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ORIGINAL ARTICLE

Pantropical distribution of short-rotation woody plantations: spatial probabilities under current and future climate

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Abstract
Short-rotation woody plantations (SRWPs) play a major role in climate change mitigation and adaptation plans, because of their high yields of woody biomass and fast carbon storage. However, their benefits, trade-offs and growing-success are heavily location-dependent. Therefore, spatial data on the distribution of SRWPs are indispensable for assessing current distribution, trade-offs with other uses and potential contributions to climate mitigation. As current global datasets lack reliable information on SRWPs and full global mapping is difficult, we provide a consistent and systematic approach to estimate the spatial distribution of SRWPs in (sub-)tropical biomes under current and future climate. We combined three advanced methods (maximum entropy, random forest and multinomial regression) to evaluate spatially explicit probabilities of SRWPs. As inputs served a large empirical dataset on SRWP observations and 17 predictor variables, covering biophysical and socio-economic conditions. SRWP probabilities varied strongly between regions, and might not be feasible in major parts of (sub-)tropical biomes, challenging the feasibility of global mitigation plans that over-rely on tree plantations. Due to future climatic changes, SRWP probabilities decreased in many areas, particularly pronounced in higher emission scenarios. This indicates a negative feedback with higher emissions resulting in less mitigation potential. Less suitable land for SRWPs in the future could also result in fewer wood resources from these plantations, enhancing pressure on natural forests and hampering sustainability initiatives that use wood-based alternatives. Our results can help adding a more nuanced treatment of mitigation options and forest management in research on biodiversity and land use change.

Keywords Tree plantations · Forest management · Land-based climate change mitigation · Spatial probability mapping · Land use modelling

1 Introduction

Planting forests is among the most widely proposed, but also heavily debated, nature-based solutions for climate change mitigation (Seddon et al. 2021), with 45% of all restoration and carbon removal commitments being represented by forest plantations (Lewis et al. 2019).

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As opposed to the steadily decreasing global forest cover, the area of planted forests has more than doubled in the last decade (FAO & UNEP 2020). About half of the global plantations extent thereby consists of intensively managed plantations (FAO & UNEP 2020), which includes short-rotation woody plantations (SRWPs), also known as industrial plantations, short rotation coppice or short rotation woody crops. SRWPs are characterised by dense rows of often one fast growing species, usually eucalyptus, acacia, poplar or willow, which are clear-cut after very short rotation times (1–15 years) (Dickmann 2006). They are often planted for the production of pulp and paper, wood pellets for bioenergy production and lumber aiming to reduce the harvest pressure on (semi-)natural forests (Pirard et al. 2016). Because of increasing demands for biofuel and other wood-based products, coupled with rising timber prices and tighter harvest restrictions for natural forests, planted forests are expected to increase in area, at least for the next four decades (Korhonen et al. 2020). It has been estimated that SRWPs will expand by 2% annually, to a total extent of 91 Mha in 2050 (Barua et al. 2014). International conflicts can cause demands for woody biofuel to increase even more than expected, as a result of rising gas and petrol prices, as well as diverting food crops planted for biofuel (Page 2022).

Besides being a quick and efficient way for wood production, SRWPs can provide numerous co-benefits. Planting trees has particularly received a lot of attention as a rather straightforward and effective measure to mitigate climate change (Bastin et al. 2019). Due to their high yield, carbon sequestration in SRWPs can be high, making them a cost-efficient climate change mitigation measure. However, when SRWPs are used for biofuel purposes, these carbon benefits are very limited (Kalt et al. 2019). Furthermore, establishing SRWPs can be attractive as they can increase land value of marginal agricultural areas due to their higher economic returns (Griffiths et al. 2018; Pirard et al. 2016). They can have benefits for ecosystems and biodiversity, if they are structurally diverse and sustainably managed (FAO & UNEP 2020; Zitzmann et al. 2021) and can support overall diversity by providing habitat for shrub-favouring species in forest dominated landscapes (Riffell et al. 2011).

Most of the benefits, however, come with trade-offs, which are often heavily location-dependent. Carbon benefits not only depend on the use of harvested wood, but also where plantations are established, i.e. what prior land use they are replacing (Waring et al. 2020). Large-scale tree planting in the wrong place can destroy valuable grassland and savannah ecosystems (Veldman et al. 2015) and deplete water resources (Jackson et al. 2005). Furthermore, if trees are planted in former grassland areas, they might be more fire susceptible, which can result in carbon emissions through vegetation loss (Waring et al. 2020). If SRWPs replace native forests, they can result in carbon losses of up to 50% (Manrique & Franco 2020). Therefore, the suitability of tree plantations as a climate change mitigation measure, especially of non-native, short rotation and/or mono-species is widely contested (Bond et al. 2019; Friedlingstein et al. 2019; Hua et al. 2022). Without careful planning of the location and proper management, they can have a detrimental impact on the local livelihoods and environmental conditions (Malkamäki et al. 2018; Fleischman et al. 2020), leading to conflicts with the local population (Coleman et al. 2021) and can result in the loss of land rights of indigenous people (Swanson et al. 2021). Additionally, it has been challenged whether marginal land is actually suitable for SRWPs (Shortall 2013). SRWPs are, furthermore, often considered 'green deserts', due to their lacking understory and composition of one or two tree species, which hamper their ability to provide habitats in the same manner as natural forests, especially if they replace forests with high conservation value (Brockerhoff et al. 2017; Brockerhoff et al. 2008; Riffell et al. 2011). As they commonly rely on intensive techniques, including weed control, irrigation and/or fertilisation, they can cause negative impacts on the surrounding environment, for example, by deteriorating water quality and availability (Bryan et al. 2015; Dickmann 2006; Griffiths et al. 2018). Impacts on the water cycle can go even far beyond the catchment area of where they have been established (Ellison et al. 2017).

