



Using remote sensing to support forest policies in Bavaria, Germany

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Abstract. In order to mitigate climate change, the German Federal Government set goals to reduce greenhouse gas emissions and reach climate neutrality by 2045. To implement it, the federal and local governments have made a series of policies to improve the forest conditions in Bavaria. In this paper, we generated annual high-resolution dominant leaf type (DLT) and above-ground biomass density maps over Bavaria to support policy-making. Specifically, two U-Net-based models were trained to predict the DLT and biomass density separately from multispectral Sentinel-2 data based on deep learning. The model achieved 92.5% DLT segmentation accuracy and an R^2 of 0.62 biomass estimation accuracy on the test set. Then, the trained model is used to derive annual DLT and biomass density maps from 2015 to 2025, where a post-processing step was proposed to exclude noisy fluctuating predictions. The results show a clear increase in tree area and broadleaved area, but this has slowed down since 2020. Besides, biomass loss due to tree degradation is higher than that due to deforestation, as suggested by the results. Subsequently, the time-series maps are used to identify hotspots in Bavaria, which is of interest to policymakers. We analyzed the tree cover and biomass loss for different administrative regions, and found that for most administrative areas, the increase of broadleaf tree areas is noticeably larger than the loss of that, except for Upper Franconia. Besides, continuous increases in both forest area and biomass amount in mountainous regions were observed. A landscape metrics-based analysis suggests that forest cover across the entire state has become increasingly fragmented. The results provide good insights into the tree status in Bavaria and suggest a new focus for forest management policies.

Keywords: biomass change; dominant leaf type (DLT) classification; Forest monitoring; deep learning

1 Introduction

Forests play a crucial role in global climate regulation, and many countries have recognized them as a key strategy for sequestering atmospheric carbon dioxide and mitigating surface temperature rise (Song et al., 2023). German forests make an important contribution to this. With an average timber stock of 335 cubic metres per hectare, they are among the most timber-rich forests in Europe (BMLEH, 2025a). Germany, one of the most densely populated countries in Europe, has seen its forest area grow by around one million hectares over the last forty years to 11.4 million hectares today (BMLEH, 2025b). In 2022, the share of forest land over the total amount of land in Germany remained nearly unchanged at around 32.69 percent (BMEL, 2021b). As the largest state in Germany, Bavaria has a forest cover of 37%, and its forest area is the highest among all German states and significantly above the national average (BMEL, 2021b). To effectively address climate change, the German federal government enacted the Climate Action Law (Klimaschutzgesetz) in 2019, initially setting a target of achieving green-



house gas neutrality by 2050. However, this goal was advanced to 2045 in the revised version published in 2021 (Bundestag, 2021). Against this backdrop, forests - as significant carbon sinks (Whitehead, 2011; Luyssaert et al., 2008)—have received unprecedented attention in climate policy and environmental management (Golicz et al., 2021; Förster et al., 2021; Nagel et al., 30 2023).

On the other hand, forests exhibit high sensitivity to climate change (Kirilenko and Sedjo, 2007; Kirschbaum and Fischlin, 1996). Since the mid-1970s, Europe has experienced significant climatic shifts, characterized by warmer and wetter winters, and hotter and drier summers (Klein Tank and Können, 2003), a trend that is projected to persist (Estrella and Menzel, 2013). This shift is largely attributed to the rise in atmospheric carbon dioxide concentrations driven by human activities (Hegerl et al., 35 2019). After World War II, Germany began large-scale planting of Norway spruce (*Picea abies*) due to its fast growth and high economic value, effectively promoting the recovery of German forest resources. However, with ongoing global warming, signs of adverse impacts on the growth and survival rates of spruce have become evident (Debel et al., 2021; Hilmers et al., 2020). It is noteworthy that up until 1860, about three-quarters of the tree species in Central European forests were broad-leaved, particularly European beech (*Fagus sylvatica*). Today, broad-leaved trees account for only about one-third of these forests. Since 40 the late 18th century, there has been a continuous trend of replacing broad-leaved species with conifers such as fir (offering higher timber yields) or pine (capable of growing in poor soils), a trend that persists to this day (alpha, 2021). In addition to addressing climate change and supporting sustainable timber production, modern forests also undertake multiple functions including promoting bioeconomic development, protecting and enhancing biodiversity, and providing quality recreational spaces. Consequently, German forests face dual pressures from anthropogenic factors (including intensive logging Bundesamt (2025); 45 Jochem et al. (2025); Spiegel (2020)) and natural threats (such as drought, extreme weather events, pests, and diseases Spiegel (2020); Hartmann et al. (2025); Wegler and Kuenzer (2024)). In response to these challenges, the German government and relevant institutions are actively seeking effective strategies to ensure the sustainability and long-term conservation of forest ecosystems.

Remote sensing has been extensively utilized to monitor forests (Coleman et al., 2024; Lechner et al., 2020). Xu et al. 50 integrated radar data (ALOS and Sentinel-1) with multispectral Sentinel-2 for global aquatic land cover types mapping, and compared the results with existing land cover maps (Xu et al., 2022). Waser et al. compared the impact of different combinations of remote sensing data for dominant leaf type (DLT) classification for Switzerland (Waser et al., 2021). Ometto et al. derived a high-resolution biomass map for tropical forest in Amazon using multi-source remote sensing data (Ometto et al., 2023). Synthetic aperture radar (SAR) data is used to estimate forest canopy height (Xing et al., 2025). Besides, remote sensing also 55 serves as a useful tool to support forest policies in a timely manner and at a lower cost. At a global scale, the scientific activities conducted by the Intergovernmental Panel on Climate Change (IPCC) provide an important basis for national policymakers worldwide. As an example in (Requena Suarez et al., 2019), above-ground biomass change rates were estimated for forests to refine the 2006 IPCC Guidelines for National Greenhouse Gas Inventories. At the national scale, Jakimow et al. quantified the deforestation and forest fire burned area from 2014 to 2020 to reveal the impact of forest protection policies (Jakimow et al., 60 2023). National field inventory and Earth observation data are integrated for forest biomass assessments to support Mexico's climate policy (Hunka et al., 2025). Nevertheless, Fassnacht et al. underline that the use of remote sensing in forestry remains



limited and underutilized in some regions (Fassnacht et al., 2024). In a review paper (Coleman et al., 2024), Coleman et al. reveal that few studies on forests in Bavaria were related to end-users. There are knowledge gaps between societal studies that drive policy-making and remote sensing studies for forest monitoring. In this paper, we explored the potential use of remote sensing technique to support forest policies taking the free state of Bavaria in Germany as a use case, to build a bridge between the societal policy making and remote sensing based monitoring.

2 Forest Policies for Bavaria

2.1 Federal Level

The forests of Germany serve multiple functions, including economic utilization, ecological protection, and providing public recreational spaces (BWaldG, 2021). The core objective of German federal forest policy is to protect forests sustainably and manage them effectively. This goal was first explicitly articulated in the Federal Forest Act (Bundeswaldgesetz) in 1975. As environmental conditions and societal needs have evolved, the Federal Forest Act has been revised multiple times to ensure alignment with state-level forest legislation, thereby safeguarding the three primary functions of forests—particularly preventing deforestation and land-use conversion (BayWaldG, Juli 2005). To further enhance the adaptability and mitigation potential of forests against climate change, the German government released the Charter for Wood 2.0 in 2021 (BMEL, 2021a). This charter emphasizes the importance of sustainable forestry and timber use in reducing greenhouse gas emissions and supports the implementation of the Climate Action Plan 2050. The Climate Action Plan 2050 (Federal Ministry for the Environment and Safety, 2016) serves as a framework strategy for modernizing the national economy, guiding domestic climate objectives consistent with the Paris Agreement, and outlining specific pathways to achieve net-zero greenhouse gas emissions.

German forest policy places significant emphasis on biodiversity conservation, advocating for sustainable forest management (SFM). The National Strategy on Biological Diversity, adopted in 2007 (Federal Ministry for the Environment and Safety, 2007), aims to maintain and enhance biodiversity by protecting existing forest resources and restoring degraded forests. With this strategy, Germany has established a comprehensive implementation plan for the United Nations Convention on Biological Diversity. The updated National Strategy on Biological Diversity 2030, adopted in 2024, further refines these goals, particularly emphasizing the strategic importance of near-natural forests (Federal Ministry for the Environment and Protection, 2024).

As societal demand for green spaces increases, German forest policy has begun to prioritize the role of forests as public recreational areas. The Forest Strategy 2020, published in 2008, addresses not only climate protection and adaptation but also issues such as forest ownership and employment income while considering how to better provide recreational spaces for the public (BMELV, 2008).

In addition to the aforementioned legal frameworks, Germany has enacted a series of specific forest-related laws, including the Forest Reproductive Material Act (FoVG), the Timber Trade Protection Act (HolzSiG), the Federal Hunting Act (BJagdG), and the Federal Nature Conservation Act (BNatSchG). Furthermore, the federal government and state governments jointly manage financial assistance programs aimed at community and private forests. Funding is allocated for near-natural forest man-



agement, forest infrastructure development, afforestation activities, and measures to mitigate the impacts of extreme weather
95 events (BMEL, 2021b).

2.2 State Level

Bavaria is among the first German federal states to implement forest transformation plans (Waldumbaupläne) aimed at address-
ing climate change (Reif et al., 2010) (p.62). Given that agricultural and forestry land account for over 80% of the total area,
the challenges posed by climate change are particularly severe in this region, prompting local authorities to develop specialized
100 strategies (Reif et al., 2010). As the most common tree species in Bavarian state forests, spruce has had a profound impact on
the forest restructuring efforts promoted by the Bavarian State Forestry Authority (Müller-Kroehling et al., 2009). It makes the
forests highly susceptible to climate change impacts. This environmental pressure significantly increases the susceptibility of
spruce to bark beetle infestations (Kölling, 2006). Experts particularly highlight that the areas dominated by deciduous forests
in hilly to mountainous landscapes with a high proportion of pine trees, such as the Tertiary hills, western central Franconia,
105 and Allgäu regions, are especially vulnerable to climate change.

