Silva Fennica vol. 58 no. 5 article id 24053
Category: discussion article
https://doi.org/10.14214/sf.24053

SILVA FENNICA

http://www.silvafennica.fi
ISSN-L 0037-5330 | ISSN 2242-4075 (Online)
The Finnish Society of Forest Science

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Inherently spatial: data and analytical insights for the identification of forest socio-ecological hotspots

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Abstract

We draw insights regarding intricacies with spatially explicit data and analyses when studying the vulnerability of forest socio-ecological systems to disruptive abiotic and biotic factors. Common issues associated with data include location precision, spatial delimitation, methodological comparability, and measurement consistency. Spatial data analyses are challenged by issues of interpolation and extrapolation, inferences using data at different spatial scales, and assessment of disruption impacts at detectable spatial scales. The inextricable empirical nature of spatial data and analyses requires carefully conducting and disclosing the sensitivity of findings, and including robustness tests to openly inform decision-makers on issues of uncertainty associated with possible interventions. These considerations might be central to identifying forest socio-ecological hotspots as forest-dominated geographic areas encompassing social and ecological systems vulnerable to disruptions caused by abiotic and biotic factors, but where risks to human wellbeing may be considerably reduced through adaptive interventions.

Keywords adaptive interventions; ecological-social systems; forest sector; robustness; spatial analyses; spatial data

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Received 5 September 2024 **Revised** 11 October 2024 **Accepted** 16 October 2024

1 Introduction

A changing climate, evolving societal demands, and the restoration of biodiverse habitats require forest management to be tailored to local conditions, for which data at fine spatial scales are instrumental (Cantarello et al. 2024). The availability of spatially explicit (e.g., latitude, longitude) data representing bio-physical and socio-economic dimensions across the forest sector is growing substantially. These include a wealth of openly accessible remotely-sensed tree cover information from local to global scales (Pickering et al. 2021; Global Forest Watch 2024). Information on forest species composition, stand age, and diameter structures, among other bio-physical attributes, can be inferred from systematically inventoried plots commonly conducted by national forest inventory (NFI) programs (Breidenbach et al. 2021; Nesha et al. 2021; US Department of Agriculture 2024). Access to spatial data on the forest sector including information on forest-using industries, landowners, and ancillary infrastructure is also expanding fast. In direct response to social and ecological needs, and reflecting localized norms, regulations and land use legacies, analyses of spatial data can help decision-makers prioritize geographic areas for adaptive interventions – as exemplified by the identification of biodiversity hotspots to target conservation (Marchese 2015; Costello et al. 2022).

Here, we draw insights regarding intricacies with spatially explicit data and analyses in the context of applications in Fennoscandia and North America by virtue of the long history of their NFI programs. We address both bio-physical and socio-economic aspects in order to capture the spatial complexity of forest-dominated socio-ecological systems (Winkel et al. 2021), when other perspectives seem to consider either only biological (Riva and Nielson 2021) or social (Lähteenmäki-Uutela et al. 2023) dimensions. We conclude by offering ideas on the importance of conducting and disclosing the sensitivity of findings, and robustness tests of both data and analyses to correctly inform decision-makers on issues of uncertainty in the spatial identification and prioritization of forest socio-ecological hotspots.

2 Spatial data and analyses of forest sector socio-ecological systems

What forests look like, the flow of ecosystem services contributing to human wellbeing, and how society values forests and their services, all carry inherent spatial dimensions (Millennium Ecosystem Assessment 2005). Forest biology and ecology are affected by location including latitude, longitude and topography (Paquette and Messier 2011). Spatially explicit data denote how location shapes bio-physical conditions that partly explain heterogeneity in forest composition and structure, ecosystem functions, and ecological dynamics (Paquette and Messier 2011; Stein et al. 2014). How geographically proximal forests are to users including human settlements, agricultural and forest industries, affects land rents that partly determine the feasibility and intensity of forest management activities, non-market externalities, and the opportunity costs underpinning land uses (Isard 1949; Aguilar 2009; Aguilar and Kelly 2019). A gradient in societal values between forest location and markets demanding raw or processed wood products and other ecosystem services is often reflected on patterns of land allocation and management intensity (Roos et al. 2018).

