Forest Policy Report SFI/2024

Analysis of temporal changes (2019-2023) of structural forest attributes using series of RS-Inventories in Ukraine

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About the Project “Sustainable Forestry Implementation” (SFI)

The project “Technical Support to Forest Policy Development and National Forest Inventory Implementation” (SFI) is a project established in the framework of the Bilateral Cooperation Program (BCP) of the Federal Ministry of Food and Agriculture of Germany (BMEL) with the Ministry of Environment and Natural Resources of Ukraine (MENR). It is a continuation of activities started in the forest sector within the German-Ukrainian Agriculture Policy Dialogue (APD) forestry component.

The Project is implemented based on an agreement between GFA Group, the general authorized executor of BMEL, and the State Forest Resources Agency of Ukraine (SFRA) since October 2021. On behalf of GFA Group, the executing agencies - Unique land use GmbH and IAK Agrar Consulting GmbH - are in charge of the implementation jointly with SFRA.

The project aims to support sustainable forest management planning in Ukraine and has a working focus on the results in the Forest Policy and National Forest Inventory.

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Disclaimer

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LIST OF ABBREVIATIONS

ALS	Airborne Laser Scanning
BA	Basal Area
CCDC	Continuous Change Detection and Classification
CI	Confidence Interval
DBH	Diameter at Breast Height
FMP	Forest Management and Planning
FNF	Forest/non-forest
GEE	Google Earth Engine
GNN	Gradient Nearest neighbor
GSV	Growing Stock Volume
HT	Height
LB	Live Biomass
LOO	Leave-One-Out
MAR	Model Assisted Regression
NFI	National Forest Inventory
RF	Random Forest
RS	Remote Sensing

SUMMARY

The RS inventory provided a strong scientific background for the assessment of forest resources in Ukraine using limited field observation data and RS technologies (Weinreich et al., 2023). This study aimed at retrospective analysis of key forest attributes using the developed approach harnessing Sentinel 2 time series and advanced methods of image processing presented in the RS-Inventory report for 2023 (Myroniuk et al., 2023). The RS-Inventory is based on the latest advances in the combined use of field observations and satellite data, which has proven to be an effective approach both for mapping and forest assessment at different levels of spatial detail. This approach was presented in the SFI project as an alternative to the regular NFI in Ukraine at the national scale (Myroniuk et al., 2024). In this study, the advantages of RS inventory are used for retrospective analysis of forest characteristics in Ukraine for the period 2019-2023.

The study is based on the same methodological framework used in the 2023 RS-Inventory. As a result, it provided forest maps and forest attribute information for 2019, which was linked to the previously obtained information for 2023. This created a framework for analysis of forest changes in Ukraine between 2019 and 2023. The obtained results showed great potential of using satellite time series and field observations collected within the NFI program to provide spatially explicit estimates of forest attributes over time, and to monitor their changes at a fine spatial scale (20-m pixel level). Thus, the study provided a basis for long-term forest monitoring in Ukraine with limited resources.

Maps and estimates of forest attribute dynamics showed that the most significant changes in 2019-2023 were associated with the war-affected areas, while net forest changes across Ukraine did not reveal significant changes. Nevertheless, the proposed approach is a valuable tool for monitoring forest dynamics across Ukraine, including areas not inaccessible for field data collection. The study also suggests that further steps are needed to increase the accuracy of the approach, which may include the incorporation of more advanced image acquisition technologies.

1. RETROSPECTIVE ANALYSIS OF FOREST ATTRIBUTES

1.1. Integration of NFI data and Sentinel 2 time series

The integration of satellite imagery into the NFI is an important step towards filling information gaps in the assessment of Ukraine's forest resources. In addition to the large area coverage, time series of satellite observations are important for monitoring forest cover change over time and for retrospective analysis of forest characteristics. The RS-Inventory of 2023 (Myroniuk et al., 2023, 2024) integrated the latest advances in satellite time series processing, thus created a strong background for the use of the developed models in a wider time range. Figure 1 illustrates the principle of integrating NFI plots data collected in 2021-2023 with satellite time series. Accordingly, the RS Inventory was based on Sentinel 2 imagery which were available in good quality throughout Ukraine since 2017. Since individual observations may show different levels of impacts of atmospheric conditions (i.e., cloudiness, aerosols, etc.), the images were screened from clouds, cloud shadows, and snow. The obtained image collections were temporally “smoothed” using one of the most popular image segmentation algorithms, namely the CCCD – Continuous Change Detection and Classification (Zhu & Woodcock, 2014). A detailed description of the algorithm as well as its advantages and limitations can be found in many published papers (Pasquarella et al., 2022; Zhu, 2017).

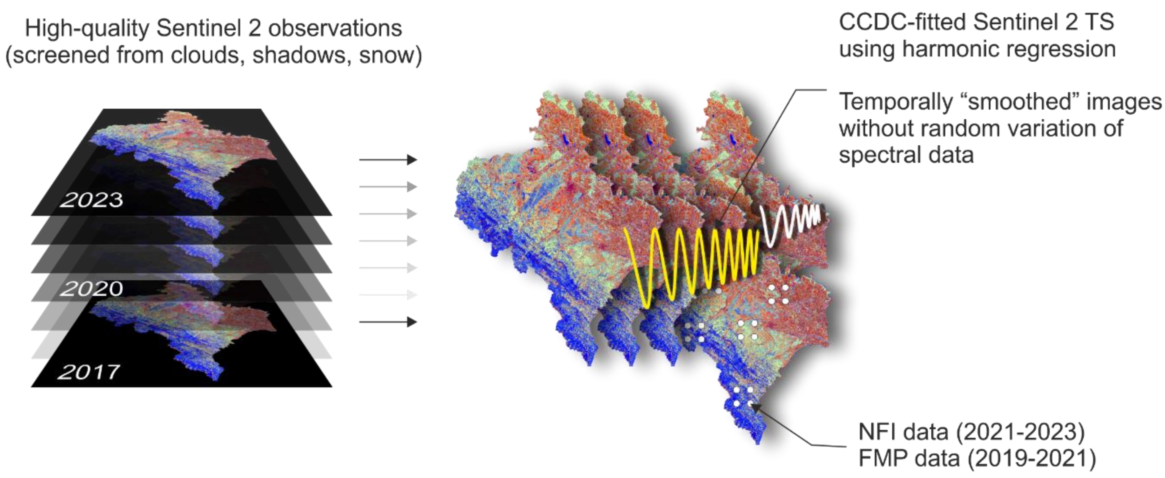


Figure 1. Principles of integration of field observations and satellite time series.

One of the most important elements of the RS-Inventory was to ensure not only an accurate match between plot locations and satellite pixels, but also between the dates of the reference field observations and Sentinel 2 images. The NFI data were collected in 2021-2023, while the forest management planning (FMP) data were available even more earlier since 2019 (in 2014 for occupied Crimea and breakaway territories in Luhansk and Donetsk oblasts). Accordingly, the plot that was forested in 2019 was not necessarily forested in the later years. Therefore, we trained models using the exact correspondence between the year of data collection both in the field and remotely. The developed models were then applied to all CCDC-fitted time series.

Unlike an alternative approach that uses a single-date median composite mosaics, the proposed approach was also designed to produce temporally consistent results over time. For example, the CCDC algorithm eliminated random variations in the spectral data of individual pixels from the observed spectral profiles that could correspond to stable forest cover, forest regrowth, or forest decline. This was achieved through a series of harmonic models developed at the 20-m Sentinel 2 pixel-level that captured a cyclical pattern of annual and inter-annual land cover change. Additionally, an abrupt inclination of large magnitude from the spectral profile, typically associated with land cover change, were identified as break points of temporal segments. Thus, temporal changes in the spectral data for each pixel were captured using a sequence of harmonic models connected in break points. The final image for a given date was produced using these models, allowing a more consistent prediction over time than that obtained with the original observations.

1.2. Mapping forest cover and forest attributes for 2019

Forest characteristics for 2019 were obtained using the same input data sets of remotely sensed imagery and field observations used for 2023 RS-Inventory of 2023. The reference observations for mapping included:

- NFI plots (2,634 circular 500-m^2 plots were used out of 4,100 inspected in 2021-2023)
- FMP reference polygons (700 manually delineated rectangular polygons of 100-800 m^2 in “typical” locations)
- Visually interpreted data at the NFI plot locations (19,370 plot locations for the 2023 NFI panel).

The detailed description of the collected reference observations is described in detail in the report on RS-Inventory of 2023 (Myroniuk et al., 2023) and in the peer-reviewed paper by Myroniuk et al. (2024).

The mapping approach was fully integrated into the Google Earth Engine (GEE) environment which significantly improved the performance of the developed classification and prediction models. The workflow included a set of algorithms designed to extract forest maps, classify dominant species, and impute (predict) forest attributes.

1.2.1. Forest cover

Mapping forest cover was the first and very important step of the analysis, as all forest characteristics were predicted within the forest mask. Similar to 2023, the forest cover was mapped using a Random Forest (RF) classifier (Breiman, 2001). As predictor variables, the RF utilized synthetic values of spectral bands (brightness, greenness, wetness components of the TCT, and NBR) predicted for the beginning (April 15), middle (June 15), and end (October 15) of a leaf-on period. The results obtained for 2023 showed that the accuracy of the forest/non-forest maps can be increased if the model additionally incorporates outputs of the CCDC models. Therefore, we supplemented the spectral data with the coefficients of the CCDC harmonic models and some other variables that were extracted from the models (phase, amplitude, density observation).

The large volume of RS information required significant amount of computation resources. To accelerate classification, the Ukraine was divided into 0.5 × 1-degree tiles which were classified successively using the same classification model. The obtained classification was seamlessly mosaiced producing wall-to-wall forest map of Ukraine at 20-m spatial resolution (Figure 2).