Additionally, there are concerns about the increasing frequency of extreme weather events in the Alpine region (Reif et al.,
2010) (p.23). To address these challenges, the Bavarian State Ministry of Agriculture and Forestry (Bayerisches Staatsminis-
terium für Landwirtschaft und Forsten, StMLF) initiated the “Forest Transformation Project for Adapting to Climate Change”,
aiming to gradually convert high climate-risk coniferous forests in state-owned lands into more resilient and site-appropriate
110 mixed broadleaf forests (StMUV, 2008). For private and corporate forests, the focus is mainly on the “Bavaria 2020 Cli-
mate Program” (StMUV, 2008), which aims to transform approximately 100,000 hectares of threatened spruce forests into
more climate-resilient mixed forests by 2020. Another initiative targeting mountain forests—the “Mountain Forest Offensive”
(Bergwaldoffensive, BWO)—aims to improve the stability of mountain forests through enhanced management and restoration
efforts. Experts believe that forest transformation includes effective measures suitable for climate adaptation strategies, which
115 can be assessed based on climate change impacts and modified when necessary. However, the effectiveness of these forest
transformation programs and mountain initiatives still requires scientific validation.

Caused by human activities or natural hazards, an integrated forest can split into a few patches, which influences the bio-
diversity of wild animals. In light of this challenge, the Bavarian State Parliament has repeatedly called upon the government
to strengthen networks of large wildlife habitats and mitigate fragmentation effects. Under the participation of specialized
120 institutions and experts, the Bavarian State Office for the Environment (Bayerische Landesamt für Umwelt) developed the
“Concept for the Conservation and Restoration of Significant Wildlife Corridors along Federal Highways in Bavaria” (für
Umwelt, 2008b). This initiative aims to protect and enhance habitat networks concerning forests and associated fauna across
the state. BayernNetzNatur¹, established in 1986, focuses on implementing Bavaria’s biodiversity strategy. It has completed
or is currently undertaking over 400 projects, playing a crucial role in enhancing the connectivity of biotic communities in
125 Bavaria.

¹https://www.naturvielfalt.bayern.de/arten_und_lebensraeume/bayernnetznatur_projekte/index.html



2.3 Remote Sensing to Support Policymaker

The main focus of this paper is to systematically explore the potential of remote sensing to support forest policies, and link societal and remote sensing studies. Specifically, we: 1) first determine the possible indicators that can be derived from remote sensing data as well as can be used to show the policy execution outcomes for each forest policy; 2) summarize the results from step (1) and determine the goals of this study; 3) use downloaded remote sensing data to derive the indicators and implement the analysis.

Based on the functions of German forests, ongoing forest policies can be divided into three categories: economic, recreational, and environmental. Assessment of the economic and recreational functions of forests is difficult to be validated via remote sensing alone, because it associates with societal and economic statistics. Therefore, this study focuses on the environmental function of the forest policies. Table 1 summarizes the first step results. Several key indicators are of particular interest to policymakers: forest map, forest type map, species distribution, timber / biomass, Greenhouse gas emission, biodiversity and fragmentation. However, due to the limited available reference data, it is extremely difficult to derive robust models for species distribution, timber volume, Greenhouse gas and biodiversity models. Based on this, we determined the goals of our subsequent analysis: 1) annual dominant leaf type mapping and change; 2) annual biomass estimation and its change; 3) based on these results, a special focus would be paid to the mountainous area and fragmentation status; 4) besides, we compared the DLT and biomass change among different administrative areas in Bavaria.

3 Materials and Methods

3.1 Research Area

The research area is the Free State of Bavaria, which located at the southeast of Germany, as shown in Figure 1. It is the biggest state, covers 70,550 km^2 area and consists of 7 administrative regions. According to the 4th Federal Forest Inventory result, forests occupies 37% of the land in the state. Although this ratio is not the highest in Germany, Bavaria has the biggest forest area (around 26.169 km^2) compared with the other states. Bavaria has the largest average wood stock density of 405 m^3/ha . Regarding the distribution of tree species in Bavaria, due to historical reasons, spruce is the main tree species which covers about 41.8% of the forest area in Bavaria, and broad-leaved trees occupy about one-third of the forest area. Besides of spruce, the common species are Pine (17.1%), Beech (13.9%), and Oak(6.8%). Due to the climate crisis including frequent droughts and increase of bark beetles, spruce has lost its marked importance since 2018. Therefore, active conversion of the coniferous dominated forests to more mixed forests is distinctively urgent. Besides, Bavaria has a diverse landscape, with elevation ranges from 104 to 2.962 m. There are mountainous forests located in southern and eastern state. Therefore, management of mountainous forests is an important part in the policy document.



Table 1. Summary of existing forest policies for Bavaria and corresponding indicators that can be derived from remote sensing data to evaluate the effect of the policies.

Forest Policy	Level	Main Goals	Indicator
Federal Forest Act	Federal	Deforestation reduction and land-use conversion	Forest/Non forest Map
Charter for Wood 2.0	Federal	Sustainable forestry and timber use to reduce greenhouse gas emission	Timber volume estimation; biomass estimation
Climate Action Plan 2050	Federal	Net-zero greenhouse gas emissions	Greenhouse gas estimation
National Strategy on Biological Diversity	Federal	Biodiversity conservation	Forest biodiversity estimation
Forest Strategy 2020	Federal	Forests as public recreational areas	Forest use type map; urban green space map
Forest Transformation Project for Adapting to Climate Change	State	Convert coniferous forests to mixed broadleaf forests	Forest type map
Bavaria 2020 Climate Program	State	Convert 100,000 hectares spruce forests to mixed forests	Forest type map; tree species map
Mountain Forest Offensive	State	Improve the stability of mountain forests	Forest/Non forest Map over mountain forest
Concept for the Conservation and Restoration of Significant Wildlife Corridors along Federal Highways in Bavaria	State	Reduce forest fragmentation	Fragmentation indicators
BayernNetzNatur	State	Enhance the connectivity of biotic communities	Fragmentation indicators

155 3.2 Remote Sensing Data

We downloaded the harmonized Sentinel-2 imagery from May to August in each year as input to the model using Google Earth Engine. The original resolution of Sentinel-2 data ranges from 10 m to 60 m for different bands. A few steps are adopted to ensure the image quality: 1) areas with cloud coverage rate > 5% are masked out to ensure the quality of the images; 2)



upsampled the low-resolution bands to keep the same size; 3) valid data are averaged through time to have a big harmonized
160 mosaic. Each Sentinel-2 mosaic was divided into tiles. Those tiles are randomly split into training and test area with a ratio
of 0.8. Each tile is then divided into patches with a size of 256×256 . Instead of randomly partitioning the patches, this
training/test set split solution ensures that two groups of data are spatially separated from each other, which helps validate the
model's generalization ability. As a result, there are 22,125 and 6,232 patches in the training and test sets, respectively.

3.3 Reference Data

165 The Copernicus Land Monitoring Service (Langanke et al., 2017) provides high-resolution pan-European dominant leaf type
map for 2012, 2015, and yearly from 2018 to 2021. It divides the pixels into three categories, non-tree covered area, broadleaf
tree area and coniferous tree area. The dominant leaf type map for 2018 was acquired as a midpoint-year reference DLT data
for optimizing the model to ensure a similar inference bias caused by temporal difference for beginning and end of the study
time span. The resolution of the product is 10 m, which is consistent with the highest spatial resolution of Sentinel-2 images.
170 The ESA Biomass Climate Change Initiative: Global datasets of forest above-ground biomass dataset (Santoro and Cartus,
2023) is widely used as reference biomass density map (Liu et al., 2025). It is available for 2010, and then yearly from 2015 to
2022. Similar to DLT estimation, we downloaded the 2019 biomass density map representing the midpoint of the time period
as reference.

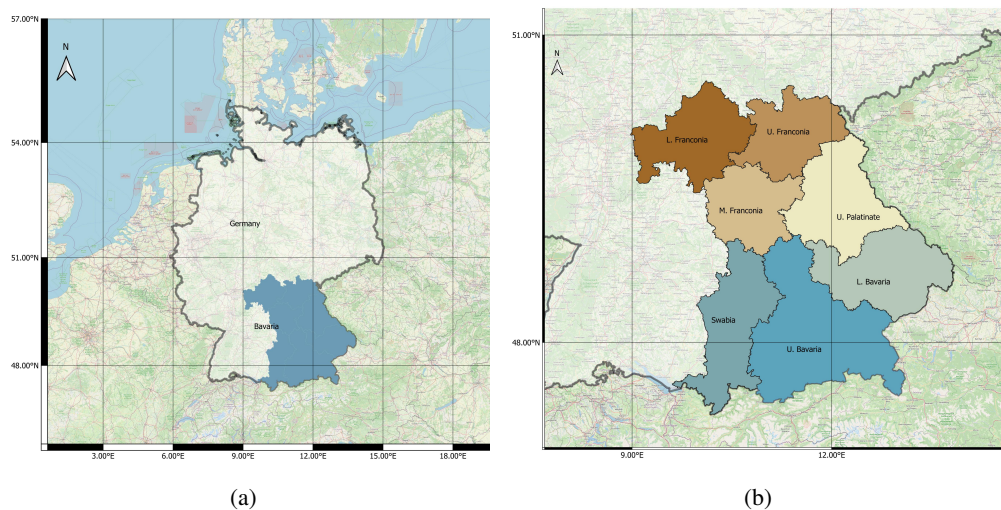


Figure 1. The research region of this study: (a) Bavaria state is located at southeast of Germany; (b) it consists of 7 administrative areas.
(Map data from OpenStreetMap.)