Next to the location dependence of the benefit and trade-offs of SRWPs (Griffiths et al. 2018), also growing success and yields are largely driven by location factors, including soil and climatic conditions (Stolarski et al. 2014). In addition, socio-economic conditions, such as market accessibility, likely restrict the occurrence of SRWPs. As future climate change will cause alterations in precipitation patterns and temperatures, habitat suitability is expected to shift for many tree species, including those that are commonly planted in SRWPs (Butt et al. 2013). Therefore, insight in the occurrence of SRWPs under current conditions and estimating future probabilities of their locations can facilitate the understanding of benefits and trade-offs of SRWPs and in turn support sustainable natural resource management, land-use planning and global commitments (Bloomfield & Pearson 2000).

Previous research has identified SRWPs based on remote sensing, but has so far been usually restricted to single countries or regions (e.g. Brazil (le Maire et al. 2014), Spain (Oliveira et al. 2020), Guangxi province, China (Deng et al. 2020)). An exception is the Spatial Database of Planted Trees (Harris et al. 2021), a comprehensive collection of locations of woody and agricultural tree crop plantations, including many countries of the world. The dataset is derived from supervised classification and manual polygon delineation of satellite imagery and is obtained from different sources, including national governments, non-governmental organisations and researchers. While this dataset provides an impressive number of locations, due to the different data sources and collection bias, some inconsistencies in terms of definitions, temporal and spatial extent cannot be avoided (Harris et al. 2021).

The aim of this study is to provide a systematic and consistent approach to estimate at which locations there is a high probability of SRWP occurrence under current conditions and how these location probabilities will be affected by future climatic changes. We thereby do not aim to predict the occurrence of future SRWPs, but explore an experimental pathway in which socio-economic and political condition remain the same and only climatic conditions change. Due to the use of absence data sampled within forest and cropland locations and by accounting for socioeconomic variables, we go beyond biophysical suitability and present the probabilities that arise from land users' decision-making, as a result of competition and compromise with other land use (such as agriculture) and opportunity in terms of favourable growing conditions, infrastructure and work force.

1.1 Study area

Our study is focused on the Pan-Tropics, i.e. tropical and sub-tropical biomes of both hemispheres in the Americas, Africa and Asia, reaching roughly from 35° North to 35° South. SRWPs are rapidly expanding in the Tropics, substantially driven by land acquisitions and foreign investments due to low opportunity costs (Overbeek et al. 2012; Davis et al. 2020; Favero et al. 2020). SRWPs have been found to be among the most deforestation-inducing land investments next to oil palm and other tree plantations (Davis et al. 2020). Tropical forests have the highest biodiversity of all global ecosystems and are among the main terrestrial carbon sinks (Sullivan et al 2017). Their increasing destruction and degradation are hence major contributors to the regional, as well as global biodiversity and climate crisis, and affect local communities that depend on the forest (Edwards et al. 2019). Due to climatic changes with increasing temperatures, tropical forests are already experiencing structural changes of ecosystems and shifts of species ranges (Pörtner et al. 2020). Future climate change is expected to exacerbate alterations of rainfall patterns and cause surface temperature increase in the Tropics, exceeding a 2 °C increase between 2030 and 2050 even under moderate emission scenarios (Pörtner et al. 2020, Corlett 2012). As for agricultural crops, these climatic changes are expected to alter the suitability range of SRWPs and taking future climatic changes into account when planning the location of SRWPs can aid to minimise the environmental costs that would come with migration of plantations (Sloat et al. 2020).

2 Methodology

To map spatially explicit probabilities for finding SRWPs in (sub-)tropical biomes, we used an evidence approach with crowdsourced and expert sampled data and determined the impact and importance of 17 different biophysical and socioeconomic variables in explaining the occurrence of SRWPs. To generate a robust empirical analysis of the relations between location factors and SRWP occurrence, three advanced methods were used and compared: (1) maximum entropy (MaxEnt), (2) random forest classification and (3) multinomial logistic regression. All three methods have been extensively used in land cover and use studies (see, e.g. Dou et al. 2021 and Skowronek et al. 2017 for MaxEnt; Bastin et al. 2019 and Nguyen & Henebry 2019 for random forest and Dendoncker et al. 2006 and Schulze et al. 2019 for multinomial regression). Each of the three methods has benefits and limitations and by comparing and combining them, our results can be considered more robust. MaxEnt has its origin in the ecological modelling community for predicting species distributions based on occurrence data only (Elith et al. 2011). Given the nature of our observations, this method fits our study. However, it can be prone to overfitting and can be susceptible to biases in the presence data (Devisscher et al. 2016). Random forest is an ensemble learning approach based on machine learning techniques, in which predictor variables without linear relationships can be included (Fox et al. 2020), thereby allowing to account for thresholds, but hindering extrapolation outside of the data range of the input data. Random forest models are rather insensitive to overfitting (Belgiu & Drăguţ, 2016) and have become widely used in the classification of remote sensing images into land cover classes. Multinomial logistic regression is a rather straightforward and comprehensible statistical approach. However, it can only account for linear relationships between the dependent and independent variables. Compared to the former two methods, multinomial regression requires rather low computational power.

