural and managed forests, 2) default IMAGE managed forest as endogenously calculated, and 3) observed managed forest following Lesiv et al. *(2022).*

5 Forest management effects on climate via biophysics

According to the LPJ-GUESS results, albedo was substantially affected by the forest management representation. Differences in albedo due to forest management were much more muted compared to differences between forest and grassland, which is included as a reference case (*cf.* Figure 8a and 8d), however they still comprised changes of up to +/- 30% in the albedo of the forest itself. Although these changes in albedo are substantially higher than those reported by Naudts et al. (2016), in that study the changes were reported for the whole grid cell, whereas in ours we only report for the albedo change for vegetation and soil in the forested area. It is therefore important to consider that much of the parts of France and Germany, where including forest management results in a higher albedo (i.e., a cooling effect), the forest cover at the landscape level is actually very low. But in eastern and especially northern parts of the domain, where forest cover is a high fraction of the landscape, the estimated changes will be consequential for local climate, likely of the order reported in (Naudts et al. 2016).

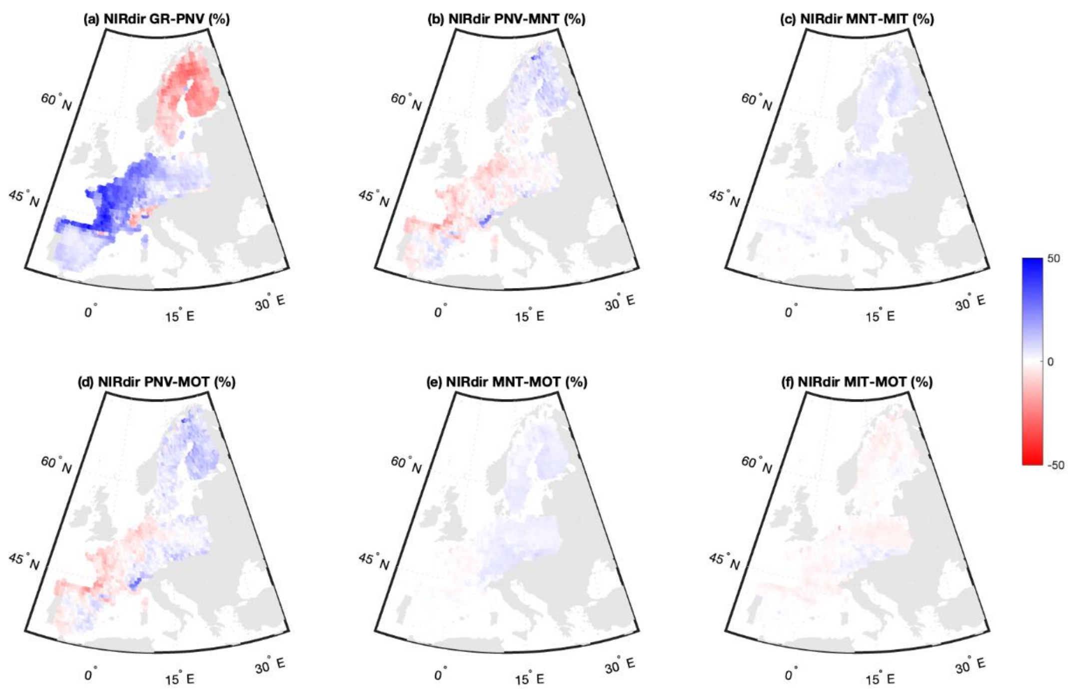

Figure 10: Relative difference in near-infrared (NIR) albedo (%) between different representations of forest averaged over 2011-2023, as simulated by LPJ-GUESS. The NIR albedo is taken as a representative of the different components of albedo used in EC-Earth. Arrangement of panels as in Figure 1.