4 Methodology

175 4.1 Dominant Leaf Type Mapping

The classical semantic segmentation network U-Net (Ronneberger et al., 2015) is adopted in this paper, as it is widely used in forest mapping tasks (Song et al., 2024; Waser et al., 2021). As shown in Figure 2, it consists of several groups of convolutional layers. The left-side convolutional groups downscale the input remote sensing images and extract their features at different scales; the right groups make use of the extracted multi-scale spatial features to gradually reconstruct the semantic map from
180 coarse to fine resolution.

As introduced in Section 3, Sentinel-2 data is averaged over the acquisitions between May to August to have a single mosaic to reduce the number of blank pixels. All the 13 bands are included and all the 20-m and 60-m bands were up-sampled to 10-m images using nearest neighbor to keep the same spatial size.. The images are normalized based on the channel-wise mean and standard deviation, so that different bands have similar distributions.

$$185 \quad I_i \leftarrow \frac{I_i - \mu_{I_i}}{\sigma_{I_i}} \quad (1)$$

The output layer is a 1×1 kernel convolutional layer to shrink the channel number to 3, which is the number of dominant leaf types considered in this studies. The predicted map $\hat{P} \in R^{256 \times 256 \times 3}$ has the same spatial resolution as the input imagery. The prediction array at each location indicates of the predicted probability of the corresponding pixel belongs to non-tree area, coniferous tree and broad-leaved tree.

190 The network is based on the original implementation from (Ronneberger et al., 2015). The loss function is cross-entropy, which is widely used for image classification/segmentation task. The no-data and cloudy pixels are masked out during the loss calculation. The network is trained with Root Mean Square Propagation (RMSprop) algorithm (Tieleman and Hinton, 2012) with a fixed learning rate of $1e^{-3}$ for 50 epochs.

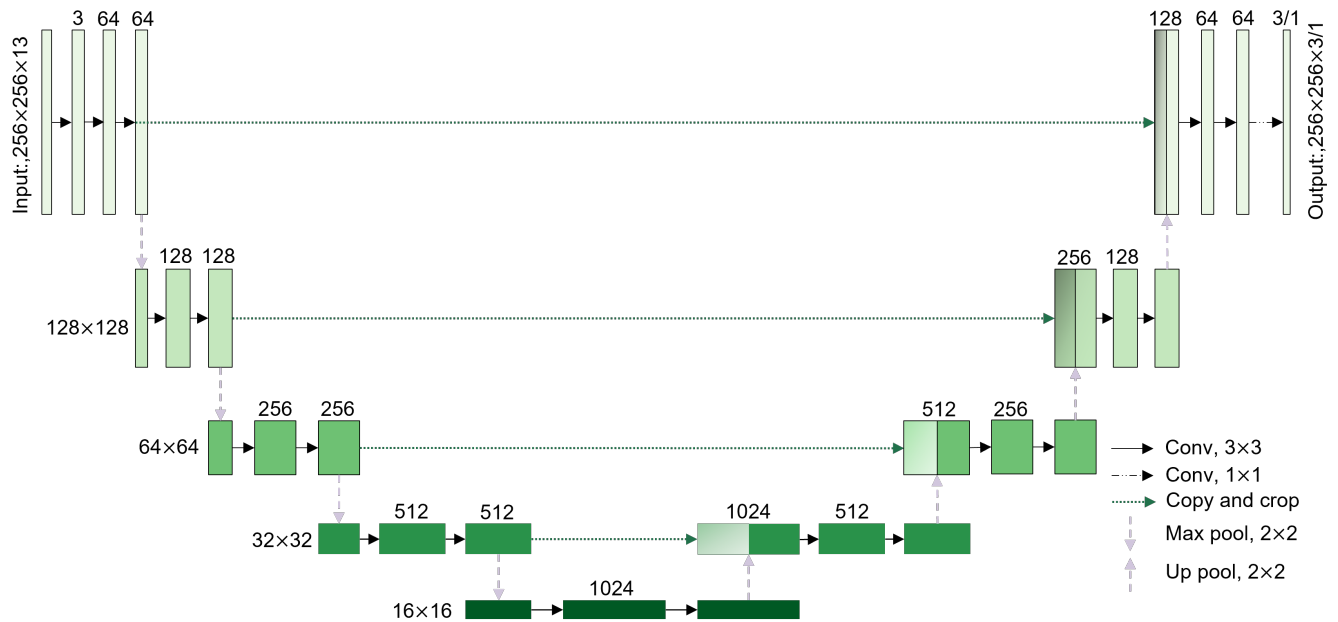


Figure 2. Network Architecture of Applied U-Net Model.

4.2 Biomass Density Mapping

195 Biomass density mapping followed the same method of DLT segmentation. The same network in Figure 2 is adopted, except
 the dimension of output is set as $256 \times 256 \times 1$. The biomass estimation is based on the spectral and spatial features of Sentinel-2
 data.

The same pre-processing pipeline in Section 4.1 is used to normalize the Sentinel-2 data. Biomass values in the reference
 data are linearly normalized via a logarithmic transformation to avoid the gradient exploding issue. To be specific, the biomass
 200 was transformed to

$$B_i \leftarrow \log(B_i + 1)/5. \quad (2)$$

Most of the biomass density values are below 180 Mg/ha, so the transformation in Equation 2 ensures most of the values
 range from [0, 1] after the normalization. Note that the reference above-ground biomass maps are designed for forest area.
 Low biomass density area is out of the scope of the estimation in this paper. Therefore, we masked out the low biomass density
 205 areas (normalized biomass density lower than 0.4, which is equivalent to 6.39 Mg/ha). The mean squared error (MSE) loss is
 used to measure the prediction error and further optimize the model. Other settings of the biomass estimation module is the
 same as the DLT classification network.



4.3 Evaluation Metrics

As a typical image segmentation task, DLT mapping model is evaluated by classification accuracy. We calculated the pixel-level
210 average accuracy, and class-specific accuracy for training and test sets separately as follows

$$P = N_{tp}/N, \quad (3)$$

$$P_c = N_{tpc}/N_c, \quad (4)$$

where the N and N_{tp} are the numbers of all pixels and the correctly predicted pixels (true positives); and the N_c and N_{tpc} are the numbers of pixels belongs to category c and the true positives.

215 For the biomass estimation, we use relative root mean square error (rRMSE), and R-square (R^2) song2023biomass for quantifying the errors of the predictions:

$$rRMSE = \frac{\sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2}}{\bar{y}}, \quad (5)$$

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2}, \quad (6)$$

where y_i , \hat{y}_i , and \bar{y} correspond to real, estimated and average biomass.

220 Besides, widely-used landscape metrics of patch density (PD), edge density (ED), and mean shape index (MSI) are adopted for evaluating the fragmentation degree of the tree areas (Ma et al., 2023). The fragmentation will limit the movement of the wild animals, the circulation of nutrition (Martínez-Richart et al., 2025). The isolation and edges are two significant patterns of forest fragmentation, as showcased in Figure 3. Therefore, the connectivity of forests is crucial for increasing the biodiversity. In this paper, connectivity is defined as queen's case, which means two tree area pixels are regarded as connected when one is
225 located at one of the 8 neighboring pixels around the other one, as shown in Figure 3(d). Each connected area is treated as a patch. Patch density presents the average number of patches per km^2 . Edge density is defined as the average length of tree area edges in every km^2 . And shape index is similar as edge density to measure the irregularity of the patch shape at patch level. MSI is the averaged shape index of all the patches found within the landscape. They are calculated as

$$PD = \frac{n_p}{A} \times 10^6, \quad (7)$$

230 $ED = \frac{\sum_i^{n_p} e_i}{A} \times 10^4, \quad (8)$



and

$$MSI = \frac{1}{n_p} \sum_i^{n_p} \frac{e'_i}{4\sqrt{A'_i}}, \tag{9}$$

where n_p and A are the number of the patches, the total area (in m^2) within the landscape, e_i and e'_i are the total edge lengths of i_{th} patch including and excluding landscape boundaries respectively, and A'_i is the trees occupied area in i_{th} patch.

235 The lower the PD and ED values, the more connected the forests. When the shape index equals to 1, the corresponding patch is considered to have a compact form like a square.