2.1 Observation data

Observation data on the occurrence of SRWPs was obtained from the training dataset 'Human impact on forests' (Lesiv et al. 2022). The dataset was compiled through several crowd-sourcing campaigns using the Geo-Wiki platform (Fritz et al. 2009, 2012). Participants visually assessed satellite images of forest locations and classified these into different types of human impact, including natural forests without management impacts, different wood harvest, regeneration and plantation types, as well as trees outside of forest, such as trees in urban areas. For our study, we included observations classified as 'woody plantations', which were in the campaign defined as single-tree plantations with rotation times of maximum 15 years in the (Sub)Tropics. In the campaign, embedded tools, in particular graphs of Normalized Difference Vegetation Index trends and Google Earth time series, supported the assessment of rotation time. As the correct identification of the tree species in a plantation is hardly possible from satellite imagery, the class woody plantations included all species that are commonly planted in short-rotation, i.e. eucalyptus, acacia, poplar and willow. The crowd-sourced dataset comprised in total more than 30,000 points of all forest classes, including 2205 locations of SRWP observations, with the majority (2070) located in the tropics. Lesiv et al. (2022), furthermore, identified additional 18,008 SRWP observations in a targeted approach, using experts' assessment of a preliminary forest management map based on the crowd-sourced classifications and remotely sensed data of different vegetation indices. While the forest classes were classified within 100×100 m^2, most predictor variables used in our study (see section further below) were available at a 1×1 km^2 resolution. Therefore, we converted the SRWP training dataset points to a presence raster at this resolution, ensuring that as soon as within the larger pixel an SRWP was observed this was reflected in the aggregated dataset. All locations that did not fall within the subtropical and tropical ecoregions (Olson et al. 2001) were excluded. In total, 8556 locations of observed SRWP presence in the (Sub)Tropics were available for this study (Supplementary Material 1.1).

2.2 Absence data

Absence data is required for the multinomial regression, the random forest algorithm, as well as for calculation of performance estimates of the models and results. Sampling random locations within an entire study area to derive pseudo-absence data can introduce biases to the model. In ecological modelling, this is often the case, when presence data is skewed towards more accessible locations and pseudo-absence is not (Phillips et al. 2009). Since presence data were here systematically collected using satellite imagery, it can be assumed that this bias is not present in our study. Furthermore, models' performances can decrease if pseudo-absence accidentally includes locations of occurrence. We avoided this by using a (simple) random sample of cropland and forest locations, as we considered SRWPs as a likely alternative for both land uses. Forest locations included naturally regrown forests with or without human impact and planted forests with longer rotation periods and were sampled from the same dataset from which SRWP locations were derived (Lesiv et al. 2022). The forest locations were masked to a raster layer with a 1×1 km^2 resolution, counting occurrences of any of the three classes only once. Cropland locations were derived from the IIASA-IFPRI cropland map (Fritz et al. 2015), selecting areas where cropland was the dominant land use (i.e. $>50\%$ cropland). Pseudo-absence locations that are too far from the environmental space of presence locations can result in over-prediction (Lobo et al. 2010). To avoid this, we ensured that absence data is generated at locations that are comparable to the observed SRWP locations with regard to the environmental location factors and somehow suitable to host SRWP. Therefore, the samples were restricted to areas where all climate, soil and terrain variables (see Table 1) are within the range of values at the SRWP locations, i.e. smaller than the maximum and larger than the minimum values of included variables. We randomly sampled 8556 crop and forest locations each (see Supplementary Material 1.2), i.e. the size of the SRWP presence dataset, following the findings by Barbet-Massin et al. (2012).

Table 1 Overview of predictor variables, including description and justification for selection

Variable	Description	Unit	Source
Climate			
Average temperature	Annual average temperature affects the growing conditions/increment (Aust et al. 2014)	°C	Brun, Zimmermann, Hari, Pellissier, Karger (2022a, b); Karger et al. (2017, 2021)
Diurnal temperature	Describes the difference between minimum and maximum temperature. Thermal stress in winter or summer affects growing conditions of plantation species (Saïdi et al. 2011)	°C	
Maximum temperature in the warmest month	Accounts for seasonality and indicates drought risk, which was found to induce tree-decline in subtropical forests (Jing et al. 2022)	°C	
Total annual precipitation	Water availability has been reported to be the most limiting factor for woody plantations (Aust et al. 2014; Saïdi et al. 2011)	mm	
Precipitation in the driest quarter	Accounts for seasonality and indicates drought risk, which was found to induce tree-decline in subtropical forests (Jing et al. 2022)	mm	
Terrain			
Elevation	Elevation and slope are both indicators for accessibility and facility of mechanisation (Dickmann 2006)	m	USGS EROS (1996)
Slope		%	
Distance to freshwater	Distance to freshwater sources, including lakes and rivers. It estimates the potential for irrigation, which can be important for growth on marginal areas and with increasing land scarcity	km	Carrea et al. (2015)
Soil conditions			
Clay content	Clay content affects aeration at roots and water availability	%	Stoorvogel et al. (2016)
Depth of the topsoil	Depth of the topsoil has an impact on nutrient availability at the fine roots	cm	
Soil depth	Soil depth impacts water and nutrient availability and the stability of the plantation (Dickmann 2006)	cm	
Soil drainage	Soil drainage affects water availability and root distribution (Dickmann 2006)	%	Hengl et al. (2014)

Table 1 (continued)

Variable	Description	Unit	Source
Socio-economic parameters			
Market accessibility index	The index is a function of distance to ports and major cities, road network and GDP. It proxies the potential of economic return and transportation costs	No unit	Verburg et al. (2011)
Population density	Population density can indicate potential competing land claims for food or shelter, as well as closeness to workers	ppl/km^2	Freire et al. (2018)
Travel time to major cities	Similar to the Market accessibility index, the travel time to major cities indicates transportation costs, as well as the distance to processing facilities and workforce	min	Nelson (2008)
Distance to roads	Distance to roads describes general accessibility for planting, harvesting and transportation	m	own calculations based on (NGIA (2015)

2.3 Predictor variables

To estimate location probability of SRWPs, we included in total 17 spatially explicit predictor variables from four groups: (1) climatic conditions, (2) terrain, (3) soil properties and (4) socio-economic variables (Table 1). For the selection of predictor variables, we followed the findings of previous research on considerable impacts on the suitability of SRWPs and availability of suitable data. This rationale for the selection is synthesised in Table 1. To avoid inflation of variance, variables had to be non-correlating. Additional to the variables summarised in Table 1, we tested different indicators for water availability, as this has been reported to be the most limiting factor for SRWPs (Aust et al. 2014; Saïdi et al. 2011). These included average annual precipitation, climatic water balance (i.e. the difference between precipitation and evapotranspiration (Aust et al. 2014)) and the aridity index (a function of potential evapotranspiration (Zomer et al. 2008)). As these variables and total annual precipitation were correlating, and either decreased (average precipitation) or only marginally increased model fit and required additional assumptions on future behaviour (climatic water balance and aridity index), we excluded them.

