THE IMPACT OF RECENT CLIMATE CHANGE ON THE ECOLOGICAL PRODUCTIVITY OF FORESTS IN ROMANIA

– Final scientific report of the project
PN-III-P1-1.1-PD-2019-0064 (CLIMFOREST) –

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According to the funding application, **the main objective** of this project was the analysis of the potential impact of recent climate change on forest productivity in Romania, based on various climatic and remote sensing data processed over the past three decades (1987–2016) by means of complex geostatistical techniques. **The specific objectives / activities** of the project were diverse, according to the table below integrated in the funding application (Table 1).

Table 1. Research planning, in accordance with the specific objectives / activities of the project.

Yr		Objectives	Specific activities	Implementation status (August 2022)
2020	**1**	Acquisition of interannual climatic and satellite data in Romania for the 1987–2016 period, necessary to test the hypothesis of the recent climate change impact on forest productivity countrywide	1.1. Reconsulting international literature on the importance of climatic and ecological parameters in the assessment of the relation between climate and forest productivity;	✓
			1.2. Acquiring ecoclimatic datasets from online databases;	✓
			1.3. Preprocessing of acquired national datasets (improving climate data, delimiting forest areas, and mosaicing satellite data).	✓
2021 / 2022	**2**	Geostatistical processing of trends in forest vegetation density in Romania, in relation to the trends of the main climatic parameters over the past three decades	2.1. Obtaining interannual data on forest density based on Normalized Difference Vegetation Index **(NDVI)**;	✓
			2.2. Processing climatic and ecological (NDVI) trends simultaneously;	✓
			2.3. National mapping of ecoclimatic trends;	✓
			2.4. Investigating the impact of climate on forest density by assessing statistical relationships between ecoclimatic data.	✓
	3	Geostatistical processing of trends in forest biomass in Romania, in relation to the trends of the main climatic parameters over the past three decades	3.1. Obtaining interannual data on forest biomass based on above-ground live biomass **(AGB)**;	✓
			3.2. Processing climatic and ecological (AGB) trends simultaneously;	✓
			3.3. National mapping of ecoclimatic trends;	✓
			3.4. Investigating the impact of climate on forest biomass by assessing statistical relationships between ecoclimatic data.	✓
	4	Geostatistical processing of trends in net primary productivity of forests in Romania, in relation to the trends of the main climatic parameters over the past three decades	4.1. Obtaining interannual data on forest carbon fluxes based on net primary productivity **(NPP)**;	✓
			4.2. Processing climatic and ecological (NPP) trends simultaneously;	✓
			4.3. National mapping of ecoclimatic trends;	✓
			4.4. Investigating the impact of climate on primary productivity by assessing statistical relationships between ecoclimatic data.	in progress *
	5	Raising awareness on the necessity of interdisciplinary scientific investigations of this important ecoclimatic issue in Romania's scientific/political spheres by disseminating the study's results	5.1. Performing research activities corresponding to the first four objectives;	✓ (excepting the specific activity 4.4.)
			5.2. Participating at relevant international and national conferences;	✓
			5.3. Publishing results in three prestigious ISI-indexed journals that are **classed on the red list** (**Q1 category** in Web of Science).	✓

Note: according to the explanations provided at the end of this report (pages 22 and 23).

The first two objectives (**1 and 2**, with their specific activities) (Table 1) were **fully met in 2020 and 2021** and explained in detail **in the previous reports** prepared during the two years. **The last three objectives** of the project were **fully met** up to present day (August 2022), as per the implementation status (Table 1) and the detailed explanations below. Therefore, even most of the objective 4 was meet, although the specific activity 4.4. will be fulfilled soon (Table 1).

This final scientific report will recount the achievements of the first two objectives (even if already presented in the previous reports) and will provide key information on the results on countrywide forest trends in biomass (objective 3) and net primary productivity (objective 4), but also about the dissemination of project results through prestigious scientific papers and conferences (objective 5). Thus, for a comprehensive picture of all research conducted in this funding application, the most important results obtained for each objective will be presented below.

Objective 1: Acquisition of interannual climatic and satellite data in Romania for the 1987–2016 period, necessary to test the hypothesis of the recent climate change impact on forest productivity countrywide

Climate data

Countrywide climate data were used in this project (for exploring the possible eco-climatic relationships in recent decades), which consist of air temperature (T, °C), precipitation (P, mm) and reference evapotranspiration (ETo, mm). These data were obtained from Meteo Romania (https://www.meteoromania.ro/) and were produced yearly based on daily values, as average (T) or sum (P and ETo) in the summer season (months of June, July and August) of each year (the season with peak biological activity in Romania) from 1987–2018. Therefore, compared to the original application, in the end it was considered necessary to update the research interval by 2 years. While ETo values were estimated by Meteo Romania based on T, sunshine duration (hours), relative humidity (%) and wind speed (m/s) data, using the Penman-Monteith method (which is the best in ETo estimation), T and P data were calculated by the same institution directly from national gridded observational data (https://www.meteoromania.ro/).

All T, P and ETo multitemporal data were provided as raster data (with a 1 km spatial resolution) by Meteo Romania, which interpolated these climate data across Romanian forestlands (Fig. 1a,b,d) using appropriate interpolation methods. More exactly, the climate data were interpolated using Regression-Kriging method, which was finally deemed the fittest (after testing the reliability of several climate data interpolation methods), based on the cross-validation procedure and several error indicators. Therefore, special thanks are addressed to Alexandru Dumitrescu from Meteo Romania, who provided the interpolated climate data necessary in this research project.

Remote sensing data

The satellite data used for the Romanian territory consisted of multitemporal Landsat images, which were downloaded (at 30 m spatial resolution) during 1987–2018 via the Google Earth Engine (GEE) platform (earthengine.google.com). In order to cover the 1987–2018 period, three collections of satellite images (downloaded within the satellite scenes) were used (Fig. 1d), i.e. LANDSAT 5 TM Surface Reflectance Tier 1 (LANDSAT/LT05/C01/T1_SR), for the period 1987–2011, LANDSAT 7 ETM+ Surface Reflectance Tier 1 (LANDSAT/LE07/C01/T1_SR), for 2012–2016 (in the context of the LANDSAT 5 satellite mission activity shutdown), and LANDSAT 8 OLI/TIRS (LANDSAT/LC08/C01/T1_SR), for 2017–2018. The imagery featured in these satellite data collections (corrected atmospherically, radiometrically and topographically) represents the reflectance of the Earth's surface and contains 4 spectral bands in the visible (Red, Green, Blue) and near-infrared (NIR) spectral ranges, 2 bands in short-wave infrared (SWIR) range, and one in the thermal infrared (TIR) range.

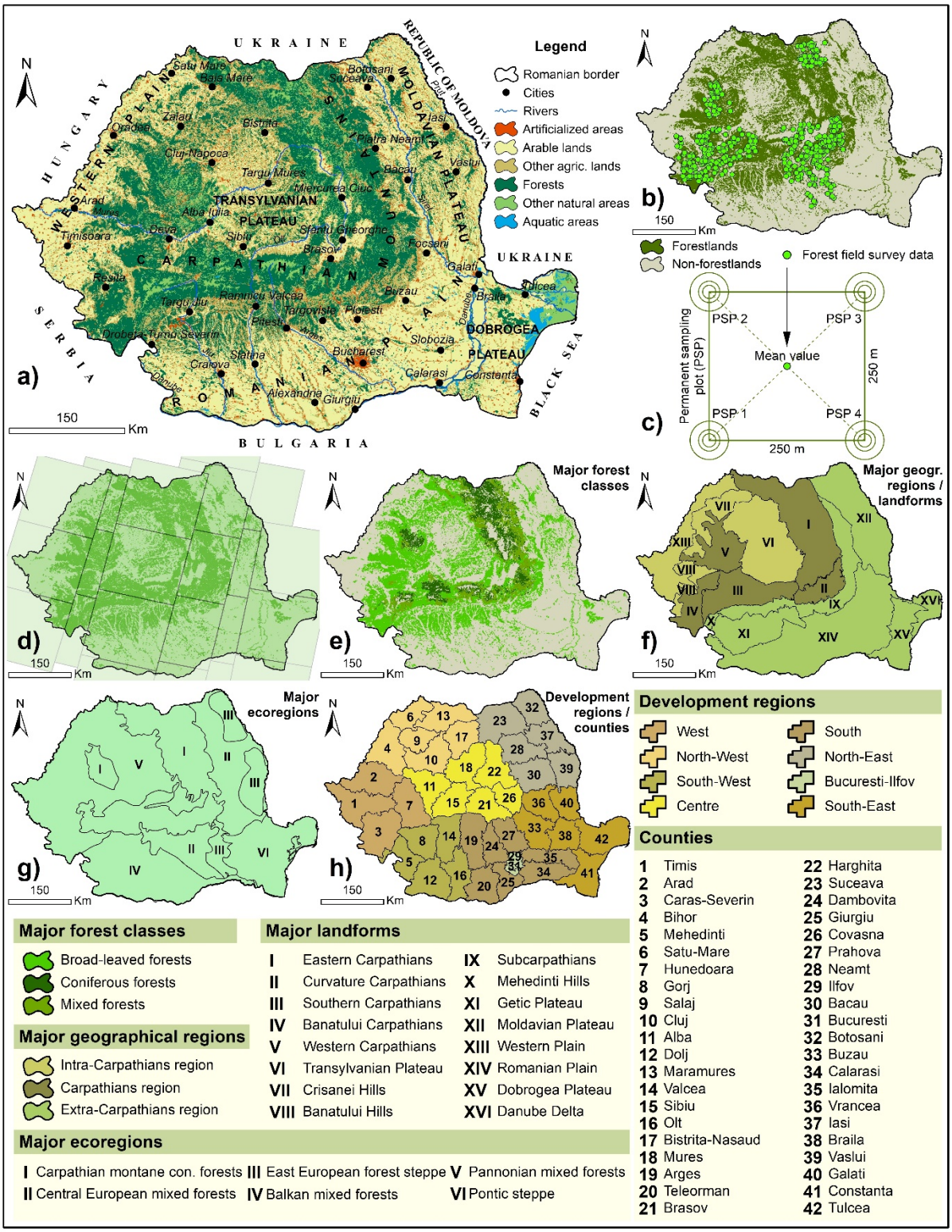

Fig. 1. Forest cover and other land cover / use classes in Romania (a), spatial distribution (b) and details (c) of the national forest inventory sample plots located across countrywide forests, the satellite scenes at which the remote sensing data were collected in Romania (d) and the countrywide spatial units where various geostatistics were extracted for this project, namely major forest classes (e), major geographical regions / landforms (f), major ecoregions (g) and development regions (NUTS 2) / counties (NUTS 3) (h). Notes: agric. – agricultural, geogr. – geographical, con. – coniferous; the general land cover/use classes in Romania (a) were extracted from the CORINE Land Cover (CLC) database (2018); the forestlands class (b,d) was obtained by overlapping / intersecting

the forestry classes of five CLC databases (1990, 2000, 2006, 2012, 2018), in order to detect constant / stable forestry areas over the past decades and allow a more direct assessment of the influence of climate change on possible changes in forest productivity; all the geospatial investigations of this project were conducted strictly within these forestland boundaries (b,d).

All these data were downloaded for the summer season (June – August) of each year, as a multispectral mosaic composed of 22 satellite scenes across Romania (Fig. 1b). Considering the number of multispectral satellite scenes and the 16-day temporal resolution of LANDSAT data, on average, 129 satellite images resulted annually for the summer period. This number varied however in certain cases, as some images were unavailable in the repository due to various sensor-related technical issues or to the unsatisfactory quality data (Table 2). In total, for the 32 analysed years, more than 4000 satellite images and almost 29000 spectral bands were used across the forest boundaries comprised in the countrywide satellite scenes (Fig. 1d).

Table 2. Number or valid satellite images (unaffected by technical errors or cloud cover obstacles) processed every year across Romania, based on remote sensing data quality downloaded in the 1987–2018 period.

Year	Number of satellite images	Year	Number of satellite images	Year	Number of satellite images
1987	135	1998	126	2009	151
1988	125	1999	149	2010	111
1989	102	2000	116	2011	113
1990	128	2001	100	2012	147
1991	121	2002	137	2013	140
1992	130	2003	103	2014	136
1993	144	2004	109	2015	155
1994	138	2005	92	2016	133
1995	141	2006	118	2017	166
1996	133	2007	143	2018	151
1997	138	2008	95		

The annual remote sensing data was obtained based on the median (for computing NDVI) / mean (AGB and NPP) values for each pixel of all satellite images selected for the summer season, within the same satellite scene. All satellite data were prepared (for computing NDVI, AGB and NPP, according to objectives 2, 3 and 4) by completing four preprocessing phases.

