Towards a global behavioural model of anthropogenic fire: The spatiotemporal distribution of land-fire systems

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Abstract

Landscape fire regimes are created through socio-ecological processes, yet in current global models the representation of anthropogenic impacts on fire regimes is restricted to simplistic functions derived from coarse measures such as GDP and population density. As a result, fire-enabled dynamic global vegetation models (DGVMs) have limited ability to reproduce observed patterns of fire, and limited prognostic value. At the heart of this challenge is a failure to represent human agency and decision-making related to fire. This paper outlines progress towards a global behavioural model that captures the categorical differences in human fire use and management that arise from diverse land use objectives under varying socio-ecological contexts. We present a modelled global spatiotemporal distribution of what we term 'land-fire systems' (LFSs), a classification that combines land use systems and anthropogenic fire regimes. Our model simulates competition between LFSs with a novel bootstrapped classification tree approach that performs favourably against reference multinomial regressions. We evaluate model outputs with the human appropriation of net primary production (HANPP) framework and find good overall agreement. We discuss limitations to our methods, as well as remaining challenges to the integration of behavioural modelling in DGVMs and associated model-intercomparison protocols.

Keywords

Fire; DGVM; behavioural model; HANPP

Code availability

Supplementary material, including model code & outputs, as well as data used to produce our results, are made freely available via Figshare under an MIT open-source licence: https://doi.org/10.6084/m9.figshare.c.5523840. Code is also shared on Github for convenience: https://github.com/OliPerkins1987/Fire_GBM.

1. Introduction

In the Anthropocene, landscape fire is best understood as a coupled socio-ecological process, driven by complex interactions between biophysical and socio-economic factors (Pausas and Keeley, 2019; Kelley et al., 2019). For example, the Amazonian fires of 2019 were caused by a combination of international trade conflict between the USA and China (Fuchs et al., 2019; Taheripour et al., 2019) and national-scale political change (Stewart et al., 2020), but also a regional drought (Dong et al., 2021). Although much debate has focused on such destructive fires, and in particular so-called 'mega-fires' (e.g., Adams et al., 2020; Pliscoff et al., 2020), humans continue to

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Cite this article as:
Perkins, O., Matej, S., Erb, K.-H., & Millington, J.D.A.
Towards a global behavioural model of anthropogenic fire: The spatiotemporal distribution of land-fire systems
Socio-Environmental Systems Modelling, vol. 4, 18130, 2022, doi:10.18174/sesmo.18130

Socio-Environmental Systems Modelling
An Open-Access Scholarly Journal
http://www.sesmo.org

use fire as a management tool for diverse purposes across land systems (Smith et al., 2022; UNEP, 2022). For example, fire is used to rejuvenate pastures and deter pests in livestock systems (Kull, 2004; Jakimow et al., 2018), to prepare fields and dispose of residues in agriculture (Van Vliet et al., 2012; Liu et al., 2019), to manage fuel loads in fire prone environments (Laris, 2002), and as a weapon in land tenure disputes (Suyanto et al., 2004).

Human approaches towards fire suppression are similarly diverse – spanning industrial fire suppression and exclusion (Silva Sande et al., 2010) to traditional fire knowledge and community fire practice amongst indigenous populations (Mistry et al., 2005), to the growing 'pyro-diversity' narrative amongst conservationists (Bowman et al., 2016). Humans also have multiple indirect impacts on fire regimes – by altering fuel loads through logging and grazing (Cochrane, 2009; Archibald, 2016), by fragmenting landscapes with roads and croplands (Archibald et al., 2012), and by draining peat swamps (Page and Hooijer 2016).

In each case above, fire regimes emerge from a combination of local land use objectives, policy goals and wider economic developments playing out in the landscape. Furthermore, although climate attribution studies have found that climate change increases the likelihood of weather patterns associated with extreme wildfire events (Goss et al., 2020), multi-faceted human impacts on global fire regimes entail that the direct relationship between climate change and fire remains poorly quantified (van Oldenborgh et al., 2020; IPCC 2022).

In this context, it is perhaps unsurprising that the first Fire Model Intercomparison project (FIREMIP) found simplistic approaches to representing anthropogenic impacts on fire are a substantial shortcoming in dynamic global vegetation models (DGVMs; Teckentrup et al., 2019). Current approaches to modelling anthropogenic fire are limited to analytic functions derived from GDP and population density data (Teckentrup et al., 2019). As a result, representations of human activity were found to be both the largest single cause of disagreement between burned area outputs of different DGVMs, and between model outputs and remote sensing observations (Forkel et al., 2019). Not only do current DGVMs have limited ability to reproduce observed patterns of fire use, but they also have little predictive power, as they do not represent the underlying processes that drive human-fire interactions (Rabin et al., 2015, 2018).

This paper contributes to improving this situation by presenting progress on behavioural modelling of anthropogenic impacts on wildfire regimes at the global scale. Importantly, this work incorporates the underlying land-system processes that drive human-fire interactions (Pyne 2001; Lauk and Erb 2016) by characterising the categorically different anthropogenic fire use and suppression systems that emerge under differing land use systems and socio-ecological contexts. Specifically, we present a novel approach to modelling the global spatiotemporal distribution of what we term 'land-fire systems' (LFSs) from 1990 to 2014. Our LFSs are derived by combining classes of land use systems and anthropogenic fire regimes (AFRs), each of which are discussed and defined below (Section 2.1).

With LFSs defined, we take a novel approach to model their spatial and temporal distribution by combining a suite of classification trees and a simple simulation of competition. As anthropogenic fire is closely linked to land use (Archibald 2016; Andela et al., 2017), we evaluate our approach with indicators from the human appropriation of net primary production (HANPP) framework. HANPP, which is derived from data independent to our model, provides a multi-dimensional, spatially explicit and functional view of human-ecosystem interactions (Haberl et al., 2014; Gingrich et al., 2015).

Our spatiotemporal modelling of LFSs is an important step towards defining and spatially allocating agent functional types (Arneth et al., 2014) in a global model of anthropogenic fire impacts. We anticipate a close, though not exact, relationship between our LFSs and agent functional types. Our ultimate intention is for this model of anthropogenic fire impacts to be coupled with the JULES-INFERNO fire-enabled DGVM (Best et al., 2011; Mangeon et al., 2016). This eventual goal informs several choices regarding model development, from spatial resolution to our choice of forcing data sets. These restrictions and their implications for future modelling are addressed in the discussion.

2. Methods

Modelling the spatiotemporal distribution of land-fire systems (LFSs) involved several steps (Figure 1). First, we drew on the global Database of Anthropogenic Fire Impacts (DAFI; Perkins et al., 2021; Perkins and Millington et al., 2021a) to define each LFS through a combination of theory and empirical data (sections 2.1, 2.2). Second, we sourced appropriate secondary data sets as independent variables to drive the model (section 2.2). Third, we assessed the representativeness of data in DAFI (section 2.3.1) and weighted these data to address sampling biases. Fourth, using this weighted data, we developed a single classification tree for each LFS (section 2.3.2, 2.3.3). Fifth, the output probabilities of these trees were used to drive a simple representation of competition for land (section 2.3.4). Finally, model outputs were evaluated against land use efficiency data from the HANPP framework (section 2.4).