Modern spatial analyses in the forest sector encompass a wide array of applications. They include: (1) wood flow analyses to minimize costs and risks along value chains, (2) regional- and national-level optimization of the delivery of ecosystem services, (3) landscape planning for the conservation of key biodiversity habitats and siting of wood-using facilities, (4) impact assessments of policies and industrial wood procurement, and (5) spatially-dependent non-market values and interactions among forest owners (Bergseng et al. 2013; Forsius et al. 2016; Aguilar et al. 2017;

Bakhtiari et al. 2018; Hyvönen et al. 2020; Jåstad et al. 2023; Tanhuanpää et al. 2023). Spatial data commonly used within defined ecological or geo-political boundaries include NFI plots, satellite and light detection and ranging-sensed information, and georeferenced industry, roads, human and other species populations. Moreover, advances in computing power and machine learning have already opened the door for imputations to generate data missing or at finer spatial resolutions than currently available (Lidberg et al. 2020).

Spatial analyses can retrospectively, contemporaneously, or preemptively help to identify forest socio-ecological hotspots. We define these as forest-dominated geographic areas encompassing social and ecological systems vulnerable to abiotic (e.g., snow, wildfire, wind throw) and biotic (e.g., anthropogenic, disease, insect) disruptions but where risks to human wellbeing may be considerably reduced through adaptive interventions. This definition is grounded on the contribution of forest ecosystem services to human wellbeing (Millennium Ecosystem Assessment 2005), and extends the concept of a biodiversity hotspot (Begum et al. 2022) in three ways. First, while biodiversity hotspots are largely defined in terms of richness and composition of species (Costello et al. 2022), forest socio-ecological hotspots are defined in terms of high social value – which includes a broader range of ecosystem services all contributing to human wellbeing. Second, biotic disturbances encompass anthropogenic factors disrupting forests – as illustrated by how public policy can drive structural and functional changes (de Oliveira Garcia et al. 2018). Third, it acknowledges that adaptive management explicit to particular socio-ecological contexts can ameliorate losses in forest ecosystem services. These make the concept highly policy-relevant as it allows prioritizing locations where adoption might yield the greatest net benefit to society.

Disturbances bring specific spatial dimensions in how these affect forests' capacity to supply and sustain the quality of ecosystem services (Millennium Ecosystem Assessment 2005; Senf and Seidl 2021), while location-specific ecological and social conditions will partly determine the degree of resilience or vulnerability (O'Brien et al. 2004). Concomitant to location-specific disturbances, a changing climate will most likely exacerbate their frequency and intensity. Examples of disturbances likely to be magnified by a changing climate in boreal and temperate forests include losses and degradation in species composition e.g., by shifting ecological zones, long-term carbon stock losses e.g., through loss of permafrost and heightened tree mortality, and net losses of forest-related employment e.g., due to changes in seasonal winter patterns affecting timber and non-timber jobs (O'Brien et al. 2004; Mahlstein et al. 2013). Impacts might spill beyond geopolitically-defined boundaries as illustrated by how forest wildfire gases, aerosols, and particulate emissions can affect human health in geographically distant areas (Sokolik et al. 2019). Trade is a specific socio-economic mechanism that bridges forest-level disruptions and value-added forest product markets, effectively coupling ecological hotspots with human wellbeing even between distant socio-ecological systems (Liu et al. 2013).

3 Challenges with spatially explicit data and their analyses to identify vulnerable socio-ecological forest systems

Spatial data and their analyses can help identify areas warranting human interventions to strengthen their adaptability and resilience to disturbances. Accounting for spatial effects, when they exist, can substantially reduce unobserved bias in modeled results and their interpretation (Anselin 2001; Riva and Nielson 2021). As an example, the inclusion of geographically salient processes e.g., albedo in boreal forest regions, in spatial modeling increases the optimality of the analyses and their policy implications (Sjølie et al. 2013; Favero et al. 2018; Lintunen et al. 2022). On the other hand, caution should be taken in how the spatial effect is modeled in order not to introduce bias or confound causal interpretation of the results (Gibbons and Overman 2012). Spatial data carry some constraints owing to how these are constructed and to the nature of forest socio-ecological processes. For instance, variation in the scale of available remote-sensed data may have a large impact in the description of ecological processes (Riva and Scott 2021; Fassnacht et al. 2024).