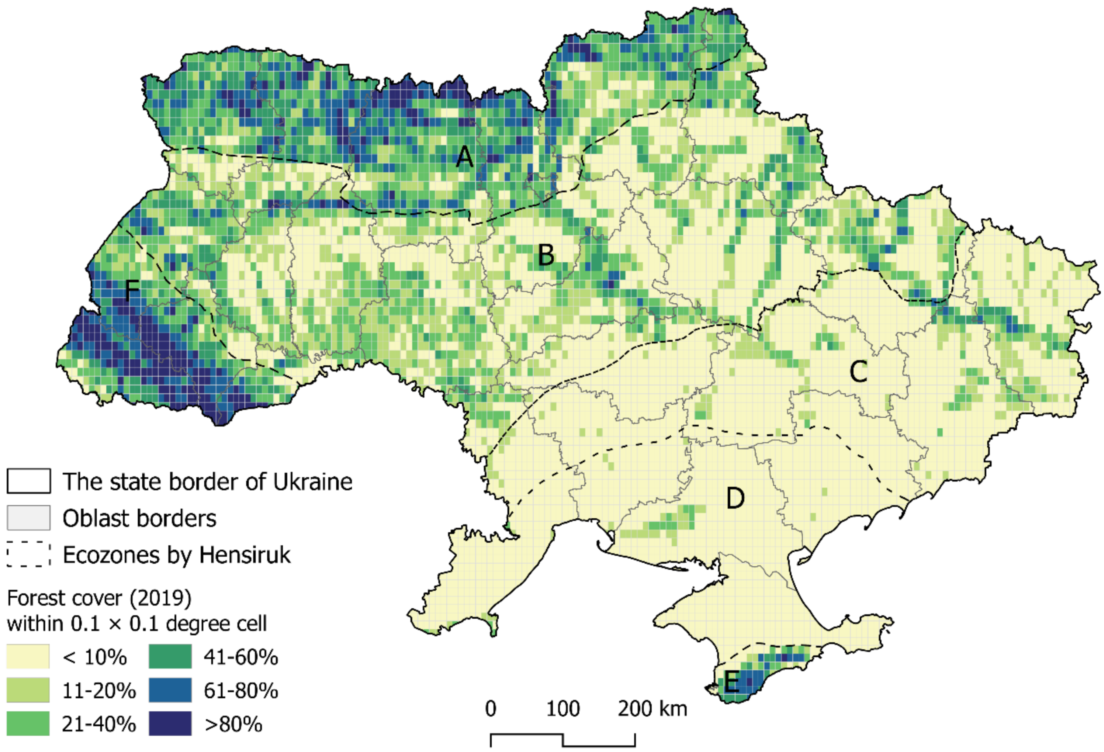


Figure 2. Forest cover estimates for 2019 within 0.1 × 0.1-degree grid: A – Polissia; B – Forest steppe; C – Northern steppe; D – Southern steppe; E – Crimean Mountains; F – Carpathians.

1.2.2. Dominant tree species

Dominant species for reference data (i.e., NFI plots and FMP training polygons) were identified as those with the highest basal area (BA) proportion. Approximately 50% of all plots represented "pure" (or monoculture) stands, i.e., where at least 80% of the overstory's BA consisted of a single species (Bravo-Oviedo et al., 2014). The highest proportion of monocultures (60%) was observed within the Polissia, while mixed-species forests were predominantly located in the Crimean Mountains (only 25% of sample plots represented "pure" stands). This study separated only the most important commercial species, while others have been grouped according to their typical habitat and environmental niches: 1) pine; 2) spruce and fir; 3) oak; 4) beech; 5) deciduous species with high life expectancy (maple, ash, linden, etc.); 6) deciduous species with low life expectancy (birch, alder, poplar, willow); 7) hornbeam. The principles for grouping tree species were fully consistent with the work done for 2023 (Myroniuk et al., 2023).

The developed forest map was used to mask CCDC-fitted time series so that the dominant species map was obtained within the forest cover of 2019. The dominant species map also had the 20-m spatial resolution (Figure 3).

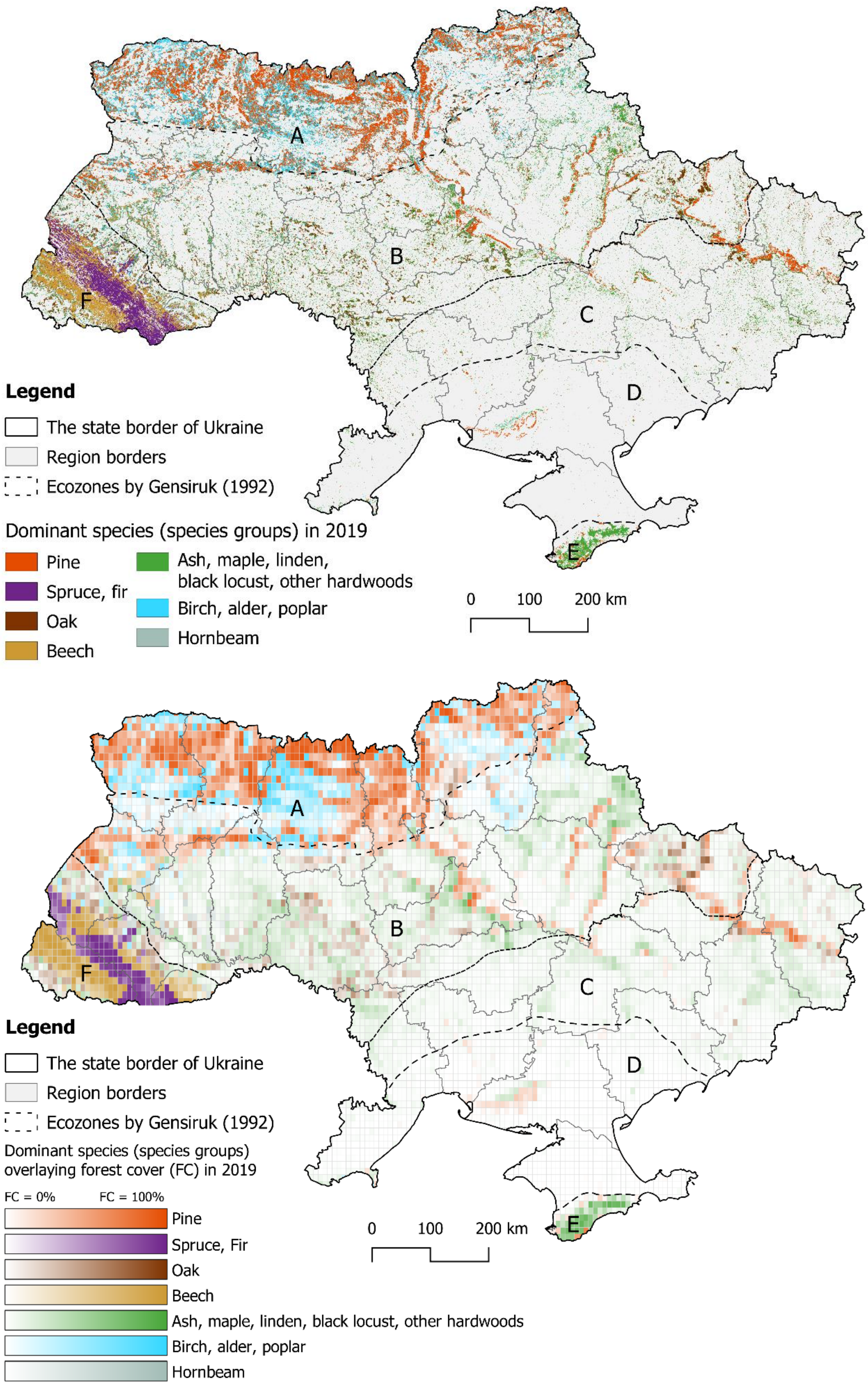


Figure 3. Dominant tree species 2019: A – Polissia; B – Forest steppe; C – Northern steppe; D – Southern steppe; E – Crimean Mountains; F – Carpathians. Top panel represents pixel-level distribution, bottom panel provides estimates for 0.1 × 0.1-degree grid along with mapped forest cover (FC).

Overlaying the dominant species within the regular grid provided somewhat better insight into their distribution at the landscape level and their contribution to the total forest area. Figure 3 shows that pine in the north and spruce, fir and beech in the west contribute most to the area of massive forests in Ukraine. Other tree species form a more patchy and fragmented forest mosaic across Ukraine.

1.2.3. Forest attributes

The following list of forest attributes were mapped in the RS Inventory of 2019:

- Basal area (BA)
- Growing stock volume (GSV)
- Quadratic mean diameter at breast height (DBH)
- Average height (HT)
- Mean age (Age)
- Live biomass (LB)
- Accumulated carbon in LB
- CO_2-equivalent of the accumulated carbon in LB.

Unlike forest and dominant species, which are categorical variables, forest attributes are continuous variables. They were predicted using imputation approach. This study used the gradient nearest neighbor (GNN) imputation, which has been well established in many previous studies in the US (Ohmann & Gregory, 2002; Wilson et al., 2012). GNN imputation has also been successfully implemented in regional (Myroniuk, Bell, et al., 2022) and nationwide (Myroniuk et al., 2024) studies in Ukraine. Nearest neighbor imputation has many advantages in NFI applications due to its ability to simultaneously predict a set of forest variables (Eskelson et al., 2009; Henderson et al., 2014). Thus, predictions can maintain realistic combinations of forest attributes in individual forest stands that may occur in real situations

Forest attributes for 2019 were predicted using a workflow implemented in the GEE environment that fully exploits the computational efficiency of the cloud-based technology and Sentinel 2 time series (Myroniuk et al., 2023). The GNN model was developed using CCDC-fitted spectral variables and reference observations obtained at sample plot locations and FMP training polygons. In general, forest attributes were predicted using the GNN model developed in the previous 2023 study (Myroniuk et al., 2023). Thus, many details of the mapping approach are available from the published report for 2023 and in the referenced peer-reviewed paper.

All forest attributes were predicted at 20-m spatial resolution within the forest map of 2019.

1.3. Statistical estimates for 2019

Estimates of forest attributes were calculated within the boundaries of 1) all of Ukraine, 2) Gensiruk's ecozones (Gensiruk, 1992), war-affected areas, and within unaffected areas. In addition, the forest area was estimated for individual administrative oblasts of Ukraine. The selection of spatial areas for which forest attributes were provided depended on available reference data used to test model performance. Since the forest map was produced using visually interpreted data at nearly 20 thousand plot locations, the amount of reference information was sufficient to obtain accuracy estimates for individual oblasts. For maps produced using field observations, statistical estimates of uncertainties could be calculated only for larger areas (i.e., ecozones, all of Ukraine).

