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Distribution of forest-based innovations across Europe

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A R T I C L E I N F O

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A B S T R A C T

Vast majority of forestry research on innovations is based on case studies, which makes it difficult to ascertain their distribution across Europe. The relation between innovating activity and the forest within which it takes place is also an under-explored research area. In this study, we address these problems by combining survey data, spatially explicit datasets and machine learning to devise geographical probability distribution of innovation development across Europe. We differentiate between innovations focused on provision of wood and those which focus on biodiversity protection, carbon storage and forest recreation. We also show that most of the variability in the data depicting innovation development can be explained by place-based variables, such as the amount of tree biomass in the forest, tree species composition, nature protection status, terrain ruggedness and road density. Results suggest the need to further explore the role of 'place-based' contextual variables in innovation development and highlight various issues that different policies might face when aiming to modify forest management practices in Europe.

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1. Introduction

Sustainability transition to a post-fossil-based economy is one of the most prominent European policy objectives, as enshrined in the EU's bioeconomy strategies (European Commission, 2012 and European Commission, 2018). The origins of bioeconomy in the European Union (McCormick and Kautto, 2013; Pattermann and Aguilar, 2018) are rooted in the idea that knowledge and innovation-based large-scale technology-oriented 'fixes' are needed to solve issues of food security, depletion of natural resources, environmental degradation (including climate change) and 'competitive threat' from East Asia and the USA. Although a more inclusive definition of bioeconomy was put in place in the second EU bioeconomy strategy as compared to the first one (e.g. the aim to '*understand the ecological boundaries of the bioeconomy*'), the core commitment to technological knowledge-based solutions of the first EU bioeconomy strategy was maintained. This left policy objectives of many stakeholders that participated in its preparation unfulfilled. Together with their allies from different segments of central EU apparatus, it energized them to pursue alternative policy venues through which their policy objectives could be reached (Lühmann, 2020). This reaction (Eckert and Kovalevska, 2021) is embodied in the EU Green Deal (European Commission, 2019). The document places itself in the same position as the EU bioeconomy strategy; as the seminal document of the EU for the sustainability transition to a post-fossil-based economy. This is explicitly stated at the beginning of the document, as it "… *aims to transform the EU into a fair and prosperous society, with a modern, resource-efficient and competitive economy where there are no net emissions of greenhouse gases in 2050 and where economic growth is decoupled from resource use*." The EU Green Deal views human-nature relation through the concept of Ecosystem Services, and in forestry emphasizes the importance of regulating Forest Ecosystem Services (FES), such as biodiversity and carbon sequestration. The prominence of regulating, but also cultural FES (such as forest recreation) is evident in science-policy interface (Borie and Hulme, 2015) and has received prominence in science as well (Pörtner et al., 2023; Kanger and Schot, 2018).

As innovations are an integral part of any sustainability transition, the dichotomy of umbrella policies between the EU bioeconomy strategy and the Green Deal in the EU's sustainability transition discussed above is reflected onto the innovations themselves (van der Jagt et al., 2020). The policy objectives of these two EU strategies can be traced to differentiation between the *technological innovation systems* and *nature-based innovation systems*. Van der Jagt *et al* also categorize the factors that lead to the development of innovations, where *technological innovation systems* are in-line with the conceptualization of bioeconomy and sustainability-transition innovations from the perspective of technology studies (Bröring et al., 2020). This perspective emphasizes value-chain, market and technological factors. *Nature-based innovation systems* on another hand, also consider the role of place-based endowments such as natural processes (e.g. soil and climate conditions – conceptually linked to regulating FES), cultural frames of reference and societal conditions and dynamics. The sustainability transitions literature continues to highlight the role of technological innovation (Geels and Schot, 2010; Kanger and Schot, 2018), where the innovation itself has a normative direction towards societal change and where geography-linked variables have mostly not been considered until 15 years ago (Smith et al., 2010). Since then, this has changed; first, the 'geography of sustainability transitions' was proposed as a research direction (Truffer and Coenen, 2012), then it has been developing (Hansen and Coenen, 2015) and is now seen as one of the priority areas to which future sustainability transitions research should develop (Truffer et al., 2022). In terms of innovation studies within the field of bioeconomy, there is very little link to the natural sciences and to the variables of 'place-based' endowment (Golembiewski et al., 2015). Although Wydra (2020) identifies that information about actual innovation activity in the field is scattered and more systematic measurement efforts are needed, the author identifies biggest research gap in assessing innovation outcomes. In forest-based bioeconomy the situation is not different; as Lovrić et al. (2020) frame development of innovations on technology-rooted open innovation concepts (Van Lancker et al., 2016), again with no reference to place-based endowments or FES.

In forestry, i.e. the 'supply-side' of the forest-based bioeconomy, a similar situation can be found to technological perspectives on innovation and sustainability transition. Although some publications, mostly focusing on non-wood forest products (e.g. Slee, 2011; Ludvig et al., 2016a; Ludvig et al., 2016b; Živojinović et al., 2017), tackle 'place-based' variables, the ones that aim for an overview of innovation activity in the field (Kubeczko et al., 2006; Rametsteiner and Weiss, 2006; Weiss et al., 2020; Weiss et al., 2021) do not. The only notable exceptions to this are the recognition of forest ownership type and area size in Rametsteiner and Weiss, 2006. Another issue is that the representative data on populations of both forest owners and managers on one side and of (innovating) organizations operating in the sector on the other side is practically unattainable and thus unknowable. As there are no central registries, different associations are only partially representative of their respective stratums of these populations, and the shares of potential respondents in the overall population of Europe are too low for any pooling agency to organize a general population random-sample survey. The study that best tried to overcome this problem was by Rametsteiner and Weiss (2006), who used a simple random sample within stratums of the population of innovators where this was possible, and combined it with quota sampling, institutional–level survey with snowball sampling and then case-study interviews. Although this approach appears very convincing, there is no way of knowing to what extent their results represent more than the opinions and experiences of people that they have directly contacted.

All of these points to the following shortcomings in the current body of knowledge on innovation development in forestry: (I) there is a lack of understanding the role of 'place-based', local-context on innovation development and (II) there is lack of innovation studies at the broader European level. As to why study 'place-based' variables in the context of innovations in the first place; "while there is a wide consensus that place-specificity matters there is still little generalizable knowledge about how place-specificity matters for (sustainability) transitions" (Hansen and Coenen, 2015). To address these shortcomings, in this study we provide an overview of how some forest-based innovations are distributed across Europe, while discriminating between those 'technology' oriented (and focused predominantly on wood – i.e. provisioning FES) and 'bio' (or nature) oriented (and focused on 'true' services – i.e. regulating and cultural FES, such as soil erosion prevention, habitat provision, climate change mitigation and forest-based recreation and tourism).