2.4 Future projections

To estimate how expected changes in future climate will affect the probability of SRWP occurrence, we varied all climate variables (i.e. average temperature, diurnal temperature, maximum temperature in the warmest month, precipitation in the driest quarter and annual precipitation) with projections from different climate models. We used the results from the Coupled Model Intercomparison Project Phase 6 (CMIP6) ensemble (Eyring et al. 2016) for 2041–2070 with midpoint in 2055. Downscaled data was derived from the CHELSA repository, which had results for five climate models available: GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0 and UKESM1-0-LL (Brun et al. 2022a, b; Karger et al. 2017, 2021). The Chelsea repository hosted at the time of the analysis the most recent spatially-explicit and globally-available climate data at a 1 km^2 scale. For each model, three Representative Concentration Pathway and Shared Socioeconomic Pathway (RCP-SSP) scenarios were included: RCP2.6–SSP1, RCP7.0–SSP3 and RCP8.5–SSP5. These scenarios provide a range of different energy and resource consumption patterns, coupled with carbon dioxide emission responses and their impact on future climate. RCP2.6–SSP1 had the lowest consumption and emission patterns and RCP8.5–SSP5 the highest (Riahi et al. 2017, van Vuuren et al. 2011). We averaged the probabilities as result of the different climate models to construct for each RCP-SSP scenario one spatially explicit map of future probability.

2.5 Statistical analysis

Estimating the geographical patterns of probability of SRWPs was based on three different methods: (1) MaxEnt, (2) random forests and (3) multinomial regression. As absence data was solely sampled in areas within the range of climate, soil and terrain conditions under which SRWPs were found, analyses were restricted to this extent, assuming that the probability of occurrence outside this range was minimal. All analyses were conducted in R (version 4.1.0.) (R Core Team 2019) and at a 1×1 km^2 resolution. We used for MaxEnt the *dismo* package (Hijmans et al. 2020), which applies the MaxEnt distribution model software (Phillips et al. 2021), and set the number of background points to 20,000 and the default prevalence to 0.9 (i.e. the estimated proportion of background points to be true absence), thereby accounting for potential classification mistakes in the presence data. For the random forest approach, we used the *randomForest* package (Liaw & Wiener 2002) in combination with the *caret* package (Kuhn 2021). The maximum number of trees was set to 125 and a tenfold cross-validation with five repetitions was applied for resampling. For multinomial regression, we used the *nnet* package (Venables & Ripley 2002), which relies on neural networks to fit multinomial log-linear models. Model selection was conducted by bidirectional elimination based on the Akaike information criterion, selecting the model with the lowest value.

For all methods, 80% of the data was used for training the model and 20% for validation. Model fit was determined with help of the receiver operating curve (ROC) calculated with the *pROC* package (Robin et al. 2011). ROC evaluates sensitivity (i.e. true positive rate) against specificity (i.e. true negative rate) for different thresholds. The area under this curve (ROC AUC) is a common index for model fit, with values ranging from 0.5 (model fail) to 1.0 (perfect model fit). To ensure that the ROC AUC values represent an unbiased evaluation of the model fit independent from location clusters, we separately calculated the values for five data partitions, using each partition once for testing and the remaining four for training the models. For each method, the ROC AUC values from the five data partitions were then averaged.

To understand the impact of different variables on the model prediction and the accuracy of prediction, the permutation variable importance was calculated. For each variable separately, values were permuted (shuffled) to break the link with the model. Based on this new dataset, probability values were calculated, which were compared with the original probabilities. A Spearman rank correlation coefficient indicated how much permuted predictions differed from the original. The higher the coefficient, the more alike the predictions were and the less impact the variable had on the probabilities. Additionally, we evaluated the impact of a variable on the prediction ability, i.e. the ROC AUC value, by determining the decrease of the ROC AUC for the permuted data. Variable values were permuted with help of the *biomod2* package (Thuiller et al. 2021). Using permutation to determine variable importance has the benefit that biases that can result from using different models are eliminated, hence allowing the comparison of variable relevance between different prediction methods (Altmann et al. 2010). Determining also the effect direction and extent of the included variables could deepen our understanding on their impact. However, while in regressions the relationships between the dependent and independent variables are linear and therefore each predictor has one effect direction, MaxEnt and random forest allow for non-linear relationship, meaning that after certain threshold values, the effect direction might change. An approach to determine the effect direction in a comparable way between the different methods is currently not available. Next to presenting and comparing the probability maps obtained with the different methods, we also created a final probability map in which the probability maps from the three methods were combined by weighting them based on their ROC AUC values, following Ramirez-Reyes et al. (2021). This so-called ensemble approach is commonly used to increase robustness of prediction results over individual methods (Diengdoh et al. 2020). The weight of each map was calculated by dividing the ROC AUC of a method by the sum of ROC AUC values of all methods. For future conditions, we determined the change in probability values in relation to the current conditions, multiplied the weights of the respective method and created future probability maps by adding the combined change to the map for present conditions.