Next, we outline some features and associated challenges with **spatial data** and **spatial analyses** in the identification of forest socio-ecological hotspots making references to both bio-physical and socio-economic information:

- Location precision: The accessibility of precise latitude and longitude coordinates can present significant opportunities and challenges to the inclusion of fine-scale data, such as a site's altitude and topography, and their subsequent analyses. Access to explicit coordinates, as in the case of NFI plot data, are often fuzzed and in some instances swapped to introduce a degree of anonymity (Burrill et al. 2018). This pseudo-random relocation can affect inferences at small scales such as stand or management area, but less so when inferences about larger areas are made (Coulston et al. 2006). Geo-referenced socio-economic information such as forest ownership and wood-using mill information brings similar concerns over explicit site identification for which they are commonly anonymized or aggregated at larger scales to avoid identification. In other cases, socio-economic information might be georeferenced to a centroid such as those in polygons of parcels or ownership data (Aguilar et al. 2017). The precision of coordinates for socio-economic data across a parcel or management unit might be less of a challenge regarding location precision when a goal is simply to control for different decision-makers behind management but aggregation across multiple ownerships or ownership classes undermines the ability to study individual- or group-specific effects.
- Disturbance delimitation: Disturbances such as abiotic drought or flooding have unclear boundaries and are often delimited by other variables e.g., pixels from remote-sensed data, socio-political boundaries (Wolf et al. 2023). By extension, biological disruptors such as bark beetle-caused mortality, may be delimited by disturbance edges, but processes of dispersion and mortality can be highly dynamic, making it nearly impossible to precisely define spatial boundaries. In the absence of direct or reliable measurements, proxies such as deadwood or indicator species for biodiversity might be used to delimit disruption boundaries; but these can oversimplify complex ecological relationships and lead to inaccurate conclusions and could miss-identify or confound main effects (Eigenbrod et al. 2010). In some data reflecting socio-economic information and dynamics, land ownership boundaries might be well-defined but social networks might influence ownership preferences and objectives across property limits (Aguilar et al. 2017). In the case of studies assessing industrial impacts on forest conditions, an overlap of procurement areas makes the delimitation of multiple industry effects a significant empirical challenge (Aguilar et al. 2022; Mirzaee et al. 2023).
- Methodological comparability: NFI programs are currently implemented across 150 countries albeit differences exist in methodologies, quality, and public accessibility (Nesha et al. 2021). NFI programs follow different traditions in response to particular data collection needs (Breidenbach et al. 2021; Nesha et al. 2021). There is a lack of harmonization in collection and estimation methods, which can challenge the direct comparability across different NFI programs, though efforts are underway to improve it (McRoberts et al. 2009; Tomppo and Schadauer 2012). Similar issues are faced with remotely sensed data collected from different sources such as satellite missions of

varying sensitivity (Fassnacht et al. 2024). The comparability of methods used for collecting socio-economic data such as ownership objectives and forest uses seems even more challenged by heterogenous sampling and objectives across national-level NFI programs (Bakkegaard et al. 2016).

- Measurement consistency: Sampling design and collection methods for NFI and other spatial data e.g., land ownership or industry, often follow irregular intervals and may be temporally mismatched, even within a single nation (US Department of Agriculture 2024). Further, while remotely sensed data detects conditions such as canopy cover at a specific time, annual NFI estimates might be derived from multi-year averages and may not accurately reflect forest conditions at a specific time (Hou et al. 2021). Changes in measurement techniques can create temporal inconsistencies in data collection, and the failure to account for changes in remotely sensed measurement techniques can gravely skew modeling results (Palahí et al. 2021). Data representing socio-economic conditions including surveys of forest owners and the forest industry are some of the most irregular, often not systematically sampled, and data are commonly derived from multi-year averages (Bakkegaard et al. 2016) or one-time collections.

Beyond spatial data, we also point to the importance of observing some issues regarding analyses and identification of forest socio-ecological hotspots including:

- Interpolation and extrapolation: Missing spatial data might be imputed to generate secondary data from within sampled areas and time periods, or outside them. NFI and remotely-sensed data are already being integrated to estimate stand-level characteristics and, while challenges persist such as detecting species-specific or biodiversity-relevant information, these might be ameliorated with advances in optical and Lidar-based sensors (Maltamo et al. 2021). NFI data have been used to interpolate land patterns and assess forest fragmentation, with reported effects between the intensity of sampling and confidence intervals of fragmentation indicators (Ramezani and Lister 2023). Spatially explicit information as in the case of soil carbon stocks reported on NFI programs might also be estimated using known auxiliary variables due to empirical challenges for their direct measurement (Domke et al. 2017).
- Inferences using data at different spatial scales: Spatial analyses may integrate data from several sources including remote-sensed and field-level data on forests, which bring their own set of empirical challenges (Fassnacht et al. 2024). Socio-economic information such as population or employment are reported at different geopolitical scales e.g., household, municipality, county, state, national, and integrated into spatial analyses. Other socio-economic data such as industrial sites and infrastructure are georeferenced in point, vector or shape information. Integrating variables measured at different scales can introduce noise in statistical estimation (Anselin 2001) and be reflected in a high degree of variability in subsequent modeling results (Tanhuanpää et al. 2023). Unexpected or not, results from modeling efforts may point to heterogeneity within smaller scale units e.g., landscape to stand-level, national to local impacts, or differences between localities e.g., impacts across latitudinal gradient, rural versus urban impacts (O'Brien et al. 2004). The issue of spatial integration and errors may only be exacerbated across temporal scales.
- Vulnerability assessment at detectable spatial scales: Projected disturbances can carry substantial uncertainty as exemplified in the downscaling of changes in global climate patterns to localized effects (Huber et al. 2021). Conversely, lower stand-scale eco-

logical processes such as species competition and succession that determine growth and regeneration may only compound and become discernible at a larger geographic scale. Stand-level inventory data have already been integrated with larger regional economic models to infer impacts from alternative forest management on total economic output (Karttunen et al. 2018). But acute economic impacts from disturbances affecting the forest sector might only be discernible at local scales, more often within rural areas, where losses in employment and added value account for a larger share of local economies. Regarding estimated economic impacts of disruptions and policy interventions, there can be substantial discrepancies in results arising from differing assumptions including the geo-political scale at which socio-economic data are aggregated. It is a concern that such apparent inconsistencies might affect credibility among policy-makers in regional assessments (Henderson et al. 2017). Plausibly, tests for data aggregated at different spatial scales could help define gradients and thresholds of detection of impacts on wellbeing.

- Robust evaluation of disturbances and interventions: It is important to evaluate impacts as the deviation from baseline/control conditions (e.g., the flow of forest ecosystem services affected by heightened abiotic disturbances compared with historic averages; the effects of adaptation interventions against status quo scenarios). A common challenge with past spatially explicit evaluations of disturbances and policy interventions is the lack of clearly identified control/baseline observations (Ceccherini et al. 2020). Although the use of counterfactual approaches such as statistical matching of NFI plots to identify comparable control and treated observations is well established (Villalobos et al. 2018; Aguilar et al. 2022), they still possess challenges e.g., in terms of knowledge required for selecting matching candidates (dos Santos Ribas et al. 2020). Robustness and sensitivity of findings with respect to precision in location and identification can help validate directional findings, and differing net values and levels of statistical significance might point to possible uncertainties associated with data, methods, or both. In some instances, researchers might be able to use different data sources and methods to estimate a degree of data accuracy and proxy uncertainty (Emick et al. 2023) of findings, but these may not be universal.

4 Final remarks

Spatial data and analyses are inextricably empirical, hence, their findings can have immediate applications and might be directly used to inform policy decisions. Recent spatial analyses (Ceccherini et al. 2020) have been called into question for possible spurious interpretations (Palahí et al. 2021; Riva and Nielson 2021) – yet findings reportedly linking forest losses to public policy have still served as the backbone to new initiatives such as the European Union's Forest Strategy for 2030 (European Commission 2021). Spatial analyses in general, and in particular those aiming at the identification of forest socio-ecological hotspots and the effect of interventions, should observe disclosure practices presenting the sensitivity of results to data issues, and report robustness in findings across analytical approaches. The transparent disclosure of challenges in spatial analyses and possible inconsistencies in findings across data and methods would allow decision-makers to be better informed when exploring any course of action to enhance the capacity of forest socio-ecological hotspots to adapt to abiotic and biotic disruptors.

All-in-all, we deem it central to qualitatively and/or quantitatively recognize the degree of uncertainty associated with spatial data and analytical methods. On data, issues of location precision, factor identifiability, measurement regularity, methodological comparability, and temporal consistency should be acknowledged where relevant. Reporting on inherent limitations and any methodological steps taken to possibly reduce these issues should be clearly disclosed. Regarding spatial methods, processes of interpolation and extrapolation of missing spatial data, inferences made using data at different spatial scales, assessment of impacts at detectable spatial scales, and the evaluation of interventions including the selection of spatial controls, should be well discussed. In addition to common guidelines for ethics in publishing and disclosure practices for open data and reproducibility, and because of their high level of empirical nature and the possibility that findings could be directly fed into public policy interventions, submissions to scientific outlets should acknowledge empirical uncertainty when spatial data and analyses are used.