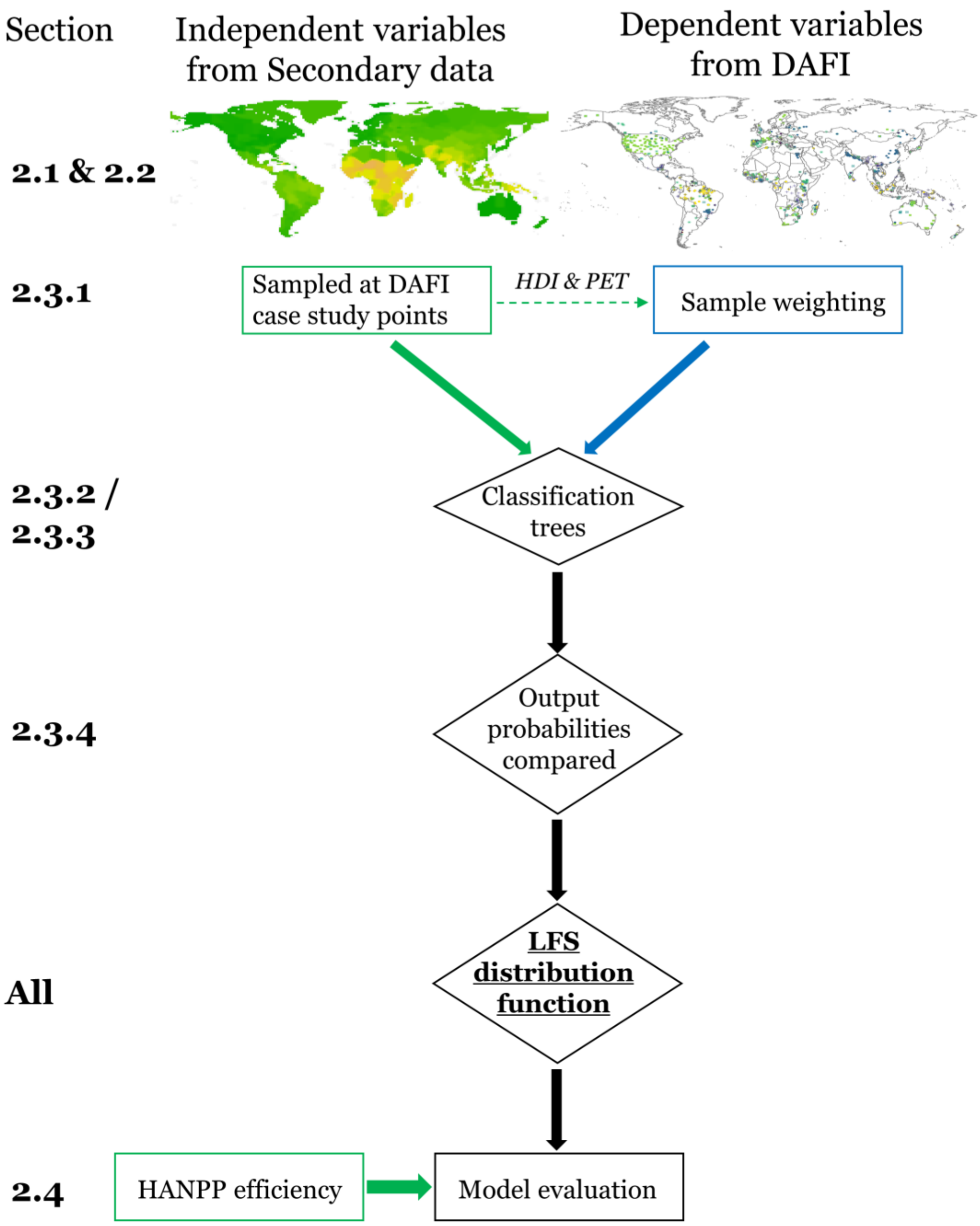


Figure 1: Overview of methods used in this paper to define and evaluate a global land-fire system distribution function. DAFI is the Database of Anthropogenic Fire Impacts, HDI is the Human Development Index, PET is potential evapotranspiration, HANPP is the Human Appropriation of Net Primary Production.

2.1 Definition of land-fire systems

Land use systems are defined based on land use intensity and land management practices (Foley et al., 2005; Václavík et al., 2013). For example, Dou et al. (2021) classified 24 land systems across Europe distinguishing high-, medium- and low-intensity use of forests, arable lands and grasslands (among others). We extend this concept and define land-fire systems (LFSs) as the fire use and management practices that emerge from a combination of local land user objectives and wider socio-cultural attitudes towards fire. Specifically, we use a conceptual framework that cross-references land use systems with 'anthropogenic fire regimes' (AFRs) to define and categorise global LFSs (Table 1).

We consider three primary land uses that dominate land systems globally – forestry, livestock and crops – in addition to a combined 'non-extractive' (recreational, residential or conservationist) land use system. Our AFRs are classified based on previous work that identifies differences in fire practices dependent on industrialisation and attitudes towards fire (e.g., Pyne, 2001; Seijo & Gray, 2012; Lauk & Erb 2016). These AFRs are:

- *Pre-Industrial* – active use of fire and limited mechanisation in land management;
- *Transition* – adopting elements of both pre-industrial and industrial regimes;
- *Industrial* – fire use replaced by mechanisation and chemical fertilisers;
- *Post-Industrial* – deliberate or unintentional re-introduction of fire to a landscape as an ecological process.

By cross-referencing AFRs with land use systems, the LFSs produced are categories of distinct fire- and land-management strategies that represent human behaviour and can be applied globally.

Table 1: Land-fire systems (LFSs) conceptualised as a combination of four land use systems (LUSs) and four anthropogenic fire regimes (AFRs). Italics give exemplar papers describing the activities and fire regimes of each LFS.

	LUS			
AFR	**Non-Extractive**	**Forestry**	**Livestock**	**Crops**
Pre-Industrial	Unoccupied N/A	Hunter-Gatherer *Fowler & Welch, 2018*	Pastoralism *Solomon et al., 2007; Johansson et al., 2019*	Swidden *Araki, 2007; Jakovac et al., 2017*
Transition	Limited or Contested Management *Sletto 2008; de Torres Curth et al., 2012*	Logging *Nepstad et al., 1999; Dennis et al., 2001*	Extensive Ranching *Eloy et al., 2017; Jakimow et al., 2018;*	Small-Holdings *Kumar et al., 2015; Liu et al., 2019*
Industrial	Pyro-Exclusion *Pavleichik & Chibilev 2018; Suhs et al., 2020*	Managed Forests *Kalies et al., 2016; Steen-Adams et al., 2017*	Intensive Ranching *Taylor, 2003; Bendel et al., 2020*	Intensive Farming *McCarty et al., 2009; Hall et al., 2016*
Post-Industrial	Pyro-Diversity *Govender et al., 2006; Fernandes et al., 2016*	Abandoned *Gomez-Gonzalez et al., 2018*	Abandoned or Subsidised *Hadjigeorgiou et al., 2011; Varela et al., 2018*	Abandoned *MacDonald et al., 2000; Dara et al., 2019*

2.2 Materials used

Our method for modelling the global spatiotemporal distribution of LFSs is empirical, using data from a recently completed and first global database of anthropogenic fire impacts (DAFI; Perkins et al., 2021; Perkins and Millington 2021a). Currently, DAFI comprises 1809 case studies from 504 academic papers, government and NGO reports. As previous work has emphasised the central role of land use in anthropogenic impacts on fire (Andela et al., 2017), DAFI presents data on anthropogenic fire use, suppression, and policy within its underlying land use context. Data on the distribution of LFSs in DAFI therefore provided the dependent variables for our modelling. DAFI is freely available online (Perkins & Millington, 2021a).

DAFI data were combined with secondary data sets, which were used as independent variables in subsequent models (Table 2). Our initial choices for independent variables began with data found to be valuable in modelling global patterns of land use by Malek and Verburg (2020). We augmented these initial choices with factors likely to be important for determining fire use. Additional variables were primarily those that could capture the 'dual-constraint' hypothesis of the biophysical drivers of fire (Krawchuk et al., 2009). Specifically, we used net primary production to capture cases where a lack of vegetation leads to a lack of fuel for fires to burn - 'the fuel constraint' - and potential evapotranspiration to capture cases where fuel is too wet to burn - 'the moisture constraint'. Data for both of these variables were drawn from the JULES DGVM (Best et al., 2011) to facilitate later integration of our model outputs.

Additionally, given the importance of politics to fire use and management (Carmenta et al., 2017, 2019), we also experimented with the 'Human Freedom Index' (Cato Institute, 2020). This was identified as a possible candidate to capture the relative importance placed on individuals' subsistence livelihoods or societal economic development within policy frameworks. Finally, as DAFI revealed that biodiversity conservation is a substantial driver of anthropogenic fire use (Perkins et al., 2021), data on the location of protected areas (UNEP-WCMC, 2020) and species' richness (IUCN, 2015) were included as possible predictors of the distribution of AFRs in non-extractive land use systems. A detailed overview of the pre-processing of secondary data sets that was conducted is given in Supplementary Material A; the resulting processed data sets are made available as Supplementary Material B.

Table 2: Overview of secondary data sets used as predictor variables in this study. Only variables used in the final model are shown. All data were resampled to the resolution of JULES-INFERNO (1.875º x 1.25º).

Variable type	Variable name	Spatial resolution	Temporal range	Source
Socio economic	Population density	0.04º	2000-2020	CIESIN, 2017
	Gross Domestic Product	0.08º	1990-2015	Kummu et al., 2018
	Human Development Index	0.08º	1990-2015	Kummu et al., 2018
	Market access+	0.08º	2000 (1990-2015)	Verburg et al., 2011)
	Human impact mask	1km^2	2016	Jacobson et al., 2019
Land cover & Land use	Fractional land cover (anthropogenic)	0.25º	1990-2020	Hurtt et al., 2020
	Land cover composition (natural)	1.875º x 1.25º	1990-2020	Clark et al., 2011
Biophysical	Potential evapotranspiration	1.875º x 1.25º	1990-2014	Best et al., 2011
	Ecosystem net primary production	1.875º x 1.25º	1990-2014	Clark et al., 2011
	Topography	30m	N/A	Van Zyl et al., 2001

Key: + single year of data extrapolated to other years from other secondary data (see Supplementary Material A). All data sets have an annual temporal resolution.

2.3 Global distribution of land-fire systems

Before using DAFI as the basis of our model, we first assessed the global representativeness of these data. Weights were then applied to address any sampling biases in DAFI (section 2.3.1). Using these weighted data, the determination of the distribution of each LFS was done in two parts (Figure 2). The first part in the fractional allocation of cells to each LFS was to divide each grid cell (1.875º x 1.25º; section 2.3.1) of a global raster map into the fractional coverage of each land use system. This was done using a combination of prescribed inputs and classification tree models (section 2.3.2). The second part was to allocate the fractional coverage of each AFR within each land system present in the cell. This was done using classification trees trained with predictor variables from secondary data sets sampled at the locations of DAFI case studies, and the LFS recorded in DAFI as the target variable (section 2.3.3).