The changes in albedo themselves are driven by both changes in total leaf area cover and by vegetation composition. Taking the example of comparing PNV and MOT (Figure 8d), the lower albedo in eastern Europe in MOT is driven by a lower conifer fraction, as conifers are less reflective than broadleaves. In western Europe there was an increase in albedo in MOT which was driven by a larger fraction of grass relative to trees, which tends to increase albedo. Northern Europe has a lower albedo in MOT, driven by a decrease in leaf area index (LAI) which makes the less reflective soil more visible. It is important to note, however, that these calculations do not include the effects of snow; the lower LAI would lead to a higher albedo in MOT in winter because the soil would be typically snow covered and therefore more reflective than the vegetation. Generally thinning results in a reduction in albedo (Figure 8c and 8e), driven by a decrease in LAI exposing the soil more.

It is important to note that the exact changes between PNV and MOT are highly uncertain because they are dependent on the composition of PNV vegetation emerging from LPJ-GUESS. The lower conifer fraction in eastern Europe in MOT compared to PNV is probably not very realistic. This area of Europe would usually be expected to have a higher fraction of broadleaves in a PNV situation (Hickler et al., 2012). This suggests that the PNV composition in LPJ-GUESS would benefit from a recalibration following the changes to improve model performance under forest management (Pugh et al., 2024). Regardless of this, however, we can conclude that the magnitude of potential change in albedo due to forest management actions is large.

The more detailed representation of forest management in MOT tends to lead to a substantial increase in evapotranspiration in our simulations in central Europe (95th percentile of grid cells 16% increase) but decreases in southern Europe (95th percentile 11% decrease), compared to PNV (Figure 9d). These changes emerge from a complex interaction of changes in age structure, species composition and leaf area index of trees versus grasses. The size of the changes was comparable to that seen in a scenario of full deforestation (i.e. comparing PNV and GR, Figure 9a). Overall, the change in evapotranspiration across the whole simulation domain is an increase of 2% in MOT vs PNV. Thinning alone (i.e. comparing MOT to MNT) acts to decrease evapotranspiration by up to 10% (95th percentile) at the grid cell level (4% in the mean across the entire domain) as a result of the reduced leaf area. These results support a substantial local effect of forest management on surface energy partitioning and thus surface temperature, but only moderate impacts on the continental scale.