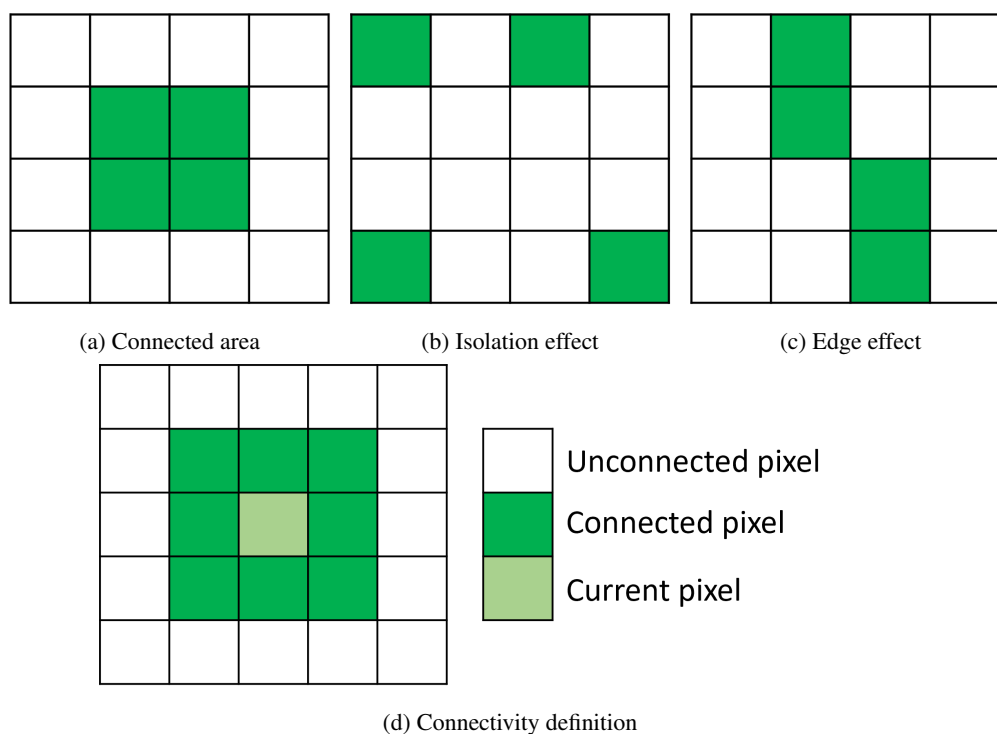


Figure 3. An example of well-connected forest (a), isolation effect (b) and edge effect (c) of forest fragments. (d) shows the definition of forest connectivity (queen’s case).

4.4 Forest Canopy Loss Calculation

The DLT maps can be polluted by a few factors, e.g. cloud and snow coverage, cloud shadow, and lack of remote sensing data. Directly counting the tree canopy cover loss using the predicted maps from the deep learning model can be problematic.

240 Therefore, a post-processing step is adopted to remove the noisy predictions.

Specifically, four-year DLT time series maps (DLT maps for last two years, current and next year) are used to identify the unreasonable results in the current DLT map. There are three types of valid results considered in this paper: new tree area pixels, tree cover loss and unchanged area, as shown in Figure 4. Unchanged area are those area that the results are consistent since



last year to this year. Tree canopy cover loss pixels are the new non-tree pixels for the current and next year that are classified
 245 as forest pixels for the last two years. New tree area is the non-tree covered area for the last two years, but are identified as
 forests of the same forest type for this and next years. We assume the before-mentioned noises are spatially and temporarily
 randomly distributed, and won't continuously show up at the same location on the DLT maps for two years. So, in this way,
 the prediction noises are removed effectively. In our case, this post-processing step won't block large area (less than 6%) to be
 further analyzed because of a high classification accuracy achieved (about 92%).

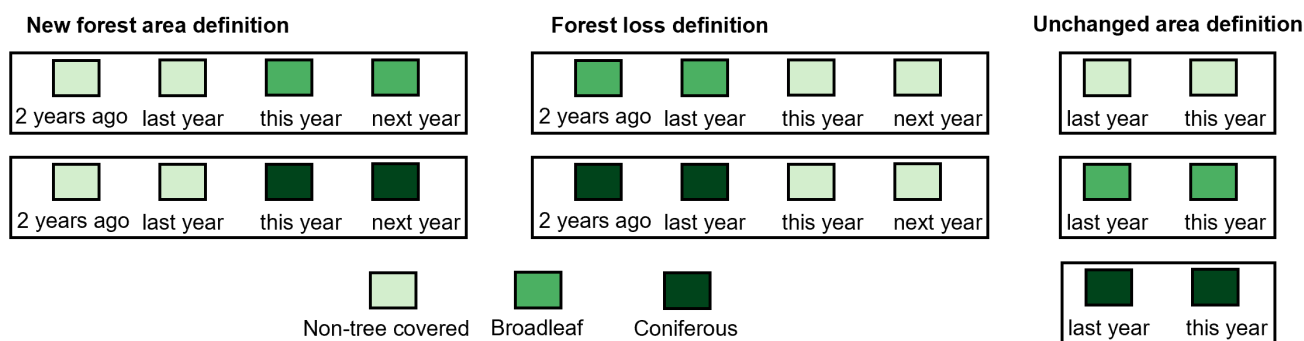


Figure 4. Three types of valid pixels using 4-year DLT prediction time series.

250 5 Results

5.1 DLT Classification

Figure 5 displays the reference and predicted DLT maps. There are no significant visual differences between them. Since
 we used Sentinel-2 images from summer months (May to August), there are some areas have no valid data (the southwest
 area of Bavaria as an example). These parts are excluded from loss calculation or result analysis. The quantitative results are
 255 summarized in Table 2. The overall classification accuracy is 92.64% and 92.5% for the training and test set respectively.
 The minor drop of the test accuracy suggests that the model isn't over-fitted, especially when taking the different geophysical
 conditions of training and test sets into consideration. As shown in Figure 5, the most part of the state is non-tree covered area.
 The coniferous tree area distributes mainly at south and east of Bavaria, while the broadleaf tree area located mostly at the
 northwest area, and is fragmentally scattered over the whole state. In Figure 6, we compared the network's dominant leaf type
 260 predictions for 2015 and 2021 with the DLT maps downloaded from the Copernicus Land Monitoring Service (Langanke et al.,
 2017). The comparison shows that though the model was trained using the data from 2018, despite broadleaf cover prediction
 for 2015, the overall and class-specific classification results are consistently good for different years.

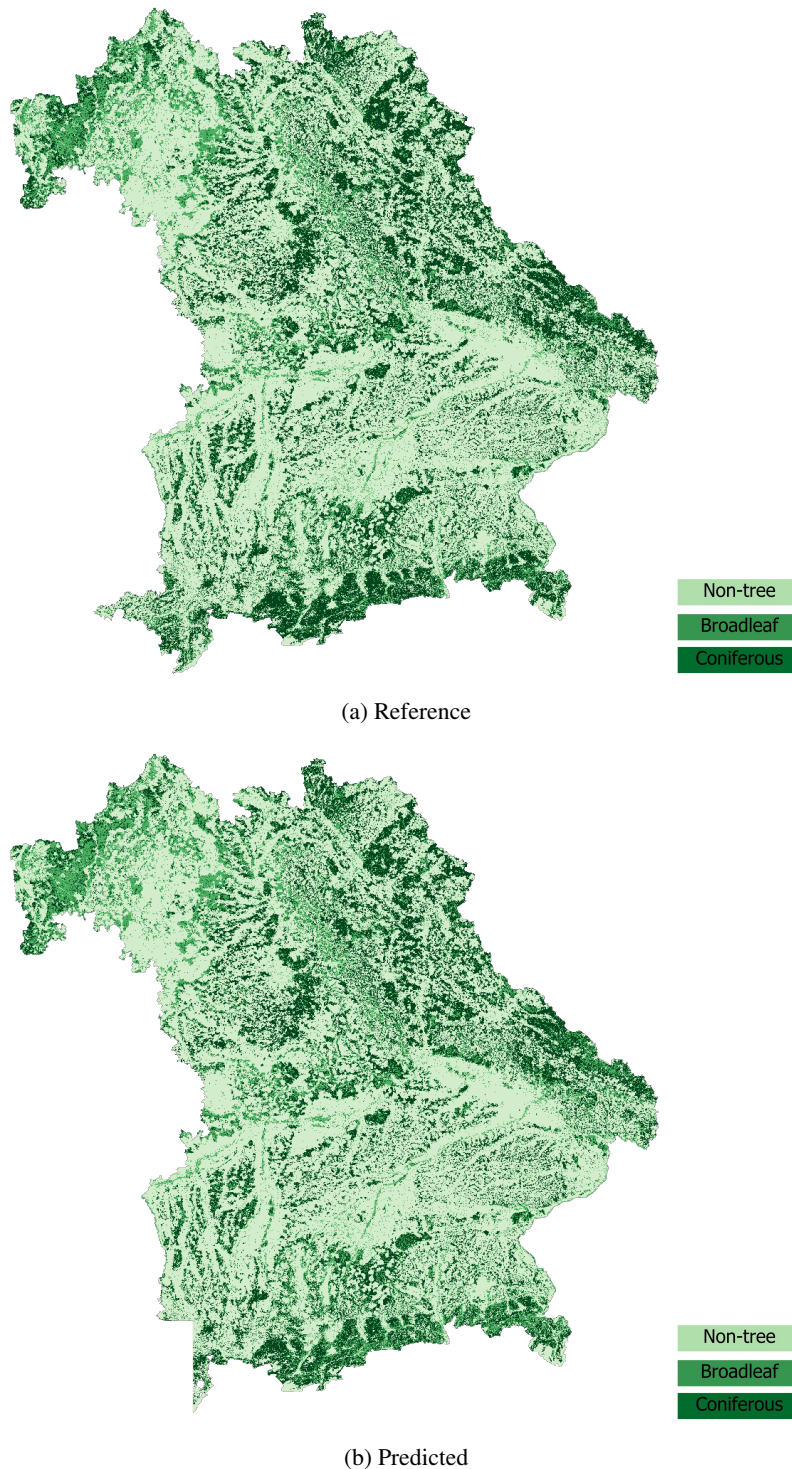


Figure 5. Comparison reference (a) and predicted (b) DLT maps for year 2018. Overall, the predicted DLT map is well consistent with the reference map. Most errors occurred in the mountainous areas in south and east Bavaria, where coniferous trees were incorrectly classified as broadleaf trees.



Table 2. Quantitative evaluation of the trained DLT classification and biomass estimation models.