In the first phase (I), Romania's boundary was uploaded onto the GEE platform, which was used for the selection of satellite scenes and for obtaining the final mosaic. In the second phase (II), the function for applying the cloud-masking to the Landsat data was created by using the template provided by the GEE platform (https://developers.google.com/earth-engine/datasets/catalog/LANDSAT_LT05_C01_T1_SR). This function consists of applying two distinct masks – the first removes pixels classified as "clouds" and their shadow in the Spectral Indices Pixel Quality Band, and the second removes fixed-pattern noise from the border of each satellite scene.

Both the boundary and the masking function were used in the third phase (III) – satellite imagery selection and processing. In this phase, the cloud-masking function (in the summer season, 01.06.–31.08., of each year) presented in the previous phase (II) was applied by selecting a filter for a cloud cover degree of 100%. This filter value was chosen in order to select as large a number of satellite images as possible in the chosen timeframe, considering that in the end the median / mean value of each pixel was computed from the annual collections in order to obtain a mosaic for each spectral band. In the fourth phase (IV), each mosaicked spectral band was then exported for each year at a spatial resolution of 30 m in a WGS84 projection, and subsequently reprojected into Pulkovo 1942 (58) / Stereo70 (EPSG: 3844), representative for Romania's territory.

Other geospatial data

Forests field survey data, acquired from the national forest inventory (NFI) database (http://roifn.ro/) (Fig. 1b), were also used in this research project. The NFI database, initiated in 2008, has a density of 4 x 4 km in hilly and mountainous regions, and of 2 x 2 km in plain areas, where forest cover is lower. NFI surveys are based on square-shaped sampling grids (clusters) with 250-m sides, the corners of which feature four circular permanent sampling plots (PSPs) (Fig. 1c). Each PSP consists of three concentric circles (Fig. 1c), with areas of 200 m^2, 500 m^2 and 2000 m^2. Essentially, forest inventory data were used for AGB and NPP modelling, in accordance with objectives 3 and 4 of the project (more details about the role of NFI in-situ surveys in the modelling of the two ecological indicators will be provided in this final report, in the sections of objectives 3 and 4).

At the same time, in this project were also used the CORINE Land Cover (CLC) databases (1990, 2000, 2006, 2012 and 2018, https://land.copernicus.eu/pan-european/corine-land-cover), in order to delimit constant / stable forest areas at the level of which satellite and climatic data was extracted and analysed (Fig. 1b,c). Other geospatial data used in this report include boundaries in vector format of some spatial units (major forest classes, major geographical regions, major landforms, major ecoregions, development regions, counties) (Fig. 1e-h), which were used for various statistical investigations carried out for this project.

Objective 2: Geostatistical processing of trends in forest vegetation density in Romania, in relation to the trends of the main climatic parameters over the past three decades

Modelling forest vegetation density and NDVI trends

Forest density was estimated based on the Normalized Difference Vegetation Index (NDVI), which was computed (yearly, for the summer period, as previously mentioned) as the difference between near infra-red and red bands divided by their sum: NDVI = (NIR - Red) / (NIR + Red). These spectral bands were included in the Landsat satellite database, described in the section of the first objective. All yearly NDVI raster data were processed strictly at the level of Romania's forest boundaries (extracted from the CLC databases, as previously mentioned), at a final spatial resolution of 1 km × 1 km, similar to the resolution of climatic data.

Once the yearly raster series of NDVI were obtained, the non-parametric *Mann-Kendall* (MK) test and *Sen's slope* estimator were used to investigate the ecological trends of Romanian forests. The NDVI trends were explored at pixel level, in terms of their direction (positive, negative or null), magnitude (the change per year) and statistical significance (at $\alpha \leq 0.1$ or 90% confidence level, which includes highly statistically significant trends, for $\alpha \leq 0.05$, and lower statistically significant trends, for α that ranges between 0.05 and 0.1). The same two statistical procedures were applied to climate data, which were also investigated as trends in this research.

NDVI was used in this project due to its numerous advantages. NDVI's strengths include the low number of constituting spectral bands (only NIR and Red), simplicity in its computation method, easy availability of long-term spectral databases required for its calculation or its overall reliability in the analysis of vegetation density and productivity.

Investigation of climate – NDVI relationships

The statistical relationships between climate (T, P, ETo and climatic water balance, CWB, expressed in mm and calculated as: CWB = P - ETo) and NDVI data were investigated by correlating the two datasets. The statistical correlations were performed based on the mean values of climate and NDVI raster data, which were extracted for three spatial units of Romania (major geographical regions, major ecoregions and major landforms) that were considered natural homogeneous areas where the climate impact on NDVI can be investigated.

The temporal eco-climatic relationships were investigated through basic statistical indicators, like the adjusted coefficient of determination (R^2) and the Pearson linear correlation coefficient (r). Also, the statistical significance of eco-climatic relationships was assessed throughout the Romanian forests by means of 0.05 and 0.1 p-value thresholds.

Results

NDVI trends

The use of the *Sen's slope* and *MK* procedures showed an overall greening of the Romanian forests (Fig. 2a), but with significant regional differences. Classifying *Sen's slope* values in decreasing (negative), increasing (positive) and null (stationary) trends, the results revealed that ~50% of Romania's forest area was affected by NDVI changes (decreasing and increasing, including statistically significant ones) in vegetation quality, while the other half remained unchanged or relatively unchanged (null trends highlighted in dark gray) (Fig. 2b).

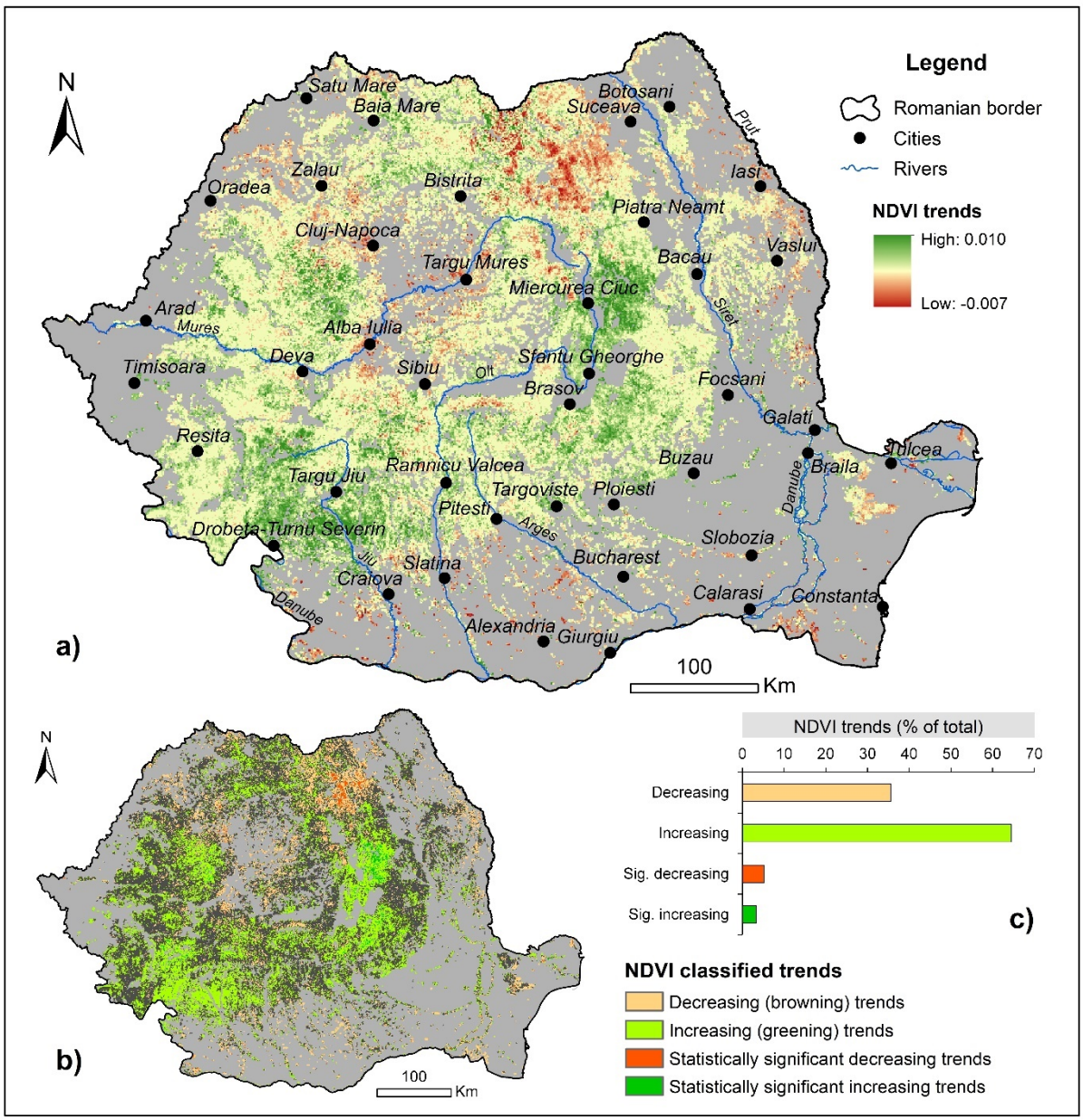

Fig. 2. General (a) and classified (b) NDVI annual trends (in the summer season) in Romania during 1987–2018 and extracted percentage-based statistics (c) of the two types of trends resulting from the NDVI trend classification. Notes: Decreasing / Increasing – percentage-based area of

negative / positive NDVI trends, reported to the total area of forest changes (Decreasing + Increasing) in Romania; Sig. decreasing / Sig. increasing – percentage-based area of statistically significant negative / positive NDVI trends, reported to the total area of decreasing / increasing trends in Romania; more details about this figure can be consulted in the published paper (Prăvălie et al., 2022a).

Statistically, of the total absolute NDVI changes (> 30.000 km^2) throughout the country's forests, ~65% experienced vegetation enhancement (positive NDVI trends, which indicate increases in vegetation density), while the remaining ~35% experienced vegetation degradation (negative NDVI trends, which indicate decreases in vegetation quality / density) (Fig. 2c). However, the two types of trends have limited statistical significance across the Romanian forests (Fig. 2c).

Regionally, by extracting percentage-based statistics for the three natural spatial units, it was found that, in terms of major geographical regions, the Carpathians region accounts for the most extensive greening trends (~35%) of the total NDVI changes of Romania (Fig. 3a). In terms of major ecoregions, the Carpathian montane coniferous forests experienced the greatest changes in vegetation density in Romania (~42% of the total), mostly consisting of positive NDVI trends (~28%) (Fig. 3b). Overall, the ecoregions were dominated by greening trends, except for forests located in the ecological units of Extra-Carpathians region (East European forest steppe and Pontic steppe), with general trends of vegetation degradation (Fig. 3b).

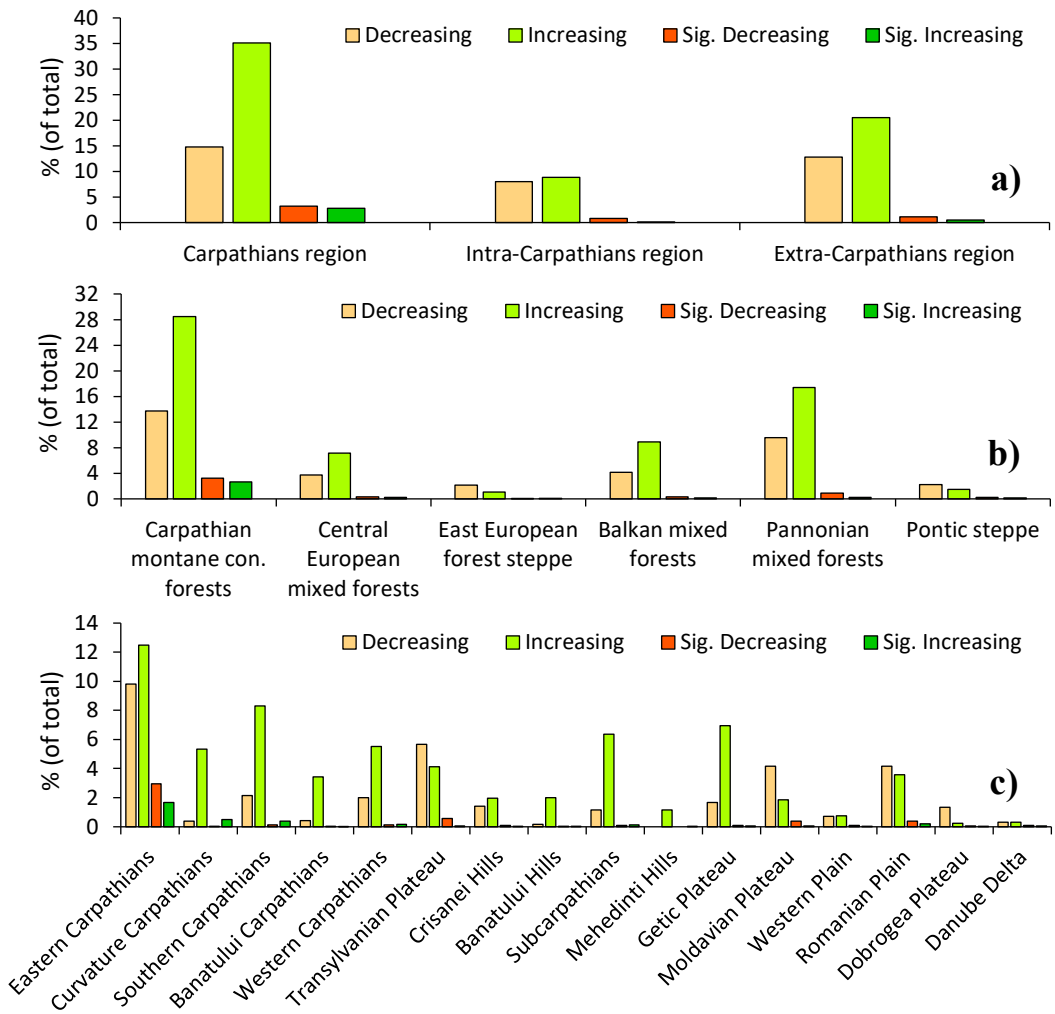

Fig. 3. Percentage-based areas of NDVI trends during 1987–2018, within major geographical regions (a), major ecoregions (b) and major landforms (c) of Romania. Note: more details about this figure can be consulted in the published paper (Prăvălie et al., 2022a).