Statistical estimation of uncertainties was based on recommendations for assessing the accuracy of categorical maps (Olofsson et al., 2014) using independent observations. In our case, we used the leave-one-out (LOO) approach to calculate the proportion of inaccurately classified observations for the forest and dominant species map using confusion matrices. In the case of nearest neighbor imputation, we used a modified version of the LOO approach using the first k = 7 independent neighbors (Ohmann & Gregory, 2002).

A specific feature of the accuracy estimation was that we applied the same classification and imputation models for both 2019 and 2023 using temporally smoothed Sentinel 2 time series. Thus, we assumed that the model performance was the same for both time periods. Therefore, the 95% confidence intervals (CI) were the same for continuous variables because of the nature of the model-assisted regression (MAR) estimator which is based only on deviations between actual and predicted observations for reference data. In terms of area estimates and associated total attribute values, the CI differs from those obtained for 2023 because the area estimator utilized map class area to obtain standard errors. A more detailed description of the estimation procedures are provided in the 2023 SFI report (Myroniuk et al., 2023) and in peer-reviewed papers by Olofsson et al. (2014) for area estimates and by McConville et al. (2020) for estimates of continuous NFI variables.

Forests covered 11.1 million ha (±1.4%) in 2019. About 65% of the total forest area was dominated by deciduous tree species. Pine occupied more than 80% of all coniferous forests. The mean age of all forests in Ukraine was 58 years (±1.6%) and was characterized by 250 $m^3 \cdot ha^{-1}$ (±2.0%). In 2019, the total growing volume was estimated to be about 2.78 billion m^3 which corresponds to 926 million tons of carbon. The obtained mean values of the main forest attributes are provided in Table 1, while their total values for all Ukraine are given in Table 2.

Table 1. The RS-Inventory estimates of forested area and mean values of forest attributes in Ukraine for 2019.

Groups2	Estimate	Area (ha)	Age (years)	DBH (cm)	HT (m)	BA ($m^2 \cdot ha^{-1}$)	GSV ($m^3 \cdot ha^{-1}$)	Density ($n \cdot ha^{-1}$)	LB ($t \cdot ha^{-1}$)	Carbon ($t \cdot ha^{-1}$)	CO_2-equiv. ($t \cdot ha^{-1}$)
All species	Map-based values	11344755	59.6	28.4	20.5	25.5	262.8	487.3	186.0	87.4	320.5
All species	Adjusted values	11109349	57.5	27.7	20.0	24.7	250.3	530.5	177.3	83.3	305.5
All species	*95% SE of adjusted values*	1.4%	1.6%	1.4%	1.0%	1.6%	2.0%	7.0%	2.1%	2.2%	2.1%
All coniferous	Map-based values	3907659	61.9	30.0	21.8	29.7	320.7	519.6	187.9	88.3	323.7
All coniferous	Adjusted values	3903509	60.0	29.7	21.3	29.0	306.2	551.1	173.1	81.4	298.3
All coniferous	*95% SE of adjusted values*	2.2%	2.3%	2.0%	1.9%	2.1%	2.9%	9.9%	3.1%	3.1%	3.1%
All deciduous	Map-based values	7437096	58.4	27.6	19.9	23.2	232.4	470.4	185.0	87.0	318.8
All deciduous	Adjusted values	7205839	56.2	26.7	19.3	22.4	220.0	519.4	179.5	84.4	309.4
All deciduous	*95% SE of adjusted values*	1.2%	2.0%	1.9%	1.6%	1.8%	2.6%	9.5%	2.8%	2.8%	2.8%
Pine	Map-based values	3173794	60.3	29.4	21.4	27.6	292.1	513.7	171.5	80.6	295.5
Pine	Adjusted values	3171119	58.8	29.2	21.0	26.9	279.3	532.0	159.9	75.1	275.5
Pine	*95% SE of adjusted values*	2.8%	2.5%	2.1%	2.4%	2.6%	3.4%	11.4%	3.6%	3.6%	3.6%
Spruce, fir	Map-based values	733865	68.7	32.5	23.7	38.9	444.7	545.5	258.8	121.6	445.9
Spruce, fir	Adjusted values	732390	64.9	31.5	22.8	37.8	422.7	634.0	230.4	108.3	397.0
Spruce, fir	*95% SE of adjusted values*	6.0%	4.9%	3.8%	3.5%	4.0%	5.1%	18.8%	5.2%	5.2%	5.2%
Oak	Map-based values	1389628	65.2	29.8	21.2	23.6	246.9	398.5	200.2	94.1	345.0
Oak	Adjusted values	1573668	73.5	32.8	21.8	24.1	259.6	249.4	219.9	103.3	378.9
Oak	*95% SE of adjusted values*	7.1%	3.1%	3.1%	2.3%	3.3%	3.9%	22.1%	4.1%	4.1%	4.1%
Beech	Map-based values	948523	68.3	32.7	22.7	31.8	346.9	440.3	307.3	144.4	529.6
Beech	Adjusted values	762652	74.5	36.0	24.6	32.9	367.3	257.1	351.1	165.0	605.1
Beech	*95% SE of adjusted values*	7.9%	4.6%	4.2%	4.1%	4.9%	6.2%	47.0%	6.1%	6.1%	6.1%
Ash, linden, maple, black locust	Map-based values	2553259	57.1	25.7	17.9	20.9	194.1	504.5	154.0	72.4	265.3
Ash, linden, maple, black locust	Adjusted values	2279034	51.2	23.1	16.6	20.1	178.7	659.2	146.7	68.9	252.8
Ash, linden, maple, black locust	*95% SE of adjusted values*	4.9%	4.1%	4.3%	3.0%	4.0%	5.2%	15.3%	5.9%	5.9%	5.9%
Birch, alder, poplar	Map-based values	2216833	51.8	26.1	19.8	21.4	212.3	489.3	152.6	71.7	263.0
Birch, alder, poplar	Adjusted values	2091277	43.2	23.5	18.4	19.4	177.7	654.1	115.3	54.2	198.7
Birch, alder, poplar	*95% SE of adjusted values*	6.1%	4.9%	4.7%	3.3%	4.6%	6.7%	19.5%	7.6%	7.7%	7.6%
Hornbeam	Map-based values	328853	56.2	28.6	21.7	26.1	273.8	468.0	227.4	106.9	392.0
Hornbeam	Adjusted values	499208	51.2	23.7	18.8	24.7	236.7	568.5	209.5	98.5	361.0
Hornbeam	*95% SE of adjusted values*	14.3%	6.8%	8.0%	6.4%	6.5%	8.7%	22.5%	9.3%	9.2%	9.3%

Table 2. The RS-Inventory estimates of forested area and total values of forest attributes in Ukraine for 2019.

Groups2	Estimate	Area (ha)	GSV (mln m³)	Density (mln)	LB (mln t)	Carbon (mln t)	CO_2-equiv. (mln t)
All species	Map-based values	11344755	2981,86	5528,75	2110,05	991,73	3636,33
All species	Adjusted values	11109349	2781,01	5893,84	1969,51	925,71	3394,01
All species	*95% SE of adjusted values*	1.4%	2,0%	7,0%	2,1%	2,2%	2,1%
All coniferous	Map-based values	3907659	1253,35	2030,56	734,05	345,01	1265,02
All coniferous	Adjusted values	3903509	1195,38	2151,28	675,72	317,61	1164,44
All coniferous	*95% SE of adjusted values*	2.2%	2,9%	9,9%	3,1%	3,1%	3,1%
All deciduous	Map-based values	7437096	1728,51	3498,20	1376,00	646,72	2371,31
All deciduous	Adjusted values	7205839	1585,63	3742,56	1293,78	608,10	2229,57
All deciduous	*95% SE of adjusted values*	1.2%	2,6%	9,5%	2,8%	2,8%	2,8%
Pine	Map-based values	3173794	927,02	1630,22	544,16	255,75	937,76
Pine	Adjusted values	3171119	885,80	1686,98	507,00	238,31	873,69
Pine	*95% SE of adjusted values*	2.8%	3,4%	11,4%	3,6%	3,6%	3,6%
Spruce, fir	Map-based values	733865	326,33	400,34	189,90	89,25	327,26
Spruce, fir	Adjusted values	732390	309,58	464,30	168,72	79,30	290,75
Spruce, fir	*95% SE of adjusted values*	6.0%	5,1%	18,8%	5,2%	5,2%	5,2%
Oak	Map-based values	1389628	343,13	553,80	278,22	130,77	479,47
Oak	Adjusted values	1573668	408,51	392,48	345,97	162,61	596,19
Oak	*95% SE of adjusted values*	7.1%	3,9%	22,1%	4,1%	4,1%	4,1%
Beech	Map-based values	948523	329,08	417,65	291,52	137,01	502,38
Beech	Adjusted values	762652	280,10	196,08	267,78	125,86	461,46
Beech	*95% SE of adjusted values*	7.9%	6,2%	47,0%	6,1%	6,1%	6,1%
Ash, linden, maple, black locust	Map-based values	2553259	495,59	1288,20	393,11	184,76	677,46
Ash, linden, maple, black locust	Adjusted values	2279034	407,24	1502,32	334,30	157,12	576,11
Ash, linden, maple, black locust	*95% SE of adjusted values*	4.9%	5,2%	15,3%	5,9%	5,9%	5,9%
Birch, alder, poplar	Map-based values	2216833	470,67	1084,62	338,35	159,03	583,10
Birch, alder, poplar	Adjusted values	2091277	371,62	1367,87	241,15	113,34	415,57
Birch, alder, poplar	*95% SE of adjusted values*	6.1%	6,7%	19,5%	7,6%	7,7%	7,6%
Hornbeam	Map-based values	328853	90,04	153,92	74,79	35,15	128,90
Hornbeam	Adjusted values	499208	118,16	283,80	104,58	49,16	180,24
Hornbeam	95% SE of adjusted values	14.3%	8,7%	22,5%	9,3%	9,2%	9,3%

2. ANALYSIS OF FOREST CHANGES

2.1. Spatial patterns of forest changes

Multidate prediction of forest characteristics is important to capture spatial patterns of forest change. Forest dynamics exhibit both positive and negative changes, which may be negligible at large spatial scales because forest losses in certain locations may be offset by forest gains in other locations. Furthermore, identification of forest dynamics for the selected five-year period (2019-2023) at the pixel level is challenging given the accuracy of the models developed. Nevertheless, the identification of hotspots with the most dramatic forest changes provides valuable information for forest management. In this study, changes in forest area and some other important forest attributes were analyzed within a systematic 0.1 × 0.1 degree grid.