3 Results

3.1 Location probability for current conditions

Our final result shows that high values of SRWP probabilities are often located at and in close vicinity of SRWP observation points, for example, in parts of the Cerrado and the Atlantic Forest in Brazil, the Eastern Cape of South Africa and South-East China (Fig. 1C–E). This indicates a high prediction ability of our models, as they present the distribution of the observations. Nevertheless, high probabilities also appear in areas where none or only few SRWP locations were observed, but with similar location characteristics. These locations include, for example, Eastern Madagascar, North of the Ganges Delta and the Philippines (Fig. 1A, B, F, G). This demonstrates that our models are able to extrapolate into areas outside of the input data, where location factors are similar to the ones from the observation locations. The resulting probability layers are available at https://doi.org/10.34894/T3A3RM. The data package also includes biophysical suitability layers, which exclude the socio-economic variables and were created through MaxEnt modelling using only presence data.

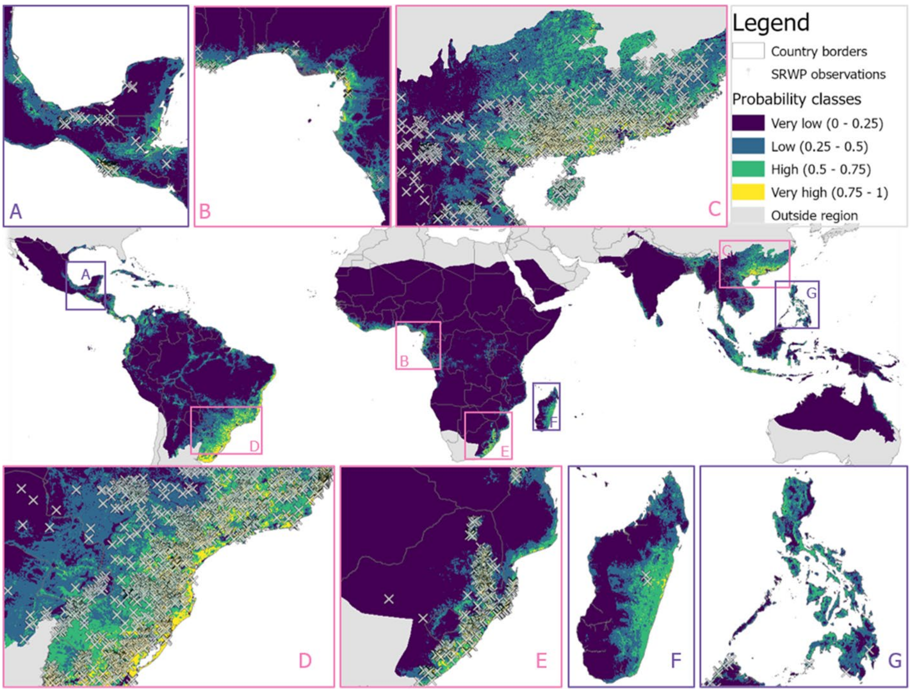

Fig. 1 Probability map for the occurrence of SRWPs in (sub)tropical biomes. The seven spotlight boxes present examples of areas with high probabilities and many observations (magenta) or few observations (purple). The same scale is used for all spotlight boxes. Note: For a better visibility, locations of SRWP observations are solely indicated in the boxes and not in the full overview (middle). An overview of SRWP observations in (sub)tropical biomes is provided in Supplementary Material 1.1

3.2 Future patterns

To understand potential impacts of climate change on the probability of finding SRWPs, probability maps were modified with future projections of temperature and precipitation. For all climate scenarios, SRWP probabilities are projected to decrease in the majority of locations and to increase in only very few areas. Areas with very low probabilities (< 0.25) show generally the least impact by changing climate and probabilities generally decrease in these locations only slightly. In areas with probabilities above 0.25, the median decrease lies around 0.1 to 0.2 depending on the climate scenario (Fig. 2). We found the differences between the magnitudes of decrease between those probability classes to be less pronounced as the difference to locations with very low probability values. When comparing the change in future probability between the scenarios, the SSP5-8.5 scenario shows overall the steepest decline in probabilities, followed by SSP3-7.0 and SSP1-2.6 scenario. This indicates that climate consequences from high emission scenarios could result in a stronger decreasing potential of plantations. The resulting layers of future probability are available at https://doi.org/10.34894/T3A3RM.

We identified areas with high probability (> 0.5), at high risk to become substantially less suitable for SRWPs due to future climate change (> 0.2 probability decrease in 2055). Most of these high probability-high-risk areas are located in Latin America, specifically along the coast of Central America, in Southern Colombia (Fig. 3A) and the Atlantic Forest in Brazil (Fig. 3B). Hotspots on the other continents include the Eastern Cape of South Africa (Fig. 3C), Sumatra Island and Southern China, Northern Vietnam and parts of Thailand (Fig. 3D). Several of these high probability-high-risk hotspots are located in highly productive paper/pulp and bioenergy production areas (le Maire et al. 2014; Overbeek et al. 2012). In other areas, SRWPs have (already) been abandoned, for example, as it is the case for some eucalyptus plantations in Brazil (Gainsbury & Colli 2014).