We also link the probability of innovation development to a plethora of place-based variables, such as growing stock and increment, tree species composition, road and population density, nature protection and ownership status. We do so by first gathering primary data on innovation development from a Europe-wide survey, combine it with spatially explicit datasets on Europe's forests and then extrapolating the survey's finding to (almost) all of Europe's forests through application of machine learning.

2. Materials and methods

2.1. Data collection

The primary input to the analysis is a survey dataset on FES (Torralba et al., 2020). The targeted population were forest owners and managers in Europe, and the distribution channels where the membership networks of European State Forest Association (EUSTAFOR), Confederation of European Forest Owners (CEPF), European Landowners Association (ELO) and European Federation of Municipal and Local Community Forests (FECOF). The questionnaire was first pre-tested with 18 researchers from different backgrounds and then with selected forest owners and managers from each of the above-listed organizations. It was then translated into 19 languages. The survey was administered through an on-line format of the *Maptionnaire* software, where respondents were asked to provide their answers with reference to a point-location of a forest that they manage and/or own. This was done through an interactive map with both satellite and Open Street Map layers, where the point-location was assigned on at least 1:25,000 scale; one that allows for an assignment within a one-kilometer radius (i.e. respondents needed to zoom-in to precisely point to where their forest plot was located). Respondents owning or managing multiple forest plots were instructed to point to the center of their largest forest plot. Respondents were asked which type of innovations they have developed (total of 10). These were later on grouped into innovations focusing on (I) Provisioning Forest Ecosystem Services (FES) and (II) Regulating and cultural FES. A further description of these innovation types (as described to the respondents in the survey) is presented in Table 1. FES categorization is based on Torralba et al., 2020. Examples of different innovations are based on inventory of FES innovations (Bottaro et al., 2019). Graphical overview of the research design is presented in Fig. 1.

Table 1
Summary representation of all the variables used in the study.

Type	Variable group	Notes
Dependent	Development of innovation focused on provisioning FES	Provisioning FES entail biomass for material and energy use, game (hunting) and wild forest products (e.g. mushrooms, berries, nuts, medicinal plants). Some examples of these innovations include: • New technology for biomass production (e.g. usage of harvester instead of chainsaws or using satellite imagery for identifying logging sites) • New way to generate value from ecosystem services (e.g. organizing auctions for high-quality timber) • Change of forest management to improve / sustain biomass production (e.g. new thinning measures for increased wood increment or for increased resilience) Survey responses were binary (0/1). Output calculations are expressed as predicted likelihood of innovation
	Development of innovation focused on regulating and cultural FES	Regulating FES entail watershed protection (water and erosion control), air quality regulation, climate change mitigation (carbon sequestration and storage) and habitat for plants and animals (habitat provision and biodiversity). Cultural FES entail cultural, emotional and spiritual values, education (e.g. for forest kindergartens, schools) and healthcare, sports and outdoor recreation (nature-based tourism). Some examples of these innovations include: • New ecosystem service (e.g. a pollination strip or burial forest was newly established); • New technology for other ecosystem services; • Change of forest management to provide other ecosystem services (e.g. new thinning measures for support nature tourism) • New communication or marketing strategy implemented (e.g. a website or a hired branding professional); • New users of ecosystem service(s) (e.g. children or urban citizens); • New trans-sectoral contract created (e.g. a new agreement with conservation groups or eco-tourism enterprises) • New transboundary cooperation created (e.g. a sustainable tourism project across country borders) Survey responses were binary (0/1). Output calculations are expressed as predicted likelihood of innovation
Independent	Coordinates	In meters, LAEA projections; country (0/1)
	Land characteristics	Average annual rainfall (mm yr-1); slope (degrees); soil bearing capacity (0-1); terrain ruggedness (meters); reference evapotranspiration (mm yr-1)
	Forest characteristics	Biomass and carbon (tons km-2), separately above and below ground; growing stock volume (m3 ha-1); increment (ton ha-1 yr-1); percentage share of a tree species from land area (for 20 tree species, coded 0-100); dominant tree species (0/1)
	Relation to people	Accessibility (travel time in 2000 and 2015); population density; share of private forest ownership; Natura 2000 protection status (SPI, SCI & SAC, joint for all classes)

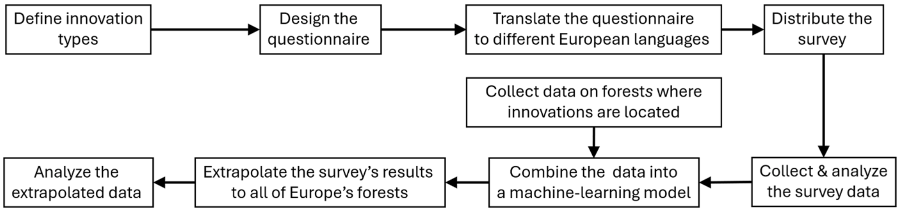

Fig. 1. Overview of research design.

The survey received a total of 1,707 responses, of which 1,145 included a forest location. The sample was further decreased to responses showing a distance between the selected forest location and the closest point in the forest data grid smaller than 750 meters (i.e. we excluded respondents who clicked on a point-location out of the forest). The final sample included 687 cases. The questionnaire that was used in this study is presented at the end of the Supplementary File, while an overview of responses is presented in Appendix. The point-locations of respondents' forests are situated in 21 different European countries with wide geographical coverage (see Supplementary Figure 1). The research design of this study entailed purposive sampling; which has a small level of ability to generalize its findings to a population that is greater than that within the sample. Or in other words, it would be imprudent to claim that the analysis of direct survey's responses produces results that are similar to the true responses of the population of European forest owners and managers. Supplementing arguments to this proposition would be the fact that responses in the survey are not randomly distributed across Europe (e.g. less in France and more in Germany, more in Western and Northern Europe and less in Eastern Europe – see Supplementary Figure 1 for details). This would also mean that even taking all the responses with little or no data pre-processing and validation, this number (i.e. 1,707) would still be too low to make inferences on the status of innovations across different parts of Europe (while bearing in mind the targeted 95% confidence interval per unit of analysis). So, in order to produce results from the survey's data that have at least generalization power on some aspects, we supplemented it with all spatially explicit data on Europe's forests that is publicly available and that can be put in a same raster dataset (i.e. onto a same spatial resolution). We then compiled the two data sources into a machine learning model and tasked it to estimate the 'probability of innovation occurrence', where the assumption was that similar forests have similar probability of innovation being developed in them. As this modelled 'probability of innovation occurrence' is based of similarity to known innovation sites, it's more prudent to frame it as 'predicted likelihood of innovation', rather than an observed outcome.