Funding

The work presented in this manuscript was supported by the Nordic Forest Research (SNS) under grant N2023-03 “CSDs-FOR: Critical spatial dimensions for climate-resilient Nordic forests”, the Research Council of Finland (Decision no. 331491), and the Swedish University of Agricultural Sciences’ Forest Damage Center. This publication is not intended to reflect the opinions of these institutions. Any errors are the responsibility of the authors.

Conflict of interest

The authors have no relevant financial or non-financial interests to disclose. The funding organizations had no role in the development of this Discussion including its writing or decision to publish it.

References

Aguilar F (2009) Spatial econometric analysis of location drivers in a renewable resource-based industry: the U.S. South lumber industry. Forest Policy Econ 11: 184–193. https://doi.org/10.1016/j.forpol.2009.02.006.

Aguilar F, Cai Z, Butler B (2017) Proximal association of land management preferences: evidence from family forest owners. PLoS One 12, article id 0169667. https://doi.org/10.1371/journal.pone.0169667.

Aguilar F, Kelly MC (2019) US family forest management coupling natural and human systems: role of markets and public policy instruments. Landscape Urban Plan 188: 43–53. https://doi.org/10.1016/j.landurbplan.2019.01.004.

Aguilar F, Sudekum H, McGarvey R, Knapp B, Domke G, Brandeis C (2022) Impacts of the US southeast wood pellet industry on local forest carbon stocks. Sci Rep 12, article id 19449. https://doi.org/10.1038/s41598-022-23870-x.

Anselin L (2001) Spatial effects in econometric practice in environmental and resource economics. Am J Agr Econ 83: 705–710. https://doi.org/10.1111/0002-9092.00194.

Bakhtiari F, Bredahl Jacobsen J, Jellesmark Thorsen B, Hedemark Lundhede T, Strange N, Boman M (2018) Disentangling distance and country effects on the value of conservation across national borders. Ecol Econ 147: 11–20. https://doi.org/10.1016/j.ecolecon.2017.12.019.

Bakkegaard RK, Agrawal A, Animon I, Hogarth N, Miller D, Persha L, Rametsteiner E, Wunder S, Zezza A (2016) National socioeconomic surveys in forestry: guidance and survey modules for measuring the multiple roles of forests in household welfare and livelihoods. Food and Agriculture Organization of the United Nations, Rome.

Begum AR, Lempert RJ, Elham A, Benjaminsen TA, Bernauer T, Cramer W, Cui X, Mach K, Nagy G, Stenseth NC, Sukumar R, Wester P (2022) Point of departure and key concepts. In: Pörtner HO, Roberts D, Tignor M, Poloczanska E, Mintenbeck K, Alegría A, Craig M, Langsdorf S, Löschke S, Möller V, Okem A, Rama B (eds) Climate Change 2022 – Impacts, Adaptation and Vulnerability. Working Group II Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, pp 121–196. https://doi.org/10.1017/9781009325844.003.

Bergseng E, Eid T, Løken Ø, Astrup R (2013) Harvest residue potential in Norway – a bio-economic model appraisal. Scand J Forest Res 28: 470–480. https://doi.org/10.1080/02827581.2013.766259.

Breidenbach J, McRoberts R, Alberdi I, Antón-Fernández C, Tomppo E (2021) A century of national forest inventories – informing past, present and future decisions. For Ecosyst 8, article id 36. https://doi.org/10.1186/s40663-021-00315-x.

Burrill EA, Wilson AM, Turner JA, Pugh SA, Menlove J, Christiansen G, Conkling BL, David W (2018) The Forest Inventory and Analysis Database: database description and user guide version 8.0 for Phase 2. US Department of Agriculture, Forest Service. Rocky Mountain Research Station.

Cantarello E, Bredahl Jacobsen J, Lloret F, Lindner M (2024) Shaping and enhancing resilient forests for a resilient society. Ambio 53: 1095–1108. https://doi.org/10.1007/s13280-024-02006-7.

Ceccherini G, Duveiller G, Grassi G, Lemoine G, Avitabile V, Pilli R, Cescatti A (2020) Abrupt increase in harvested forest area over Europe after 2015. Nature 583: 72–77. https://doi.org/10.1038/s41586-020-2438-y.