		Train	Test
DLT classification	Average	92.64	92.5
	Non-tree	97.84	97.25
	Broadleaf	82.38	85.63
	Coniferous	86.93	87.35
Biomass estimation	$rRMSE$	0.42	0.45
	R^2	0.70	0.62

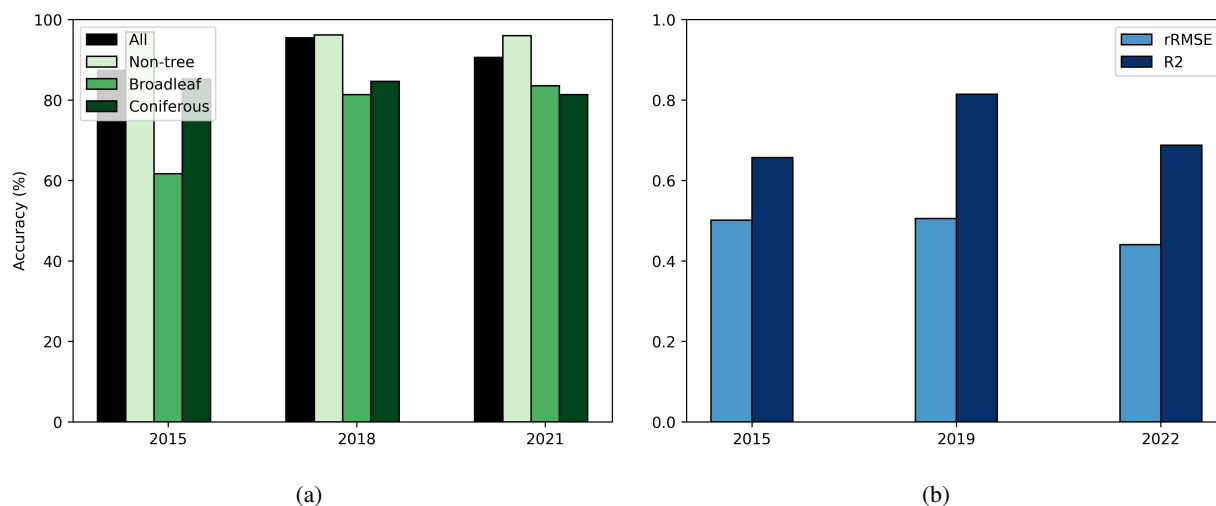


Figure 6. Evaluation of the DLT (a) and biomass (b) predictions of U-Net with reference data from different years.

5.2 DLT Change

Considering the random noises in the predictions, we applied a cleaning step to remove unreliable predictions in DLT map from further analysis. To be specifically, the DLT maps for each year from 2015 to 2025 was produced using the trained model. Due to the significant amount of missing data for 2016, the DLT map for 2016 is therefore removed. Then, we use every four consecutive years' DLT maps to identify suspect predictions for year 2018 to 2024. Table 3 lists the proportions of valid pixels after the cleaning step. At this step, about 5% of pixels are treated as invalid results. Besides, the invalid rate of the DLT maps for different years are similar (maximum difference of 1.95%), which suggests the classification results are consistent for different years. Figure 7 shows the changes of different forest type in Bavaria from 2018 to 2024. From 2018 to 2024 the tree area increased by about 0.44% of the total area. Broadleaved tree area increased by 1.94%, while coniferous area decreased by 1.49%.



Table 3. List of Proportions of Invalid Pixels after the DLT Prediction Screening Step.

Year	2018	2019	2020	2021	2022	2023	2024
Invalid pixel (%)	5.52	5.99	4.38	5.25	4.61	4.04	4.85

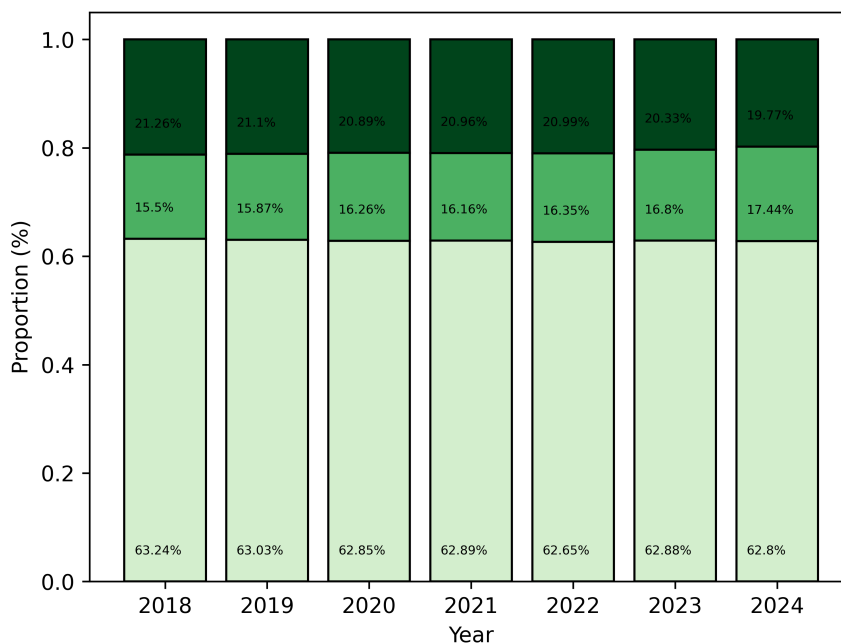


Figure 7. DLT change from 2018 to 2024.

5.3 Biomass Estimation

The R^2 scores of biomass estimation for training and test sets are 0.70 and 0.62 respectively. The relative RMSE of the training and test sets read as 0.42 and 0.45. Figure 8 compared the predicted biomass density map with the CCI Biomass map for 2019. The estimation errors mainly distributed in the centre regions. Figure 9 shows the changes of average biomass density from 2018 to 2024. The results indicates that though a sudden drop is identified in 2022, the biomass density is clearly increased from 2018 to 2024 overall (171.05 Mg/ha to 171.76 Mg/ha). Besides, we noticed that the mean state-level average biomass density has increased from 72.22 Mg/ha to 74.62 Mg/ha, which shows a clearer trend. Therefore, the selection of metric can influence the evaluation of the forest change. Even though new broadleaf trees are constantly planted, the average broadleaf tree stocked biomass increased from 122.14 Mg/ha to 129.42 Mg/ha. Besides, currently coniferous tree area are the most dense carbon stocks areas (nearly twice of that of broadleaf tree areas). Besides, we calculated and compared the relative RMSE and

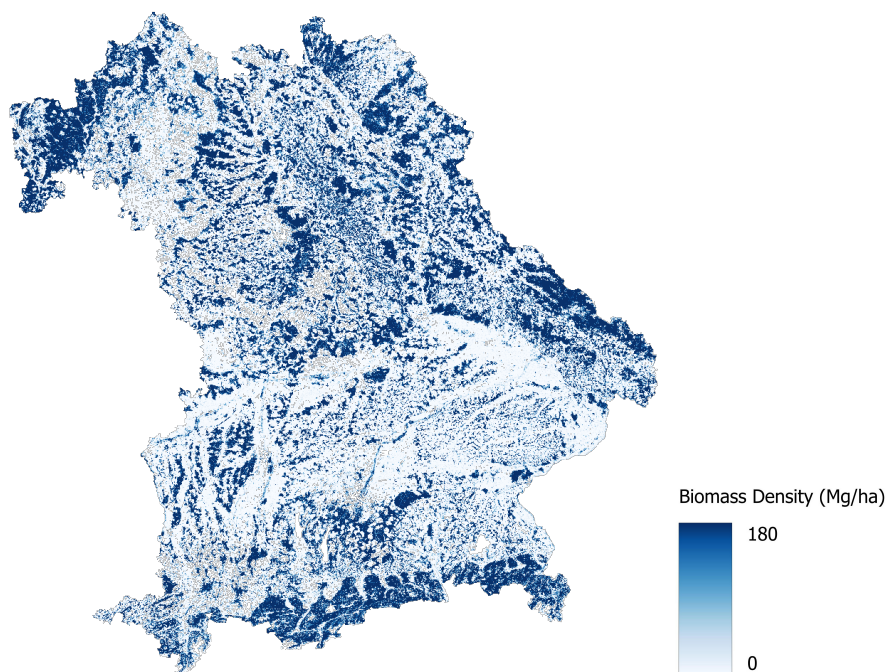
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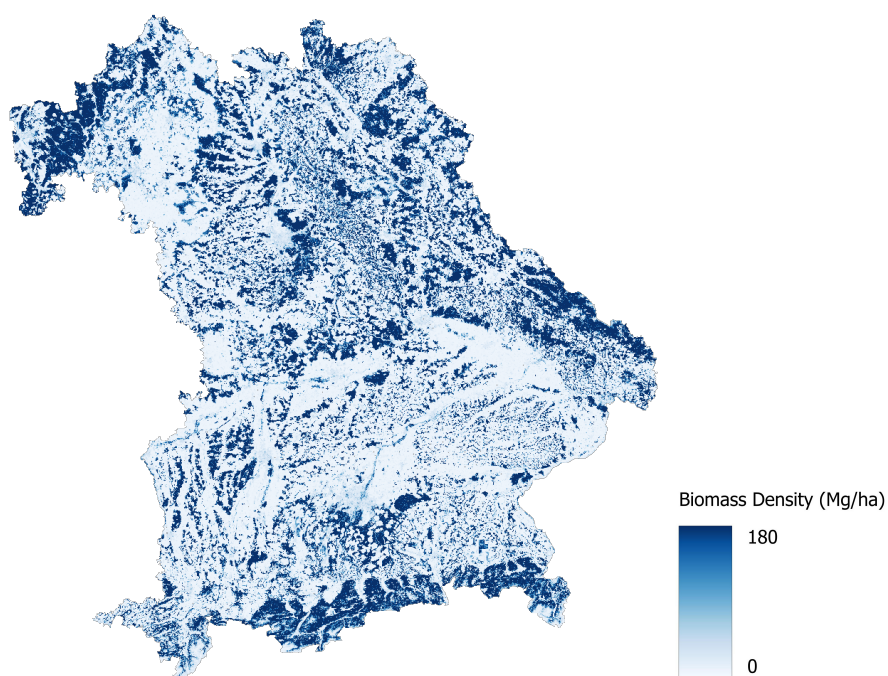
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R^2 of biomass estimation for 2015, 2019 and 2022 in Figure 6 (b). Though the R^2 scores decreased for 2015 and 2022, a slight reduction in the relative RMSE was also observed, and the results are still acceptable.