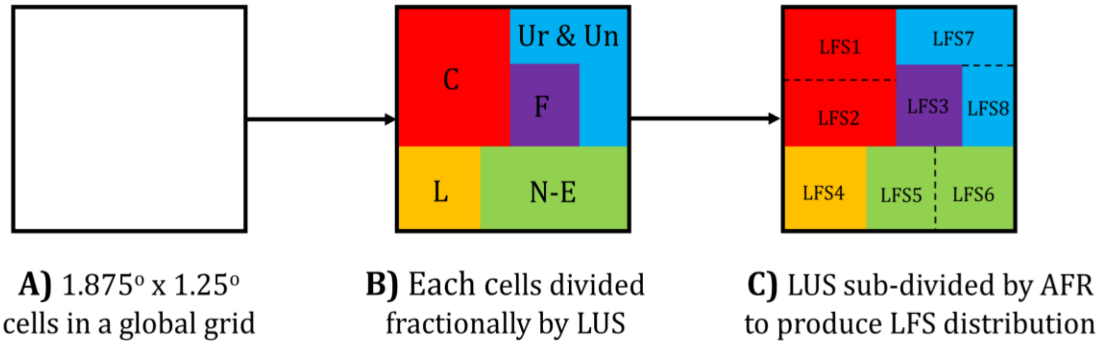


Figure 2: Process of allocating a grid cell proportionally by land-fire system (LFS) through the combination of land use systems (LUSs) and anthropogenic fire regimes (AFRs). All AFRs were distributed using the classification tree method set out in the main text, whilst the fractional coverage of LUS was determined through a combination of external forcing and inter-system competition. The fractions of a grid cell occupied by crops (C) and livestock farming (L) were determined from forcing data (Hurtt et al., 2020). Forestry (F) and non-extractive (N-E) LUSs were determined through a combination of JULES-INFERNO plant functional type outputs and statistical functions (see sections 2.3.2 & 2.3.4). The unoccupied fraction (Un) was determined by a classification tree, as with the AFRs, whilst the urban fraction (Ur) was also driven by CMIP6 forcing data. All fractional coverage was non-spatial within a cell.

2.3.1 Data representativeness check and weighting

The first potential source of bias in DAFI was the imbalance of the database towards few studies that reported results relating to the same LFS from multiple sites in close proximity. This imbalance is reflected in the large difference between the median and maximum number of locations reported in a single source (1 and 84 respectively). For example, Araki (2007) reported fire use in shifting cultivation across 51 different villages in the Muchinga region of Zambia. Although this information is valuable for understanding variability in anthropogenic fire use, concentrations of case studies in localised areas could skew results at the global extent. Therefore, four locations were randomly sampled when a source reported data from more locations (for the same LFS in the same country) than the overall mean number per source (3.7). Additionally, case studies that reported policy or other information at the country level were excluded as they likely lacked spatial specificity. Consequently, from an initial set of 1809 case study locations, 1170 were used for modelling.

The global representativeness of the chosen 1170 case studies from DAFI were assessed by comparing the distribution of values for the human development index (HDI) and potential evapotranspiration (PET) at locations for DAFI case studies against their respective global distributions. HDI was chosen to represent the availability of social and economic resources as it is focused on the fundamentals of human development across the broad base of a population (UN, 2020). Furthermore, HDI was chosen over GDP as fire is often conceptualised as a land management strategy used in the absence of alternative industrial tools such as machinery (Carmenta et al., 2019; Cammelli et al., 2020). PET was used as a proxy for the 'dual-constraint' hypothesis (Krawchuk et al., 2009), which describes the global biophysical variation in fire regimes.

To conduct this comparison, values of the reference variables were sampled from raster grids at the locations of DAFI case studies (Table 2). As our eventual goal is to work with the JULES-INFERNO DGVM, secondary data were first aggregated to that model's coarse resolution for global runs: 1.875° x 1.25°. The means of the distributions in DAFI were found to be substantially different from the global values (t-tests: all $p < 0.0001$; Figure 3). The source of bias is that DAFI oversamples data from fire-prone areas - where anthropogenic fire use is more likely - and from economically poorer areas - where people have tended to use fire because other land management approaches are unavailable.

Therefore, a process of 'raking' (Lovelace et al., 2015) was used to weight DAFI such that it more closely reflected the global distributions of HDI and PET. First, the 25th, 50th and 75th percentiles of the global distributions of HDI and PET were calculated. Each DAFI case study was then allocated to a quartile of the global distribution for the two reference variables. Where DAFI was found to over- or under-sample a particular quartile of the global distribution, data were down- or upweighted. For example, if 27.5% (respectively 22.5%) of DAFI case studies were in the second quartile of the global PET distribution, then those case studies would receive an PET weight of 0.909 (respectively 1.11). The weights for HDI and PET were multiplied together to produce a final case study weight. Trimming thresholds were applied at values of 0.7 and 3 to avoid excessive emphasis being placed on a single data point (Elliot, 2008).

The central tendency of the weighted data was found to approximate the global distribution of HDI (t-test: p = 0.47). For PET, a bias persisted as areas of very low evapotranspiration (principally the Northern Boreal Forest and Arctic Circle) remained under-sampled. These areas have very low human impacts on fire regimes, and when they were excluded, the distributions had converged acceptably (t-test; p = 0.82). This process was repeated for each of our four land use systems. For each land use system, the global values of HDI and PET were filtered to include only cells that contained >1% of the land use system in question, and this subset of the data was compared against DAFI case studies containing an LFS from the relevant land use system. Similar results were achieved at the land system level as for the data overall (t-tests: all p > 0.05). These weighted data formed the basis of subsequent modelling.

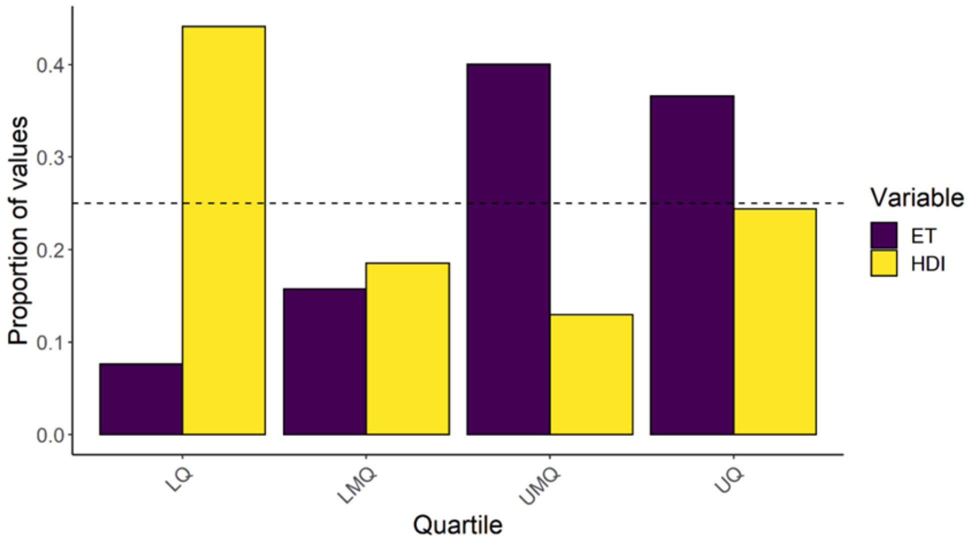


Figure 3: Distribution of data in the database of anthropogenic fire impacts (DAFI) by quartile of two reference variables, potential evapotranspiration (ET), and the human development index (HDI). DAFI oversamples low HDI (poorer) locations where anthropogenic fire is a dominant land use strategy and higher ET environments, which are more likely to be more fire prone. LQ, LMQ, UMQ, UQ refer to lower, lower middle, upper middle and upper quartiles. Dashed line represents an equal proportion of values across quartiles.

2.3.2 Modelling the spatiotemporal distribution of land use systems

To ensure our model outputs could be consistently integrated with JULES-INFERNO, we needed to consider the two ways in which land cover types are defined in the DGVM. First, the distribution of vegetation within 'natural' ecosystems is calculated based on competition between plant functional types (PFTs; Harper et al., 2016). Second, the presence of anthropogenic land systems (currently crops, livestock farming and urban) is determined through prescribed inputs. These inputs to JULES-INFERNO are currently typically the standardised land cover inputs for the CMIP6 (Coupled model intercomparison project simulations; Hurtt et al., 2020). CMIP6 was the standardised model protocol that informed climate projections for the IPCC AR6 (Eyring et al., 2016). JULES-INFERNO then only allows grass PFTs to occupy anthropogenic or 'disturbed' portions of a grid cell (Burton et al., 2019). Therefore, for the land use system component of our LFS distribution modelling, the fraction of each grid cell covered by crops, pasture, rangeland, and urban areas were taken directly from the CMIP6 forcing data. In these forcing data, Hurtt et al. (2020) divided grazing lands into planted pastures and 'rangelands' (semi-natural grasslands). We assumed that livestock land use systems dominated in both land cover types. The consequences of this division for model outputs are discussed in section 4.3.

The remaining fraction of the grid cells were then allocated between forestry, non-extractive land uses, and 'unoccupied' – the absence of any human land management. To do this, classification trees were used (Krywinski and Altman, 2017). Classification trees have been widely applied in agent-based modelling (Rounsevell et al., 2012) - their advantages include simplicity and an ability to represent categorically different behaviours. For the classification trees allocating non-extractive and forestry land use systems, the target variable was the respective land use system in DAFI. However, given that DAFI does not include case studies without at least one anthropogenic fire impact, it could not form the basis of the 'unoccupied' model. Therefore, the dependent variable for the 'unoccupied' model was the 'very low (anthropogenic) impact areas' defined by Jacobson et al. (2019). The full process used for defining the classification tree models is presented in section 2.3.3.

2.3.3 Modelling the distribution of anthropogenic fire regimes

Multinomial regression has frequently been used for statistically-derived distribution of land use/cover types (e.g. Millington et al., 2007; Lin et al., 2014). Here, we adopted an alternate approach based on a suite of classification tree models, in which a classification tree was defined for each LFS (Figure 4). The principal benefit of this approach was that it allows the socio-ecological niche of each LFS to be defined individually, and for that niche to be evaluated both quantitatively and relative to our understanding of process. For example, although soil composition and hydrology may play a role in determining the suitability of a given region for intensive agriculture (Malek and Verburg, 2020), including this as a variable across our LFSs risks making it a proxy for the trend towards lower economic development in tropical regions. Because only a sub-set of independent variables need be included in a given tree, the effect of these variables can be separated from each other, and isolated to where they are warranted from a process perspective. Our approach therefore substantially reduces multi-collinearity concerns. Furthermore, grounding the foundations of the model in both empiricism and process should make future projections robust.