Costello M, Vale M, Kiessling V, Maharaj S, Price J, Talukdar G (2022) Cross-chapter paper 1: biodiversity hotspots. In: Pörtner HO, Roberts D, Tignor M, Poloczanska E, Mintenbeck K, Alegría A, Craig M, Langsdorf S, Löschke S, Möller V, Okem A, Rama B (eds) Climate Change 2022 – Impacts, Adaptation and Vulnerability. Working Group II Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press Cambridge University Press, pp 2123–2161. https://doi.org/10.1017/9781009325844.018.

Coulston J, Ritters K, McRoberts R, Reams G, Smith W (2006) True versus perturbed forest inventory plot locations for modeling: a simulation study. Can J Forest Res 36: 801–807. https://doi.org/10.1139/x05-26.

de Oliveira Garcia W, Amann T, Hartmann J (2018) Increasing biomass demand enlarges negative forest nutrient budget areas in wood export regions. Sci Rep 8, article id 5280. https://doi.org/10.1038/s41598-018-22728-5.

Domke G, Perry CH, Walters B, Nave L, Woodall CW, Swanston C (2017) Toward inventory-based estimates of soil organic carbon in forests of the United States. Ecol Appl 27: 1223–1235. https://doi.org/10.1002/eap.1516.

dos Santos Ribas LG, Pressey RL, Loyola R, Bini LM (2020) A global comparative analysis of impact evaluation methods in estimating the effectiveness of protected areas. Biol Conserv 246, article id 108595. https://doi.org/10.1016/j.biocon.2020.108595.

Eid T, Gobakken T, Næsset E (2004) Comparing stand inventories for large areas based on photo-interpretation and laser scanning by means of cost-plus-loss analyses. Scand J Forest Res 19: 512–523. https://doi.org/10.1080/02827580410019463.

Eigenbrod F, Armsworth PR, Anderson BJ, Heinemeyer A, Gillings S, Roy DB, Thomas CD, Gaston KJ (2010) The impact of proxy-based methods on mapping the distribution of ecosystem services. J Appl Ecol 47: 377–385. https://doi.org/10.1111/j.1365-2664.2010.01777.x.

Emick E, Babcock C, White G, Hudak A, Domke G, Finley A (2023) An approach to estimating forest biomass while quantifying estimate uncertainty and correcting bias in machine learning maps. Remote Sens Environ 295, article id 113678. https://doi.org/10.1016/j.rse.2023.113678.

European Commission (2021) Communication from the commission to the European parliament, the council, the European economic and social committee and the committee of the regions: new EU forest strategy for 2030. European Commission, Brussels.

Fassnacht F, White J, Wulder M, Næsset E (2024) Remote sensing in forestry: current challenges, considerations and directions. Forestry 97: 11–37. https://doi.org/10.1093/forestry/cpad024.

Favero A, Sohngen B, Huang Y, Jin Y (2018) Global cost estimates of forest climate mitigation with albedo: a new integrative policy approach. Environ Res Lett 13, article id 125002. https://doi.org/10.1088/1748-9326/aaeaa2.

Forsius M, Akujärvi A, Mattsson T, Holmberg M, Punttila P, Posch M, Liski J, Repo A, Virkkala R, Vihervaara P (2016) Modelling impacts of forest bioenergy use on ecosystem sustainability: Lammi LTER region, southern Finland. Ecol Indic 65: 66–75. https://doi.org/10.1016/j.ecolind.2015.11.032.

Gibbons S, Overman HG (2012) Mostly pointless spatial econometrics? J Regional Sci 5: 172–191. https://doi.org/10.1111/j.1467-9787.2012.00760.x.

Global Forest Watch (2024) https://www.globalforestwatch.org. Accessed 11 October 2024.

Henderson JE, Joshi O, Tanger S, Boby L, Hubbard W, Pelkki M, Hughes DW, McConnell TE, Miller W, Nowak J, Becker C (2017) Standard procedures and methods for economic impact and contribution analysis in the forest products sector. J Forest 115: 112–116. https://doi.org/10.5849/jof.16-041.

Hou Z, Domke G, Russell M, Coulston J, Nelson M, Xu Q, McRoberts R (2021) Updating annual state-and county-level forest inventory estimates with data assimilation and FIA data. Forest Ecol Manag 483, article id 118777. https://doi.org/10.1016/j.foreco.2020.118777.