(a) Reference



(b) Predicted

Figure 8. Comparison reference (a) and predicted (b) biomass density maps for year 2019. While the predictions generally align with the reference data, a significant underestimation is observed in the central and mountainous regions.

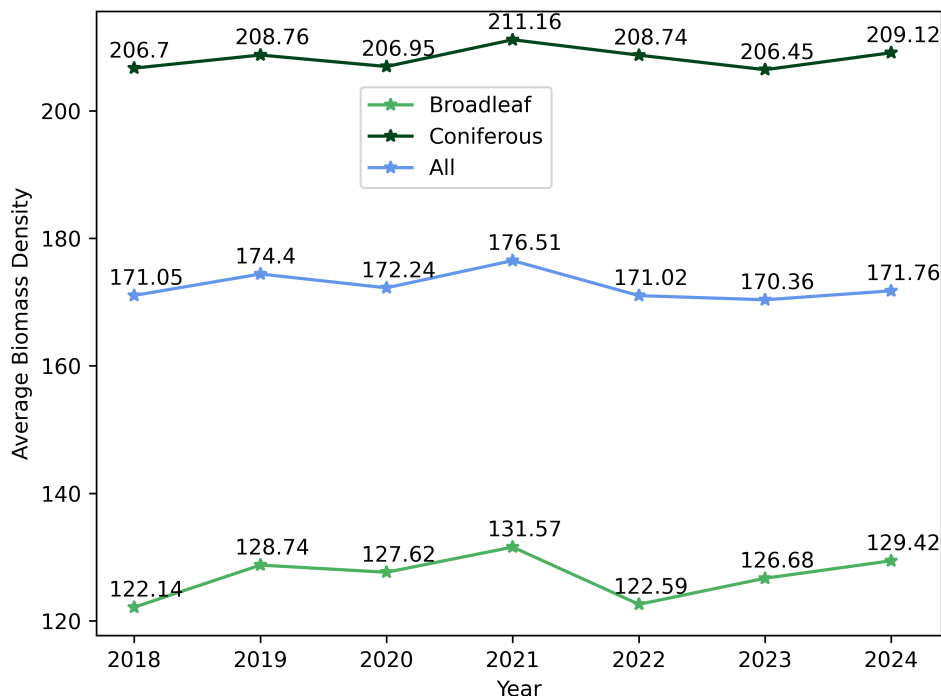


Figure 9. Average biomass density (Mg/ha) change from 2018 to 2024. The results show a remarkable biomass density increase within this 6 years.

285 6 Discussion

6.1 Carbon Loss Patterns

In addition to quantifying the amount of canopy and carbon loss, there is interest to distinguish between the different factors that lead to the loss. In (Seidl and Senf, 2024), Seidl et al. analyzed the increased forest opening canopy in Europe and attributed it to both planned and unplanned canopy openings. Csillik et al. categorized the carbon loss sources into clearing, 290 fire logging, windthrow and other disturbances (Csillik et al., 2024). In this study, we focused on two types of biomass loss patterns: deforestation induced fast biomass loss that is accompanied with cover loss usually due to logging activities, and slow biomass loss that is without observed cover loss caused by degradation such as pests invasion, drought etc.

Figure 10 shows the results of the calculated proportions of the biomass loss to the total amount of the biomass from 2018 to 2024 for different tree cover types and loss patterns. We found that biomass loss caused by degradation is considerably higher 295 than that from deforestation. The fast biomass loss occupies less than 0.73% of the total amount, while biomass loss as a result of forest degradation ranges from 4.04% to 10.40%. This implies that the main reason of carbon loss is not logging activities, and the forest disturbances caused by natural factors needs more attention. Secondly, while the biomass loss proportions from



300 broadleaf and coniferous trees are similar as a result of deforestation, degradation induced biomass loss ratios from broadleaf trees are significantly larger than that from coniferous trees. This suggests that broadleaf tree covered areas are more fragile in terms of biomass change.

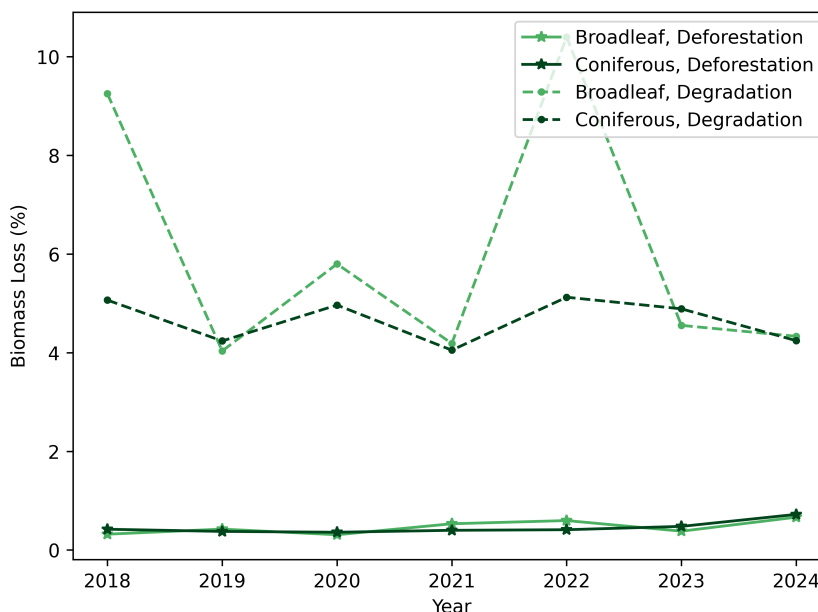


Figure 10. Comparison of biomass changes of different DLTs due to deforestation and degradation from 2018 to 2024. The ratio is calculated as biomass loss of broadleaf/coniferous trees for current year (2018 - 2024) divided by the total amount of biomass of broadleaf/coniferous trees for last year (2017 - 2023).

In addition, we compared the spatial differences of tree area and carbon loss among different administrative areas. As shown in Figure 11, for most administrative areas, the increase of broadleaf tree areas is noticeably larger than its reduction, except for Upper Franconia. During the summers of 2018 and 2019, the Upper Franconia region experienced historically unprecedented heatwaves and droughts, which had severe impacts on local tree populations². As noted by Dr. Peter Pröbstel, Director of the Bavarian State Institute of Forestry (LWF), in 2023, more than 1,700 hectares of forest has succumbed to extreme weather events in this region³. The forests of Upper Franconia have also been severely affected by bark beetle infestations. Local officials from districts such as Kulmbach and Kronach had already raised early warnings several years prior to this (StMELF, 2024). Besides, 2022 was a particular year that a markable decrease of broadleaf tree areas growth and increase of broadleaf tree area loss were observed in Lower Franconia, Middle Franconia, and Upper Palatinate. The year of 2024 is also notable for an intensified increase in broadleaf tree cover. Regarding the carbon stock, biomass density gains and losses show greater fluctuations. Nevertheless, in Upper Bavaria, Lower Bavaria and Swabia, there is a clear decrease trend of biomass loss of

²<https://www.aelf-ck.bayern.de/forstwirtschaft/wald/297540/index.php>

³<https://www.wochenblatt-dlv.de/regionen/franken/waelder-trockenstress-572605>



coniferous trees (shown as deep orange rectangle). Besides, except for Lower Franconia, the coniferous trees loss/absorb more carbon than broadleaf trees in other administrative areas.

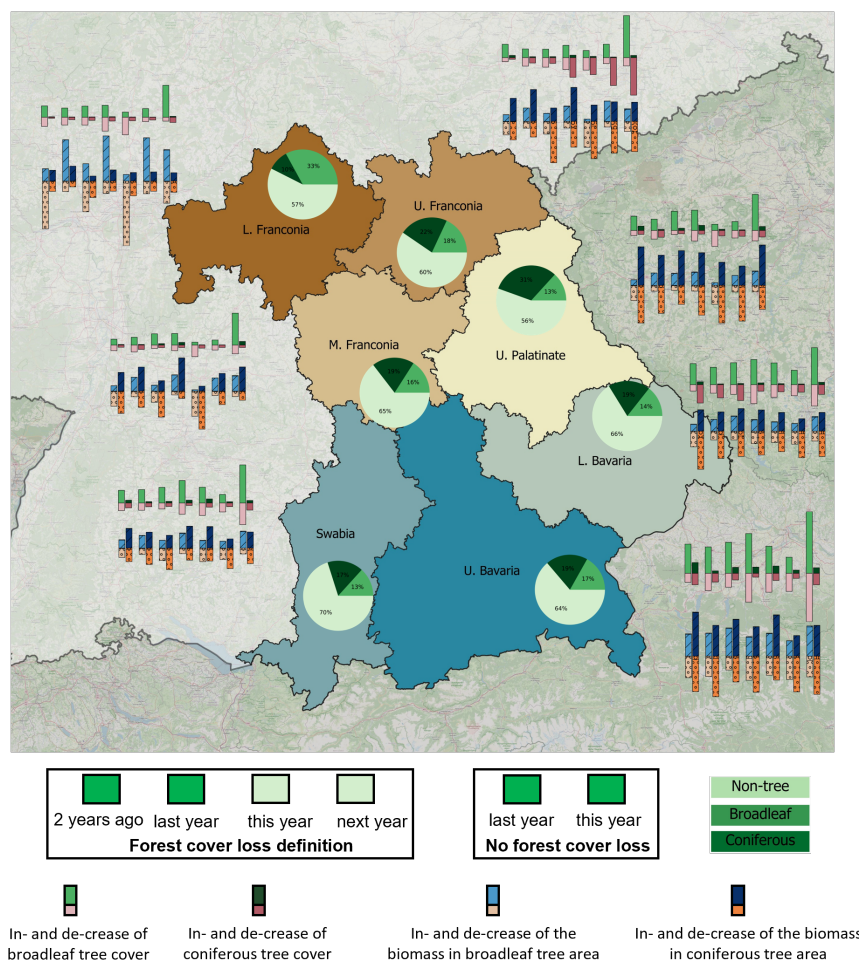


Figure 11. DLT and biomass change from 2018 to 2024 for different administrative areas. (Map data from OpenStreetMap.)