Some LFS had few (< 20) instances in DAFI, meaning that several AFRs accounted for less than 10% of cases in some land use systems. This risked the classification-tree algorithm returning a null tree predicting all absence cases, which is little use for our modelling purposes. Therefore, for each LFS, a training set was developed with 50% presence and 50% absence cases of the relevant LFS. Absence cases were up-sampled to the number of presence cases in the initial training data and 20% of the resulting data were first held back as a testing set. On this training set, an initial process of variable (or 'feature') selection was conducted to identify viable predictor variables. In this process an initial tree was learned against the training set with no restrictions on the number of nodes it contained. This was then 'pruned' based on misclassification of data points, to identify a simpler model, less prone to out-of-sample prediction variance due to overfitting (Mingers et al., 1989). The pruned trees were then evaluated against the testing set, to assess trade-offs between parsimony and predictive accuracy.

As classification trees are known to be sensitive to small changes in the training data (Krywinski and Altman 2017), bootstrapping of the training data is commonly employed to improve the stability of their out-of-sample prediction. In machine learning algorithms such as the random-forest, an ensemble of differing tree structures then forms the final model (Breiman, 2001). However, given our goal is to build a global, process-based behavioural model, we wanted to avoid the lack of interpretability associated with random-forests (Haddouchi and Berrado, 2019) and thereby to ensure each of our trees were robustly grounded in process. Therefore, rather than using bootstrapping to develop an ensemble of tree structures, we used it to identify the most robust single structure across samples.

Having conduced an initial variable selection, therefore, we made 1000 bootstrap samples of the full data set used for variable selection – the training and test data with equal proportions of presence and absence cases (section 2.3.1). Using a subset of variables defined during variable selection, a classification tree structure was learned on each sample and pruned to the level identified as robust against over-fitting during variable selection. From these 1000 trees, the most frequent tree structure was identified and chosen as a final model. In some cases, two variables formed the initial model split approximately 50% of the time. In these instances, convolutions of variables were attempted to define a single variable that consistently formed the first split. For example, HDI was multiplied by the logarithm of GDP for the Small-Holdings (transitional crop) LFS and the single resulting HDI-GDP hybrid variable was subsequently found to be valuable in seven other cases.

In addition to defining a resilient tree structure, the added advantage of our approach is that it creates a numerical distribution of values for the thresholds and output probabilities of a tree, based on their values for each bootstrapped sample. This allows a degree of data and sampling uncertainty to be captured and expressed.

For this study, we took 100 random deviates for each set of tree split thresholds and their associated output probabilities and present this as a quantification of parameter uncertainty.

The process described above created a single classification tree structure per LFS, where each split in the tree was given a numerical distribution and each node an associated set of output probabilities. The outputs of each classification tree are best interpreted as the probability that a given LFS is the dominant type in the fraction of a grid cell occupied by the relevant land use system. This allows, for example, that Swidden (i.e. pre-industrial crops) and Managed Forests (i.e. industrial forestry) could be the dominant LFS in their respective land use fractions of a single model cell.

2.3.4 Simulating competition between LFS

To produce maps of the fractional coverage of each LFS in each model grid cell we take a two-step process (Figure 2). The first step of combining the outputs of individual classification trees was to assign fractional coverage of each grid cell to each of our four land use systems (Figure 2b). Crop, pasture, rangeland and urban areas were derived directly from CMIP6 land cover (Hurtt et al., 2020). The remaining vegetation area was then allocated based on outputs of classification trees for forestry, unoccupied and non-extractive areas of a cell. Forestry was calculated as:

$$Forestry_i = Treecover_i * (1 - Nonextractive_i) * (1 - Unoccupied_i) \quad (1)$$

Where $Forestry_i$ is the proportional allocation of the *i*th grid cell to forestry. The remaining area covered by grass, shrubs and trees falling outside human land use was allocated between unoccupied and non-extractive land systems. This was done by summing the output probabilities of their two respective classification trees and dividing by the total. For example, the fraction of the ith grid cell allocated to non-extractive land uses was calculated as:

$$Nonextractive_i = Vegetation_i * \frac{Nonextractive_i}{Nonextractive_i + Unoccupied_i} \qquad (2)$$

where $Vegetation_i$ is the fraction of the grid cell not allocated to extractive land uses. Having allocated each grid cell fractionally between land use systems, LFS distribution within each corresponding grid-cell fraction was then calculated (Figure 2c). This was done by representing 'competition' between LFSs using output probabilities of the trees for each AFR:

$$AFR_{ij} = {}^{p(AFR_{ij})}\Big/_{\sum p(AFR_j)} \qquad (3)$$

where AFR_{ij} is the fractional coverage of the *i*th AFR in the *j*th cell, and $p(AFRij)$ and $\sum p(AFRj)$ are the probability of the classification tree for the *i*th AFR and for all AFRs respectively.

Before calculating the fractional coverage by AFR using equation (3), a threshold (θ) of 0.1 was applied: output probabilities from a given classification tree less than this threshold were set to 0. The θ parameter was applied to prevent very small output probabilities for a given AFR from influencing LFS distributions inappropriately. This occurs because we used simple tree structures to avoid overfitting, and so the smallest output probability of a given tree was typically 0.05-0.1. For example, the Swidden LFS could be projected to occupy a small-fraction of cropland in the intensive USA corn belt (where such a land management strategy simply does not exist). This θ value will eventually become a free parameter when this model is coupled with JULES-INFERNO. After applying equation (3) to classification tree outputs, the relevant AFR and land use system fractions were multiplied together to produce LFS fractions within each cell.

2.4 Model Evaluation

Model outputs were evaluated in two ways. First, the classification-tree based approach set out above was compared against a reference (and more parsimonious) multinomial regression approach using the area under the ROC curve or 'AUC' – a standard measure of classification accuracy (Melo, 2013). To ensure a fair comparison, one multinomial regression was fit per land use system. A brief description of the multinomial model is available as Supplementary Material F. Second, model outputs were compared against independent data in the form of global maps of Human Appropriation of Net Primary Production (HANPP; Kastner et al., 2021).

HANPP is a measure of the intensity of land use. It quantifies the extent of human domination of an ecosystem and therefore also provides a measure of land use as a planetary boundary to socioeconomic development (Vitousek et al., 1997; Running, 2012; Haberl et al., 2014). The HANPP framework has been used to analyse long-term trajectories of land systems (Krausmann et al., 2012, 2013), disentangle processes of area change, intensification and efficiency gains (Gingrich et al., 2015), and understand impacts on biodiversity (Haberl et al., 2005) and other ecosystem services (Mayer et al., 2021). HANPP quantifies the effects of land use and land-cover conversions (HANPPluc), as well as of biomass harvest (HANPPharv) on terrestrial net primary production and is thus a multi-dimensional indicator for land-use intensity (Erb et al., 2013).

The ratio between HANPPharv and HANPP gives the fraction of appropriated biomass that can be used for human purposes related to the overall land-use pressure on ecosystem productivity. The resulting metric – HANPP efficiency (HANPPe) – provides a measure of land use efficiency. HANPPe has been shown to be useful to depict land-use transitions, in particular from the agrarian to the industrial mode of subsistence (Fetzel et al., 2014; Niedertscheider et al., 2014). While production increases in agrarian societies tend to rely on expansions of existing land-use practices, and thus result in a stable HANPPe, industrialisation-based production increases are usually associated with increases in plant productivity that result in strong, often sudden, increases in HANPPe.

Here, we use global maps of HANPP to derive HANPPe for 1990, 2000 and 2010 (Haberl et al., 2007; Kastner et al., 2021). The compilation of these maps relied on the integration of census statistics (FAOSTAT, 2021) with information on potential ecosystem net primary production derived from a model run with the LPJ-GUESS DGVM (Smith et al., 2014) assuming a hypothetical no-land-use situation. Therefore, HANPP calculations were based on separate data from those used to develop the LFS distribution, with the exception of the land-use information which were derived from related CMIP6 and Hyde data sets (Goldewijk et al., 2017; Ellis et al., 2020; Hurtt et al., 2020). Model evaluation using HANPPe focused on the crop land use system, where HANPPe dynamics are most pronounced. Therefore, cells with less than 10% cropland in the CMIP6 land cover data were excluded from evaluation. Since HANPPe should increase with industrialisation, we expected HANPPe to increase from pre-industrial, to transitional, to industrial crop LFS.

2.5 Model simulations and code

We ran our model from 1990-2014. These years represent the beginning of the time-period covered by DAFI (1990) and the end of CMIP6 historical simulation runs (2014) respectively. Analysis code to create tree structures is written in R version 4.0.1. Principal packages used were 'tree' version 1.0.4 (Ripley, 2019) for classification trees and 'tidyverse' version 1.3.0 (Wickham et al., 2019) for data manipulation and processing. Code to integrate tree models into a cohesive simulation is written in Python 3.8, using the 'Agentpy' framework version 0.0.1 (Formatti, 2021). Code is made available as Supplementary Material C and Github (Perkins and Millington, 2021b).