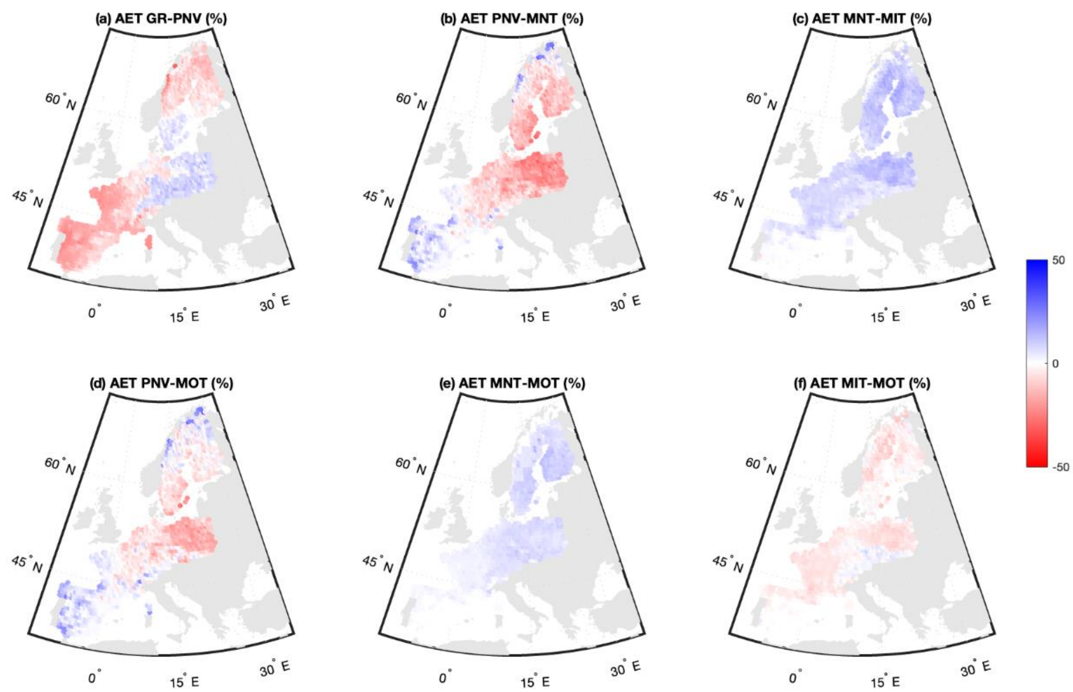

Figure 11: Relative difference in actual evapotranspiration (i.e. latent heat flux) (%) between different representations of forest averaged over 2011-2023, as simulated by LPJ-GUESS.

The RCA-GUESS simulations show a substantial summer cooling effect from higher levels of disturbance (defined in these simulations as the combination of natural disturbances and clearcut harvest) (Figure 10). The sensible heat flux generally decreases, likely associated with a higher albedo, which itself is linked to a lowleaf area index, obscuring less of the relatively reflective ground cover. In addition, a general increase in humidity and cloud cover is simulated, which is likely a strong driver of the reduction in temperatures. This change at first glance appears broadly opposite to that reported by (Naudts et al., 2016), who found a warming as a result of less evapotranspiration and a drier atmosphere. There are, however, several differences between our scenario and that of Naudts et al. Whereas we compare natural vegetation with vegetation undergoing a clearcut harvest intensity equivalent to the period 1985-2023 with no change in forest area, Naudts et al. compare a preindustrial and heavily utilised forest realm from ca. 1750 with a relatively afforested present day period with a substantial prevalence of industrial forestry. So effectively Naudts et al. compare a more disturbed situation with a less disturbed situation, finding a warming, and we do the opposite, finding a cooling. Considered in this light, the two studies offer complementary, and broadly consistent, viewpoints into the effect of considering forest management actions. Regardless of simulation set-up, however, our results corroborate that the way in which forests are managed does indeed have a substantial effect on estimates of summer temperature in Europe.

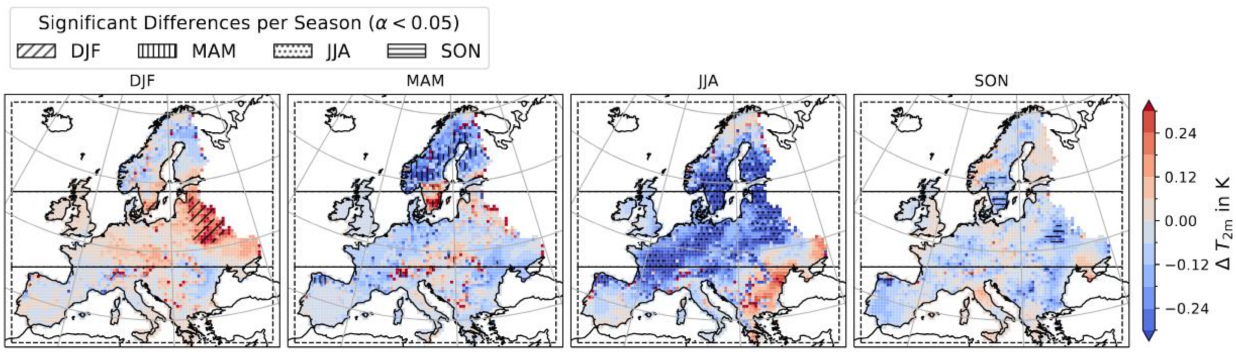

Figure 10. Seasonal mean 2m temperature differences between the RCA-GUESS experiment runs. Areas with significant differences (t-test with α < 0.05) are hatched for the respective seasons. Blue values are cooler in the simulation with present day clearcuts and disturbances.