In the case of the 16 landform units of Romania, a general pattern of NDVI changes was also observed. All units overlapping Carpathian territories (Eastern, Curvature, Southern, Banatului and Western Carpathians) recorded a positive net balance of NDVI changes (positive trends more widespread than negative trends) (Fig. 3c). At the opposite pole, large landform units in the Extra-Carpathians area (Moldavian Plateau, Romanian Plain, Dobrogea Plateau) experienced dominant degradation (especially the Romanian Plain and Moldavian Plateau, each with ~4% decreasing trends of the total NDVI changes) or balanced mixed (Danube Delta) trends of NDVI (Fig. 3c). In landforms located in the Intra-Carpathians region forests experienced a slight ecological improvement, except for the Transylvanian Plateau, which recorded a general decline in forest vegetation density (Fig. 3c).

Climate change impact on NDVI dynamics

The analysis of the climatic variable trends, which are potentially driving factors of NDVI dynamics, showed an exclusive warming statistically significant across 99% of Romanian forestlands, in case of T (Fig. 4). P recorded a more heterogeneous dynamics compared to T, characterized by wetter conditions throughout the Carpathians and some hilly and plain regions, and drier conditions in some parts of the Intra- and Extra-Carpathian regions (Fig. 4). ETo intensified across almost the entire territory of Romania, largely due to the exclusively positive trends of T (Fig. 4).

The analysis of the CWB highlighted that most of the country's forestlands became wetter during summer, although the statistical significance of CWB trends is relatively limited nationally, similar to P and ETo trends (Fig. 4). All these trends indirectly suggest that climate change is a driving force of NDVI changes, but the ecological response to climate dynamics must be concretely investigated through statistical correlations.

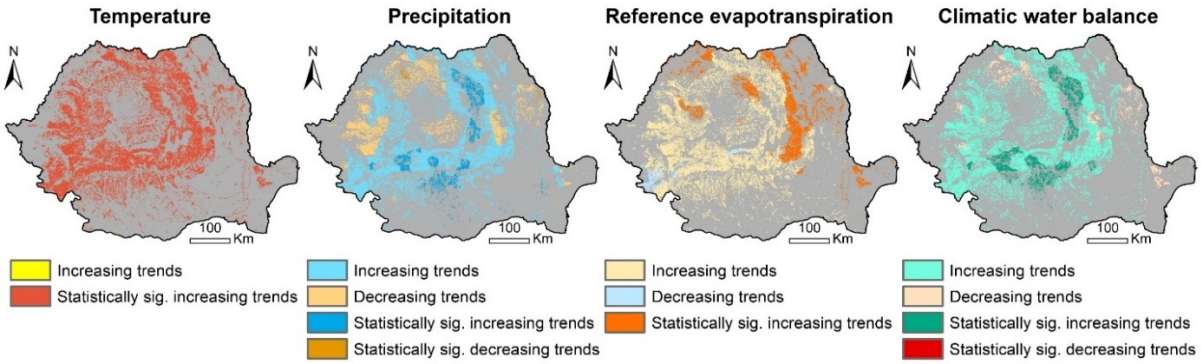

Fig. 4. Classified annual trends (in the summer season) for temperature, precipitation, reference evapotranspiration and climatic water balance (precipitation minus reference evapotranspiration), across the Romanian forestlands during 1987–2018. Note: more details about this figure can be consulted in the published paper (Prăvălie et al., 2022a).

The correlation of the annual climatic (T, P, ETo and CWB) and ecological (NDVI) datasets, for the three spatial units, revealed some interesting statistical relationships. With regard to the temperature – NDVI relationship, peak R^2 values in the Carpathians region, Carpathian montane coniferous forests and Eastern Carpathians showed that the NDVI dynamics can be explained by T changes in the three selected hotspots of the three natural unit categories (Table 3). While the R^2 values seem relatively low, their statistical significance is high, not only in these cases, but also in other cases generally located in mountainous areas (Table 3).

Also, given the computed *r* values in the three exemplified cases, it was found at least a moderate intensity (~50%, expressed as percentage) of eco-climatic relationships in the high-

altitude areas, but also the fact that NDVI is significant positively correlated with T in the mountain regions (Table 3). This statistical clue reveals that forest vegetation density increased in temperature-limited mountainous areas of Romania, as a consequence of the recent climate warming that affected the country's high-altitude areas. The precipitation-NDVI statistical analysis showed a general lack of correlations between NDVI variability and that of P, due to the very low R^2 and r values and the general lack of statistical significance (Table 3).

Table 3. Statistical correlations (1987–2018) between mean air temperature (°C) / precipitation (mm) and NDVI data, investigated across various natural spatial units in Romania.

No.	Spatial units	Temperature – NDVI				Precipitation – NDVI			
		R^2 adjusted	r	p-value	Sig. [a]	R^2 adjusted	r	p-value	Sig. [a]
1	Romania	0.179	0.453	0.009	high	0.041	0.268	0.138	not signif.
2	Carpathians region	0.220	0.495	0.004	high	0.030	0.248	0.171	not signif.
3	Intra-Carpathians region	0.175	0.449	0.010	high	0.002	0.186	0.309	not signif.
4	Extra-Carpathians region	0.062	0.303	0.092	low	0.070	0.317	0.077	low
5	Carpathian montane con. forests	0.236	0.510	0.003	high	0.036	0.259	0.153	not signif.
6	Central European mixed forests	0.062	0.304	0.091	low	0.041	0.269	0.137	not signif.
7	East European forest steppe	0.000	0.119	0.516	not signif.	0.060	0.301	0.095	low
8	Balkan mixed forests	0.015	0.216	0.236	not signif.	0.065	0.308	0.086	low
9	Pannonian mixed forests	0.158	0.430	0.014	high	0.015	0.215	0.236	not signif.
10	Pontic steppe	0.034	0.256	0.157	not signif.	0.182	0.457	0.009	high
11	Eastern Carpathians	0.261	0.533	0.002	high	0.023	0.233	0.199	not signif.
12	Curvature Carpathians	0.151	0.423	0.016	high	0.004	0.191	0.296	not signif.
13	Southern Carpathians	0.195	0.470	0.007	high	0.049	0.282	0.118	not signif.
14	Banatului Carpathians	0.098	0.356	0.045	high	0.007	0.160	0.382	not signif.
15	Western Carpathians	0.164	0.437	0.012	high	0.003	0.171	0.350	not signif.
16	Transylvanian Plateau	0.231	0.506	0.003	high	0.007	0.199	0.276	not signif.
17	Crisanei Hills	0.100	0.359	0.044	high	0.002	0.185	0.311	not signif.
18	Banatului Hills	0.043	0.271	0.133	not signif.	0.016	0.129	0.481	not signif.
19	Subcarpathians	0.083	0.336	0.060	low	0.048	0.281	0.120	not signif.
20	Mehedinti Hills	0.103	0.363	0.041	high	0.020	0.228	0.210	not signif.
21	Getic Plateau	0.022	0.232	0.201	not signif.	0.079	0.330	0.065	low
22	Moldavian Plateau	0.018	0.223	0.220	not signif.	0.019	0.117	0.524	not signif.
23	Western Plain	0.030	0.248	0.171	not signif.	0.078	0.328	0.067	low
24	Romanian Plain	0.015	0.215	0.236	not signif.	0.151	0.422	0.016	high
25	Dobrogea Plateau	0.002	0.184	0.313	not signif.	0.203	0.478	0.006	high
26	Danube Delta	0.115	0.379	0.033	high	0.008	0.200	0.272	not signif.

Notes: Sig. – Significance; signif. – significant; a – statistical significance is considered high for p-values < 0.05, and low for p-values between 0.05 and 0.1; more details about this table can be consulted in the published paper (Prăvălie et al., 2022a).

In contrast, evapotranspiration seems to play a far more important role in the ecological dynamics of forests, mainly in the Extra-Carpathian areas. The R^2 and r findings showed a peak impact of Eto on NDVI in the Moldavian Plateau, Western Plain, Danube Delta, Romanian Plain, Dobrogea Plateau (landforms), East European forest steppe and Pontic steppe (ecoregions) (Table 4). Also, the negative r coefficient values indicate a significant negative correlation between Eto and NDVI (Table 4), which suggests that the amplification of the evapotranspiration regime in recent decades caused a decline in density and health of forest ecosystems, especially in the mentioned lowland and hilly areas. In the last case, although the statistical information indicated a positive impact of the CWB in the greening trends of NDVI, there still are many situations with relatively low R^2 and r values and with low statistical significance across the country.

Table 4. Statistical correlations (1987–2018) between reference evapotranspiration (mm) / climatic water balance (mm) and NDVI data, investigated across various natural spatial units in Romania.

No.	Spatial units	Reference evapotranspiration – NDVI				Climatic water balance – NDVI			
		R^2 adjusted	r	p-value	Sig. [a]	R^2 adjusted	r	p-value	Sig. [a]
1	Romania	0.096	-0.354	0.047	high	0.120	0.386	0.029	high
2	Carpathians region	0.099	-0.358	0.044	high	0.105	0.366	0.039	high
3	Intra-Carpathians region	0.081	-0.333	0.063	low	0.091	0.346	0.052	low
4	Extra-Carpathians region	0.088	-0.343	0.054	low	0.138	0.407	0.021	high
5	Carpathian montane con. forests	0.108	-0.370	0.037	high	0.115	0.379	0.032	high
6	Central European mixed forests	0.074	-0.322	0.072	low	0.104	0.365	0.040	high
7	East European forest steppe	0.139	-0.408	0.020	high	0.160	0.432	0.014	high
8	Balkan mixed forests	0.065	-0.309	0.086	low	0.117	0.382	0.031	high
9	Pannonian mixed forests	0.074	-0.322	0.072	low	0.086	0.340	0.057	low
10	Pontic steppe	0.182	-0.456	0.009	high	0.261	0.533	0.002	high
11	Eastern Carpathians	0.100	-0.359	0.044	high	0.107	0.368	0.038	high
12	Curvature Carpathians	0.065	-0.308	0.086	low	0.052	0.288	0.110	not signif.
13	Southern Carpathians	0.088	-0.343	0.054	low	0.102	0.362	0.041	high
14	Banatului Carpathians	0.057	-0.296	0.100	not signif.	0.038	0.263	0.147	not signif.
15	Western Carpathians	0.085	-0.338	0.058	low	0.068	0.312	0.082	low
16	Transylvanian Plateau	0.063	-0.305	0.090	low	0.085	0.339	0.058	low
17	Crisanei Hills	0.096	-0.353	0.047	high	0.090	0.345	0.053	low
18	Banatului Hills	0.089	-0.344	0.054	low	0.069	0.314	0.080	low
19	Subcarpathians	0.060	-0.300	0.095	low	0.098	0.356	0.045	high
20	Mehedinti Hills	0.059	-0.298	0.097	low	0.073	0.321	0.073	low
21	Getic Plateau	0.045	-0.275	0.128	not signif.	0.117	0.381	0.032	high
22	Moldavian Plateau	0.122	-0.387	0.029	high	0.075	0.323	0.071	low
23	Western Plain	0.125	-0.391	0.027	high	0.186	0.461	0.008	high
24	Romanian Plain	0.151	-0.422	0.016	high	0.228	0.503	0.003	high
25	Dobrogea Plateau	0.166	-0.439	0.012	high	0.265	0.538	0.002	high
26	Danube Delta	0.137	-0.406	0.021	high	0.131	0.398	0.024	high

Notes: Sig. – Significance; signif. – significant; a – statistical significance is considered high for p-values < 0.05, and low for p-values between 0.05 and 0.1; more details about this table can be consulted in the published paper (Prăvălie et al., 2022a).