This study showed that most of the forest area loss was associated with areas directly or indirectly affected by the war. Similar to previous studies (Matsala et al., 2023, 2024), we detected three hotspots with forest area loss (Figure 4). They are located in the north (the Chornobyl exclusion zone), in the east (Luhansk oblast), and in the south (Kherson oblast). These areas were most affected during the full-scale Russian invasion in 2022. It was also reported in previous studies that a large forested area (more than 30 thousand hectares of forest stands) in the Luhansk region was burned during a large fire in 2020 (Myroniuk, Zibtsev, et al., 2022; Soshenskyi et al., 2022). Similarly, severe forest fires in the Chornobyl exclusion zone in 2020 burned in a total about 60 thousand hectares of forest (Fedoniuk et al., 2021). This area increased somewhat after the fires that started after the Russian invasion in 2022 and then steadily increased due to the lack of a proper fire management. Forest losses in Zhytomyr oblast and in the Carpathians can be explained by harvesting of mature forests and salvage logging in forests after massive dieback of pine stands (bark beetle infestation).

The increase in forest cover in Ukraine has been observed mainly in the northern regions and can be attributed to the abandonment of agricultural fields, which have grown back into forests. Protection of such forests is one of the important steps to increase the forest area in Ukraine.

Identified hotspots of forest loss do not necessarily indicate the large losses in growing volume. Therefore, this study also reports estimated volumes of wood loss due to fires, the war, or logging during regular forest activities (Figure 5). Generally, the spatial pattern of the changes in the total GSV is consistent with the changes in forest area . However, we note the most dramatic negative dynamics in GSV for areas that were affected during the war.

This study demonstrated that remote sensing technologies combined with a limited field observations can help to reveal very valuable information over a large spatial domain with very limited resources. It was also found that local forest changes can be detected even within a relatively narrow five-year interval.

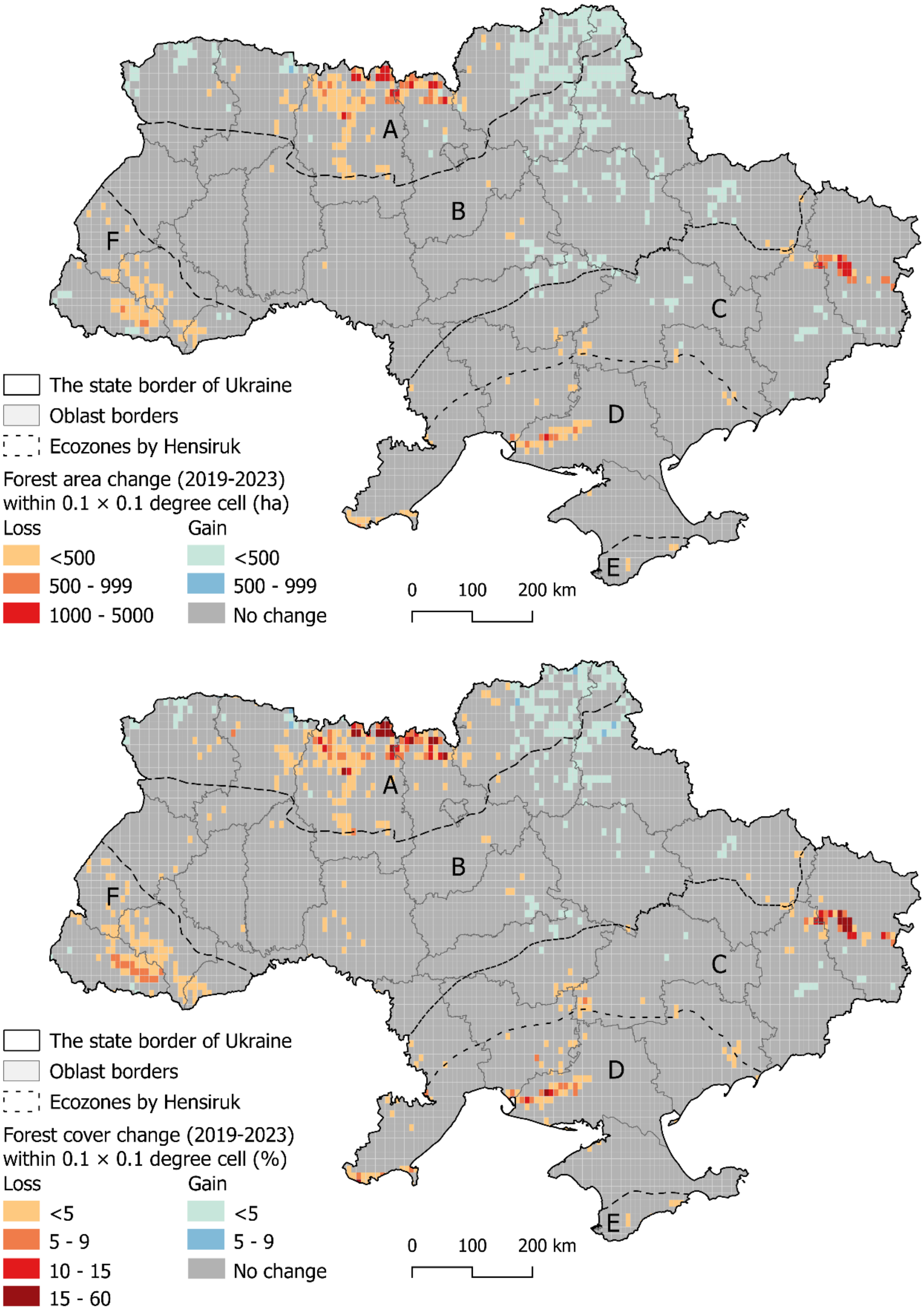


Figure 4. Detecting changes in forest area for 2019-2023. Top panel represents the absolute changes in forest area, while the bottom panel represents the changes in forest cover within the 0.1 × 0.1-degree grid.

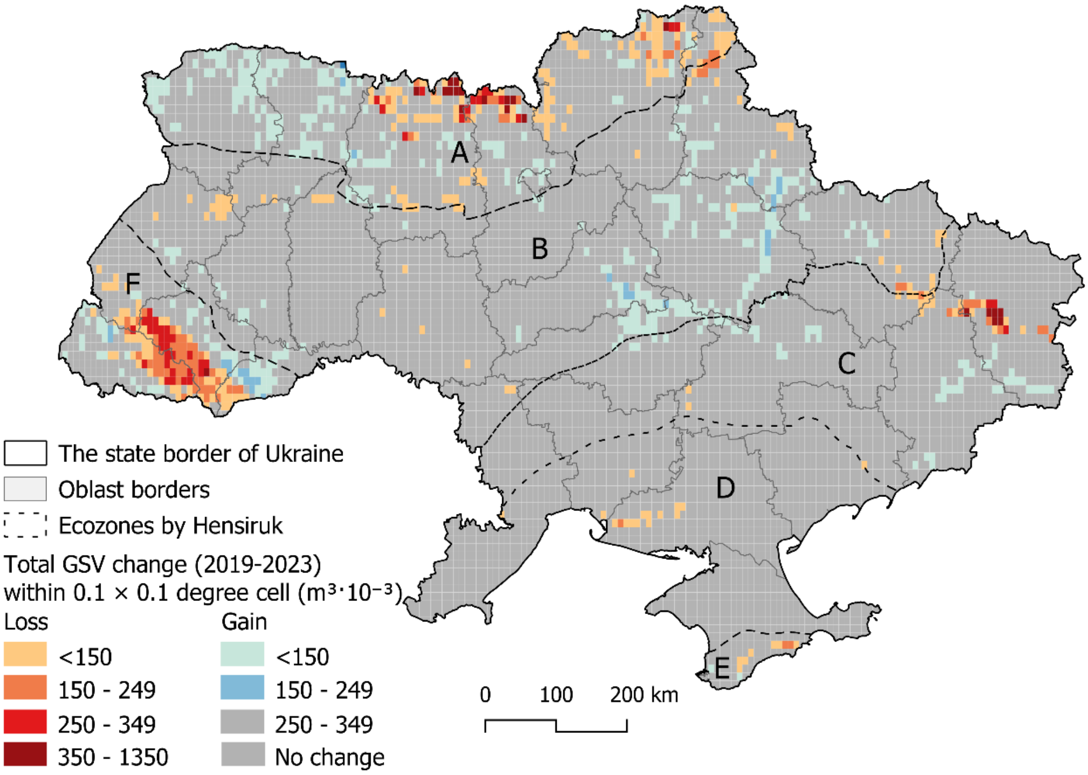


Figure 5. Total GSV change (2019-2023) within the 0.1 × 0.1-degree grid.

2.2. Net forest changes in Ukraine from 2019 to 2023

Forests at the national level did not experience significant changes between 2019 and 2023. The analysis did not reveal any statistically significant changes in forest area or total wood volume at the national level (Figure 6). Interestingly, coniferous forests generally experienced negative dynamics in both total area and GSV, while deciduous forests experienced positive dynamics.

War-related forest losses in the northern and eastern regions affected the reduction in area and GSV of pine forests (Figure 7). The area changes for pine forests were within the 95% confidence intervals of the obtained estimates, while the GSV losses were much more significant. Thus, we obtained almost non-overlapping 95% confidence intervals of total GSV estimates for 2019 and 2023 within the war-affected areas for pine-dominated forest stands. This suggests that war-induced forest damage was more pronounced in older stands, which accumulate larger volumes of wood.

The obtained results made it possible to recognize that there was no statistically proven evidence of significant changes in forest resources in areas that were not affected during the war (Figure 8). This was mainly due to the balance between forest losses and forest gains in different regions of Ukraine. A positive aspect of the forest change analysis is that the mapping approach provided consistent results over time. Thus, the RS-Inventory has provided a strong background for long-term forest monitoring in Ukraine.