6 Recommendations

It is clear from the results in this deliverable that the effect of management on forest composition and demography is highly influential both for carbon exchange and for the surface energy balance. This provides strong support for broader inclusion of harvest, or of forest management more generally, and demography in ESMs and IAMs. However, the benefits of doing so in making more realistic simulations will only be realized if appropriate input datasets are available to provide the necessary composition and harvest information. Currently, appropriate data is increasingly available at the European scale (McGrath et al., 2015; Pucher et al., 2022; Suvanto et al., 2025; Verkerk et al., 2015) (McGrath et al., 2014; Pucher et al., 2020; Suvanto et al., 2025) but is only partially available or absent in most locations globally.

The simulations with LPJ-GUESS show that stand age structure and composition are highly influential for carbon fluxes, as well as for biophysical variables. The size of the potential impact of forest management on surface temperature was confirmed by the RCA-GUESS simulations. This is consistent with previous work by Naudts et al. (2016), Luyssaert et al. (2018), Pugh et al. (2019) and Sullivan et al. (2024). Representing these is relatively straightforward for land surface models with a demographic component, so long as the area of stands established each year is incorporated into the land-use change data with which the models are forced. There is currently no published dataset which incorporates best information on forest age structure with the land-use change transitions needed to run ESMs, but in principle a blending land-use change and forest age information is relatively straightforward. Very few ESMs, however, are run with demographic vegetation. In the case of non-demographic models, it will be possible to achieve better biomass estimates by using forest age information to inform historical harvest rates, however, these models cannot be expected to generate the correct carbon sink dynamics because they will still not capture the resulting change in age structure and associated carbon sink effects.

A stand-out result from our simulations is the extent to which thinning also emerges as hugely influential in both carbon and biophysical fluxes. From a carbon sink perspective, the effect of including thinning is as impactful as that of including age structure, but typically offsetting the age structure effect. The sink across our European domain during 2011-2020 was 32.0 Mt C yr^{-1} without any forest management representation, 50.6 Mt C yr^{-1} if age structure and composition was represented and 20.9 Mt C yr^{-1} if realistic thinning was also included. Furthermore, thinning alone caused differences in the simulated evapotranspiration and albedo over forest areas of the order of 10% or more in many regions. In areas where forest is a major component of the landcover, previous coupled model simulations suggest that this will have a significant effect on surface temperature. It therefore appears to be crucial to include realistic representations of thinning, as well as stand-replacement disturbance events (i.e. both natural disturbances and clearcut harvest), in ESMs.

The IMAGE simulations show that including or excluding timber harvest significantly affects the global carbon sink, with 272-323 MtC per year on the global scale, 42-53 MtC of which occurs in Europe. The substantial effect on the carbon sink highlights the importance of a realistic forest management representation in IAMs, which is especially important in scenario assessment with strong climate mitigation efforts. The comparison to NFI data shows that the current IMAGE implementation leads to a substantial underestimation of standing carbon stocks in Europe, most likely due to an underestimation of tree growth after harvest. The results herein from two models with among the most detailed representations of forest management in their class emphasises the importance of evaluating and calibrating such models against observations of forest growth, in addition to the more commonly considered primary productivity, biomass and net carbon exchange. Benchmarking suites for ESMs such as ESMVal tool (Eyring et al., 2020) and iLamb (Collier et al., 2018) should incorporate such metrics among their standard sets. As it will remain difficult to eliminate all growth biases in process-based models, a practical recommendation would be to apply area-based harvesting in ESM simulations and IAM simulations where carbon fluxes are an important part of the study, as opposed to mass-based harvesting.

The comparison of IMAGE carbon fluxes with different accounting methods to UNFCCC GHGI data and bookkeeping models shows a wide range of results highlighting the uncertainty in LULUCF emission reporting. Including or excluding forest management has a small effect on LULUCF emissions if the default IMAGE approach is used which only includes fluxes on recently harvested areas. Including all carbon fluxes (both anthropogenic and natural) or only fluxes on observed managed forest areas bring LULUCF emission estimates closer to UNFCCC reported emissions, but also shows a much larger effect of forest management. If the goal is to better match the UNFCCC-style reporting, improved representation of forest management is key.

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