6.2 Mountain Forest Regions

315 Mountain forests occupy a vital position in the Alps, with about half of the area covered by forests. These mountain forests play a crucial protective function. According to the Bavarian Forest Protection Act, 60% of mountain forests are designated as protective forests to prevent disasters such as avalanches, rock falls, and floods (StMELF, 2026). On the other hand, the mountain forests in Bavaria face severe challenges brought by climate change. With the accelerated rate of temperature rise and the frequent occurrence of extreme weather events, climate change poses a serious threat to mountain forests. Since
 320 the mid-19th century, the average temperature in the Alps has risen by 1.5°C, almost twice the global average temperature



(StMELF, 2016). In addition to climate change, storms, pests, and wild animals living there have also caused serious damage to mountain forests (Triebenbacher et al., 2022; Fröhlich et al., 2012).

In addition to natural factors, in the 19th century, for economic benefits, people planted extensive spruce trees on the hillsides, replacing natural mountain mixed forests (alpha, 2021). Over the centuries, the tree line has shifted downwards in many places, resulting in a significant decline in the deciduous tree population. Today, more than half of the trees in the Alps (almost 60%) are spruce. Almost one-tenth of the shelterbelts (about 14.000 ha) can no longer fulfil their protective function, thus their biodiversity needs to be gradually restored.

Therefore, it is interesting to check the status of the mountainous tree areas over Alps. Here we define the area of interest by the elevation larger than 1000 m. The elevation data was acquired from the Terra Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model (GDEM) Version 3 (ASTGTM)⁴. As shown in Figure 12, in the mountainous region, the total biomass stock is steadily increasing except for a drop in 2021. From 2018 to 2024, the broadleaf tree area increased from 18.54% to 22.38%. The coniferous area dropped from 51.71% to 44.94% in 2020, and increased to 47.23% in 2023. Nevertheless, the results indicate that the forest condition over mountainous regions in Bavaria is recovering, and the forest type is slowly transferring to mixed forests. According to the Bavarian Ministry of Food, Agriculture and Forestry, restoration targets have been achieved to date in almost two-thirds of the restoration areas.

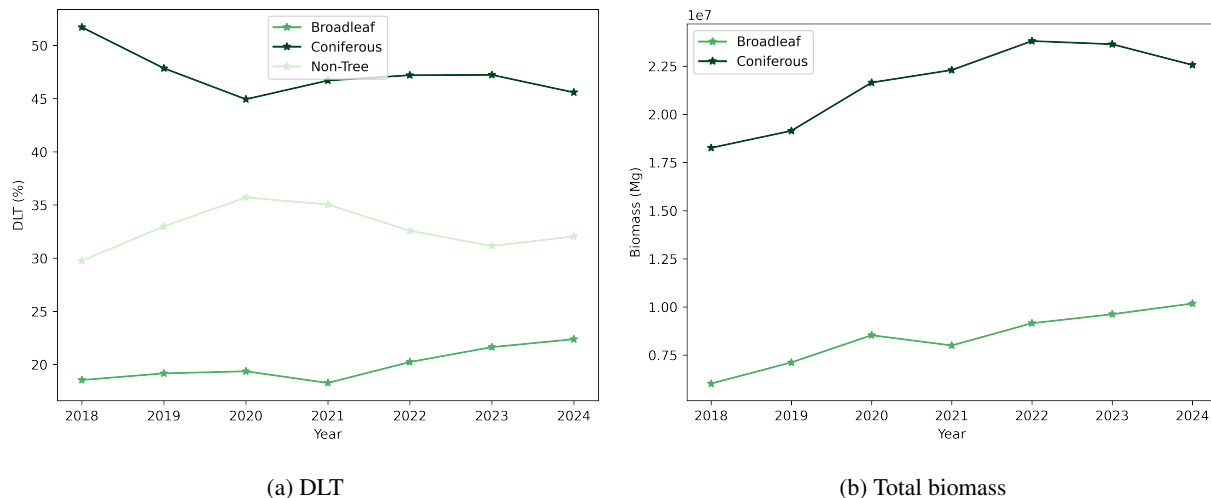


Figure 12. DLT change (a) and total biomass amount (b) over Alps region from 2018-2024.

6.3 Forest Fragmentation

As mentioned above, forests, among Earth’s most biodiverse ecosystems, face severe threats, primarily from deforestation, which leads to substantial habitat loss and fragmentation (Köhler, 2012; Assmann et al., 2020). Fragmentation refers to the spatial division of natural landscapes due to human activities (Roth et al., 2006), endangering species and disrupting ecological

⁴<https://lpdaac.usgs.gov/products/astgtmv003/>



340 processes. Mitigating fragmentation is thus crucial for maintaining healthy forest ecosystems. In Bavaria, many large wildlife
species depend on extensive lowland and Alpine forests and require interconnected habitats - often linked by migration corri-
345 dors - due to their extensive daily movements over tens of kilometers. Key threats to these species include habitat fragmentation,
transportation infrastructure, and the disruption of movement corridors (für Umwelt, 2008a). To assess the extent of this issue,
we use two landscape metrics to quantify forest fragmentation across Bavaria: patch density and edge density.

345 The two fragmentation metrics were calculated based on the Python package PyLandStats (Bosch, 2019). Fragmentation of
the whole state and individual administrative regions are presented separately. As shown in Figure 13, the metrics, both patch
and edge density, suggest that the tree areas in Bavaria are becoming more fragmented. Possible reasons are 1) the scattered
forest cover loss which leads to more isolated patches, 2) weak connections between different tree patches that are easily
affected by removing few trees; and 3) the uncertainty of the predicted cover maps introduces unreal fragmentation results.

350 Spatially, the Upper Franconia is identified as a hot region where the fragmentation situation is worse than other administrative
areas. Further analysis of the fragmentation drivers falls out of the scope of this paper. In the future, detailed study will be
conducted to dive into the reasons behind and provide practical suggestions for policy makers. On the other hand, the tree areas
have relatively regular patch shapes, and the mean shape index are similar for different years and different regions.

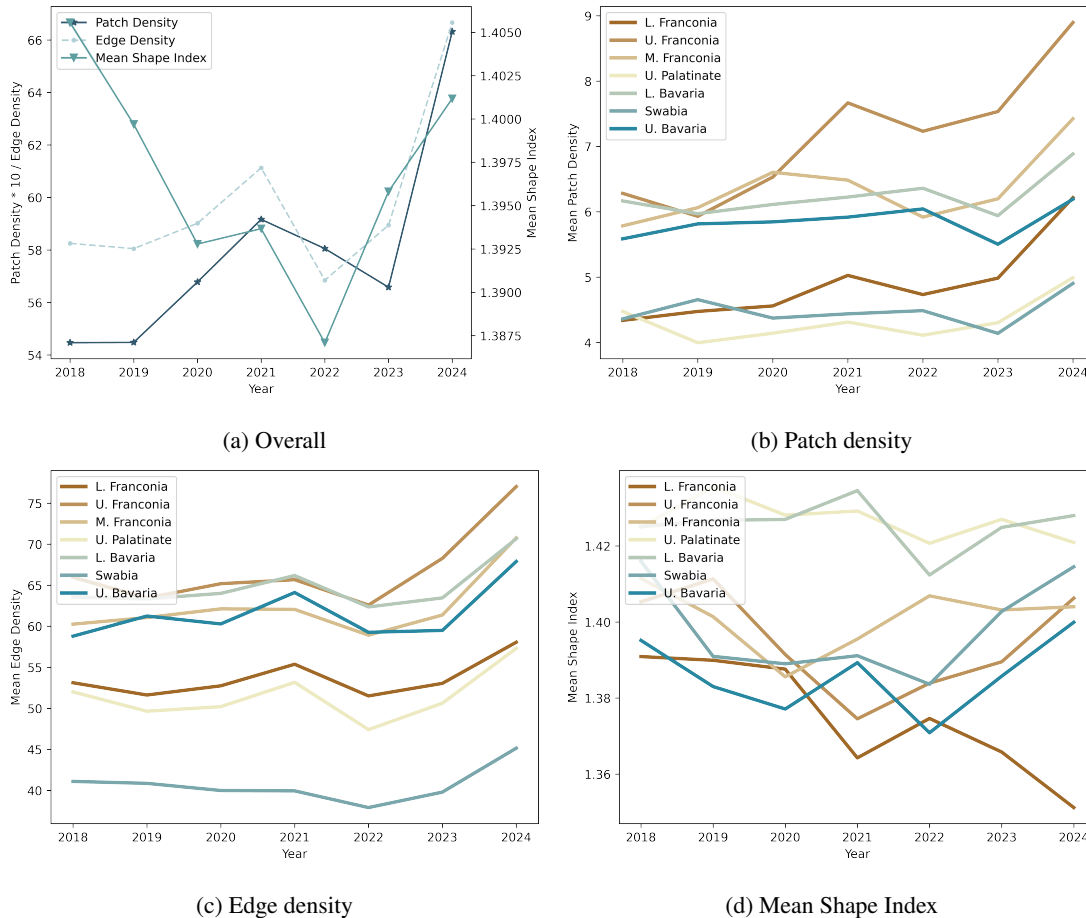


Figure 13. Changes of the state-level (a) and administrative region level (b-d) landscape metrics from 2018 to 2024. The figure shows a clear fragmentation trend, especially after 2022.