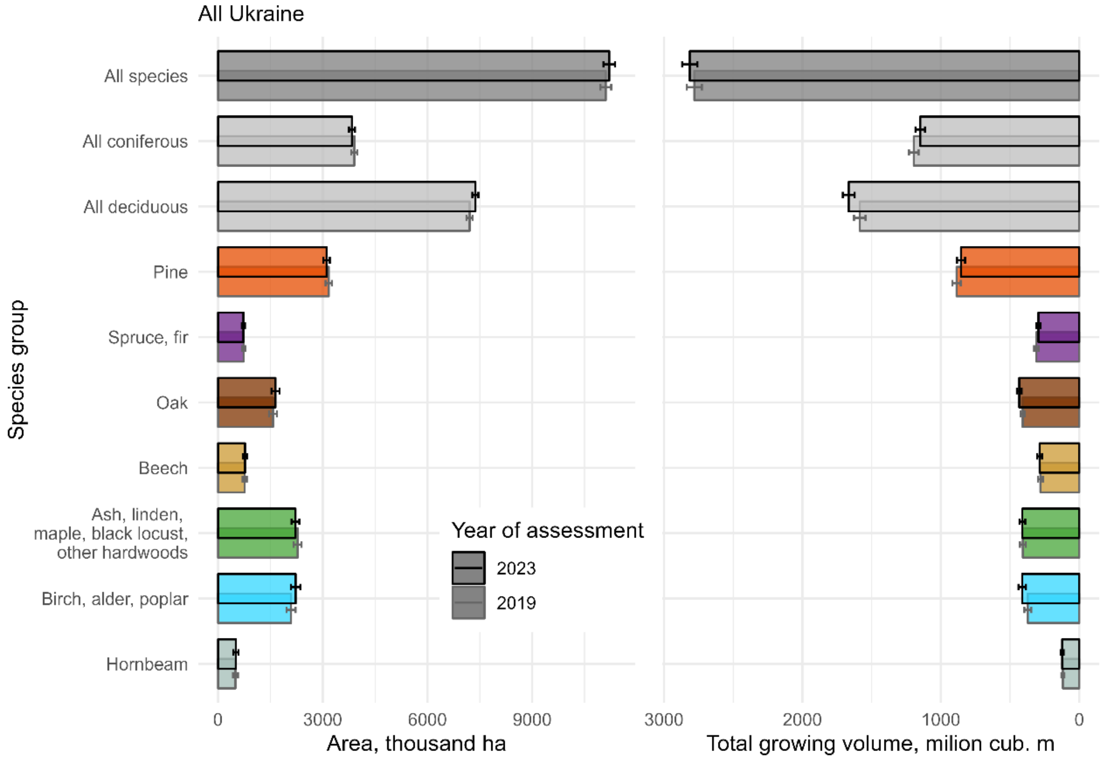


Figure 6. Forest area and total GSV in Ukraine.

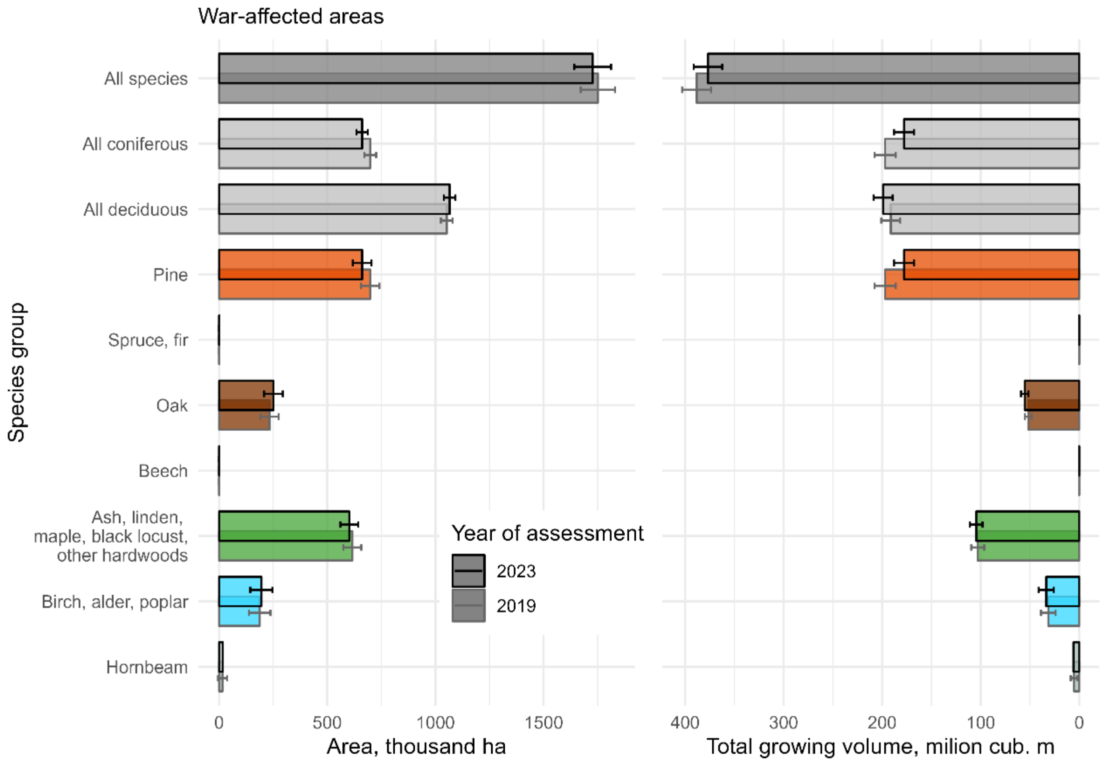


Figure 7. Forest area and total GSV in the war-affected areas.

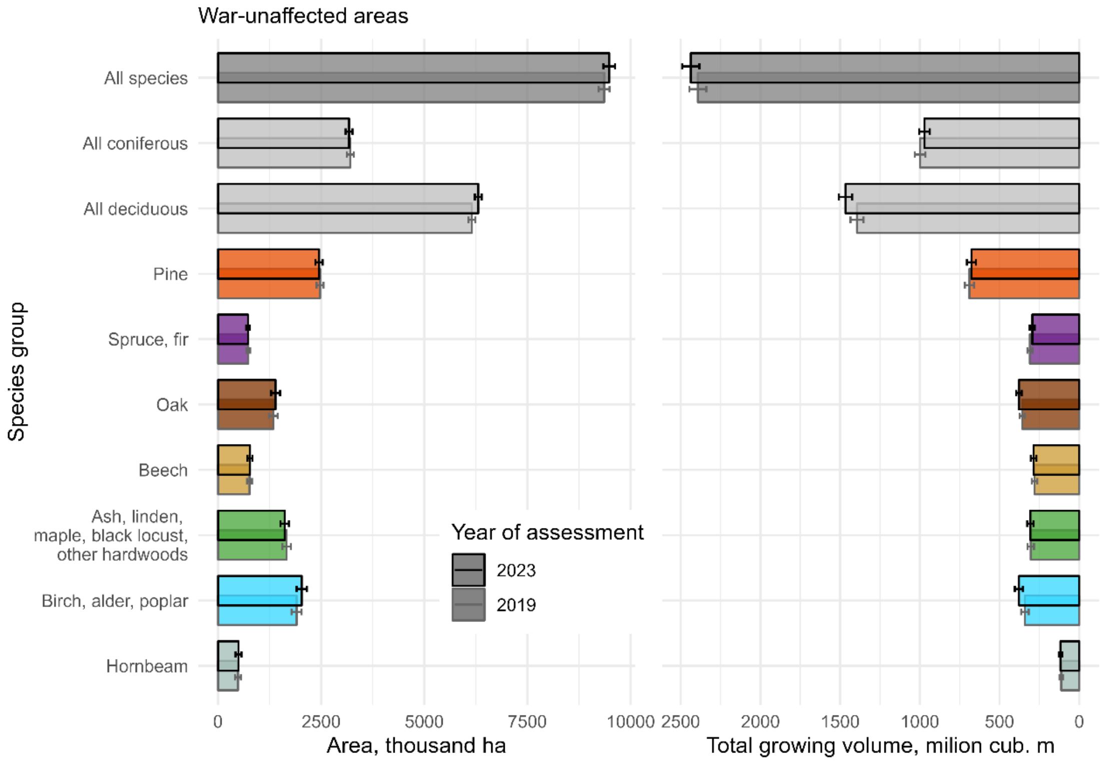


Figure 8. Forest area and total GSV in the war-unaffected areas.

2.3. Forest area change

2.3.4. Revealing flows of dominant tree species area between 2019 and 2023

Forest maps created for 2019 and 2023 were used to assess changes in forest area observed at the 20-m pixel level. In contrast to the calculation of net forest changes, this approach allowed to track the transition between mapped classes. This can be interesting to understand the redistribution of dominant species area. The Sankey plot in Figure 9 shows forest area changes at the state level. In this diagram, colored bars represent the proportion of land cover classes for 2019 (left) and for 2023 (right). The width of the gray connecting bands visualizes the redistribution of area between classes. Although, there are many narrow bands that can be associated with classification errors than actual changes, the figure helps to capture some interesting trends in the redistribution of dominant tree species.

The most noticeable (in terms of band width) is the transition of species areas to non-forested areas and vice versa. Figure 9 shows that pine forests and forests dominated by ash, linden, maple, and black locust contributed most to the transition from forest to non-forest. In contrast, forest regrowth, indicated by gray bands extending from "Non-forest" on the left side, was mostly associated with deciduous species.