This study is complementary to Mann *et al*, 2020, who focus on analyzing direct survey responses and take into account many socio-economic-institutional variables. Focusing just on providing (to the extent possible) a representative overview of innovation activities and the link to forests within which their development occurs has its drawbacks. The main one is that, aside from the place-based' variables, no other independent variables are accounted for. Or in other words, this paper does not consider institutional frameworks, ownership models, or the presence (or absence) of entrepreneurial support structures; all the variables that the literature typically associates with innovation development. For effects of these, please review Mann *et al*, 2020.

The next step was to gather spatially-explicit data on Europe's forests, which would be used to extrapolate the survey's findings to the majority of Europe's forests. The data was compiled on a 1×1 km spatial resolution in the LAEA (Lambert Azimuthal Equal-Area) projection on 94 different variables. Summary overview of the variables is presented in Table 1. For details, please see Supplementary Table 1. Forested parcels were defined as cells with above-zero value of above- and below-ground biomass according to the forest biomass map of living forests produced by the Joint Research Centre of the European Commission (Barredo Cano et al., 2012). The data grid covers 34 out of 51 European countries, and in general has weak coverage of Eastern Europe. Countries not covered in the data include Andorra, Armenia, Azerbaijan, Belarus, Bosnia and Herzegovina, Cyprus, Georgia, Iceland, Kazakhstan, Malta, Moldova, Monaco, Russia, San Marino, Ukraine and Vatican City. Russia and Turkey were excluded as most of their forest area is out of Europe. Only complete cases in this data grid were used. This led to a data set with 1,458,941 observations (equalling 1.46 mil km^2), representing 86.94% of all forest area in Europe. Point-locations of the forests which as indicated by the respondents in the survey were associated to the closest point-location on the spatially explicit 1×1 km raster data; and the attributes from these closest point-locations were copied to the point-locations to which the respondents had marked on a map. Only forest plots located less than 750 meters from known, actual forests were included in the analysis. Or in other words, we have copied the values on growing stock, tree species composition and on all other independent variables listed in Table 1 from the closest known actual forest to the point-locations that marked the center of the forest that the respondents have managed and/or owned at the time of the survey's distribution.

2.2. Data analysis

The extrapolation of the survey's results to (almost) all of Europe's forests was implemented through a deep neural network model. This was done on the machine learning platform *TensorFlow* (Abadi et al., 2016). Spatially explicit co-linear (correlated) variables were removed. As the variables above-and-below ground biomass, above-and-below ground carbon, above-ground biomass and above-ground carbon proved highly correlated, only the above-and-below ground biomass variable was kept in the estimations. Country location of forest point locations were specified with 'one-hot-encoding'; i.e. each country membership was coded as a separate binary variable (0 / 1 or 'point is not in this country' / 'point is in this country'). We removed the binary variables of country association for countries from which we had no responses. As discussed above, the survey data is non-randomly distributed in Europe; i.e. some countries have many more responses than others. This issue of country-level representativeness was tackled both in the data pre-processing and post-processing. In the pre-processing, country membership variables for which there were less than 10 responses in the survey's data were removed. In the post-processing, data on predicted likelihood of innovation was normalized by country. All input variables were also separately normalized. Summary explanations of deep neural networks and description of their implementation are presented in Appendix 1. The 'goodness of fit' of the model, which can be proxied with binary accuracy on validation data, was 0.9562. This means that on a sub-sample representing 20% of the whole dataset (i.e. the sub-sample is only used for validation as the model has not learned from it) the model was able to correctly predict 95.62% of the time whether an innovation would be developed or not. The output of the model is expressed as a predicted likelihood of innovation.

Ordinary Least Squares regression – based Analysis of covariance (ANCOVA) was performed on likelihoods of innovation development as dependent variables, where all interval-type input data was used as covariates. *Pingouin*-version (Vallat, 2018) of ANCOVA was used to calculate the partial eta-squared effect sizes. This was done in a loop for all covariates separately. For this ANCOVA, development of innovation focused on provisioning FES was used as a covariate where the dependent variable was development of innovation focused on regulating and cultural FES; and vice-versa. This led to 38 ANCOVA tests per innovation type. Mean partial eta-squared effect sizes were used as the final ones (i.e. as presented in the Results section and in Supplementary material). The choice of having two dependent variables (i.e. innovation types) was inductive. Initially, we started with modeling the likelihood of innovation development for each of the ten innovation types listed as bullet-points in Table 1. But the best accuracy under this choice was 0.6143, there were fewer independent variables that were significant in ANCOVA tests and effect sizes were on average smaller. After noticing that the biggest effects in ANCOVA tests were the occurrence of other innovation types, we identified the ones that tend to occur together. This led to classifying individual innovation types to two groups – one focused on provisioning FES and another one focused on regulating and cultural FES; as they are presented throughout this paper. Analysis was implemented in the Python programming language. The survey data extrapolation expressed as predicted likelihood of innovation is presented in Fig. 2.

It appears from Fig. 2 that the development of both innovation types is akin to a normal distribution. However, when the data is put to Shapiro-Wilk Test, it rejects that data is normally distributed ($p < 0.0001$). The distribution of probability of innovations focused on provisioning FES has a mean of 0. 5315, median of 0.5730, skewness of -0.5363 and kurtosis of -0.3991. The distribution of probability of innovations focused on regulating and cultural FES has a mean of 0.4867, median of 0.4996, skewness of -0.0601and kurtosis of -1.0682. As in absolute terms, skewness values are smaller than 1 and kurtosis values are smaller than 2, it can be stated that the innovation probabilities are 'akin' to normally distributed (Hair et al., 2022) where the results of the Shapiro-Wilk Test are more indicative of how large the data is (i.e. number of degrees of freedom), than what the distributions look like. Dichotomizing the innovation development probability at 0.5, innovations focused on provisioning FES could develop on 61.88% of forest point-locations in Europe, while same is true for 49.96% of forest-point locations in the case of innovations focused on provisioning and regulating FES. All the results, including the independent variables describing Europe's forests and the dependent variables of innovation development, are publicly available in a form of 1×1 km raster data on *Zenodo* with DOI 10.5281/zenodo.12699294.