3. Results

3.1 Model outputs

Overall, our model suggests that in 2014, 54.15% of the Earth's land surface was in either transitional or industrial fire regimes (Figure 4). By contrast, just 9.37% of the planet was occupied by the pre-industrial AFR and 12.70% was occupied by the post-industrial AFR. The largest shift globally between 1990 and 2014 was an increase in industrial and post-industrial AFRs. The Industrial AFR grew from 22.47% of the global land surface in 1990 to 27.61% in 2014 (Figure 5). This increase was predominantly driven by an increase in the industrial crops LFS. The industrial crops LFS increased from 40.20% to 50.70% of cropland area globally (Figure 6). There was a smaller increase in the industrial livestock LFS, which increased from 31.95% to 35.00% of livestock land use systems globally. This picture of increased land use intensity is complemented by unoccupied areas of the land surface decreasing from 23.23% to 17.78% over the study period.

By contrast, the largest change in non-extractive LFSs was the increase of the post-industrial AFR ('Pyro-Diversity'), which grew by 6.69%. However, the industrial ('Pyro-Exclusion') AFR also grew by 4.48% in the non-extractive land use system. Furthermore, the distribution of AFRs within the non-extractive land use system was more static than in extractive land use systems. In 1990, the four non-extractive AFRs occupied between 20.93% and 29.54%, whilst by 2014, this range had changed only to 16.12% to 32.05%.

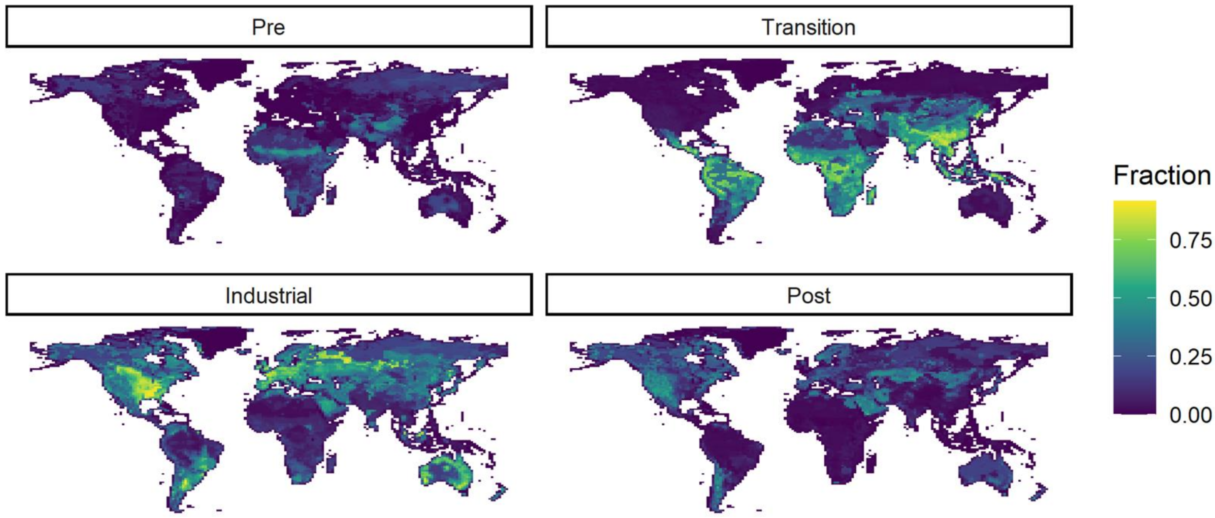


Figure 4: Fractional coverage of the global land surface by anthropogenic fire regime (AFRs) in 2014. The transition and industrial AFRs form the largest share of global land surface coverage.

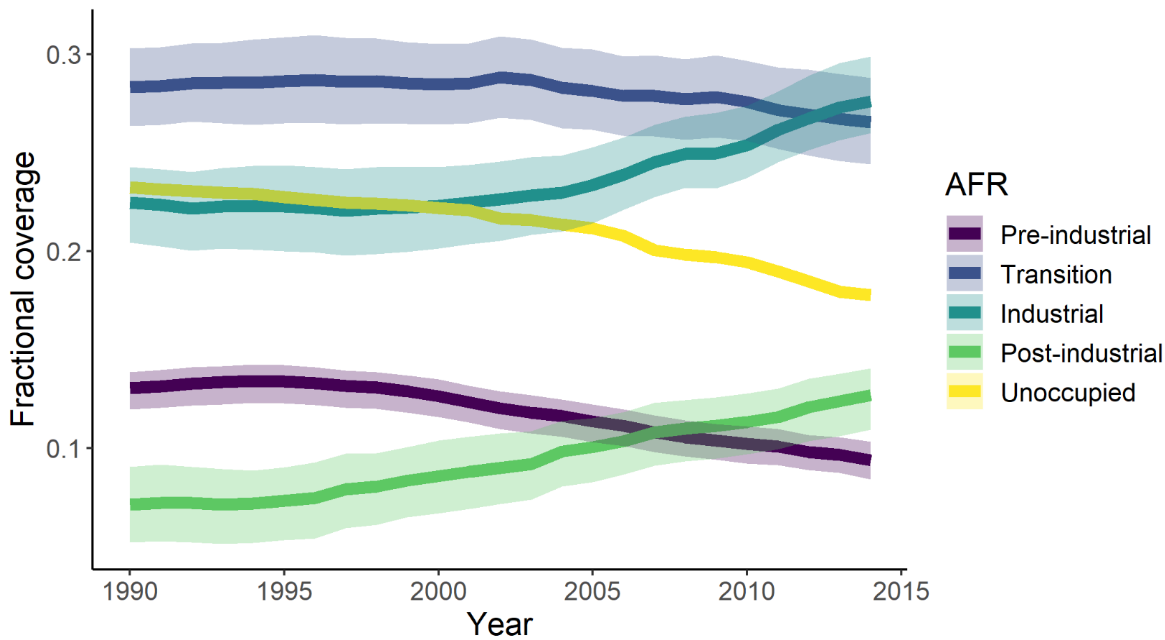


Figure 5: Fractional coverage of global land surface by anthropogenic fire regimes (AFRs) from 1990-2014. Shading represents 95% confidence interval around the mean, derived from bootstrapped numerical distribution of classification tree thresholds. The largest change in AFR distribution is an increase in the industrial AFR, accompanied by declines in the pre-industrial AFR and unoccupied areas.

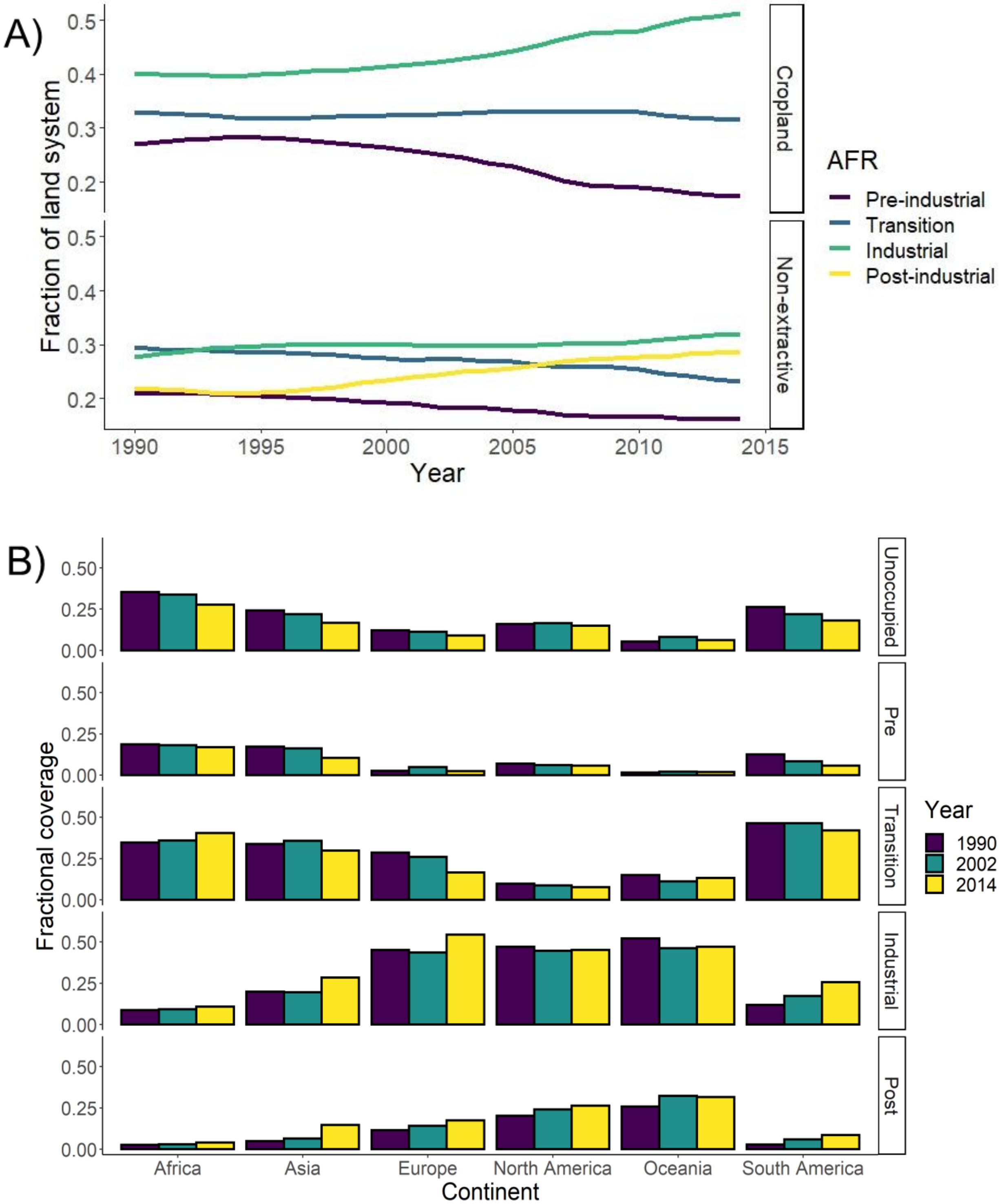


Figure 6: Change in global land-fire systems (LFSs): A) distribution of anthropogenic fire regimes (AFRs) in the cropland and non-extractive land use systems through time and B) AFR by Continent. Together, model outputs point to a substantial increase in the intensive crops LFS in Asia and South America. The accompanying decline in shifting cultivation (pre-industrial crops) is particularly acute in Asia. The increase in post-industrial regimes, particularly in Europe and North America, points to land abandonment, but also the growth of 'pyro-diverse' land management strategies (Fernandes et al., 2016).