In addition, we discovered that the fragmentation metrics could vary a lot in terms of the calculation strategy it used. The boundaries of tree areas are in general more unstable, thus have a big impact on the results. For example, when the edge part of the tree areas are removed with a erosion operator by 100 pixels, as to exclude the patchy areas and edges, the patch and edge density will significantly decrease. Besides, as shown in Figure 14, the fragmentation degree drops in 2021 and increase again in 2022, instead of a peak in 2021 in Figure 13. And in this case, Upper Bavaria is the most patchy region regarding the center parts of the tree areas, while edge effects are distinct for Lower Franconia. However, a noticeable subsidence in tree area fragmentation in Swabia are observed in both cases. This suggests that the stakeholders should select the evaluation criteria carefully when assessing the effect of forest related public policies.

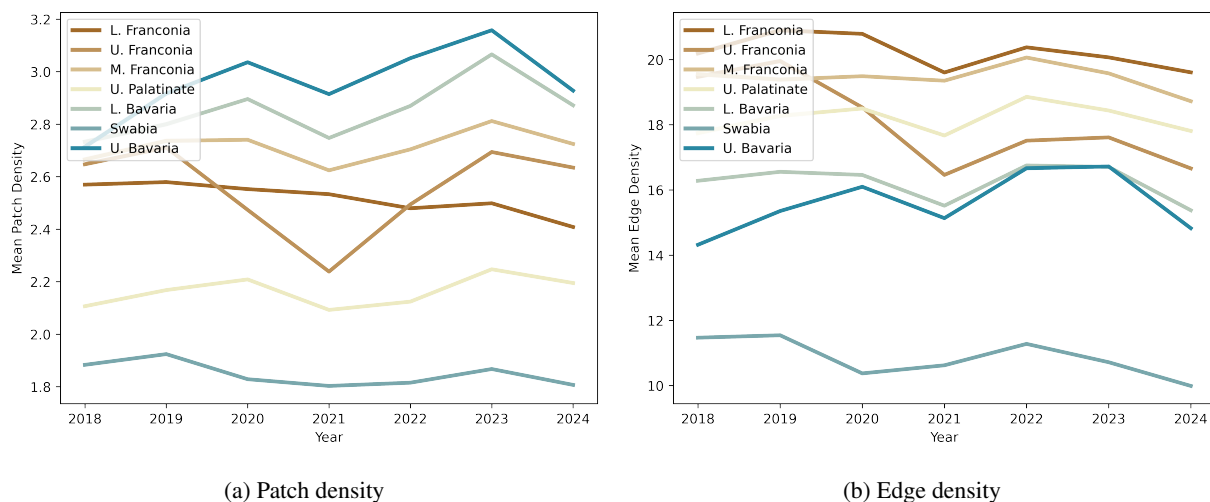


Figure 14. Changes of the patch (a) and edge density (b) of different administrative regions from 2018 to 2022 after the erosion operation applied to the tree area map.

6.4 Uncertainty Sources

Germany conducts national forest inventory (NFI) every 10 years (1987, 2002, 2012, and 2022) to census the forest variables, e.g. forest area, growing stock, age, species, etc (Kleinn et al., 2020). However, NFI data need labor-extensive field survey, and therefore are expensive and time-consuming to collect. Remote sensing data, on the other hand, are accessible with a high revisit frequency. Take Sentinel-2 for example, the revisit time is 5 days for most regions. Therefore, it can serve as a tool to evaluate the results of public policies independently, timely and quantitatively. However, it should be noted that there are certain extend of uncertainties in remote sensing data as well as analysis methods that will affect the results. We want to draw the stakeholders' attention with a few known uncertainty factors that might influence the conclusions.

1. Imperfect model: The current forest cover mapping and biomass estimation models are imperfect. In our case, the DLT classification task achieved 92% accuracy, while biomass estimation task is worse ($R^2 = 0.62$). Well, the performances of different models are different among the scale, methods, and specific task (e.g. number of forest cover types). We identify three groups of uncertainties that contribute to model imperfection: data uncertainty, model uncertainty and applicable conditions. Data uncertainty refers to the noise, missing data including cloud coverage, and the resolution limit of the remote sensing data used. These factors hinder the model from extracting useful features for the specific task. Depending on the specific tasks and algorithms, the models used can affect the performance a lot, which is known as model uncertainty (Wang et al., 2024). Besides, usually the trained models are applicable only at a certain spatial and temporal scale. In our case, the model is trained with single-year reference data (2018 and 2019), which introduces additional uncertainty for long-term mapping.



- 380 2. Forest definition: The definition of forest and deforestation can have a significant impact on the forest status report (Zalles et al., 2024). In this paper, our study contributes to trees covered area because of the reference data we have. However, forest is defined, by the Food and Agriculture Organization (FAO) for example, as an area where at least 10% tree canopy cover taller than 5 m within the 0.5 ha unit (Zalles et al., 2024). The governmental documents, e.g. national forest inventory, often included only forests status in the report. Therefore, our reported occupation of coniferous and broadleaved area should be overestimated in general. Nevertheless, based on our analysis, around 37.35% of the Bavaria state is covered by trees, which is close to the reported forest ratio of 37% in NFI report. In addition, the fragmentation degree can also vary a lot as suggested by our study.
- 385
3. Model validation: A validation set is essential to evaluate how trustworthy the algorithm or model is. The validation strategies applied in the existing researches can be divided into three groups: without validation set, with semi-independent and independent validation. Ideally, a fully independent, complete and high-quality validation set is preferred, yet costly. In our case, the validation set comes from the same source as, but spatially distributed differently from the training data. We cast it into semi-independent validation. As a complementary, we applied a post-processing step to clean the results based on the common knowledge. Nevertheless, the evaluation scores reported in this study contain certain degree of uncertainty. In the future, using independent forest cover labels such as NFI data to validate the results is suggested.
- 390
- 395

7 Conclusion

In this paper, deep learning-based models were developed to derive annual dominant leaf type and biomass maps from Sentinel-2 images for Bavaria, Germany, to support policy making. Then annual DLT and biomass density change maps for 2018 to 2024 are derived, where a result cleaning step is applied to ensure robustness when calculating canopy loss. The results reveal that from 2018 to 2024, the tree cover in Bavaria increased by 0.44% of the total tree area. Broadleaved area increased by 1.94%, while coniferous area decreased by 1.49%. Nevertheless, the results also show that the tree area is increasingly fragmented. Spatially, the Upper Franconia is the most dynamic administrative regions. The biomass density time series suggests that the carbon loss mainly comes from forest degradation without tree cover loss, which indicates that the impact of logging activities is acceptable. In addition, a close look at the mountainous regions in Bavaria (elevation larger than 1000 m) reveals that both the tree cover ratio and total biomass amount are steadily increasing. Our conclusions agree with existing studies, including public and national forest inventory reports. Finally, we summarized the possible sources of uncertainties of the results to alert the stakeholders about the potential biases of the remote sensing techniques.

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Our findings indicate that forests in Bavaria are undergoing a gradual transition to mixed forest compositions, accompanied by a notable increase in carbon stock. To better integrate remote sensing in forestry and to improve forest conditions, we note the following points need to be considered by policy-makers:

410

1. Leverage remote sensing as a valuable tool for informed decision-making, while recognizing that its relevance may vary across different policies.



2. Acknowledge that the accuracy of remote sensing data can differ significantly, depending on the specific application and evaluation strategies employed.
- 415 3. Implement policies to reduce forest degradation.
4. Take the spatial differences in forest types and biomass density changes into consideration.
5. Monitor and respond to increasing forest fragmentation, with further investigation needed to understand its underlying causes and spatial patterns.

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Author Contributions

- Conceptualization, Xiaoshan Ni; Methodology, Qian Song and Xiaoshan Ni; Software, Qian Song; Validation, Qian Song and Xiaoshan Ni; Formal Analysis, Qian Song and Xiaoshan Ni; Data Curation, Qian Song and Xiaoshan Ni; Writing – Original
425 Draft Preparation, Qian Song and Xiaoshan Ni; Writing – Review and Editing, Qian Song and Xiaoshan Ni; Visualization, Qian Song.

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Conflicts of Interest

- 430 The authors declare that there is no conflict of interest regarding the publication of this article.

Data Availability

- The Sentinel-2 data can be downloaded from Sentinel-2 from Copernicus Data Space Ecosystem at <https://dataspace.copernicus.eu/explore-data/data-collections/sentinel-data/sentinel-2>. The reference DLT map is accessible at Copernicus Land Monitoring Service. The reference biomass map can be downloaded from <https://data.ceda.ac.uk/neodc/esacci/biomass/data/agb/maps/v5.01/geotiff/2019>. The derived annual DLT and biomass maps, as well as the code can be shared upon request via email.
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