A 'synthetic' data-set has been used to shed light on the relation between the dependent variables and the independent variables that were used in the estimation. This data-set was created by the following procedure: first, relevant independent variables were selected based on their partial eta-squared effect sizes using ANCOVA. Then mean, minimal and maximal values of all independent interval variables per country (from the entire data-grid representing Europe's forests) were calculated. We then made a table where a single row represents mean values for all independent variables in each country. This same row was then multiplied many times over, corresponding to the range of a selected independent variable in that country with the increment of one. The values of the selected independent variable in that table were replaced with the values corresponding to the range of that variable in that country (with the increment of one). The procedure was iterated over all countries and all selected variables. As with all other steps of analysis, the data

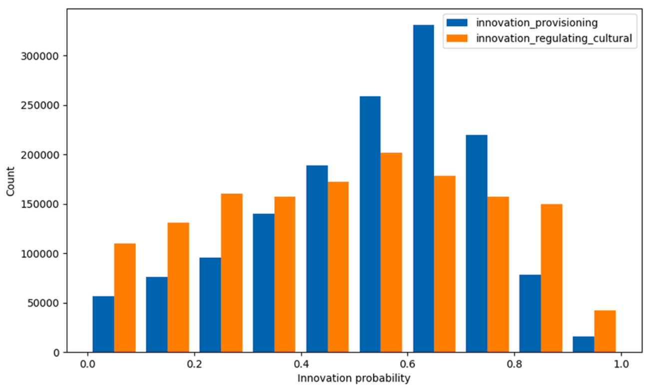

Fig. 2. Histogram of innovation development.

was normalized by country. On example of population density variable, this procedure would create (I) a table for one country were all rows have the mean values of all independent variables except for the population density; and the values on the 'population density column' would correspond to all the values of population density for that country. The produced scatterplots that show the relation between selected independent variables and the two innovation types are displayed at Fig. 4. Trend-lines of a nonparametric locally weighted linear regression model have been plotted over the scatter-data. Several selected variables have shorter range than others. These are share of private forest ownership, share of broadleaved and share of coniferous species. For these variables, synthetic data was produced with a 'value-step' of 0.01 instead of 1, as it was done with other variables. This change was introduced to make the comparison among all the selected variables uniform (e.g. for variable 'share of private forest ownership' that that ranges from 0 to 100 step of 0.01 produces 10 000 values within it it's range, and for variable 'above-ground biomass' that ranges from 1 to 25000 tons of biomass per square kilometer step 1 produces 25 000 values within it it's range).

3. Results

3.1. Geographic distribution of innovation

The geographic distribution of predicted likelihood of innovation development is presented in Fig. 3.

In terms of broad geographical strokes of distribution of predicted likelihood of innovation focused on provisioning FES, the following patterns can be seen: (I) they are lower in Southern Europe, higher in Central Europe and lower again in Northern Europe; (II) West-to-East 'belt' of higher innovation probability area can be observed and (III) it is lower in the mountainous areas of Europe (Alps, Carpathians, Dolomites, Pyrenees, etc.) than in the low-land areas of Europe. In terms of broad geographical strokes of distribution of predicted likelihood of innovation focused on regulating and cultural FES, following patterns can be seen: (I) it decreases from West to the East; (II) it is lower in the mountainous areas of Europe than in the low-land areas of Europe and (III) more-pronounced differences can be found on the borders of individual countries (e.g. France in Germany) than it was the case for innovations focused on provisioning FES.

3.2. Co-variability of multiple determinants and innovation development

As for the ANCOVA models for innovation development, in the case of innovations focused on provisioning FES it describes 79.9% of variability in the data (i.e. adjusted R^2), while for innovations focused on regulating and cultural FES it describes 87.5% variability in the data. For details, see supplementary Tables 2 and 3. In the case of variables that positively affect the predicted likelihood of innovations focused on provisioning FES, development of innovations focused on regulating and cultural FES has a large effect size. For the same relation, increase in the above-ground biomass, higher increment and occurrence of Birch, Eucalyptus and Larch species have medium size effects. For the same relation, decrease in the soil bearing capacity, higher rainfall, higher share of coniferous species and growing stock volume have small size effects. In the case of variables that negatively affect the predicted likelihood of innovations

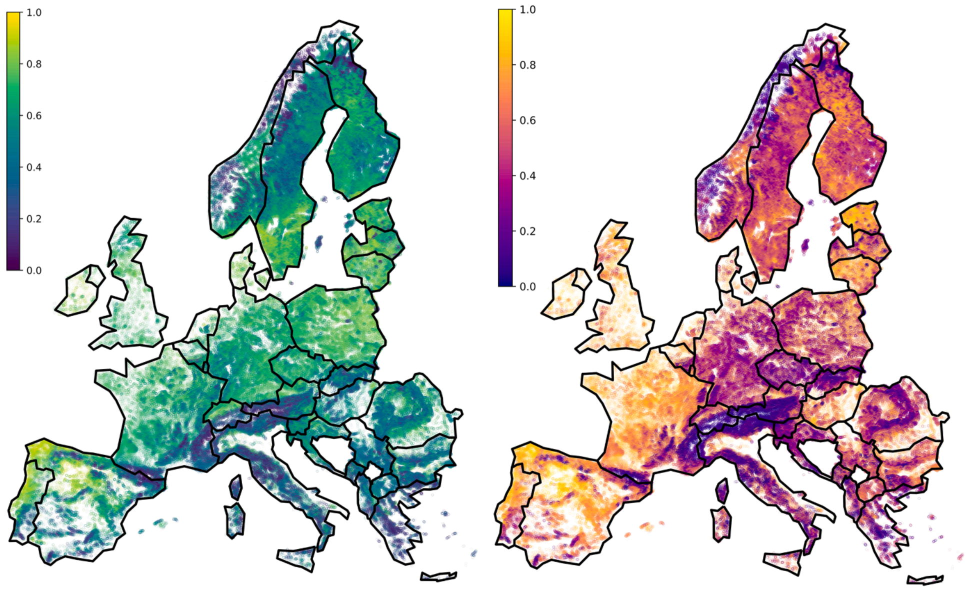

Fig. 3. Geographical distribution of predicted likelihood of innovation development for innovations focusing on provisioning FES (left) and for innovations focusing on regulating & cultural FES (right).