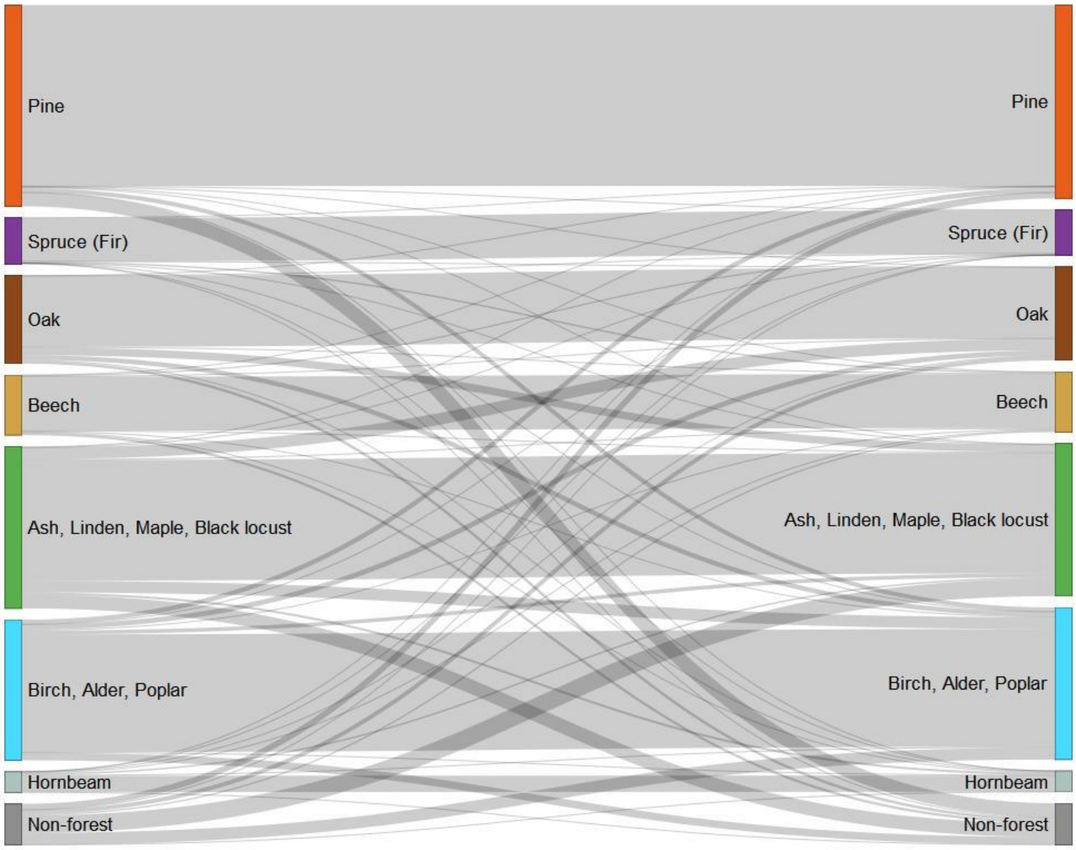
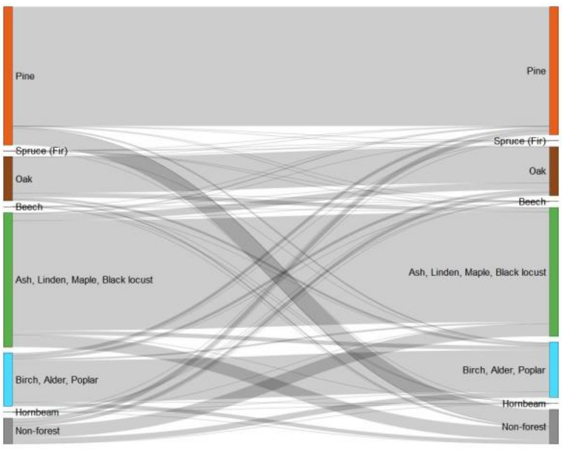


Figure 9. Sankey diagram showing redistribution of dominant tree species area between 2019 and 2023 in Ukraine.

The most significant increase in non-forest was observed for the Southern steppe (Annex B, Figure B.1). This ecozone is mostly associated with war zones. In addition, Figure 10 shows that war impacts contributed to the decrease of forest area in Ukraine.

War-affected areas



War-unaffected areas

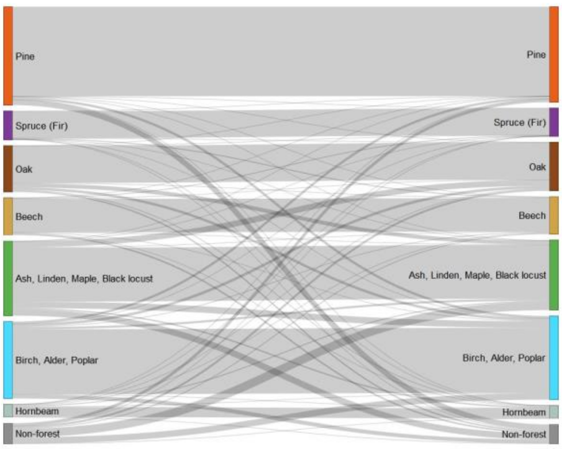


Figure 10. Changes in dominant species area in war-affected and war-unaffected areas. Y-axis represents proportional distribution of the total area by dominant species.

2.3.5. Prospects for monitoring changes in forest attributes

Changes in continuous forest attributes can be assessed similarly to dominant species using discrete intervals of their values and associated area. In this work, we focused on forest age and GSV.

The redistribution of forest area by age intervals (Figure 11) can be used to forecast timber harvest potential for the next decades. In general, we found that the results obtained are consistent with the predictive performance of the classification models. In particular, there are some misclassifications in age classes leading to a rapid conversion of unforested areas and young forests (1-20 years) towards mature age classes.

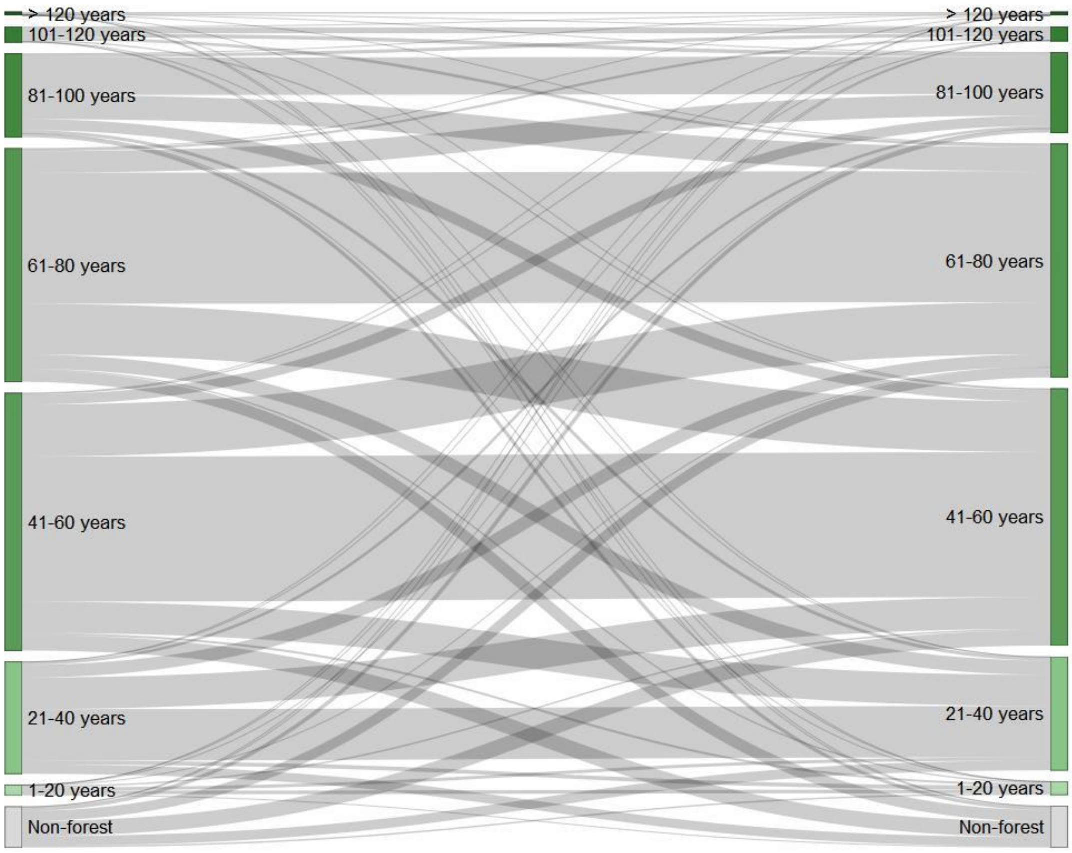


Figure 11. Changes in forest age in Ukraine between 2019 and 2023.

A more detailed examination of the age classes obtained for 2019 and 2023 in a form of confusion matrix (Table 3) showed that about 50% of the area fell within the main diagonal of the matrix, indicating no change. In addition, the confusion matrix showed that 25% of the forest stands (including non-forest) became older between 2019 and 2023, which can be partially explained by forest growth. However, the transition across more than one age class indicates misclassification problems. The remaining 25% of the area became younger in 2023, which can be explained by thinning and selective logging. However, we acknowledge that the uncertainties associated with the inaccurate performance of the predictive models may affect our understanding of the true forest dynamics.

Table 3. Confusion matrix (in % of the total area) between mapped age classes in 2019 and 2023.

2019 \ 2023	Non-forest	1-20 years	21-40 years	41-60 years	61-80 years	81-100 years	101-120 years	> 120 years	Total
Non-forest	**0,0**	0,2	1,3	2,0	1,3	0,5	0,1	0,0	5,4
1-20 years	0,2	**0,5**	0,4	0,2	0,1	0,0	0,0	0,0	1,4
21-40 years	1,2	0,5	**6,8**	4,2	1,7	0,4	0,0	0,0	14,8
41-60 years	2,0	0,3	4,1	**19,2**	6,9	1,3	0,2	0,0	34,0
61-80 years	1,5	0,2	1,9	6,7	**17,3**	2,9	0,3	0,0	30,8
81-100 years	0,5	0,0	0,4	1,5	3,2	**4,9**	0,5	0,1	11,1
101-120 years	0,1	0,0	0,1	0,2	0,4	0,5	**0,8**	0,1	2,1
> 120 years	0,0	0,0	0,0	0,0	0,0	0,1	0,1	**0,2**	0,5
Total	**5,5**	**1,8**	**15,0**	**33,9**	**30,9**	**10,6**	**1,9**	**0,5**	**100**

The situation with the volume of growing stock is similar (Figure 12), but the changes in the redistribution of forest area among different GSV classes can be easily explained. For example, selective logging can both decrease and increase the mean GSV if larger or smaller trees are removed from the forest stand. Note, that this analysis was performed at 20-m pixel resolution, so even the smallest interventions in the forest can lead to significant changes in its characteristics. One can imagine that the pixel covers two trees of different size (small and large). Thus, a removal from the stand the small tree leads to an increase of the remaining GSV (mean value), while the removal of the large tree leads to a dramatic decrease in the mean GSV. However, **these results are more related to the scientific outputs of the project than to the practical applications**.