Conclusions

The analyses on the detailed dynamics of NDVI and of its relationship with climatic factors, conducted for the first time on the entire forested area of Romania, highlighted diverse ecological and climatic changes across the country's forestland boundaries, over approximately the past three decades. Essentially, an overall greening of Romania's forests was observed, due to large scale increasing NDVI trends detected in the Carpathians region. Regionally, in contrast with mountain regions, it was found that extensive forest areas in the Intra- and especially the Extra-Carpathians regions were affected by decreasing NDVI trends, which suggests that in many cases forest vegetation was degraded or, at least, devitalized. Nevertheless, as clearly signalled throughout this research, these findings must be interpreted with caution, considering the limited statistical significance of forest ecological trends in Romania.

Moreover, the analyses conducted on eco-climatic trends and correlations showed that the increasing (greening) NDVI trends, mainly specific to mountain regions, are best explained by warmer conditions in the Carpathians, which are more limited by temperature than the Extra- and Intra-Carpathian areas. Also, it seems that the intensification of the evapotranspiration regime over recent decades accounts at least in part for decreasing (browning) NDVI trends, especially in the Extra-Carpathians area. In terms of precipitation, the role of changes in this climatic parameter in NDVI dynamics remains uncertain throughout Romania. Overall, a moderate intensity of the specified eco-climatic changes was detected, which indicates an

additional influence of other (non-climatic) factors in the forests' ecological dynamics, which were not considered in this analysis and which should be a priority in future similar studies.

Much more details about all these NDVI results explored for the first time in Romania, which were obtained in accordance with the objective 2 of the project, were featured in Prăvălie et al. (2022a): **Prăvălie, R.,** Sîrodoev, I., Nita, I.A., Patriche, C., Dumitrașcu, M., Roșca, B., Tişcovschi, A., Bandoc, G., Săvulescu., I., Mănoiu, V., Birsan. M.V., 2022a. *NDVI-based ecological dynamics of forest vegetation and its relationship to climate change in Romania during 1987–2018*. **Ecological Indicators** 136, https://doi.org/10.1016/j.ecolind.2022.108629.

Objective 3: Geostatistical processing of trends in forest biomass in Romania, in relation to the trends of the main climatic parameters over the past three decades

Modelling forest biomass and AGB trends

Forest biomass was investigated based on the above-ground live biomass (AGB, in tonnes/hectare or t/ha), which is a crucial metric of forest ecosystem productivity and which includes stems, branches, stumps, bark, seeds and foliage. This ecological indicator was initially calculated for the years 2010 and 2015, for the PSPs of 440 NFI in-situ surveys (http://roifn.ro/) distributed relatively uniformly across Romanian forestlands (Fig. 1b,c). Subsequently, AGB modelling was performed using empirical prediction based on NFI and Landsat surface reflectance data, which were crucial by providing continuous temporal and spatial coverage across Romanian forests, during 1987–2018. More details about the calculation procedure of NFI biomass, in 2010 and 2015, are available in Prăvălie et al. (2022b).

Essentially, AGB data was modelled for 2010 based on NFI surveys (and satellite data) conducted in the same year, and the modelling errors of the 2015 AGB dataset were estimated and subsequently compared to the real AGB data from 2015 NFI surveys (Table 5). This extra-domain validation is crucial because it shows the generalization power of the statistical models which were applied in the AGB modelling in the two years.

The applied statistical models are linked to many complex statistical (machine learning) algorithms: multiple linear regression (MLR), partial least squares regression (PLSR), support-vector regression (SVR), Recursive Partitioning (RPART), random forest (RF), Adaptive Boosting (AdaBoost), XGBoosting (XGBoost), neural networks (NN) and Multilayer Perceptron (MLP) (Table 5). All these algorithms were used in a tuning approach by testing several parameters and choosing the ones that performed best. In literature there are many ways of computing and reporting the validity of AGB estimations (or of other environmental parameters). Usually, the accuracy assessment is performed by computing the residuals between predicted and real AGB values, based on the Root Mean Squared Error (RMSE). The main approaches use intra-domain validation by train / test split or cross-validation and RMSE.

In this case, RMSE values obtained by applying various models in Romania range from 86.3 t/ha (SVR) to 178.5 t/ha (NN) (Table 5). Although SVR appears to have the lowest RMSE, for this model it can be noticed that AGB values of the 2015 prediction are distributed in a narrow interval, between 50.3 and 347.5 t/ha (Table 5, Fig. 5), which is highly unrealistic considering the value range and the distribution of the real AGB data in 2015 (Fig. 5).

Therefore, in choosing and applying the best statistical model / algorithm for estimating AGB, the present approach did not only use the RMSE criterion (1), but also other relevant statistical indicators, such as minimum and maximum values (2), and data distribution shapes (3). Simultaneous consideration of the three criteria indicated that the XGBoost algorithm provided the best results, according to the arguments presented below for each statistical indicator taken into account.

Table 5. Prediction and validation results for the AGB modelled using NFI and Landsat surface reflectance data.

No.	Algorithm	2010 AGB (t/ha)				2010 RMSE (t/ha)			
		min	mean	max	sd	min	mean	max	sd
1	MLR	99.7	211.2	385	37.8	0.3	82.7	510.8	66
2	PLSR	130.4	211.2	306.7	28.2	0.1	85	517.8	67.8
3	SVR	45.2	205.1	338.6	42.5	0.04	75.7	493.6	67.1
4	RPART	104.4	211.2	373.5	52.8	0.5	77.8	389.7	61.6
5	RF	65.5	212.3	552.1	71.5	0.13	36.2	211.1	30.3
6	AdaBoost	1.6	211.2	763.2	112.4	0	0.02	0.33	0.02
7	**XGBoost**	**1.8**	**211.2**	**761.4**	**112**	**0**	**0.7**	**5.1**	**0.7**
8	NN	-10.2	211.2	719.4	109.6	0.01	13.6	148.1	19.8
9	MLP	-0.4	212.3	605.8	59.8	0.002	31.9	556	108
	AGB *	1.6	204.6	763.2	112.4				
No.	Algorithm	2015 AGB (t/ha)				2015 RMSE (t/ha)			
		min	mean	max	sd	min	mean	max	sd
1	MLR	-342.9	90.2	1224	62.2	0.4	90.16	816	84.8
2	PLSR	150.3	202.3	304.4	22.5	0.1	92.3	580.7	76.4
3	SVR	50.3	233.5	347.5	45.3	0.1	86.3	581.2	73.5
4	RPART	104.4	281.2	373.5	72.1	0.28	107.3	640.3	80
5	RF	129.3	226.4	335.4	32.7	0.6	87.1	595.7	73.4
6	AdaBoost	39.5	211.7	481.9	73.6	0.15	100.3	477.1	81.7
7	**XGBoost**	**65.3**	**232.2**	**491.8**	**76.2**	**0.008**	**98.7**	**586.2**	**78.9**
8	NN	-134.5	204.7	742.6	187.6	0.2	178.5	597	128.5
9	MLP	-4.8	225.7	480.9	85.1	0.07	106.8	662.8	73.2
	AGB *	9.19	230.7	810	115.3				

Notes: min. – minimum values; max. – maximum values; sd – standard deviation; * – real measured data (NFI surveys); values in bold are representative for the best model chosen for modelling yearly AGB values, as per the information presented for the three selection indicators (criteria).

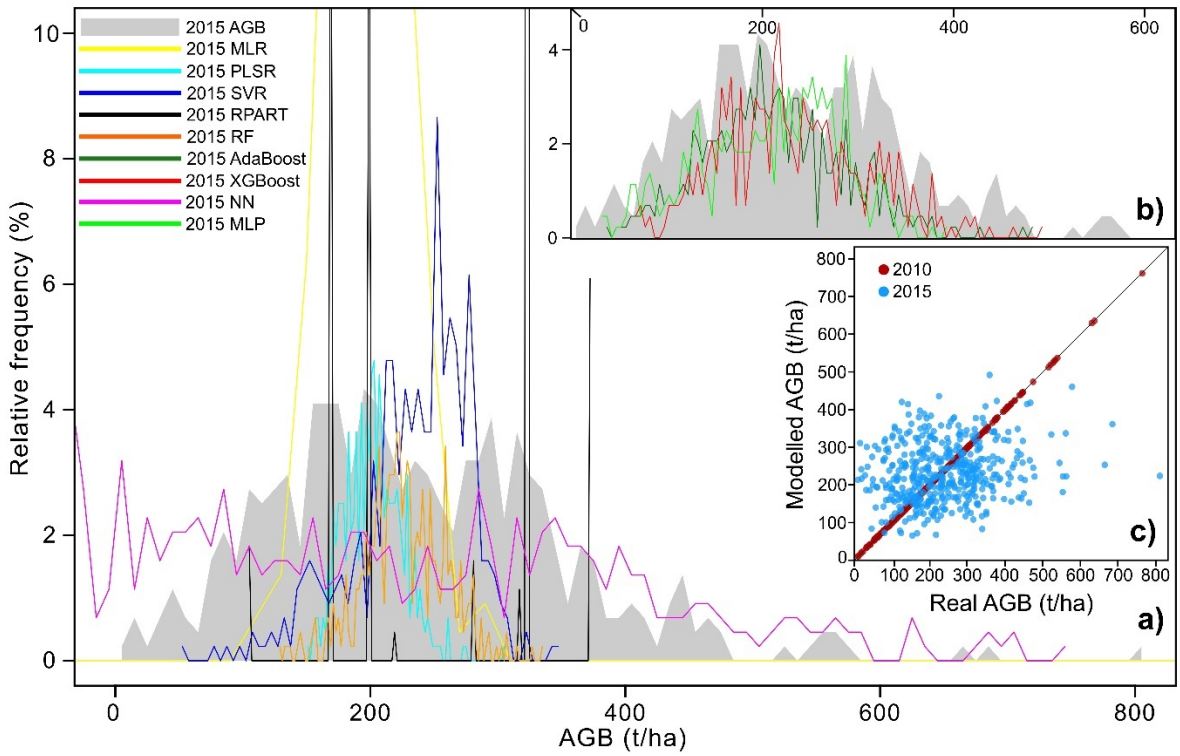

Fig. 5. The histograms of the real / measured AGB data for 2015 (in grey) and its prediction (for the same year) based on the several statistical algorithms / models applied in this study (a); the top right inset is a selection of AdaBoost, XGBoost and MLP models, which provide the best visual / empirical predictions for AGB (b); the bottom right chart is a scatterplot with real vs. predicted AGB data for 2010 (training) and 2015 (testing) for the XGBoost model (c), finally selected for modelling AGB in Romania, as per the information presented for the three selection indicators (criteria).

In the first case (1), the RMSE value (98.7 t/ha) of the XGBoost model falls within the range reported in literature and is even better than what was reported in certain multi-temporal studies, mentioned in Prăvălie et al. (2022b). The second statistical criterion (2) showed that the minimum and maximum values generated by the XGBoost algorithm are among the most realistic compared to the real ones in 2015, extracted from the NFI database (Table 5). This criterion is an important one, since most of the other models used indicated exaggerated or even completely unrealistic predicted minimum and maximum values for the status of Romanian forest biomass (Table 5). Regarding the third statistical indicator (3), the XGBoost model best predicts AGB data distributions, compared to the 2015 real distributed data on the histogram (Fig. 5).

Considering all these results and arguments, the XGBoost was finally selected for modelling the 32 yearly AGB rasters (1987–2018) across Romanian forests. Once interannual AGB data were modelled, the resulting yearly raster values were explored (at pixel level) in terms of trends over the period 1987–2018, using the MK test and *Sen's slope* estimator. Similarly to the analysis of NDVI trends, the two statistical tools were applied in order to detect the direction (positive, negative or null trends), magnitude (intensity of change per year) and statistical significance (at the significance level $\alpha = 0.1$ or 90%) of forest AGB changes across Romania.

Investigation of climate – AGB relationships

In order to detect the possible climatic impact in forest biomass dynamics, climatic and ecological data sets were extracted during the summer period and analyzed using the linear regression method. The eco-climatic data sets were extracted (for each of the 32 years) at the level of natural spatial units (entire Romania, major forest classes, major geographical regions, major landforms, major ecoregions), as an arithmetic mean of pixel values of T, P, ETo and AGB. The values were mediated yearly to remove local eco-climatic variations and to detect a more general pattern of climate-forest biomass statistical relationships.

Also, the five natural spatial units were chosen for regression because they were considered homogeneous / relatively homogeneous, where the AGB response to climate dynamics can be more easily examined. The analysis of the linear regression results was conducted based on regression parameters, such as *Slope* values, coefficients of determination (R^2) and the Pearson correlation coefficients (r).