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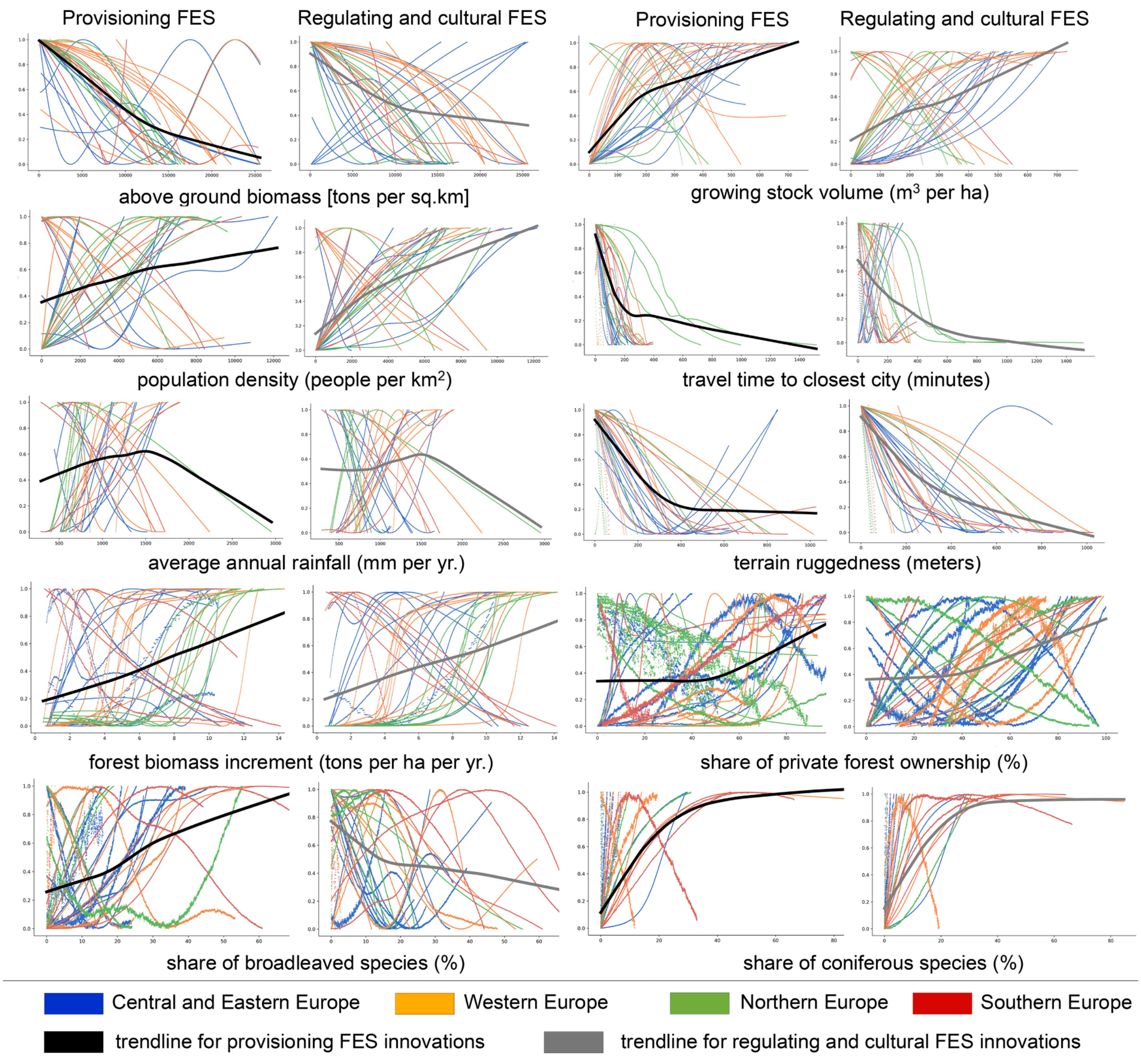

Fig. 4. Co-variability of individual determinants and innovation development. Y axis is predicted likelihood of innovation development for all sub-graphs.

focused on provisioning FES, the following variables have small effect sizes: being protected under Natura 2000 within areas designated under Habitats Directive and jointly under Habitats and the Birds directive, being more privately owned forest, having higher population density, increased terrain ruggedness and higher share of Oak, Poplar, Beech and Fir species. In the case of variables that positively affect the predicted likelihood of innovations focused on regulating and cultural FES, development of innovations focused on provisioning FES has a large effect size. For the same relation, variables that have medium-size effect are having lower soil bearing capacity and being protected in Natura 2000 network under the Birds Directive. For the same relation, variables that have a small effect size are having larger increment, being located in areas with higher population density and more Poplar, Pine and Alder species. In the case of variables that negatively affect the predicted likelihood of innovations focused on regulating and cultural FES, having more above biomass has a medium size effect. For the same relation, variables that have small effect size are having more growing stock volume and more of Scots pine. For details, please see Supplementary Table 3.

3.3. Co-variability of individual determinants and innovation development

The relation between individual determinants and predicted likelihood of innovation development is further explored in Fig. 4, which shows (I) the relation between respective determinant and predicted likelihood of innovation on national level and (II) regression-trendlines between the two variables across all countries.

The main finding that can be discerned from Fig. 4 is that the conclusions from ANCOVA which show European-wide relations among the innovation development and its determinants actually mask the wide diversity of the ways these variables co-vary across different regions of Europe. Or in other words, independent variables don't have a uniform relation to innovation development across different countries of Europe. This also diminishes the utility of the regression trends of Fig. 4. Growing stock volume has in general positive effect on innovation development; but this is not true for Western and Southern Europe in the case of innovations focused on regulating and provisioning FES. The variable travel time to closest city has a clear-cut detrimental effect on innovation development – the further the forest plot is located from a city, the less innovation development. The same is true for terrain ruggedness, and the opposite is true for share of coniferous tree species. As for forest biomass increment, rainfall, share of private forest ownerships and of broadleaved species; their variability across Europe is so diverse that interpreting their generalized trend-lines is meaningless.