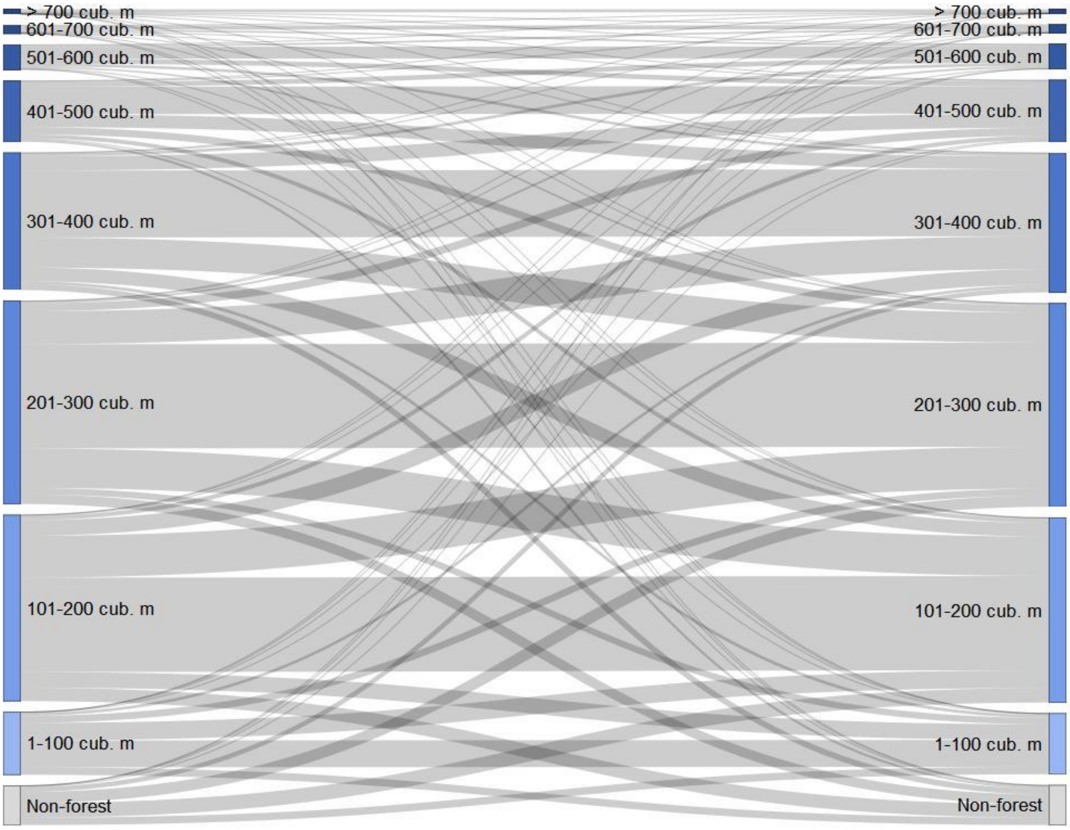


Figure 12. Changes in mean GSV of forests in Ukraine between 2019 and 2023.

CONCLUSION

The RS-Inventory showed great potential not only to assess the forest resources in Ukraine for the years in which the field data were collected but also to provide valuable insights into forest resource dynamics. We linked the field data collected on the NFI plots in 2021-2023, the historical FMP data with Sentinel 2 time series to track changes in forest cover and associated forest attributes for the time period of 2019-2023. This is a major output of the SFI project, which provided both actual estimates of the key forest attributes and their retrospective analysis over the time. In a situation where Ukraine cannot conduct regular forest assessments due to the war and lack of financial resources for the NFI, the RS-Inventory provides excellent opportunities for forest assessment at the nationwide level with limited resources. There are strong sides of the retrospective analysis of forest resources via RS-Inventory, however, we also acknowledge some limitations that worth considerations.

Advantages of the approach. This study has shown that the NFI is an important source of field observations that can be combined with RS data to describe the current state and dynamics of forest resources in Ukraine. This is especially important when a large area is unavailable for field data collection. Thus, this study provided wall-to-wall estimates of forest cover and associated forest attributes over time. The current report provides estimates for all of Ukraine for 2019, including unavailable areas that could not be conducted without advanced use of RS technologies. Optical satellite data, namely the Sentinel 2 time series, have shown great potential for mapping forest characteristics at fine spatial scales. However, we foresee much greater opportunities in the future to improve the quality of the predictive performance of the approach with the use of advanced satellite and airborne technologies. In particular, the quality of maps can be improved using active scanning, including airborne laser (ALS), which contributes to more accurate mapping of stand height and GSV. This is an important step to further improve the concept of RS inventory in Ukraine.

Limitations and prospects. A major limitation of the approach is related to the limited field observations used in combination with the RS data. Therefore, we assume that the provision of continuously collected field data at the NFI sample plots is an important step towards the development of reliable forest monitoring in Ukraine. In this study, we were also limited in the use of the Sentinel 2 data, which shows good potential in mapping land cover, but in many cases has limitations in predicting structural forest attributes. Therefore, the maps of forest cover and dominant species were more accurate than the maps of continuous forest attributes. We expect that the proposed mapping approach can be improved by using modern active scanning technologies, which provide accurate measurements of forest stand heights and canopy densities. This may be crucial to providing consistent estimates of forest attributes dynamics even within relatively short time domains that in many cases in this study were associated with uncertainties of the derived estimates.

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ANNEX A. NET FOREST CHANGE BY HENSIRUK'S ECOZONES

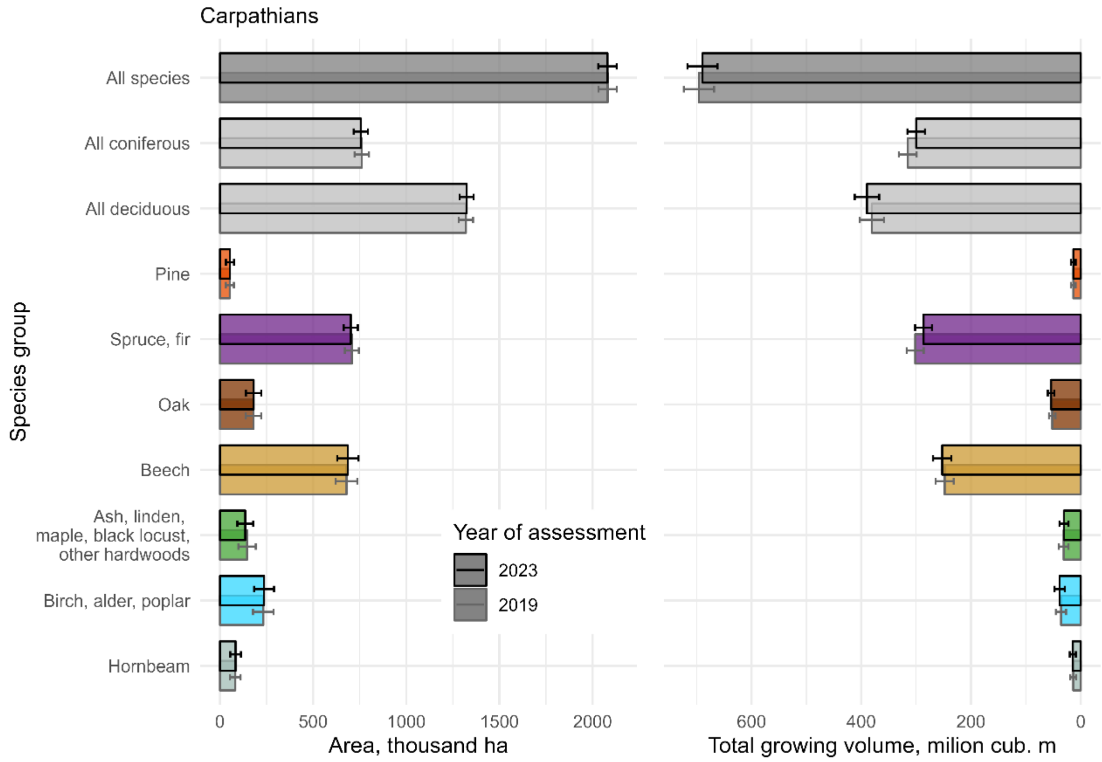

Figure A.1. Forest area and total GSV in the Carpathians.

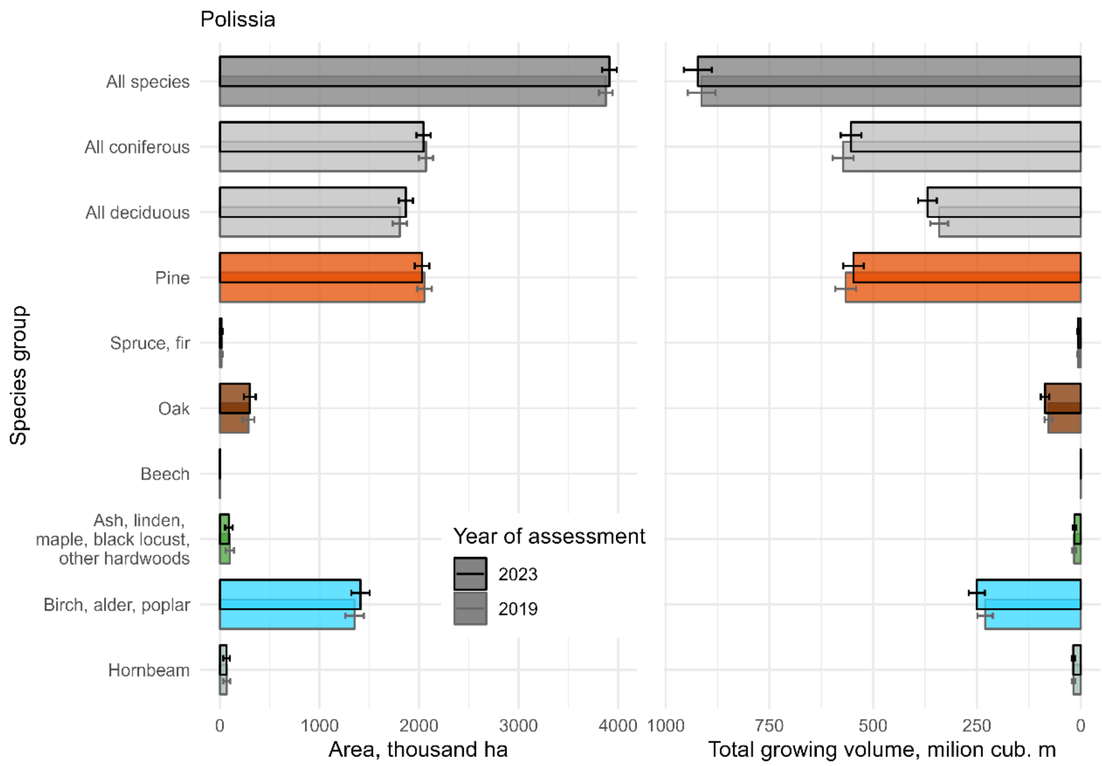

Figure A.2. Forest area and total GSV in the Polissia.