Results

AGB trends

The analysis of AGB trends in Romania, using the statistical tools *Sen's slope* and MK (Fig. 6), revealed annual change rates ranging between -15 and 18 t/ha/yr, which are however dominated by increasing (positive) trends in most of the country (Fig. 6a). More specifically, by examining the data processed via the trend histogram, it was found that the positive changes in biomass fall, to the greatest extent (~64%), in the range of values greater than 0 (more precisely, >0.001) and 6 t/ha/yr (Fig. 6b). The general assessment of mapped trends showed that positive AGB trends mainly cover hilly and plain areas (in both Extra-Carpathian and Intra-Carpathian regions), while decreasing (negative) trends are specific to Carpathian (highland) regions (Fig. 6a). Overall, it was found that ~70% of the total area of national forest changes (that occurred almost across the country's entire forest area, considering that null / stationary changes are extremely limited) was affected by increasing trends, while 30% was affected by decreasing trends (Fig. 6c,d). Also, it is noteworthy that, while almost half (~48%) of all positive AGB trends are statistically significant, statistically significant negative trends are considerably lower (~21%) in Romania (Fig. 6c,d).

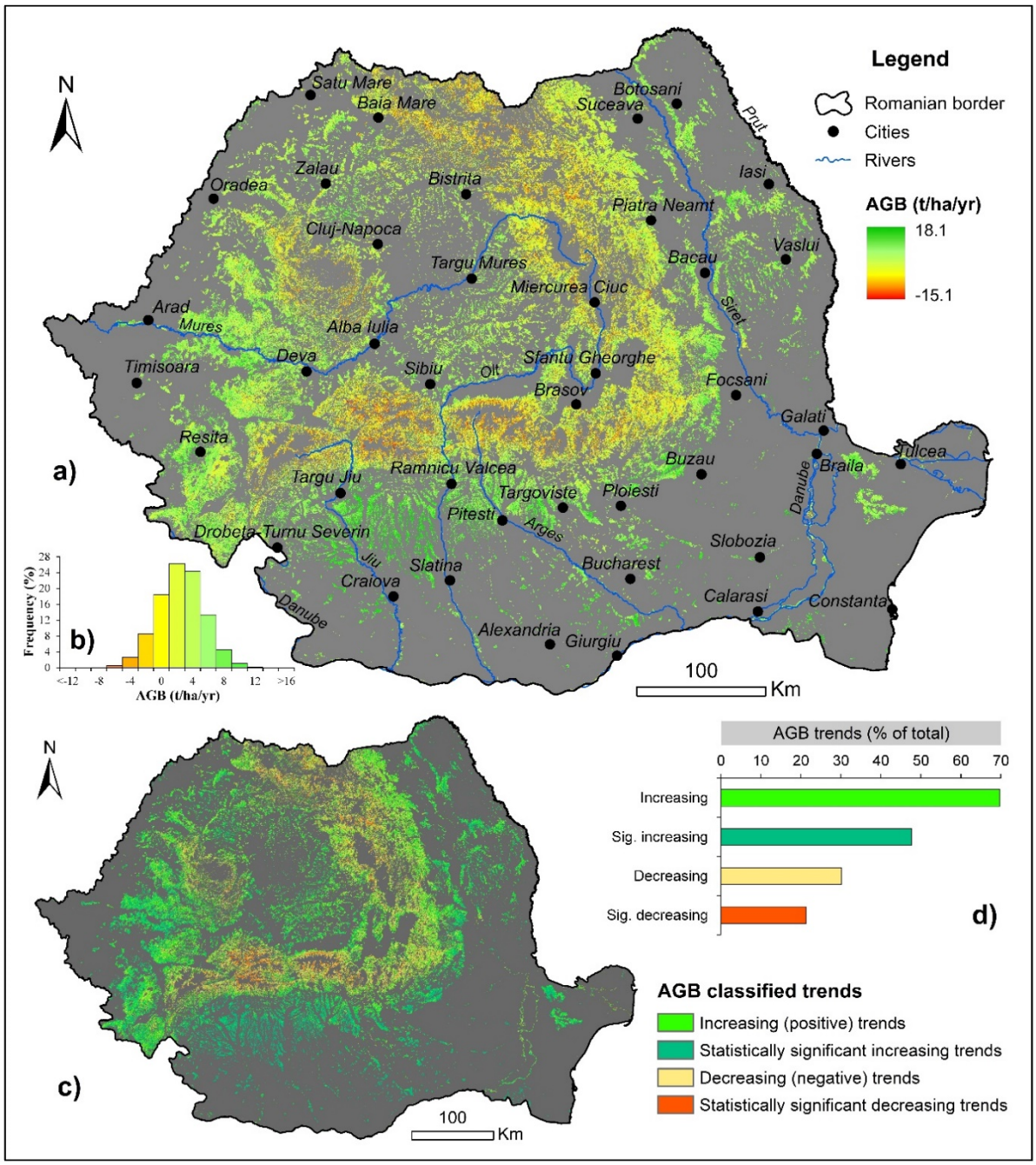

Fig. 6. Annual AGB trends in Romania during 1987–2018, unclassified (a) and with their distribution percentages across the country (b), and classified (c) and with extracted percentage-based statistics of the four types of trends resulting from the AGB trend classification (d). Notes: Increasing / Decreasing – percentage-based area of positive / negative AGB trends, reported to the total area of forest changes (Increasing + Decreasing) in Romania; Sig. increasing / Sig. decreasing – percentage-based area of statistically significant positive / negative AGB trends, reported to the total area of increasing / decreasing trends in Romania; more details about this figure are available in Prăvălie et al. (2022b).

A far more diverse spatial pattern of AGB changes can be identified within natural (major forest classes, major geographical regions, major landforms and major ecoregions) and administrative (development regions, counties) spatial units (Fig. 7). Unlike NDVI, exploring AGB trends in a larger number of spatial units can be useful as a complex informational support for other scientific studies (ecological, climate, etc.) or policymakers (especially for AGB trends examined in counties and development regions), considering that AGB is a more quantitative indicator and, consequently, a more useful tool for forestry stakeholders and policymakers.

Therefore, at the level of major forest classes, broad-leaved ecosystems account, by far, for the highest AGB increases countrywide (over 80% of all positive AGB trends in Romania, many of which are statistically significant), while coniferous and mixed forests are largely dominated by negative trends (together totaling almost 60% of the national total of negative trends, but with limited statistical significance) (Fig. 7a). Consequently, the Carpathians region and most of the constituting landform units / ecoregions (where coniferous and mixed forests are located) recorded the highest AGB decreases – with record lows in the Eastern Carpathians landform unit (~39%) and in the Carpathian montane coniferous forests ecoregion (76%) –, which in most cases, however, have a low statistical significance (Fig. 7b-d).

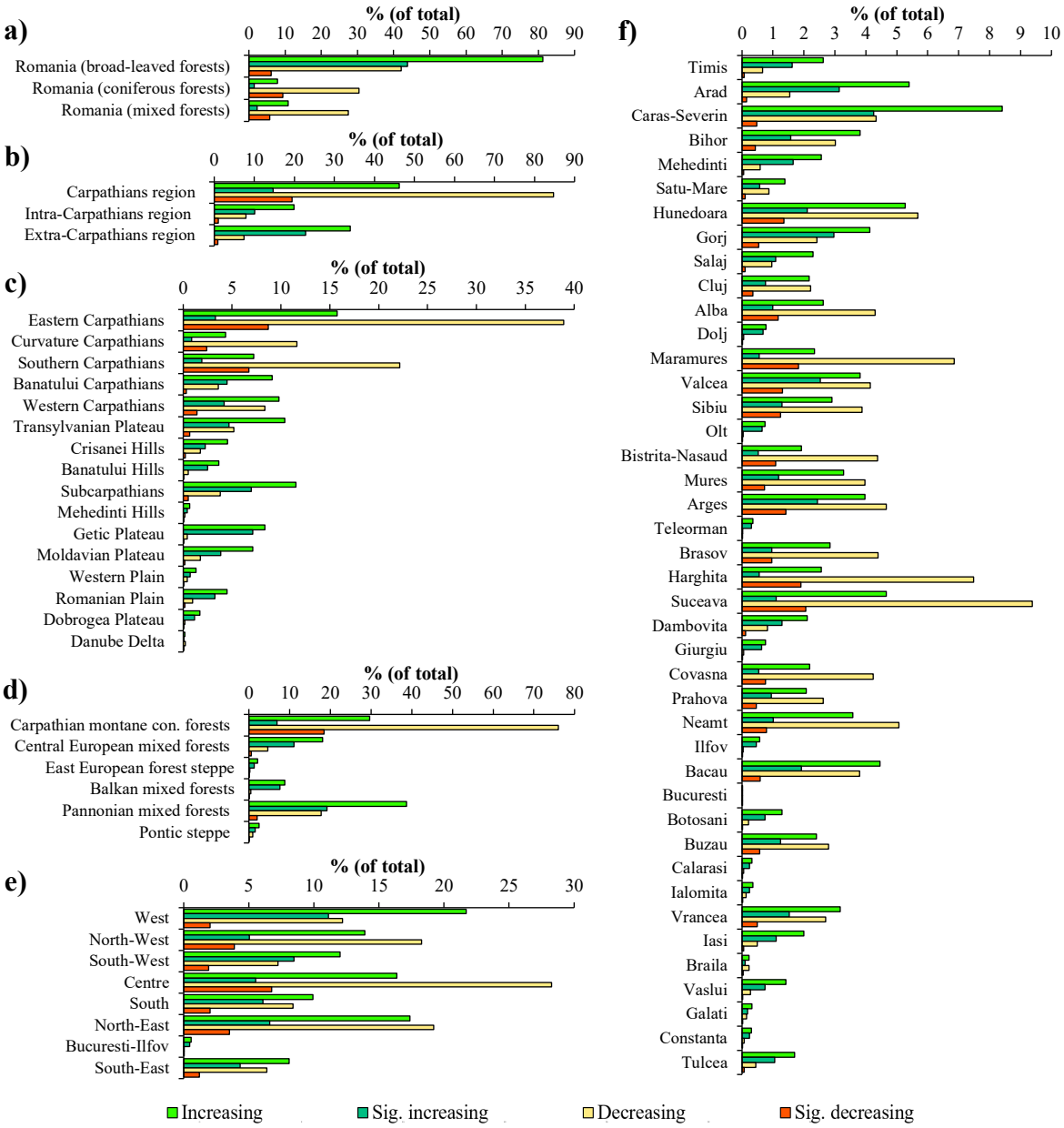

Fig. 7. Percentage-based areas of AGB changes (trends) during 1987–2018, at the level of major forest classes (a), major geographical regions (b), major landforms (c), major ecoregions (d), development regions (e) and counties (f) of Romania. Notes: con – coniferous; more details about this figure are available in Prăvălie et al. (2022b).

In contrast, Intra- and Extra-Carpathians regions (dominated by broad-leaved forests) were affected by predominantly positive trends (peak values in the Subcarpathians landform unit, ~12%, and in the Pannonian mixed forests ecoregion, ~39%), which are characterized by

a generally higher statistical significance (Fig. 7b-d). Also, administrative data highlighted the West (~22%) / Centre (~28%) development regions with the country's amplest positive / negative trends, and Caras-Severin (~8%) / Suceava (9%) counties with the most extensive increasing / decreasing changes in forest biomass (Fig. 7e,f). In this case as well, positive AGB trends are generally more statistically significant, compared to negative ones (Fig. 7e,f).

The four types of trends reveal a mixed picture of biomass changes, which is why a more important statistical summary of AGB trends can be made via annual mean AGB trend, net mean AGB change and total AGB change (Table 6). By computing the arithmetic mean of reliable positive and negative trends (all pixels of trends with statistically significant values), a positive AGB trend of ~3 t/ha/yr was found for the country's entire territory (Table 6).

Table 6. Mean spatial values of annual trends (t/ha/yr), net changes (t/ha/32 yrs) and total changes (t/32 yrs) in AGB across the country (1987–2018), extracted for the forest area of the entire national territory (1), major forest classes (2–4), major geographical regions (5–7), major landforms (8–23), major ecoregions (24–29), development regions (30–37) and counties (38–79) of Romania.