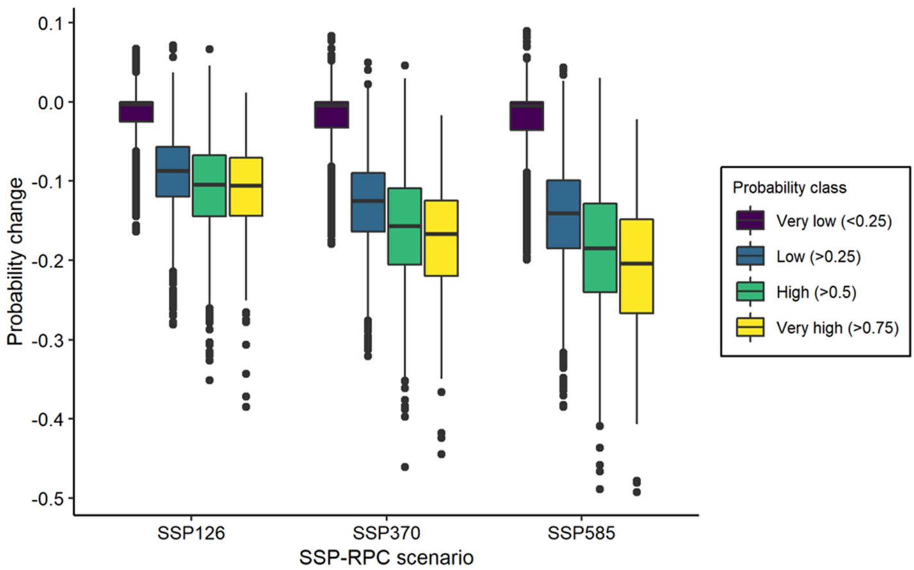

Fig. 2 Grouped boxplots representing changes in probability separately for probability classes and following three future scenarios for climate variables (SSP126: RCP2.6–SSP1, SSP370: RCP7.0–SSP3, SSP585: RCP8.5–SSP5)

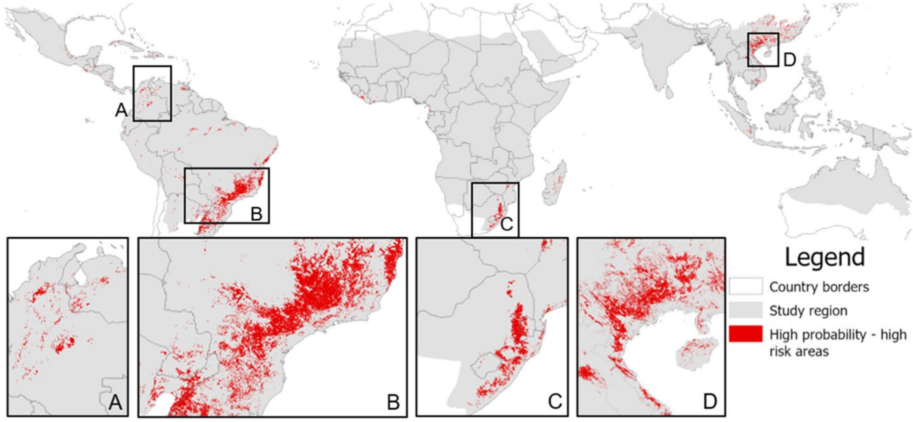

Fig. 3 Areas of high probability areas (> 0.5), which are at high risk of becoming substantially less suitable (> 0.2 decrease) for SRWPs due to future climate change in 2055, following the SSP3-RCP7.0 scenario. The same scale is used in all spotlight boxes. Maps of high probability areas at high risk following SSP1-RCP2.6 and SSP5-RCP8.5 scenarios are provided in the Supplementary Material

3.3 Comparison between methods

The models' prediction ability, measured by the ROC AUC, is high for all three methods, with random forest having the highest value (0.95), followed by MaxEnt (0.90) and multinomial regression (0.83). When combining the probability maps, the ROC AUC increases to a value of 0.97. To compare the spatial patterns of the three methods, we calculated the mean absolute difference of the resulting probability maps. For current conditions, the mean difference is rather small in most areas (Fig. 4), with some outliers especially for locations adjacent to very high probability values (see Supplementary Material 2.4.1). Locations of very high (> 0.75) and very low probabilities (< 0.25) show the smallest difference between the methods, meaning these probability classes are the least sensitive to the choice of method (Supplementary Material 2.4.5). The patterns resulting from future scenarios are more similar between the methods, demonstrated by smaller mean absolute differences between the methods compared to current

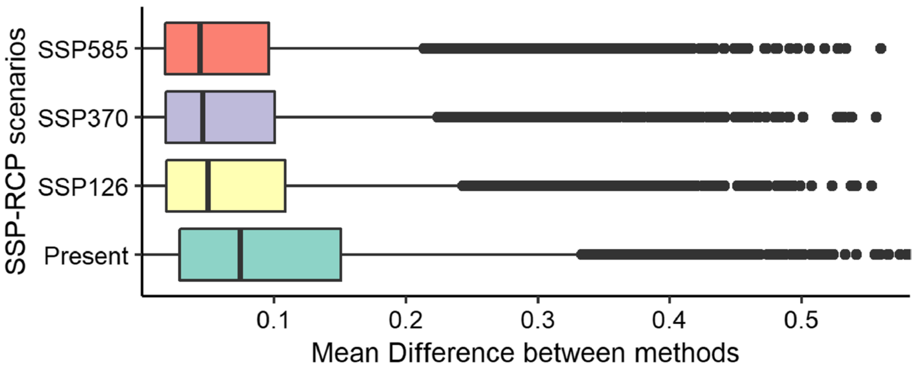

Fig. 4 Boxplots showing the distribution of absolute mean difference between the three methods for current (~ 2015) conditions and future scenarios (SSP126: RCP2.6–SSP1, SSP370: RCP7.0–SSP3, SSP585: RCP8.5–SSP5)

conditions (Fig. 4). Again, locations with very low and very high probabilities are generally the least sensitive to the choice of method, indicated by the low standard deviation values for these probability classes (Supplementary Material 2.4.5).

Determining the permutation variable importance shows that especially climate and socio-economic variables are important predictors for the occurrences of SRWPs (see Fig. 5). Maximum temperature in the warmest month, followed by elevation have on average (i.e. across the three methods), the highest contributions, with comparatively lower impacts in the random forest model. Annual precipitation and precipitation in the driest quarter are furthermore variables with a high impact among the different models. There are noticeable differences between the contributions of climate variables to the different models. Precipitation in the driest quarter and diurnal temperature rank high in their contribution to the Random Forest model, but have less impact on the results of the other two methods. These differences can be explained by similar direct and indirect impacts on SRWP probabilities, which are also reflected in the correlation coefficients of their pairwise comparison (see Supplementary Material 2.5). Accessibility, measured in travel time to major cities, and market access are further variables that have an important contribution to the predicted probability of SRWP occurrence. Overall, soil variables and terrain conditions, except for elevation, show only a small contribution to model predictions. The impact of the variables on prediction ability (i.e. ROC AUC, see Supplementary Material 2.6) shows similar patterns, with some minor differences in the ranking order of variables.