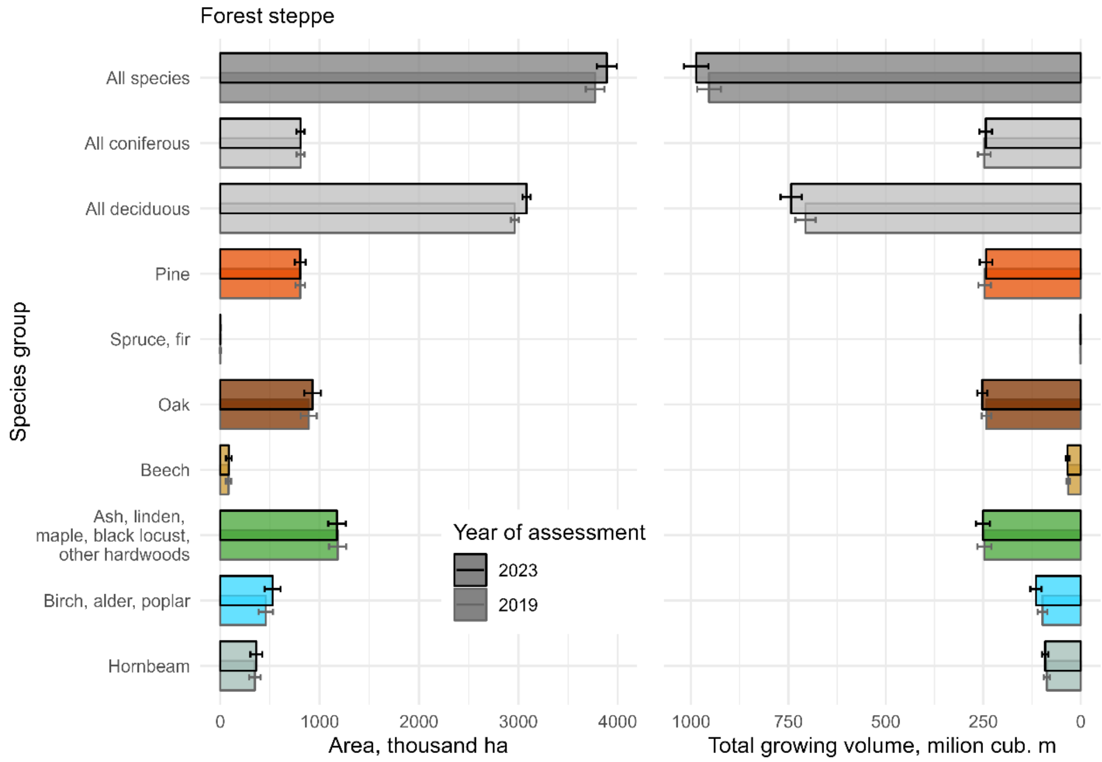

Figure A.3. Forest area and total GSV in the Forest steppe.

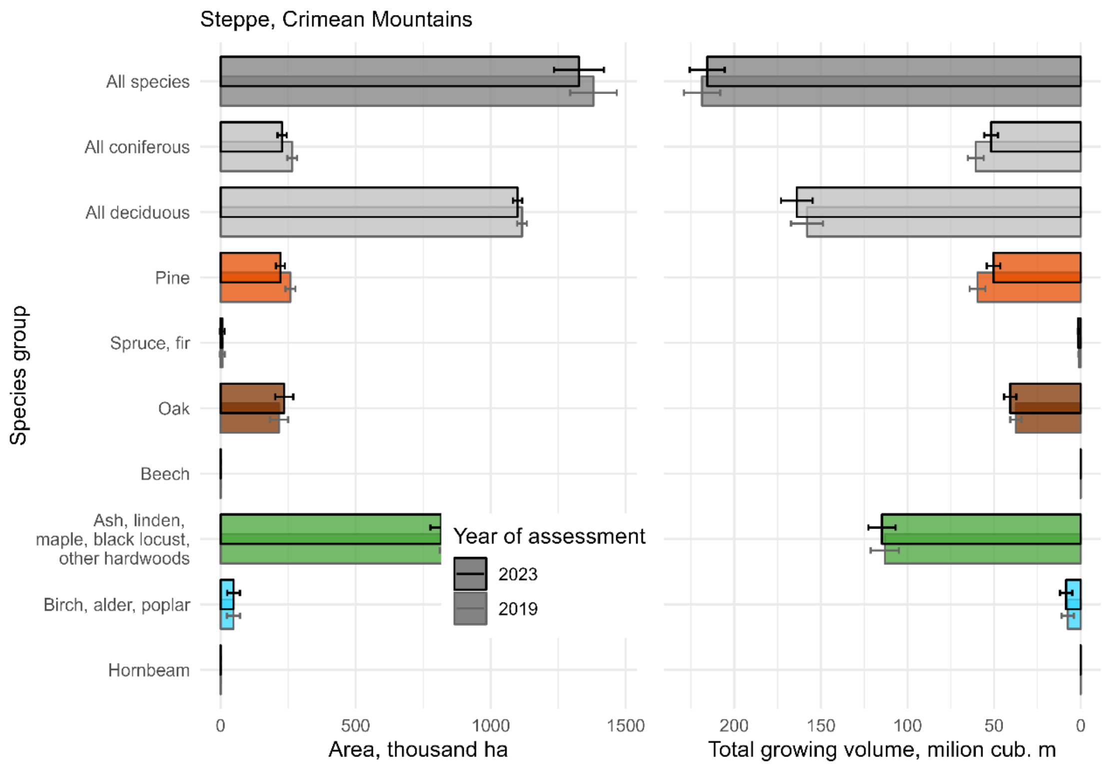

Figure A.4. Forest area and total GSV in the Steppe and the Crimean Mountains.

ANNEX B. SANKEY DIAGRAMS BY HENSIRUK'S ECOZONES

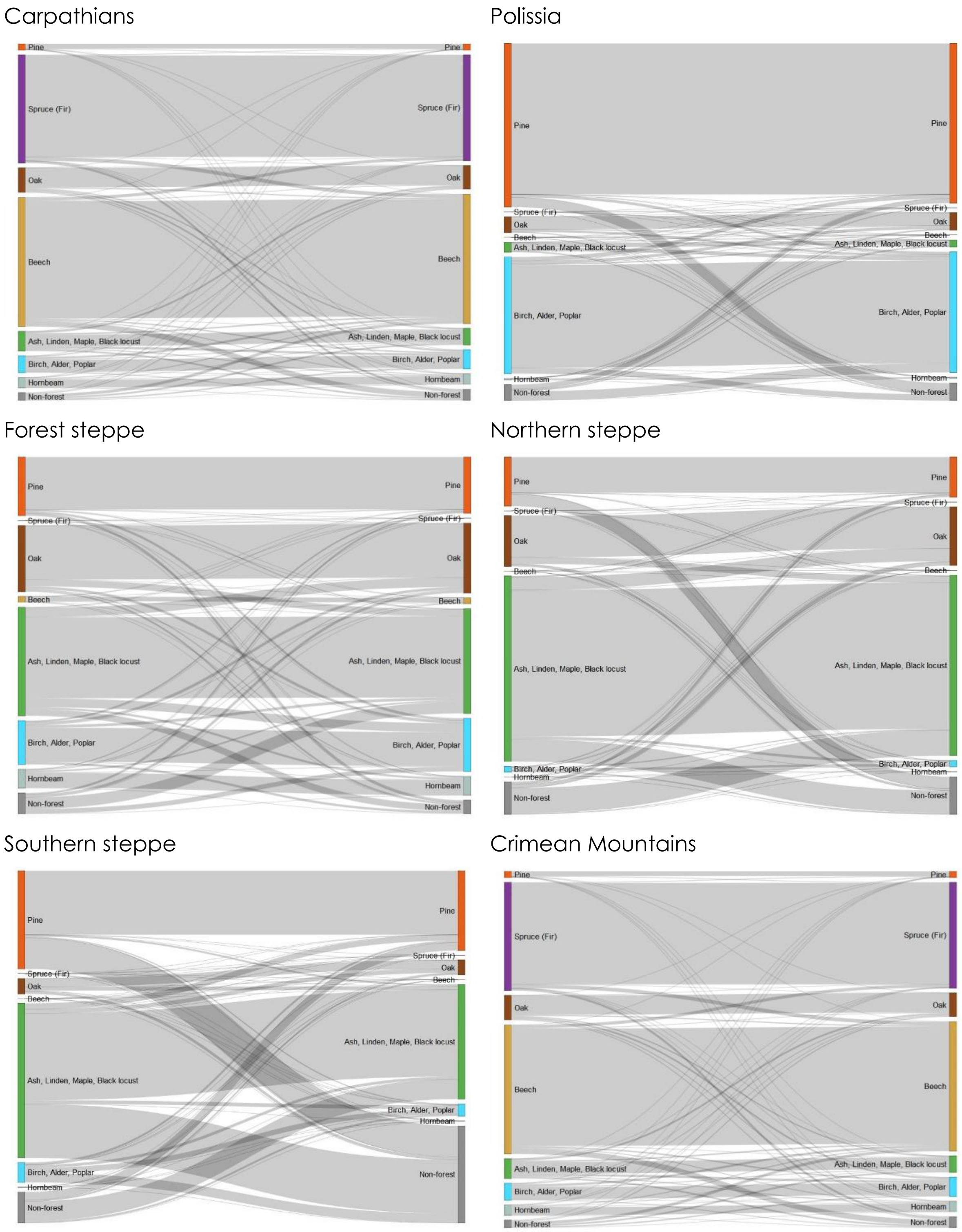

Figure B.1. Redistribution of dominant tree species area by Hensiruk's ecozones.