No.	Spatial units	Annual mean AGB trend (t/ha/yr)	Net mean AGB change (t/ha/32 yrs)	Total AGB change (t/32 yrs)	No.	Spatial units	Annual mean AGB trend (t/ha/yr)	Net mean AGB change (t/ha/32 yrs)	Total AGB change (t/32 yrs)
1	Romania	3.16	101.2	6416652.0	41	Bihor	3.14	100.4	196815.7
2	Romania (broad-leaved forests)	4.14	132.4	6662127.7	42	Mehedinti	4.97	159.1	295773.8
3	Romania (coniferous forests)	-2.06	-65.8	-392368.2	43	Satu-Mare	3.50	112.1	76180.3
4	Romania (mixed forests)	-0.33	-10.4	-52800.6	44	Hunedoara	2.57	82.4	246853.6
5	Carpathians region	1.15	36.9	949997.1	45	Gorj	4.74	151.8	541465.6
6	Intra-Carpathians region	3.86	123.6	1451208.0	46	Salaj	3.98	127.4	159425.6
7	Extra-Carpathians region	4.85	155.2	4015904.4	47	Cluj	2.67	85.6	86176.2
8	Eastern Carpathians	-0.38	-12.2	-95536.3	48	Alba	1.25	40.0	66522.4
9	Curvature Carpathians	-0.51	-16.2	-34219.3	49	Dolj	6.06	193.9	145908.3
10	Southern Carpathians	-0.99	-31.8	-170280.3	50	Maramures	-0.81	-26.0	-38936.1
11	Banatului Carpathians	4.29	137.1	701395.1	51	Valcea	3.77	120.6	415613.6
12	Western Carpathians	3.20	102.4	548637.9	52	Sibiu	1.59	50.8	103538.1
13	Transylvanian Plateau	3.61	115.5	642579.9	53	Olt	5.59	179.0	129711.8
14	Crisanei Hills	3.75	120.1	310144.1	54	Bistrita-Nasaud	0.11	3.5	3878.2
15	Banatului Hills	4.45	142.5	398430.6	55	Mures	2.26	72.3	121068.7
16	Subcarpathians	4.43	141.9	1133613.1	56	Arges	2.89	92.3	314176.0
17	Mehedinti Hills	4.87	155.8	73169.2	57	Teleorman	5.24	167.6	55336.9
18	Getic Plateau	5.65	180.9	1440101.8	58	Brasov	1.50	48.0	73826.5
19	Moldavian Plateau	4.31	138.0	602895.2	59	Harghita	-0.85	-27.2	-41550.1
20	Western Plain	3.90	124.9	100053.3	60	Suceava	0.31	9.9	21909.2
21	Romanian Plain	4.73	151.3	558696.4	61	Dambovita	4.49	143.6	214516.6
22	Dobrogea Plateau	4.84	154.8	201220.5	62	Giurgiu	5.09	162.7	115307.3
23	Danube Delta	2.18	69.8	6208.1	63	Covasna	1.00	32.1	31194.3
24	Carpathian montane con. forests	-0.42	-13.6	-224592.4	64	Prahova	2.95	94.5	121429.0
25	Central European mixed forests	4.40	140.9	1780969.1	65	Neamt	2.04	65.4	98091.8
26	East European forest steppe	4.91	157.2	232338.4	66	Ilfov	4.37	139.7	72231.9
27	Balkan mixed forests	5.69	182.0	1557952.3	67	Bacau	3.32	106.4	257234.4
28	Pannonian mixed forests	3.93	125.6	2807709.0	68	Bucuresti	2.75	87.8	797.0
29	Pontic steppe	4.55	145.7	262760.9	69	Botosani	4.17	133.4	110939.7
30	West	3.79	121.2	1620441.5	70	Buzau	3.42	109.4	182015.9
31	North-West	2.01	64.5	483539.9	71	Calarasi	5.40	172.8	45850.3
32	South-West	4.61	147.7	1528473.1	72	Ialomita	5.05	161.5	44660.8
33	Centre	1.18	37.7	354600.1	73	Vrancea	3.45	110.3	214368.8
34	South	3.67	117.4	911277.0	74	Iasi	4.32	138.4	172645.0
35	North-East	2.71	86.8	785876.3	75	Braila	3.70	118.3	15136.7
36	Bucuresti-Ilfov	4.34	138.8	73028.9	76	Vaslui	4.64	148.4	125056.1
37	South-East	3.81	121.8	659887.6	77	Galati	4.80	153.7	31494.1
38	Timis	4.25	136.0	249609.6	78	Constanta	5.40	172.8	45754.1
39	Arad	4.13	132.1	470973.6	79	Tulcea	4.41	141.0	171117.9
40	Caras-Severin	4.10	131.3	653004.8					

Notes: con – coniferous; more details about this table are available in Prăvălie et al. (2022b).

This mean annual trend corresponds to a mean net biomass change of >100 t/ha and a total AGB increase of ~6.4 Mt in Romania, over the entire 1987–2018 period (Table 6). Mean positive trends (~4 t/ha/yr or ~132 t/ha over the 32 years) were also found across broad-leaved forests, where AGB increased in total by ~6.7 Mt over the three decades (Table 6). On the opposite end, coniferous forests recorded AGB losses of ~2 t/ha/yr, on average, or ~0.4 Mt, in total, while mixed forest changes were very low, close to stationary (Table 6).

It is interesting to note that the three statistical indicators show AGB increases for all three major geographical regions, including the Carpathians region, where forest biomass increased at an average rate of ~1 t/ha/yr or by a total amount of close to 1 Mt (Table 6). This overall mountainous increase is explained by the intense biomass growth seen in the Western Carpathians and, especially, in the Banatului Carpathians (with a peak increase of over 4 t/ha/yr, on average, or ~0.7 Mt, in total), which counterbalanced the lower / much lower biomass decreases in Eastern, Curvature and Southern Carpathians (Table 6). Much higher biomass increases occurred in the Intra-Carpathian and especially the Extra-Carpathians regions – where average trends reached almost 5 t/ha/yr (or ~155 t/ha/32 yrs), while the total biomass gained in the 32 years accounted for ~4 Mt (Table 6). Among the landform units of this region, it seems that Getic Plateau forests had the highest AGB increases (almost 6 t ha/yr or ~1.4 Mt) (Table 6). Also, all ecoregions were marked by AGB gains (with record values in Balkan mixed forests, considering the mean value of 6 t/ha/yr, and in Pannonian mixed forests, with a total increase of ~2.8 Mt), except for Carpathian montane coniferous forests (small losses) (Table 6).

Administratively, biomass grew after 1987 in all forests of development regions, with a maximum mean rate of almost 5 t/ha/yr (or ~148 t/ha/32 yrs) in the South-West, or by a total record value of ~1.6 Mt in the West (Table 6). At the same time, county statistics revealed mean AGB gains ranging between about 0.1 (Bistrita-Nasaud) and 6 t/ha/yr (Dolj) across the country, and only two counties (Maramures and Harghita) with forest biomass losses (<1 t/ha/yr) (Table 6). Regarding the total changes over the entire 32-year period, evidence showed biomass gains ranging from several hundreds / thousands of tonnes (Bucuresti / Bistrita-Nasaud) to over 0.5 Mt (Caras-Severin and Gorj), and losses of under 0.1 Mt in two counties (Maramures and Harghita) (Table 6).

Climate change impact on AGB dynamics

Following the climate – AGB regressions (performed during summer period) based on statistically significant *p*-values, a response of AGB to T changes was identified in almost half (14) of analysed cases, and a general effect of AGB increase (in some spatial units located both in highland / hilly and lowland / plain areas of the country) was noticed as a result of climate warming (13 cases with positive *r* values) (Table 7). Still, despite the *p*-values' reliability (which is however relative, considering that most of the 14 cases have *p*-values with low statistical significance), a low impact of T on AGB increase can be discussed in these cases.

This finding is based on the fact that, in the highlighted natural units, R^2 coefficients do not exceed the 0.12 threshold (in the Intra-Carpathians region and Banatului Hills, which means that AGB dynamics in response to T changes is explained to an extent of maximum 12% in these cases, and to a lesser extent in the other units countrywide), and *r* values are below the 0.4 threshold (which indicates a weak intensity of the T – AGB statistical relation, considering that the *r* coefficient's intervals 0–0.19, 0.20–0.39, 0.40–0.59, 0.60–0.79 and 0.80–1 are generally interpreted as very weak, weak, moderate, strong and very strong correlations) (Table 7). However, a more significant sensitivity of AGB dynamics can be observed when changing (increasing) T by one unit (1 °C), which in most of the 14 cases exceeds 10 t/ha (with a peak in the Getic Plateau, where forest biomass gained for a 1 °C warming reaches ~18 t/ha, according to *Slope* values) (Table 7). Nationally (all of Romania), the T – AGB relations do not indicate statistically significant results (Table 7).

The P – AGB regression analysis indicates a non-existent precipitation footprint in forest biomass changes, except for two regional cases (Mehedinti Hills and Danube Delta) where statistical relationships are statistically significant, but with very low / low *Slope*, R^2 and *r* values (Table 7). Thus, the role of P in AGB changes is unclear / uncertain in Romania, at least according to the data and statistical methods used in this research.

A more obvious impact can be observed in the case of the ETo – AGB relation, which is statistically significant (*p*-values) in 15 cases (52%) of the 29 spatial units examined in Romania (Table 7). Compared to T, at regional level it seems that ETo had a greater (and opposite) influence on AGB, the variation of which, caused by ETo changes (R^2 values), reached and exceeded 15% (up to 19%) in several spatial units in the Extra-Carpathians area (Mehedinti Hills, Moldavian Plateau, Danube Delta, East European forest steppe and Pontic steppe) (Table 7). In these limited cases, the intensity of correlations is moderate, since the negative *r* values (which suggest a negative influence of ETo increase on forest biomass state) exceed the 0.4 threshold (Table 7). At the same time, the sensitivity of the AGB response (decrease) to ETo dynamics (increase) seems to be relatively low across Romania (in all cases, below 1 t/ha for a 1 mm ETo increase, according to *Slope* values) (Table 7).

Table 7. Regression parameters resulting from mean air temperature (°C) / precipitation (mm) / reference evapotranspiration (mm) – AGB (t/ha) analyses (1987–2018 period), which were applied across the forest area of various natural spatial units in Romania, i.e. entire national territory (1), major forest classes (2–4), major geographical regions (5–7), major landforms (8–23), and major ecoregions (24–29) of Romania.

No.	Spatial units	Temperature – AGB				Precipitation – AGB				Reference evapotranspiration – AGB			
		Slope	R^2 adj.	r	p-value	Slope	R^2 adj.	r	p-value	Slope	R^2 adj.	r	p-value
1	Romania	6.41	0.04	0.26	0.15	0.03	0.00	0.08	0.65	**-0.12**	**0.09**	**-0.34**	**0.06 ***
2	Romania (broad-leaved forests)	**9.82**	**0.07**	**0.31**	**0.08 ***	0.04	0.00	0.10	0.60	**-0.14**	**0.08**	**-0.33**	**0.06 ***
3	Romania (coniferous forests)	-1.30	0.00	-0.09	0.65	-0.02	0.00	-0.15	0.41	-0.03	0.00	-0.12	0.52
4	Romania (mixed forests)	-4.83	0.03	-0.24	0.19	0.03	0.00	0.15	0.42	**-0.11**	**0.10**	**-0.36**	**0.04 ****
5	Carpathians region	-0.51	0.00	-0.03	0.89	0.47	0.00	0.11	0.56	-0.95	0.06	-0.29	0.10
6	Intra-Carpathians region	**11.79**	**0.12**	**0.38**	**0.03 ****	-0.29	0.00	-0.13	0.47	-0.56	0.02	-0.24	0.20
7	Extra-Carpathians region	**14.32**	**0.10**	**0.36**	**0.04 ****	0.24	0.00	0.12	0.52	**-0.69**	**0.10**	**-0.36**	**0.04 ****
8	Eastern Carpathians	0.10	0.00	0.01	0.98	-0.03	0.00	-0.13	0.48	-0.09	0.04	-0.26	0.15
9	Curvature Carpathians	-7.36	0.04	-0.27	0.14	0.07	0.03	0.25	0.17	-0.10	0.03	-0.24	0.18
10	Southern Carpathians	**-7.23**	**0.07**	**-0.31**	**0.08 ***	0.03	0.00	0.15	0.40	**-0.12**	**0.08**	**-0.33**	**0.07 ***
11	Banatului Carpathians	5.01	0.00	0.15	0.42	0.07	0.01	0.21	0.26	-0.12	0.03	-0.24	0.18
12	Western Carpathians	3.46	0.00	0.12	0.50	0.02	0.00	0.05	0.80	-0.05	0.00	-0.13	0.48
13	Transylvanian Plateau	**10.66**	**0.08**	**0.34**	**0.06 ***	-0.08	0.00	-0.18	0.32	-0.11	0.03	-0.25	0.16
14	Crisanei Hills	**9.50**	**0.07**	**0.31**	**0.08 ***	-0.02	0.00	-0.04	0.83	-0.10	0.02	-0.22	0.22
15	Banatului Hills	**16.10**	**0.12**	**0.39**	**0.03 ****	-0.03	0.00	-0.05	0.77	-0.06	0.00	-0.11	0.55
16	Subcarpathians	10.91	0.06	0.29	0.10	0.07	0.00	0.18	0.32	**-0.17**	**0.09**	**-0.34**	**0.06 ***
17	Mehedinti Hills	6.49	0.00	0.17	0.36	**0.10**	**0.06**	**0.30**	**0.10 ***	**-0.23**	**0.15**	**-0.42**	**0.02 ****
18	Getic Plateau	**17.88**	**0.10**	**0.36**	**0.04 ****	0.07	0.00	0.14	0.46	-0.18	0.04	-0.27	0.14
19	Moldavian Plateau	**13.28**	**0.09**	**0.34**	**0.06 ***	-0.07	0.00	-0.12	0.53	**-0.24**	**0.16**	**-0.44**	**0.01 ****
20	Western Plain	**11.44**	**0.10**	**0.36**	**0.05 ****	0.07	0.00	0.12	0.51	-0.10	0.01	-0.20	0.27
21	Romanian Plain	7.17	0.01	0.19	0.29	0.13	0.03	0.24	0.18	**-0.18**	**0.11**	**-0.37**	**0.04 ****
22	Dobrogea Plateau	**15.00**	**0.08**	**0.33**	**0.07 ***	0.13	0.00	0.18	0.32	**-0.24**	**0.12**	**-0.39**	**0.03 ****
23	Danube Delta	1.61	0.00	0.08	0.67	**0.14**	**0.07**	**0.32**	**0.08 ***	**-0.12**	**0.19**	**-0.47**	**0.01 ****
24	Carpathian montane con. forests	-2.86	0.00	-0.15	0.42	0.01	0.00	0.03	0.86	-0.09	0.05	-0.29	0.11
25	Central European mixed forests	**12.71**	**0.08**	**0.33**	**0.07 ***	0.04	0.00	0.07	0.69	**-0.18**	**0.09**	**-0.35**	**0.05 ****
26	East European forest steppe	7.77	0.00	0.16	0.38	0.07	0.00	0.10	0.61	**-0.31**	**0.18**	**-0.46**	**0.01 ****
27	Balkan mixed forests	**14.86**	**0.07**	**0.32**	**0.08 ***	0.09	0.00	0.18	0.32	**-0.19**	**0.06**	**-0.30**	**0.10 ***
28	Pannonian mixed forests	**9.56**	**0.07**	**0.31**	**0.08 ***	0.01	0.00	0.04	0.85	-0.10	0.03	-0.24	0.19
29	Pontic steppe	10.42	0.04	0.27	0.13	0.14	0.03	0.24	0.19	**-0.23**	**0.17**	**-0.45**	**0.01 ****