Beneath this global picture, there is substantial regional heterogeneity. For example, at the continental level, whilst the pre-industrial AFR decreased from 17.24% to 10.50% in Asia across the study period, the pre-industrial AFR remained broadly static in Africa (18.64% to 16.95%). By contrast in Europe and North America, a prevailing trend is the growth of the post-industrial AFR, which increase from 11.48% to 17.47% in Europe and 20.21% to 26.40% in North America. The decline in unoccupied area was most sharp in South America - from 26.37% to 18.13% of the land surface - reflecting rapid deforestation of the Amazon. A complete set of model outputs, including maps for all years and LFSs, are made available as Supplementary Material E.

3.2 Overview of model performance

When compared to reference multinomial regression models, the classification tree approach demonstrates a slight improvement in quantitative performance. On average the classification trees achieve an AUC of 0.018 higher than the multinomial models (Table 3). Classification trees perform particularly well for livestock and non-extractive systems. Management practices in these systems have been found to drive substantial differences in fire regimes at both landscape and global scales (Bird et al., 2012; Rabin et al., 2015). Therefore, the classification trees' improved performance in these land use systems will support robust projections of anthropogenic fire use and suppression when coupled with JULES-INFERNO.

Table 3: Model performance of classification tree approach in comparison with reference multinomial regressions. Values are mean area under the ROC curve ('AUC'), weighted by the number of DAFI case studies in each land use system. Although the better performance of the classification tree approach is modest in a purely quantitative sense, the approach also captures a more nuanced view of process that should aid the credibility and interpretability of future forecasts.

Land use system	Multinomial	Classification trees
Crops	0.807	0.785
Livestock	0.742	0.761
Forestry	0.899	0.915
Non-extractive	0.729	0.785
Overall	0.794	0.812

Additionally, the classification tree approach captures a wider range of socio-ecological processes compared to the multinomial models (Figure 7): the most robust multinomial fits contained HDI and market access as independent variables (Table 4). By contrast, the classification trees are derived from a final set of seven independent variables, and therefore capture important inter-relationships between socio-economic and ecological factors that enable improved performance in critical areas (Figure 8). For example, the spatial distribution of the pre-industrial livestock LFS ('Pastoralism') is found to be concentrated towards higher altitude regions with less socio-economic development. As pastoralism is typically found in more marginal and sometimes harsher environments, such a parameterisation is consistent with prior knowledge of the process (Saladyga et al., 2013; Easdale and Aguiar, 2018).

Table 4: Mean regression coefficients for the reference multinomial models. The industrial anthropogenic fire regime (AFR) was taken as a reference (zero values for all coefficients). Taken together, the model is indicative of a linear progression through the four AFRs in step with economic development. HDI is the human development index.

AFR	Intercept	HDI	Market access
Pre-industrial	11.495	-18.085	-1.261
Transition	9.236	-15.254	11.486
Post-industrial	-5.524	5.149	9.307

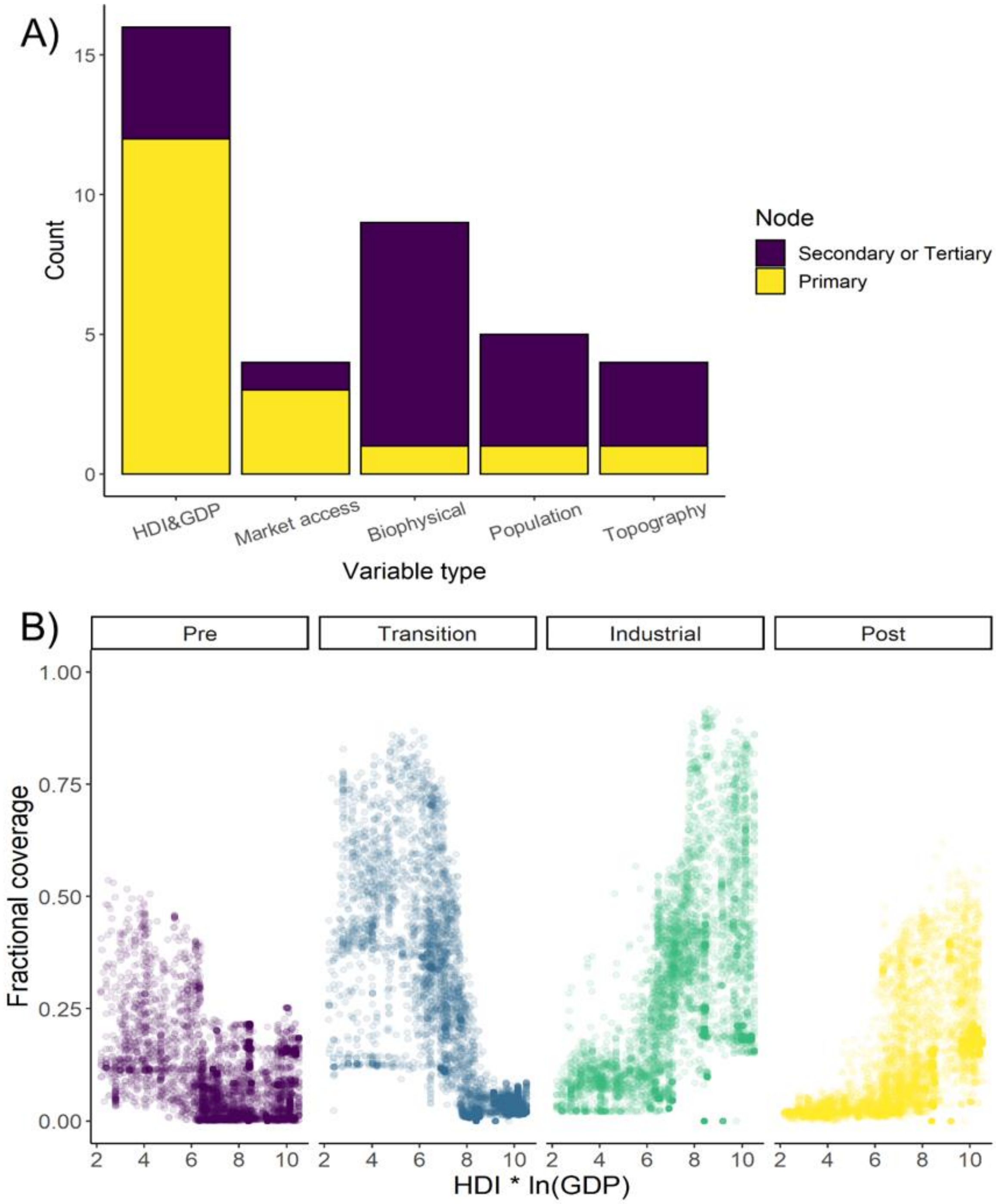
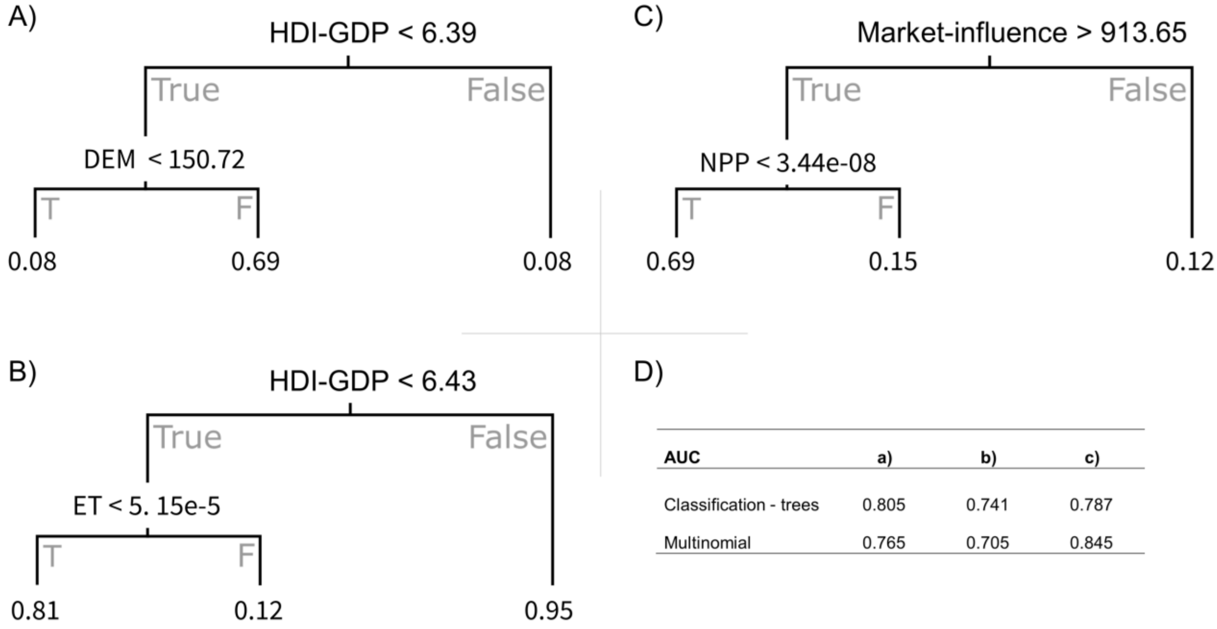


Figure 7: Relationship of model outputs to predictor variables. A) Frequency of variables as primary or subsequent splits in classification tree models, and B) relationships of global fractional land surface coverage with the HDI & GDP hybrid variable (by anthropogenic fire regime (AFR) for 2014 model output). Economic factors, represented by HDI & GDP as well as market access, dominate classification trees and play a substantial, though not exclusive, role in driving AFR distribution. Biophysical factors represented by potential evapotranspiration and ecosystem net primary productivity provide important second and third order effects, highlighting the socio-ecological dynamics at the heart of anthropogenic fire impacts.