4. Discussion

4.1. Contextualizing results and next steps

The most striking finding of the study is the very high accuracy through which innovation development can be predicted by a dataset that is almost exclusively focused on the forest itself and not on the data on who the innovators are, what resources they possess, and what their organizational, institutional and political environment is. The main implication of this is the adequacy of variables that we consider to be causal to innovation development – how much are they defined by the 'noise' of local, contextual, 'place-based' variables? This is an under-explored field of inquiry, and authors of the study hope that this work will affect development of new research that can establish causal inferences between the two. This problem (of disregarding place-based factors) has long been evidenced in social sciences and in studying human behavior (Blalock, 1984; Liska, 1990); researchers tend to focus on the dependent variable and independent micro-level variables that directly affect their unit of analysis (i.e. innovators in our case), where contextual factors explain only small share of variance; and thus are treated as 'noise' and rarely incorporated in the research design of macro-level studies. Given the fact that building scientific knowledge itself is a social process (Kuhn, 1997), perhaps we should not be surprised by exclusion of local-contextual variables from this specific sub-field of forest-based innovations where vast majority of research is on case-studies (Weiss et al., 2020).

In terms of testing external validity, we note that while one would perhaps a priori expect a positive association between on one side innovations focused on regulating and cultural FES and on the other forests protected by EU under Natura 2000 network (Sarvašová et al., 2019). We find that the reverse is true. It is striking that being protected under Natura 2000 has a negative effect on development of innovations focused on provisioning FES (see supplementary Table 2). One possible explanation could be that selection of Natura 2000 may not independent from economic considerations and profitability of forests; and thus, favors less profitable forests (Apostolopoulou & Pantis, 2009; Von Haaren & Reich, 2006; Lovrić et al., 2018). The finding that private forest ownership is detrimental to development of innovations focused on provisioning FES (see supplementary Table 2) can be linked to the fact that private forests tend to have smaller plots under management (Forest Europe, 2020) than state-owned forest do, where having a large plot size is one of the key determinants of wood-linked innovations (Rametsteiner and Weiss, 2006). Another explanation could be that large public sector involvement with forestry in Europe can create 'crowding out' effects, whereby innovation in the public sector inhibits rather than enables opportunity in the private sector (Slee, 2011). However, it can be seen in Fig. 4 that this relation is not uniform across Europe and that no clear regional pattern can be observed; rather, that this relationship is determined more on the level of individual countries. Mann et al. (2022) found that high profitability (or high economic viability) of the forest before the innovation developed had a positive effect on development of innovations focused on provisioning FES, and that it had a negative effect on those focused on regulating and cultural FES. This is in-line with our findings; that development of innovations focused on provisioning FES is more likely in more productive forests with higher above-ground biomass, increment, better soil bearing capacity and higher growing stock. And the opposite can be stated for innovations focusing on regulating and cultural FES; as above biomass, larger growing stock and better soil bearing capacity are detrimental to their development (see supplementary Table 3). In terms of the latter innovation type, this is aligned with the literature about the geography of sustainability transitions (Hansen and Coenen, 2015), which shows that resource scarcity stimulates innovations, and that low productive forests tend to have low level of active forest management practices focused on wood production (González-Sanchis et al., 2019). Our results also point to a demand-driven effect by which being close to a city is detrimental for innovation focused on provisioning FES, while at the same time supportive for development of innovations focused on regulating and cultural FES (see supplementary Tables 2). Our finding that development of one innovation type fosters the development of another one can be interpreted as supportive to Lovrić et al. (2020), who found that organizations who are internally very supportive of innovation development tend to develop more different innovations than those who rely on external factors. This can be labeled as an 'additive' effect or 'propensity to innovate'; a concept familiar to innovation studies (Carayannis and Provance, 2008; Radosevic and Yoruk, 2013) and to social sciences in general (Rigney, 2010). The geographical distribution of predicted likelihood of innovations focusing on provisioning FES show that they are unlikely in Southern Europe, where forestry is not profitable (and thus willingness to innovate is low); but it also shows that they are unlikely in Northern Europe, where it is very profitable. As for these parts of Europe where forestry is profitable; their low willingness to innovate in relation to provision of wood might be seen as a reflection of the unwillingness of forestry actors to modify their forestry practices in relation to enhancing the role of regulating FES (Gordeeva et al., 2022), where there are trade-offs between their supply (Wang and Fu, 2013). In similar fashion, the issue of low economic importance of forestry may be the underlying variable for explanation of geographic distribution of predicted likelihood of innovations focused on regulating and cultural FES; the likelihood is higher in countries where forestry represents low share of GDP (Forest Europe, 2020). This is especially true for Western Europe.

The main conclusion from the analysis of the synthetic data is that, when looking for measures to enhance innovation development in forestry, there is no 'one-size fits all' interpretation of what supports or hinders their development, and that regional-approaches are preferred. Some examples of this that are evident from Fig. 4 are as follows. If we look at relationships between above ground biomass and likelihood of developing innovations focusing on regulating and cultural FES; In Central and Eastern Europe this relation is positive, while in Southern Europe it's negative. It's also negative in Southern Europe for population density, while it's positive for almost all countries that are not in Southern Europe. The effect of population density being negative for innovation development in Southern Europe would be a clear example of regionalized approach, where the policy implication of this effect would be a need for strengthening rural and forestry innovation support systems – in a region that's known for its relatively low level of innovation support systems (Prokofieva et al., 2014). Higher increment has positive effect on innovation development in Central, Eastern and Western Europe – but a negative effect in Northern Europe. The relation between innovation development and explanatory variables can also be non-linear; for example, in Central and Eastern Europe innovations focused on provisioning FES tend to develop either on very rugged terrain and on terrain that's not rugged at all.

4.2. Limitations of the study

A limitation of the study is the core data from which its results stem – the survey data. The survey was distributed in a top-down fashion, from large organizations representing different strata of forest owners and managers, to national and regional associations and then finally to the target population – forest owners and managers. The parameters of the actual population of forest owners and managers are unknown – as this population is *de-facto* unreachable. The conceptual difference between the reached sampling frame and the targeted population is that the sampling frame favors organized forest owners and managers, and also possibly people for whom forest-based income is more important than for those who are not organized (and thus unreachable in this research design). If our sample underrepresents those that associate lower economic importance to forest-based income, that would imply that we have overestimated the potential for innovation development. The choice to have just two innovation types has produced a model with high accuracy – but this focus has a strong trade-off as well. First, it oversimplifies the diversity of innovation activities, not only in comparison to individual innovation-type questions from the survey (see Table 1), but also in comparison to innovation types that exist in the forestry sector (see for example Fig. 3 in Weiss et al., 2020). Second, it also does not acknowledge that innovations exist on a spectrum of different novelty levels, ranging from small and gradual changes to totally new and radical innovations (Golembiewski et al., 2015; Lovrić et al., 2020). On average, the predicted likelihood of innovation development on European level, for both innovation types, is around 50%. This was evident also from the results displayed in Fig. 2. Such a high average likelihood supports the self-selection bias of respondents discussed above. It also has to be repeated that results have been normalized by country, in order to make cross-country and cross-variable comparison viable. This decreases the validity of actual likelihood of innovation development and increases the validity of comparison between the probabilities. We thus kindly ask readers to take this into account when interpreting the results; for example, it's not really precise to say that general innovation probability is 50%, but it's more precise to say that, for example, innovation probability is lower in the mountainous areas of Europe than in the low-land areas of Europe, or that innovation probability decreases with the distance to the nearest city. Another issue that can be observed is that it seems that some of the ANCOVA results and the trendlines from the synthetic data are saying the opposite. On the example of share of private forest ownership; ANCOVA states that it has negative effect on development of innovations focused on provisioning FES and positive for the ones focused on regulating and cultural FES. The trendlines from the synthetic data show that it has negative effect on both innovation types. This 'mismatch' is due to the difference in the underlaying data; ANCOVA uses actual the distribution of Europe's forests where all countries are not equally represented, while in the synthetic data all countries have similar number of data-points. But this data interpretation issue is dwarfed by the problem that we cannot know how the respondents in the study are matched to their general population with respect to spatial and socio-economic variables. No methods or supplementary data can truly rectify this shortcoming completely.