Notes: con – coniferous; adj. – adjusted; ** high statistical significance; * low statistical significance; statistical significance is considered high, for p-values < 0.05, and low, for p-values between 0.05 and 0.1; all cases with the two types of statistical significance are highlighted in bold, while values written in regular font are not statistically significant; more details about this table are available in Prăvălie et al. (2022b).

Conclusions

Modelling forest biomass and changes in this key ecological attribute of forest ecosystems is a difficult task, but this methodological challenge was addressed in this project using a large number (9) of statistical algorithms, with which an immense volume of satellite (and forest inventory) data was processed. This challenge was all the more complicated given that AGB modelling was conducted nationally (across all Romanian forestlands), on a multi-temporal level (32 years) and at a very high spatial resolution (30 m × 30 m). In order to better highlight the difficulty of conducting such a detailed geospatial investigation, unprecedented in Romania, it must be kept in mind that the AGB results are based on modelling about 2 billion total pixel values, considering the analysed forest area (~64000 km^2), the area of a satellite pixel (900 m^2) and the mean annual number of pixels processed (> 60 million, a value influenced by cloud formations) over the 32 years.

The results of this extensive research showed that, in the period 1987–2018, while ~70% / ~30% of the total area of national forest changes was affected by increasing / decreasing trends, about half / one fifth of all positive / negative AGB trends are statistically significant nationally. Considering the statistically significant positive and negative trend data (highly reliable), it was found that forest biomass in Romania increased after 1987 at an average rate of ~3 t/ha/yr or by a total amount of ~6.4 Mt over the entire investigated period of 32 years. Regionally, the AGB change pattern is more complex. At the same time, eco-climatic statistical analyses showed that AGB changes are explained by climate dynamics to a small (or moderate, at most) extent, so further research is needed on other environmental variables that controlled recent changes in forest biomass.

Much more details about all these AGB results explored for the first time in Romania, which were obtained in accordance with the objective 3 of the project, can be consulted in Prăvălie et al. (2022b), a scientific paper which is currently under publication: **Prăvălie, R.,** Niculiță, M., Roșca, B., Patriche, C., Dumitrașcu, M., Marin, G., Nita, I.A., Bandoc, G., Birsan, M.V., 2022b. *Modelling and mapping recent forest biomass changes in Romania using complex data and machine learning algorithms*. **Stochastic Environmental Research and Risk Assessment** (in revision process).

Objective 4: Geostatistical processing of trends in net primary productivity of forests in Romania, in relation to the trends of the main climatic parameters over the past three decades

Modelling net primary productivity of forests and NPP trends

Net primary productivity (NPP, in t C ha^{-1} yr^{-1}), which indicates the amount of carbon fixed by photosynthesis in plant biomass, is an important ecological indicator for understanding the productivity, health and carbon storage capacity of forest ecosystems. For this project, this last indicator was initially calculated / estimated for the years 2013 and 2017, based on the PSPs of 291 NFI field survey data (http://roifn.ro/) distributed relatively uniformly across Romanian forestlands (Fig. 1b,c). The 291 field survey data, with NPP computations for 2013 and 2017, were selected from the 440 NFI in-situ surveys (Fig. 1b,c), after some statistical corrections performed in order to eliminate several outliers for achieving a normal distribution of NPP data. More details about the calculation procedure of NFI-based NPP, in 2013 and 2017, are available in Prăvălie et al. (2022c).

Therefore, similarly to the AGB modelling, countrywide NPP modelling was performed based on the Landsat and forest NPP inventory data, which were used in the application of several prediction models (mostly machine learning algorithms). This approach was chosen because of the remote sensing data availability for the 1987–2018 period, which provided

continuous temporal and spatial coverage across Romanian forests. Thus, the NPP real (calculated) data for 2013 was used for model training, and the 2017 data for testing (validating) the robustness of the applied statistical models (Table 8). In this way, the analysis of the 2017 modelling results against the real (original) data of the same year gives a clear view of the generalization power of the models and of the uncertainties related to the use of algorithms to predict the multitemporal NPP rasters from the 1987–2018 interval (Table 8).

In this case, 10 prediction models (algorithms) were tested for NPP modelling, which are the same as in the case of AGB (MLR, PLSR, SVR, RF, RPART, AdaBoost, XGBoost, NN, MLP), plus the k-nearest neighbours regression (KNN) model (Table 8). In this case as well, in choosing and applying the best statistical algorithm for estimating the NPP, besides the lowest RMSE criterion (1), the minimum and maximum predicted values (2), and data distribution of similarity (3) were also used. Considering the balancing results of the three criteria, the AdaBoost algorithm provided the best results, according to the arguments below.

Table 8. Prediction and validation results for the NPP modelled using Landsat and forest NPP inventory data.

No.	Algorithm	2013 NPP (t C ha^{-1} yr^{-1})				2013 RMSE (t C ha^{-1} yr^{-1})			
		min	mean	max	sd	min	mean	max	sd
1	MLR	4.02	7.57	10.80	1.32	0.02	1.37	7.7	1.13
2	PLSR	4.51	7.57	10.76	1.18	0.009	1.44	7.23	1.19
3	KNN	3.45	7.63	10.50	1.40	0	1.32	5.99	1.09
4	SVR	3.58	7.53	9.40	1.37	0	1.19	6.66	1.15
5	RF	2.87	7.60	12.60	1.76	0.01	0.51	2.62	0.45
6	RPART	4.32	7.57	6.69	1.65	0.002	1.13	4.92	0.95
7	**AdaBoost**	**2.25**	**7.57**	**15.54**	**2.21**	**2E-10**	**5E-06**	**7E-06**	**6E-06**
8	XGBoost	2.26	7.58	12.54	2.20	8E-05	0.01	0.015	0.01
9	NN	2.03	7.56	12.45	1.86	8E-04	0.79	4.20	0.73
10	MLP	2.26	7.50	14.90	2.17	8E-05	0.49	0.43	0.84
11	NPP *	2.25	7.57	15.54	2.21				
No.	Algorithm	2017 NPP (t C ha^{-1} yr^{-1})				2017 RMSE (t C ha^{-1} yr^{-1})			
		min	mean	max	sd	min	mean	max	sd
1	MLR	3.41	7.66	10.30	1.28	0	1.41	15.9	1.45
2	PLSR	4.81	7.80	10.30	1.19	0.009	1.43	7.24	1.19
3	KNN	3.62	7.62	10.40	1.30	0.02	1.66	15.40	1.56
4	SVR	4.04	7.63	9.35	1.20	0	1.39	1.86	1.43
5	RF	4.31	7.74	10.20	1.41	0	1.48	15.20	1.43
6	RPART	4.32	7.74	10.14	1.41	0.002	1.48	15.23	1.43
7	**AdaBoost**	**2.69**	**7.68**	**12.60**	**1.74**	**0.01**	**1.69**	**15.40**	**1.57**
8	XGBoost	3.60	11.70	17.05	2.60	0.047	4.50	15.43	2.29
9	NN	-41.3	12.10	76.50	10.12	0.004	8.30	69.50	7.90
10	MLP	2.94	9.80	20.11	3.12	0.02	3.10	15.86	2.73
11	NPP *	0.185	7.41	18.15	2.32				

Notes: min. – minimum values; max. – maximum values; sd – standard deviation; * – real (measured / calculated) data (NFI surveys); values in bold are representative for the best model chosen for modelling yearly NPP values, according to the three mentioned statistical criteria.

In the case of RMSE values (1), all the model results, with the exception of XGBoost, NN and MLP, are very close (values under 2 t C ha^{-1} yr^{-1}) (Table 8). Considering the minimum and maximum values (2), i.e. the spread, AdaBoost and XGBoost give the best range. However, since XGBoost has a less favorable RMSE, AdaBoost is considered the best candidate. Further, when the distribution shapes of 2017 predicted data (3) are analysed visually (Fig. 8), it is clear that the AdaBoost estimation is the closest one to the real data.

Considering the above-presented results and arguments, the AdaBoost algorithm was selected to predict the yearly NPP rasters (1987–2018) across national forests. Finally, the 32 NPP rasters produced through the AdaBoost model were investigated as trends using the MK test and *Sen's slope* estimator. The two geostatistical tools were applied at pixel level, and the results on the direction, intensity and statistical confidence of NPP trends have been explored so far at the national level.

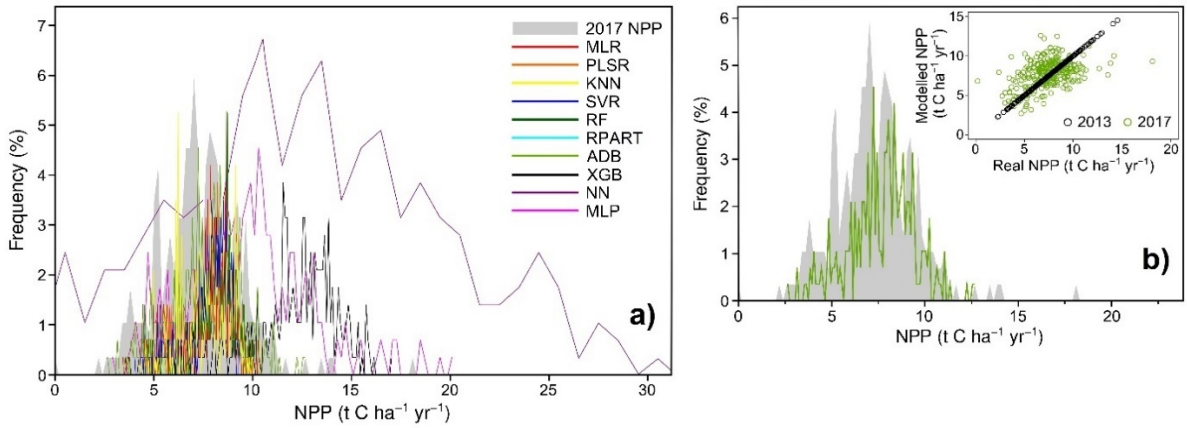

Fig. 8. Histograms of real (computed) NPP data for 2017 (in grey) and its prediction (for the same year) resulting from applying ten statistical algorithms (a) and the AdaBoost model (b). Notes: the histogram on the righthand side (b) is a selection (for a better visualisation) of the best results on distribution similarities of real (in grey) and modelled (AdaBoost) data in 2017; the scatterplot inside the histogram (b) features visual results on the real vs. modelled (AdaBoost) NPP values for 2013 training and 2017 testing data.