AUC	a)	b)	c)
Classification - trees	0.805	0.741	0.787
Multinomial	0.765	0.705	0.845

Figure 8: Selected land-fire system (LFS) classification trees: A), pre-industrial livestock ('Pastoralism'), B) post-industrial non-extractive ('Pyro-Diverse'), C) industrial crops (Intensive Farming). D) shows model performance for each compared to reference multinomial models. These trees illustrate how the approach enables representation of interactions between socio-economic and ecological factors in the models. In A) both economic development and the more fertile conditions associated with lower altitude (DEM) serve to constrain the system. Conversely, in B) the combination of comparatively more prosperous and populated areas and lower NPP are conducive to the system (and at very high NPP, moisture can limit the 'natural' role of fire; McWethey et al., 2013). The intensive crops LFS (C) is found in wealthier areas, and also areas in the developing world where the hydrological cycle permits appropriate conditions for intensive agriculture. In two of three cases, capturing the additional ecological process leads to improved area under the ROC curve (AUC; D).

Similarly, the presence of the post-industrial non-extractive ('Pyro-Diverse') LFS is found not only nearer to wealthier cities, but also outside of very high NPP environments – where fire does not play a substantial 'natural' role in the ecosystem and so its use in biodiversity conservation is not as widely adopted (e.g., Barnett et al., 2016). By capturing the details of these processes, the classification tree approach achieves an average AUC 0.038 greater than the multinomial models for these particular LFSs (Figure 8d).

Finally, the Intensive Farming LFS is found to be influenced not only by socio-economic development, but also by PET in the classification tree approach. Specifically, at very high PET, intensive farming becomes much less likely. This may reflect the poorer soil quality typically found in such regions (Sanchez et al., 2003), mirroring findings of Malek and Verburg (2020). However, for this LFS, the reference multinomial (with a purely socioeconomic approach) performs better (AUC 0.845 vs. 0.787). This is addressed further in the Discussion. A complete set of classification trees used to define the distribution of LFSs is presented in Supplementary Material D.

3.3 Model evaluation

Overall, there is good agreement between model outputs and HANPPe (Figure 9). For example, in 2010, the pre-industrial crops LFS (Swidden) has mean area weighted HANPP efficiency (wHANPPe) that is 41.68% lower than the industrial crops LFS and 36.67% lower than the transition crops LFS. This pattern is repeated in both 1990 and 2000. Likewise, there is a similar, but smaller proportional increase in wHANNPe from the transition to industrial cropland LFS of 33.15% in 1990. However, the relative increase from transition to industrial AFRs decreases to just 7.78% in 2010. The trend is driven by increases in wHANPPe in eastern China, a region where wHANPPe has increased rapidly, but which remains in the transitional crops LFS (Small-Holdings) in model outputs (Figure 10). This temporal trend towards convergence in wHANPPe between the transition and industrial cropland LFS is assessed further in section 4.2.

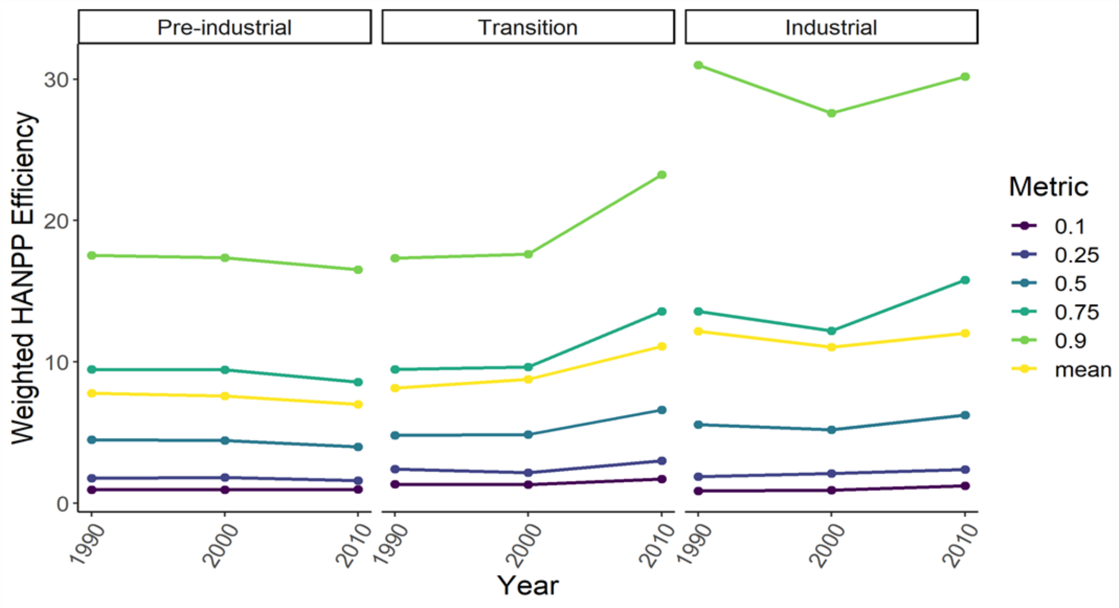


Figure 9: HANPP efficiency weighted by fractional cell coverage for the three productive crops land-fire systems. In all cases, mean HANPP efficiency increases in line with increasing land use intensity, although this trend becomes weaker between the transitional and industrial anthropogenic fire regimes through time. Metrics give mean and quantiles of the respective distributions.

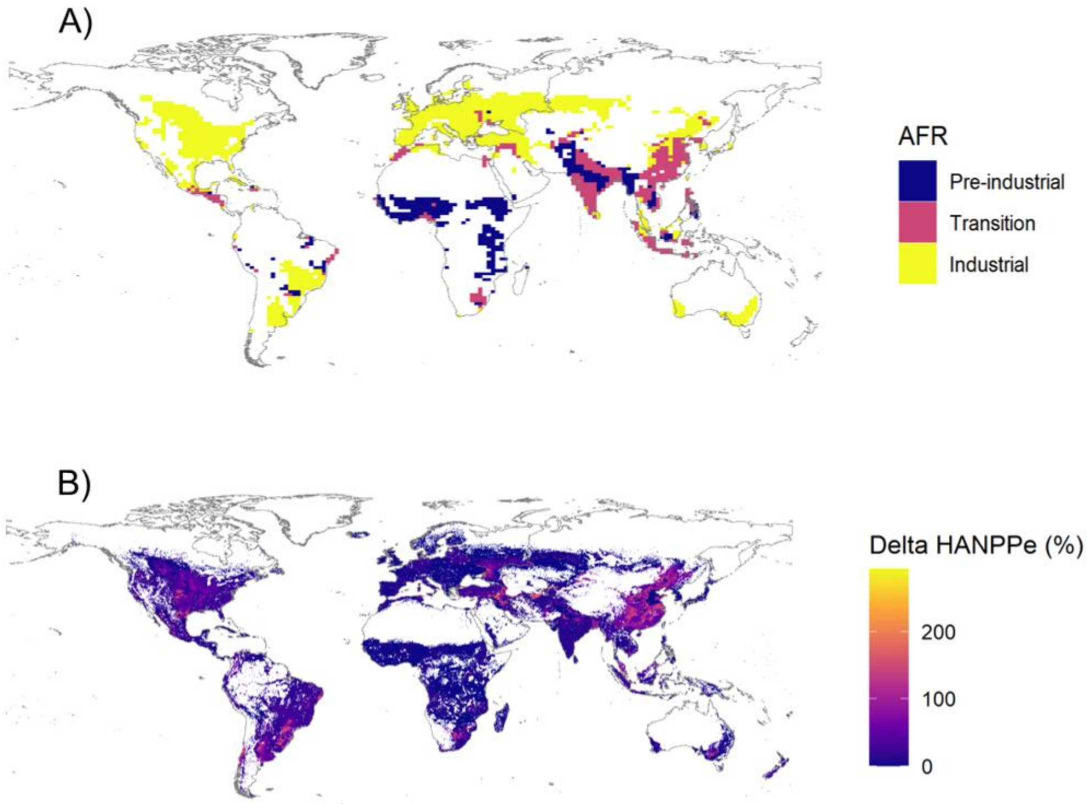


Figure 10: Drivers of converging HANPP efficiency (HANNPe) between crops land-fire systems (LFSs). A) Dominant cropland land fire-system in cells with > 10% cropland coverage & B) change in HANPPe between 1990 & 2010. Very large increases in land use intensity are reflected in increased HANPPe in China, but much of these areas remain within the transitional LFS ('Small-Holdings') in model outputs.

4. Discussion

4.1 Contribution to modelling of socio-ecological systems

Our approach using a new conceptualisation of land-fire systems (LFSs) with classification trees represents an important step forward in modelling the impacts of human behaviour on global fire regimes. The use of classification trees is (modestly) quantitatively better than multinomial regression (Table 3, Figure 8), and produces a similar degree of predictive accuracy as other models of human behaviour at a global scale (e.g. land use change; Malek and Verburg, 2020). Furthermore, using an ensemble of classification trees, our approach provides two additional key benefits in underpinning a robust process-driven model.