5. Concluding remarks

The authors hope this study will influence others on including local-contextual factors when preparing their research design on studying innovations, especially on a macro-level. This issue has already been known in the context of sustainability transition and human-nature relationships (Ives et al., 2017), where researchers focus on individuals on local scales as the main unit of analysis, leaving local context and 'nature' to a large degree undefined. This is aligned with the claim that we need to address 'place-based factors' (Van der Jagt et al., 2020), which until now have been mainly explored in urban context (Hansen and Coenen, 2015). A practical implication of this issue is the possible implementation of Payments for Ecosystem (or Environmental) Services (Engel et al., 2008) schemes in Europe. One of the basic feature of such schemes is spatial targeting: knowing in which types of forests and under what local conditions their implementation would be feasible is paramount for the success of their large-scale uptake (Wunder et al., 2020). Adoption of these schemes and the recognition of innovative potential of the forest owners and managers would strengthen the 'good ownership storyline' (Holmgren et al., 2022), that bridges the gap between various other, conflicting storylines on what the transition to forest-based bioeconomy should look like. But wider adoption of these changes cannot happen on its own. In their conceptualization of green economic development, Coenen et al. (2012) point to what's needed next; after the implementation of initial innovations and identification of best practice examples, the next step is the development of strategic documents that promote these practices. After this, policy entrepreneurs as agents of change can push for development and implementation of actual policies which with their policy instruments can assure the wide-spread adoption of these practices. For now, it seems that the EU is heading towards such development (European Commission, 2023). Also, one has to be realistic with regards to what extent policies themselves can affect innovation development. By this I mean that in forestry and in rural innovation more general, the main determining factor behind innovation development is the initiative and self-reliance of the innovators. Many other factors, such as collaboration within local networks, innovation support systems and access to market knowledge can foster innovation development – but the culture of innovators is the key (Freire-Gibb and Nielsen, 2014; Živojinović et al., 2017; Lovrić et al., 2020).

Another important feature of the study is the over-simplification of the survey's data on innovation, where we basically have just two binary variables. This masks the diversity of innovation types that characterizes the sector (Weiss et al., 2020), and it is also devoid of all socio-economic-political-institutional variables associated with innovation development. While possibly being an over-simplification, this approach enabled us to focus on the generalization of this small data-segment that describes innovation development to all of Europe's forests – and even more importantly, enabled us to draw inferences on the relation between innovation development and the descriptors of forests within which they are developed. This is something that has never been done before. In terms of analytical procedures, the high accuracy of the deep neural network and the high share of variance explained by the ANCOVA models guarantee the robustness of the study's findings.

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CRediT authorship contribution statement

Marko Lovrić: Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Mario Torralba:** Writing – review & editing, Validation, Methodology, Investigation, Data curation, Conceptualization. **Francesco Orsi:** Writing – review & editing, Validation, Methodology, Investigation, Data curation. **Davide Pettenella:** Writing – review & editing, Validation, Funding acquisition, Conceptualization. **Carsten Mann:** Writing – review & editing, Validation, Project administration, Funding acquisition, Conceptualization. **Davide Geneletti:** Writing – review & editing, Validation, Supervision, Investigation. **Tobias Plieninger:** Writing – review & editing, Validation, Methodology, Conceptualization. **Eeva Primmer:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Monica Hernandez-Morcillo:** Writing – review & editing, Validation, Data curation. **Bo Jellesmark Thorsen:** Writing – review & editing, Validation, Supervision, Funding acquisition, Conceptualization. **Thomas Lundhede:** Writing – review & editing, Validation, Methodology, Conceptualization. **Loft Lasse:** Writing – review & editing, Validation, Conceptualization. **Sven Wunder:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Georg Winkel:** Writing – review & editing, Validation, Supervision, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.eist.2025.101066.