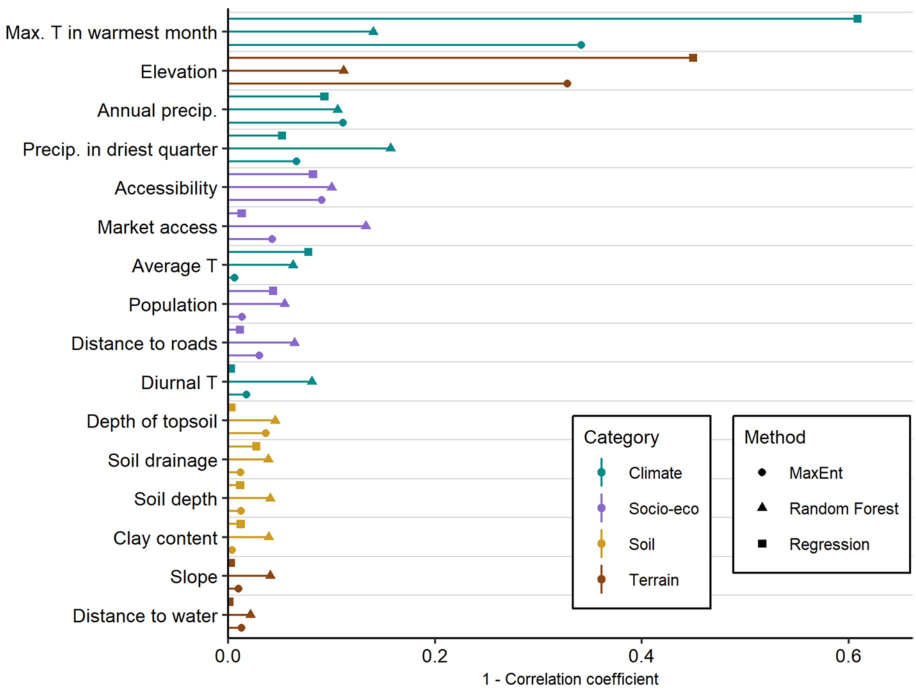

Fig. 5 Contribution of predictor variables for the three methods used to predict SRWP probabilities. Variable contribution was estimated by calculating Spearman correlation coefficients for original predicted probabilities and probabilities based on a permutated dataset (i.e. shuffling variable values). The less the probabilities correlate, the higher the contribution of the variable (therefore 1 – correlation coefficient on the *x*-axis). Variables are ranked by their average values for all three methods. Categorisation follows Table 1

4 Discussion

We present the first empirical estimation of the spatial probability of SRWP distribution in tropical and subtropical biomes, based on a comprehensive dataset of observed locations. By combining three advanced spatial models, we increased prediction capability of our method and minimised drawbacks inherent to each individual model, shown by a higher ROC AUC value for the combined map as compared to the performance of the individual methods. In the absence of complete databases of SRWPs, our map, indicating the probability of SRWP occurrence, adds additional insights to the existing body of evidence. The probabilities for occurrence of SRWPs can be interpreted as an indication of the suitability of these areas, based on the physical and socio-economic location characteristics considered in this study. The probabilities, however, do not necessarily present optimal suitability, but rather the likelihood for a land user to establish an SRWP in a location. The occurrence of SRWPs is, thereby, also a result of competition and compromise with other land uses and depends on a locations opportunity, for example, regarding infrastructure or favourable growing conditions.

SRWPs are one of the most important measures in global climate change mitigation plans, for example, as part of the Paris Agreement (Hasegawa et al. 2018). Our results show that there is a rather large variation in SRWP probability in the tropical and subtropical biomes. These variations indicate that SRWPs are not everywhere a likely or feasible solution and it is important to account for these differences in occurrence probability, when targeting investments. Our results clearly indicate that the probability SRWP occurrence is constrained by elevation and climate factors, but also by accessibility constraints. These differential likelihoods need to be accounted for. Previous studies on the suitability of plantations commonly did not include socio-economic variables (see, e.g. Aust et al. 2014, Zomer et al. 2008). However, our result shows that accessibility and market access had a rather large impact on the predictions. Both variables are indicators for the ease of access to processing facilities, interactions with markets and the availability of workforce, which in turn all affect the economic profitability (Vanbeveren et al. 2017). Enhancing accessibility in locations that are otherwise suitable is not always feasible and often expensive, requires resources and might be detrimental to the environment. On the other hand, areas that are highly accessible and hence profitable might be used for more lucrative land systems, such as crop production.

As a first to estimate the impact of future climate change on the location probability for SRWPs, our study suggests that changing seasonality and overall climatic conditions might cause SRWP suitability to decline in several locations in the (Sub)Tropics. This could result in less yield, less profit and potentially abandonment, as well as less area available for expansion of new SRWPs. This could lead to diminishing amounts of wood from (sub) tropical SRWPs, resulting in increased harvest pressure on natural forests and consequently more degradation (Silva et al. 2018). From a demand side perspective, less wood available from SRWPs could interfere with initiatives to reduce plastic production and waste by switching to wood-based alternatives, or to decrease emissions from construction by using wood instead of steel and concrete. Additionally, as countries try to make the shift to more renewable energy sources, the use of biofuel has been encouraged as an alternative to fossil fuels, due to its higher flexibility compared to, for example, solar and wind power (Hunkin & Krell 2020). To achieve a future with a temperature increase below a 1.5 °C or 2 °C, bioenergy with carbon capture and storage (i.e. BECCS) has been considered the main strategy (besides reduction in energy demands) (Fuss & Johnsson 2021; Masson-Delmotte et al.