Results

NPP trends

The spatio-temporal analysis of changes in this ecological indicator (Fig. 9) showed unclassified national trends from -0.07 to 0.22 t C ha^{-1} yr^{-1}, in which, visually, positive NPP change are dominant nationally (Fig. 9a). By classifying trends into negative (NPP trends < -0.001 t C ha^{-1} yr^{-1}) and positive (> 0.001 t C ha^{-1} yr^{-1}), it was noticed, surprisingly, that NPP increasing trends are by far dominant nationally, as they cover 99.6% of all NPP national changes of forest ecosystems (Fig. 9b,c). Moreover, most of these positive trends (~73%) are statistically significant, which highlights a recent intensification of carbon fluxes between countrywide forests and the atmosphere, and an increase in carbon storage in Romanian forests, fixed through photosynthesis.

In the immediate future, detailed NPP regional trends will be explored and eco-climatic relationships will be examined, in a similar manner to the analyses of statistical correlations between climatic parameters and NDVI and AGB ecological indicators. Therefore, the results on NPP dynamics in relation to climate change are being finalised and will soon be submitted for publication (most likely in September 2022).

Much more details about all these NPP results explored for the first time in Romania, which were obtained in accordance with the objective 4 of the project, can be consulted in Prăvălie et al. (2022c), a scientific paper which is currently being finalised and which will be submitted for publication soon: **Prăvălie, R.,** et al. (author list being defined), 2022c. *Machine learning-based prediction and assessment of recent dynamics of forest net primary productivity in Romania*. **Environmental Research** (planned for publication).

Therefore, via countrywide modelling, mapping and assessment of the results of the three indicators of forest productivity, NDVI, AGB and NPP, all objectives and specific activities of this project were met. The one exception consists of specific activity 4.4. of objective 4 (Table 1), which will be implemented soon by investigating climate – NPP relationships in Prăvălie et al. (2022c). These eco-climatic relationships are analysed with a delay compared to the working plan of the funding application, considering the immense volume of processed data (e.g **the 2 billion total pixel values modelled for AGB only**, as previously mentioned) or the complexity of spatial analyses conducted.

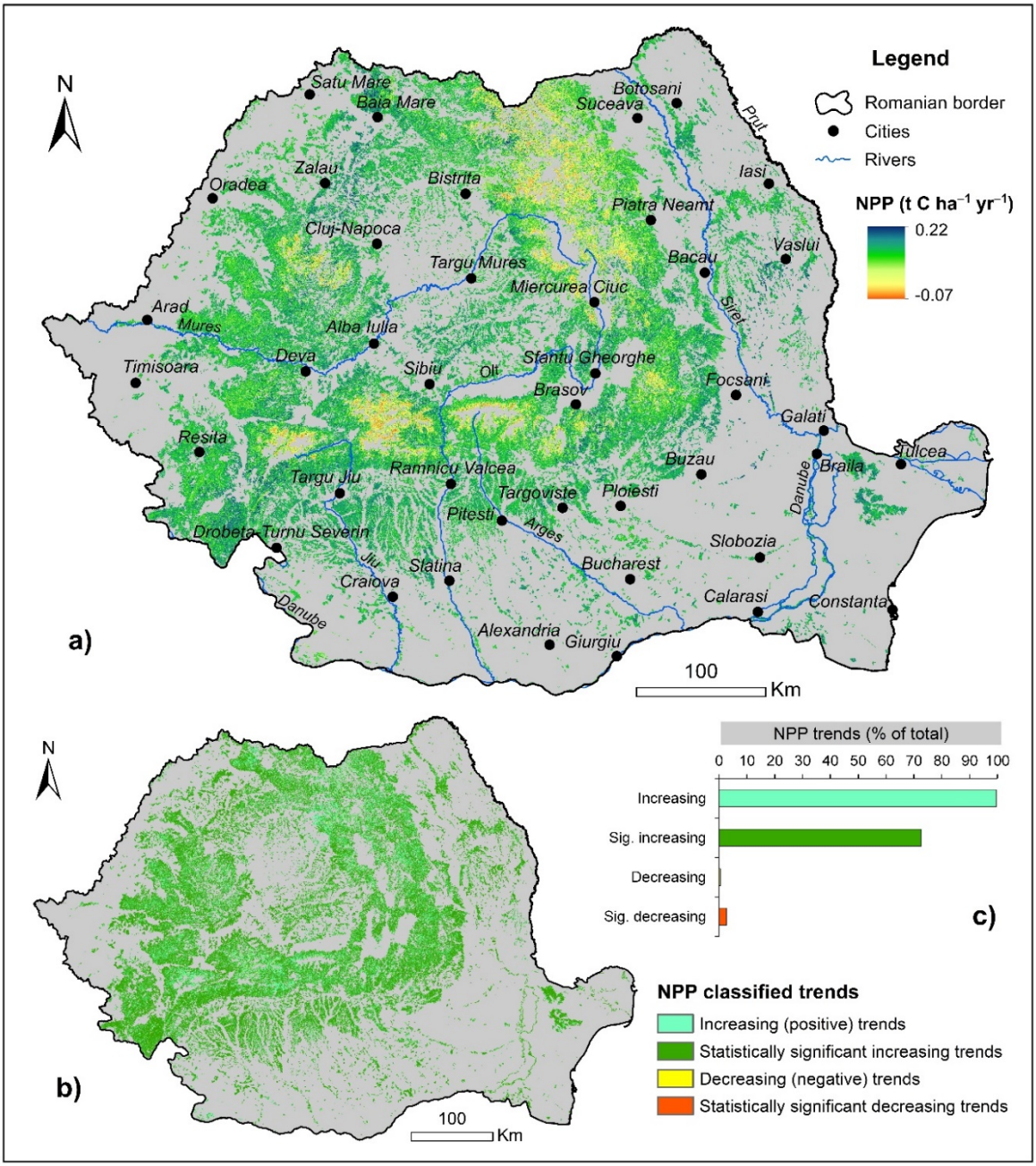

Fig. 9. Annual NPP trends in Romania during 1987–2018, unclassified (a), classified (b) and with extracted percentage-based statistics of the four types of trends resulting from the NPP trend classification (d). Notes: Increasing / Decreasing – percentage-based area of positive / negative NPP trends, reported to the total area of forest changes (Increasing + Decreasing) in Romania; Sig. increasing / Sig. decreasing – percentage-based area of statistically significant positive / negative NPP trends, reported to the total area of increasing / decreasing trends in Romania; more details about this figure are available in Prăvălie et al. (2022c).

Considering the latter case, **all regional investigations** (in terms of forest classes, geographical regions, landforms, ecoregions, development regions and counties) of NDVI, AGB and NPP trends and of eco-climatic correlations **are additional analyses** compared to the working plan of the project, which is an additional reason that explains the delay in implementing activity 4.4. In other words, while the funding application foresees the analysis of forest productivity dynamics in relation with climate change **only at national (general) level** (Table 1), regional (detailed) investigations were subsequently considered important for forestry stakeholders and policymakers, as per the explanations provided in this final report.

Objective 5: Raising awareness on the necessity of interdisciplinary scientific investigations of this important ecoclimatic issue in Romania's scientific/political spheres by disseminating the study's results

This objective was automatically implemented by meeting the four previous objectives and by disseminating the project results in **three scientific papers**, published, under publication or in the process of being finalised and submitted for publication:

- **Prăvălie, R.,** Sîrodoev, I., Nita, I.A., Patriche, C., Dumitrașcu, M., Roșca, B., Tişcovschi, A., Bandoc, G., Săvulescu., I., Mănoiu, V., Birsan. M.V., 2022a. *NDVI-based ecological dynamics of forest vegetation and its relationship to climate change in Romania during 1987–2018*. **Ecological Indicators** 136, https://doi.org/10.1016/j.ecolind.2022.108629, **Impact Factor (IF) 6.3, red zone (Q1)**;
- **Prăvălie, R.,** Niculiță, M., Roșca, B., Patriche, C., Dumitrașcu, M., Marin, G., Nita, I.A., Bandoc, G., Birsan, M.V., 2022b. *Modelling and mapping recent forest biomass changes in Romania using complex data and machine learning algorithms*. **Stochastic Environmental Research and Risk Assessment** (current status: accepted with major revisions; thus, the article is in revision process), **IF 3.8, red zone (Q1)**;
- **Prăvălie, R.,** et al. (author list being defined), 2022c. *Machine learning-based prediction and assessment of recent dynamics of forest net primary productivity in Romania*. **Environmental Research** (planned for submission for publication in September 2022), **IF 8.4, red zone (Q1)**.

Two other papers were already published in highly prestigious journals (with the acknowledgment of the project), which analysed various degradation processes globally (including in Romania), influenced directly or indirectly by the state of forest (or non-forest) vegetation productivity:

- **Prăvălie, R.,** 2021. *Exploring the multiple land degradation pathways across the planet*. **Earth Science Reviews** 220, https://doi.org/10.1016/j.earscirev.2021.103689, **IF 12, red zone (Q1)**;
- **Prăvălie, R.,** Nita, I.A., Patriche, C., Niculiță, M., Birsan, M.V., Roșca, B., Bandoc, G., 2021. *Global changes in soil organic carbon and implications for land degradation neutrality and climate stability*. **Environmental Research** 201, https://doi.org/10.1016/j.envres.2021.111580, **IF 8.4, red zone (Q1)**.

Moreover, results were also disseminated by attending **seven international conferences** (with presentations directly or indirectly related to the project theme), held (especially online) in Romania or abroad:

- **Prăvălie, R.,** 2020. *Forest perturbations across the planet. A major pathway of global land degradation*. International Conference "Dimitrie Cantemir", 40th Edition, October 24, Iași, Romania;
- **Prăvălie, R.,** Bandoc, G., 2020. *Spatio-temporal trends in land susceptibility to degradation in Romania due to climate change, vegetation degradation and anthropogenic pressures*. International Conference "Present Environment and Sustainable Development", 15th Edition, November 21, Iaşi, Romania;
- **Prăvălie, R.,** Bandoc, G., 2021. *Analysis of forest ecological changes in Romania based on detecting recent trends in Normalized Difference Vegetation Index*. "9th Annual

International Conference on Ecology, Ecosystems and Climate Change", 12–15 July, **Athens, Greece**;

- **Prăvălie, R.,** 2021. *Recent impact of climate change on forest productivity in Romania*. "27th International Conference on "Agriculture, Biological and Environmental Sciences" (MABES-21)", August 11–13, **Barcelona, Spain** (the presentation was awarded the **prize for the best oral presentation** in this international conference);
- **Prăvălie, R.,** Bandoc, G., 2021. *Detecting land-atmosphere carbon fluxes at global scale after 2001*. The 2nd International Conference "Geographical Sciences and Future of Earth", November 12, Bucharest, Romania;
- **Prăvălie, R.,** Bandoc, G., 2022. *Exploring forest biomass changes in Romania in the last three decades*. International Conference on Forest Ecosystem Carbon Dynamics and Climate Change, January 14–15, **Zurich, Switzerland**;
- **Prăvălie, R.,** Niculiță, M., Roșca, B., Patriche, C., Bandoc, G., 2022. *Examining trends in forest above-ground live biomass in Romania after 1987*. International Conference "Present Environment and Sustainable Development", 17th Edition, June 3–4, Iaşi, Romania.

All these deliverables, along with the general project information and research reports, can be consulted on the **project web page**: https://cccpm.unibuc.ro/postdoctoral-project-2/.

The impact of the project results

The project results have at least a double impact, namely *in the scientific field* and *in the socio-economic and applicative fields*. **The scientific field impact** primarily consists of generating, for the first time, various scientific information on forest productivity dynamics in relation to recent climate change in Romania. This valuable information, presented briefly in this report and in detail in the three scientific papers (Prăvălie et al., 2022a,b,c), can be useful for forestry stakeholders (e.g the scientific community, foresters, local communities, etc). In perspective, *new research directions* can emerge following the results obtained in this project. For example, considering that only a moderate climate signal in forest productivity changes was detected, future studies can emerge for exploring the additional non-climatic factors that controlled the forest NDVI, AGB and NPP changes in recent decades.

The socio-economic and applicative impact consists of using the resulting information *in developing more effective strategies* for better adapting forest ecosystems to current and future climate change or for combating climate change itself, by maintaining their optimal productivity. Considering the latter case, the results of this project can be useful for the current "Romania's national strategy for climate change 2013–2020" (or rather for the future climate strategy, which is being prepared), one of the strategic objectives of which is increasing the CO_2 absorption capacity via major natural pools such as forests. Consequently, the project results can be useful for government climate policies, but they can also serve for other strategies (which are directly or indirectly aimed at the forestry sector), like "National Forestry Strategy 2018–2027", or "National Strategy for the Sustainable Development of Romania 2030".

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