Appendix

Machine learning procedure

Deep neural networks are a sub-set of machine learning. The guiding principle is that the network is 'deep', i.e. it has several layers. These networks consist out of input layer (the data we have collected and/or want to draw inferences from), output layer (user-specified, could be for example correlation or classification) and hidden layers. Hidden layers lay between input and output layer, and through them input data is transformed to the output data. Multiplicity of hidden layers allows for modelling of complex, non-linear relations between the input and the output layer. All layers consist out of neurons, and their activation across hidden layers transforms input to output. In the input layer, they represent the number of variables in the data-set which we want to draw inferences from. In the output layer, they represent the desired inference. Neurons are connected across layers with connections (or synapses) into a network, where the neurons in the subsequent layer can be activated through synapses that connect it to the neurons in the previous layer. We have used a version of machine learning called supervised machine learning. In our case, this means that we have labelled the targeted variables (i.e. development of innovations), set the input data (the independent variables listed in Table 1 and Supplementary Table 1), set the network architecture and then tasked the model to 'learn' the rules how the input data (description of the forest) can be transformed to probability of innovation development as based on the survey's responses. After the model has 'learned' the rules (i.e. minimized the error of estimation) on how to transform input to outputs, we have then tasked the model to estimate the output (predicted likelihood of innovation development) from a new input data-set that it has not worked with before (i.e. the 1.46 mil. data-points from the 1×1 km raster data). We have pre-processed the independent variables by using standard scaler separately on each of them (i.e. scaled them to 0-1 range). We have used a model with multiple input branches; one branch for interval type of inputs (e.g. growing stock, distance to the nearest city, increment, etc.) and another one for categorical variables (country-affiliation and dominant tree specie type). Hyperbolic tangent function was used in the input-branch for interval data and in the joined branch. Sigmoid activation function was used in the branch for categorical inputs in the output layer. Dropout layers were set between each hidden dense layer (their function is to increase the generalizability of models' inferences). Binary cross-entropy was selected as the loss function. Accuracy was selected as the monitoring metrics. Adaptive Moment Estimation (ADAM) was used as the optimizer, where learning rate was set to 0.001 and batch size was set to 1. From the total sample data, 20% has been randomly set-aside as validation data. Maximum epochs were set to 500 as based on minimal validation loss with early-stopping set to patience of 1. Hyper-parameter tuning was performed sequentially. By this we mean (I) each hyper-parameter was set to a list of 7-10 values. Then, (II) the initial values were set to the median points on the list. Then, (III) model run in a loop for all values of a single hyper-parameter. Selected value of this single parameter was then set to the value where the model had achieved the smallest loss on the validation data. Then, (IV) the model run in a loop for all the subsequent hyper-parameters. After one cycle of the loops, the lists describing possible values of hyper-parameters were modified to be more centrally dispersed around the best-performing value from the previous iteration of loops. The process was repeated three times, until no increase in model's performance was observed. In total, 378 different network architectures were tested. The final architecture is presented in Appendix Fig. A1.

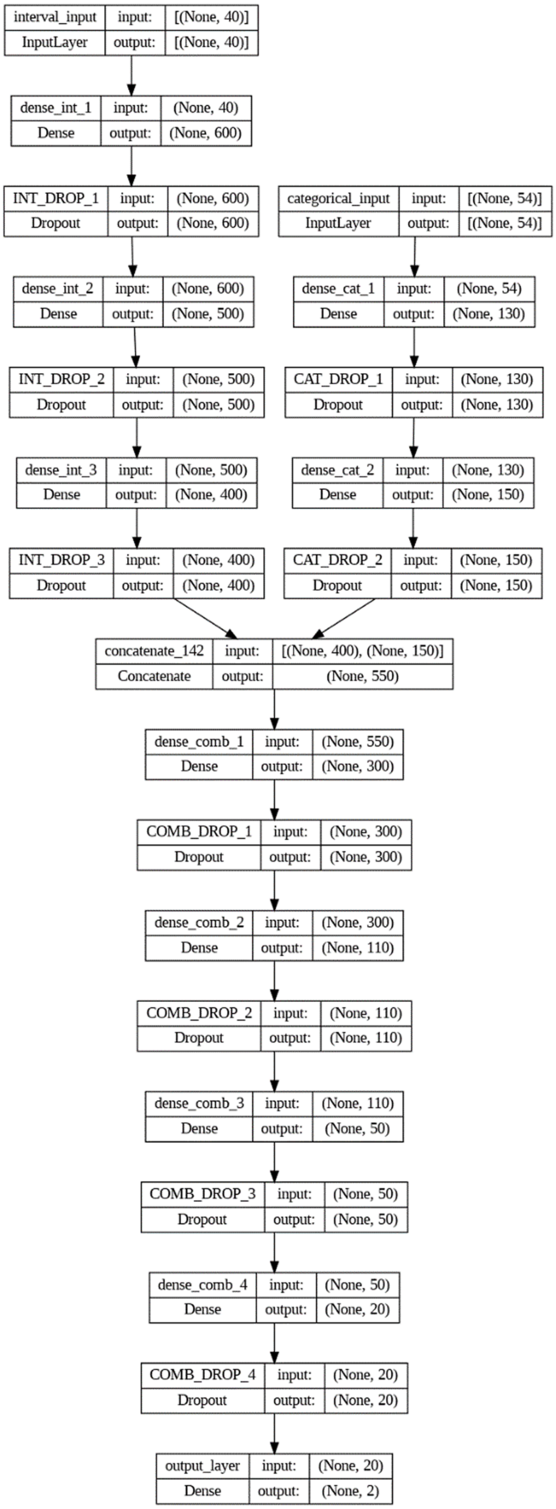

Fig. A1. . Final architecture of the deep learning model.

Table A1. Descriptive information on the final sample used in the analysis

COUNTRY	count
Slovakia	2
Denmark	28
Germany	228
United Kingdom	53
Spain	50
Estonia	32
Finland	91
France	10
Croatia	8
Italy	25
Latvia	15
Lithuania	1
Belgium	59
The Netherlands	56
Poland	2
Portugal	2
Slovenia	2
Sweden	19
Ireland	1
Romania	2
Greece	1

Plot size	count
below 1 ha	19
1 - 10 ha	187
11- 100 ha	185
101 - 1000 ha	182
1001 – 10 000	84
Above 10 0001 ha	30

Ownership type	count
Private ownership by individual and family	524
Private ownership by private business entity	33
Private ownership by private institution (e.g. church, foundation, etc.)	21
Public ownership by local government (municipality or equivalent)	70
Public ownership by the State at national level	9
Public ownership by the State at sub-national (regional) level	15
Other	15

Type of activity	count
Managing the forest (but not owning it)	87
Owning and managing the forest	482
Owning the forest but not managing it	33
Responsible for certain segments of forest management (e.g. reforestation or sale of wood) but not owning it	62
Other	23

Innovation type	count
New ecosystem service (e.g. a pollination strip or burial forest was newly established)	48
New technology for biomass production (e.g. usage of harvester instead of chainsaws or using satellite imagery for identifying logging sites)	67
New technology for other ecosystem services (e.g. a new technology for extracting resin)	207
New way to generate value from ecosystem services (e.g. organizing auctions for high-quality timber or water protection)	48
Change of forest management to improve / sustain biomass production (e.g. new thinning measures for increased wood increment or for increased resilience)	105
Change of forest management to provide other ecosystem services (e.g. new thinning measures for growth of mushrooms or support nature tourism)	60
New communication or marketing strategy implemented (e.g. a website or a hired branding professional)	38
New users of ecosystem service(s) (e.g. children or urban citizens)	48
New trans-sectoral contract created (e.g. a new agreement with conservation groups or eco-tourism enterprises)	44
New transboundary cooperation created (e.g. a sustainable tourism project across country borders)	22

Data availability

Data on independent variables and results is already published on Zenodo. Link is provided in the paper. Survey data will be available upon request

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Further reading

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