First, the approach enables explicit representation of socio-ecological processes, such as the relationship between net primary production and the emerging 'pyro-diversity' land management perspective. Because we have a unique tree for each of our defined LFSs, we can isolate these effects to where they are warranted from a process perspective. The specificity of the role of different independent variables in our approach should also improve the prognostic value of future predictions: we will be confident that any feedbacks diagnosed in coupled model runs are based on observed processes and not spurious collinearity effects. Conversely, the reference multinomial models suggest a linear progression through AFRs from pre-industrial to post-industrial. Specifically, the pre-industrial AFR is typified by low HDI and market access, the transition AFR by low HDI but high market access, the industrial AFR by high HDI but low market access, and the post-industrial AFR by high values for both predictor variables (Table 4). Such a linear conceptualisation has been criticised in the context of anthropogenic fire use for not capturing the nuance and diversity of how humans use and manage fire in diverse contexts (Coughlan and Petty, 2012).

Second, our results show that the classification tree approach can represent systematic change within land systems, identified as a grand challenge in socio-ecological systems' modelling (Elsawah et al., 2020). This can be seen in Figure 7 in which a clear threshold effect is seen in the industrial crops LFS at HDI-GDP ~6.5. However, our model is also able to reproduce more gradual change thanks to the bootstrapped distributions we apply to the threshold values in each tree. In the context of coupling our model with JULES-INFERNO, this represents a substantial advantage over multinomial regression, which would be more limited in projecting land systems' responses to changes in socio-ecological circumstances. An example benefit of this nuance is that our model reproduces the noted rapid decline of swidden agriculture in Asia simultaneous with swidden's persistence in much of sub-Saharan Africa (Figures 6 & 10; Van Vliet et al., 2012).

4.2 Evaluation of model outputs

The overall agreement between our model and independent data for the empirically-derived HANPPe measure (Haberl et al., 2007) establishes the credibility of the model outputs, particularly for delineating between the pre-industrial crop LFS and the industrial crop LFS (Figure 9). More fundamentally, the alignment between our LFS modelling and the HANPPe measure of land use intensity strengthens the case for a tight link between land use and anthropogenic fire. However, the apparent convergence of HANPPe in transitional and industrial AFRs from 1990-2010 warrants further exploration.

In eastern China, we observe large increases in HANPPe, but model outputs to 2014 continue to place much of this region in the transitional crops LFS (Figure 10). Case studies in this region were assigned the transitional crops LFS in our model input data (i.e., DAFI) not on the basis of yields, but because they are areas of widespread burning of crop residues in arable regions (e.g. Sun et al., 2019). Indeed, residue burning in many parts of Asia has become so widespread as to have a substantial negative impact on air quality (Peng et al., 2016; Sembhi et al., 2020). This is indicative of a lack of cohesive fire management, and hence is classified in the transition AFR. By contrast, in the industrial crops LFS, residue burning is typically absent due to concerns around public health that drive legislation to restrict or ban it (Smil, 1999). To some degree, this tension may be resolved through the assignment of agent-functional types to our LFS. For example, Malek et al. (2019), identified distinct market-oriented and subsistence-oriented small-holder land user types. We may find that such a sub-division in our Small-Holding LFS, to create a market-oriented small-holder agent class, would better represent high-yielding farming with limited associated management of fire use.

Fundamentally, however, the observed tension points to the nature of transitions in the land system – with multiple and often concurrent factors leading to varied, lagged, and non-linear responses in the system (Brown et al., 2018). More longitudinal and location-specific research is required to understand the drivers of change in fire practices and land use intensity and efficiency and the degree to which they are related.

4.3 Future modelling challenges

Two primary challenges in the modelling presented here relate to available data and the intended future coupling to existing models. Firstly, although the creation of global spatially disaggregated HDI and GDP data (Kummu et al., 2018) has been important in our ability to model the spatiotemporal distribution of LFSs, we also made multiple simplifications to our representation of human behaviour due to data constraints and concerns. Secondly, our focus on coupling with the JULES-INFERNO DGVM caused us to lose a degree of information, not only by working at JULES-INFERNO's coarse spatial resolution (1.875 x 1.25 degrees), but also by refraining from using data sets that would have conflicted with JULES-INFERNO outputs yet otherwise may have added value to the model. These two related issues are now discussed further, in turn.

Due to a lack of data, the primary simplification important for modelling global anthropogenic fire is the absence of an explicit representation of policy. This must be considered a substantial limitation as the inherently political nature of fire governance determining who can use fire, for what purpose and when, is often a proxy battle for the favoured land system and land tenure type in a given location (e.g., Kull, 2004; Trigg et al., 2012). To account for this, we initially experimented with the 'Human Freedom Index' (Cato Institute, 2020) as a measure of the degree of centralisation of a government system. However, this was dropped from the analysis, primarily because of concerns regarding the neutrality of the index (Plehwe, 2021). Furthermore, as we plan to use this model for future scenario-based projections, we were concerned that making projections about such an index for the shared socio-economic pathways (SSPs; Popp et al., 2017) would be an inherently subjective process.

Therefore, a representation of government policy will need to be defined through theory in combination with information on fire policy (such as that gathered in DAFI). However, such a top-down parameterisation of policy impacts on the land system will need to be careful not merely to mirror or double effects already captured implicitly in existing data. For example, the consequences of political efforts to eradicate swidden in Southeast Asia (Mertz et al., 2009) are already seemingly captured in our empirical modelling. This question of circularity, and the degree to which empirical and strictly behaviourally-driven model components may be combined in a coherent manner will likely only become clear once coupling with JULES-INFERNO is completed and assessed.

A further data-related simplification made during model construction was to remove variables representing species richness and the distribution of protected areas. These variables were moderately useful in defining the distribution of non-extractive AFRs but would have added substantial challenges to scenario forecasting – likely requiring complex assessments and calculations of future anthropogenic impacts on biodiversity globally. Together, these data issues reiterate the argument of Verburg et al. (2019) that a lack of future projections in land system modelling and its underlying data sets remains a major challenge.

A second set of challenges in our approach is found in our planned model coupling with the JULES-INFERNO DGVM. As we plan for our model to be used in model runs following the CMIP6 protocol, we adopted the CMIP6 land cover data as the primary driver of our land use system distribution (Figure 2). The consequences of this are perhaps most pronounced for the livestock land use system. One positive outcome was that pastoralism could be restricted to the 'rangeland' land cover class, as by definition this nomadic LFS cannot occur on managed pastures. However, a substantial resulting issue is the representation of land abandonment. For planted pastures, coherence demands the rate of abandonment must be driven by declining fractional coverage in the land cover data. Conversely, in rangelands, abandonment can occur without substantial change to land cover (Peco et al., 2006). Therefore, in this case abandonment need not be dictated from forcing data and can be represented behaviourally. Indeed, the post-industrial AFR for rangelands was among the best performing aspects of the model (AUC = 0.862).

This tension in the relationship of CMIP6 land cover data with our land use systems points to similar structural challenges for modelling of future scenarios. Although CMIP6 land cover data for the recent past are derived from observations, for future scenarios they are based on Integrated Assessment Model outputs (Hurtt et al., 2020). Therefore, future projections from our model will be somewhat reliant on the assumptions of Integrated

Assessment Models to drive the distribution of land systems, whilst the distribution of AFRs will be driven entirely by our behavioural approach. This may cause issues with the coherence of future scenarios but is a necessary issue to tackle if behavioural modelling is to be integrated into the coupled model intercomparison project and associated protocols. Furthermore, by separating concerns between land use system distribution and AFR distribution, our modelling approach should be readily adaptable for modellers interested in other discrete aspects of anthropogenic land use such as water consumption or biogeochemical cycling.

Finally, to allow seamless transmission of information between our models, we adopted JULES-INFERNO outputs as synthetic data sets for NPP and PET. However, data derived from remote sensing and field observations may have been preferable. This limitation may be at the heart of our model's modest performance in predicting the industrial crops LFS. Although Malek and Verburg (2020) used soil type to capture the biophysical constraint on such intensive or market-oriented production, including such a data set in our model would have involved substantial enhancements to the ways in which JULES-INFERNO represents changes to soil biogeochemical composition due to agriculture (Osborne et al., 2015; Burton et al., 2019). Recognising this, and to ensure our model is readily integrable with other DGVMs, we plan to create a version of the model using only remotely-sensed (empirical) inputs.

5. Conclusion

We have presented a new approach to modelling the global distribution of land use systems and their inter-relationship with anthropogenic fire regimes, through the concept of land-fire systems (LFS). Our spatiotemporal modelling of LFS distributions is an important step towards a substantial improvement in the representation of anthropogenic fire in dynamic global vegetation models. We have demonstrated how a reasonably simple empirical approach can capture complex non-linear interactions in land systems whilst being derived from just seven independent variables (with corresponding data sets). However, a major implication of this study is that effective large-scale behavioural land system modelling under the shared socio-economic pathways will require development of standardised and spatially disaggregated data sets, with associated future projections, across a range of socio-ecological indicators.

Acknowledgements

OP & JM are funded by the Leverhulme Centre for Wildfires, Environment and Society through the Leverhulme Trust, grant number RC-2018-023. SM & K-H E gratefully acknowledge funding from the Austrian Science Fund, Project Furnaces (I 4271). The authors wish to thank Matt Kasoar & Apostolos Voulgarakis for advising on integration with JULES-INFERNO, and two anonymous reviewers for their thoughtful and insightful comments.

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