2021). However, scarcity of land for the supply of bioenergy has been found to be the main constraining factor (Creutzig et al. 2021; Strefler et al. 2021). Our results show that future climate change might exacerbate this scarcity and reduce the potential of land-based mitigation through SRWPs and BECCS, which emphasises the necessity to include demand side mitigation measures. Larger climate impacts reduce the potential of mitigating further climate change by land-based mitigation. It needs to be noted that due to our focus on (sub)tropical biomes, we do not account for potential probability increases in temperate and boreal regions, which could be the result of higher temperatures and changing precipitation patterns, and might be able to counterbalance some of the lost land availability. The same is true for changes in the socio-economic and political situation, which can make areas accessible and suitable, which are currently not. The observed patterns of decreased probabilities driven by climatic changes are also relevant for SRWPs that are used as measure against land degradation and to increase the land value of marginal agricultural areas. In the Atlantic Forest in Brazil, for example, SRWPs have been planted on degraded grassland, following sustainability principles and enhancing productivity, biodiversity and economic value of the land (FAO & UNEP 2020). Our results suggest that the opportunity to restore land through such measures might decrease in the future and especially in scenarios with more pronounced changes in temperature and precipitation patterns, for which land degradation is expected to worsen (Borrelli et al. 2020).

Next to the high predictive ability of our models indicated by the ROC AUC values, our map also shows agreement with existing datasets. When overlaying the locations of wood fibre and eucalyptus plantations derived from the Spatial Database of Planted Trees (Harris et al. 2021) with our probability map, we found that these plantations were more often in locations with high and very high SRWP probabilities, as compared to a random sampled (see Supplementary Material 3.1).

Although our study differs in its approach to previous studies on the location factors of SRWPs, our ranking of variable importance shows similarity. Previous studies have also identified temperature and water availability as most important location factors and soil conditions to have a smaller impact (Aust et al. 2014; Saïdi et al. 2011). For two of our three methods, temperature had a larger impact than precipitation, which can be explained by reduced photosynthesis due to more cloud cover when precipitation increases (McMahon & Jackson 2019). Similarly, cloud cover and lower temperatures are likely the main reasons why elevation had a rather high importance for the predictions of all models. While irrigation has been suggested as a measure to overcome water limitations in coppice plantations in dry Mediterranean areas (Oliveira et al. 2020), the small contribution of the distance to fresh water resources found in this study indicates that irrigation currently only plays an overall minor role in (sub)tropical SRWPs. It is likely that this will change in the future with more frequent droughts and land scarcity due to competing demands (Stenzel et al. 2019).

There are several limitations attached to our method. Misclassification of SRWP locations is possible, due to the way the data was collected. Generally, this was avoided, by including only locations, where at least three citizen scientists agreed. The target approach enabled a relatively fast collection of a large number of points, but generally classifications of one expert might be less reliable due to lacking quality control (Schepaschenko et al. 2017). While it is possible to address potential errors in classifications with MaxEnt, it is not possible to address these with the other methods applied. However, the large similarity between the results of MaxEnt and the other two methods indicates a low sensitivity to potential classification mistakes. Empirical approaches, especially on a large scale, are always a generalisation of the actual dynamics that occur on the ground. By using statistical models over several continents, we ignored relationships potentially resulting from national politics that dictate the allocation of SRWPs. Our study did not include future scenarios of socio-economic development as this would require additional assumptions and their effect would be difficult to disentangle from the impacts of climate change. Future studies could build upon our analysis and also include socio-economic scenarios, to identify how those will impact the probability of SRWP occurrence. We furthermore generalised over different tree species that are used in SRWPs. Acacia and eucalyptus, for example, have different requirements for soil conditions (Saïdi et al. 2011). Additionally, pine plantations were not included in the observation data, even though some studies determine rotation periods of these plantations to be below 15 years (Fagan et al. 2018). While we did update climate variables, we only considered proxies for climate extremes, such as droughts, which might not fully present potential increases of tree mortality or pests, or aggravated competition with agricultural land.

Despite the limitations, the results of this study can have several applications, most notably leading to more realistic plans and assessments of land-based climate change mitigation. First, they can be used to account for potential future changes in suitability when planning the location of new plantations. Second, the probability maps can be used to downscale national statistics on SRWPs and spatially-explicitly allocate their occurrence. While a global dataset on the exact amounts of SRWPs is currently lacking, better estimates might become available in the future for many countries with the increasing importance of SRWPs. Using national or regional data on the actual extent of SRWPs could help overcome the lack of political drivers in our study. Third, the results could be used in models of future land use changes, thereby providing more nuance on forest cover and planted forests (Bahar et al. 2020). Explicitly accounting for SRWPs goes beyond earlier studies accounting for forest management (Doelman et al. 2018; Schipper et al. 2020; Schulze et al. 2020). This can have implications for global assessment results in providing refined assessments of biodiversity, land degradation or changes in the water cycle resulting from SRWPs. Finally, our results can support and refine estimates of the potential future availability of wood fibre for biomass, paper and pulp (Roe et al. 2021). Our method goes beyond previous estimates on the suitability of locations, by including socio-economic variables (for current conditions) and relying on an empirical approach. These improved estimates can support policy recommendations, for example, on the potential of SRWPs as a climate mitigation option and refined identification of trade-offs and synergies of SRWPs, which would lead to more sustainable SRWPs.

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Data availability All spatial layers produced in this study are openly accessible at https://doi.org/10.34894/T3A3RM. Statistical results are provided in the Supplementary Material. All input data is available from the respective references. The R-scripts can be requested from the lead author.

Declarations

Conflict of interests The authors declare no competing interests.

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