Huber N, Bugmann H, Cailleret M, Bircher N, Lafond V (2021) Stand-scale climate change impacts on forests over large areas: transient responses and projection uncertainties. Ecol Appl 31, article id 02313. https://doi.org/10.1002/eap.2313.

Hyvönen P, Lempinen R, Lappi J, Laitila J, Packalen T (2020) Joining up optimisation of wood supply chains with forest management: a case study of North Karelia in Finland. Forestry 93: 163–177. https://doi.org/10.1093/forestry/cpz058.

Isard W (1949) The general theory of location and space-economy. Q J Econ 63: 476–506. https://doi.org/10.2307/1882135.

Jåstad E, Nagel N, Hu J, Rørstad P (2023) The location and capacity-dependent price impacts of biofuel production and its effect on the forest industry. Silva Fenn 57, article id 23001. https://doi.org/10.14214/sf.23001.

Karttunen K, Ahtikoski A, Kujala S, Törmä H, Kinnunen J, Salminen H, Huuskonen S, Kojola S, Lehtonen M, Hynynen J, Ranta T (2018) Regional socio-economic impacts of intensive forest management, a CGE approach. Biomass Bioenerg 118: 8–15. https://doi.org/10.1016/j.biombioe.2018.07.024.

Lähteenmäki-Uutela A, Rantala S, Swallow B, Lehtiniemi H, Pohjola T, Paloniemi R (2023) Increasing access to forest data for enhancing forest benefits to all. Silva Fenn 57, article id 23034. https://doi.org/10.14214/sf.23034.

Lidberg W, Nilsson M, Ågren A (2020) Using machine learning to generate high-resolution wet area maps for planning forest management: a study in a boreal forest landscape. Ambio 49: 475–486. https://doi.org/10.1007/s13280-019-01196-9.

Lintunen J, Rautiainen A, Uusivuori J (2022) Which is more important, carbon or albedo? Optimizing harvest rotations for timber and climate benefits in a changing climate. Am J Agr Econ

104: 134–160. https://doi.org/10.1111/ajae.12219.

Liu J, Hull V, Batistella M, DeFries R, Dietz T, Fu F, Hertel TW, Izaurralde RC, Lambin EF, Li S, Martinelli LA (2013) Framing sustainability in a telecoupled world. Ecol Soc 18, article id 26. https://doi.org/10.5751/ES-05873-180226.

Mahlstein I, Daniel J, Solomon S (2013) Pace of shifts in climate regions increases with global temperature. Nat Clim Change 3: 739–743. https://doi.org/10.1038/nclimate1876.

Maltamo M, Packalen P, Kangas A (2021) From comprehensive field inventories to remotely sensed wall-to-wall stand attribute data – a brief history of management inventories in the Nordic countries. Can J Forest Res 51: 257–266. https://doi.org/10.1139/cjfr-2020-0322.

Marchese C (2015) Biodiversity hotspots: a shortcut for a more complicated concept. Global Ecol Conserv 3: 297–309. https://doi.org/10.1016/j.gecco.2014.12.008.

McRoberts R, Tomppo E, Schadauer K, Vidal C, Ståhl G, Chirici G, Lanz A, Cienciala E, Winter S, Smith B (2009) Harmonizing national forest inventories. J Forest 107: 179–187. https://doi.org/10.1093/jof/107.4.179.

Millennium Ecosystem Assessment (2005) Ecosystems and human well-being: wetlands and water synthesis. World Resources Institute, Washington DC.

Mirzaee A, McGarvey R, Aguilar F, Schliep E (2023) Impact of biopower generation on eastern US forests. Environ Dev Sustain 25: 4087–4105. https://doi.org/10.1007/s10668-022-02235-4.

Nesha MK, Herold M, De Sy V, Duchelle AE, Martius C, Branthomme A, Garzuglia M, Jonsson O, Pekkarinen A (2021) An assessment of data sources, data quality and changes in national forest monitoring capacities in the Global Forest Resources Assessment 2005–2020. Environ Res Lett 16, article id 054029. https://doi.org/10.1088/1748-9326/abd81b.

O'Brien K, Sygna L, Haugen J (2004) Vulnerable or resilient? Climatic Change 64: 193–225. https://doi.org/10.1023/B:CLIM.0000024668.70143.80.

Palahí M, Valbuena R, Senf C, Acil N, Pugh TA, Sadler J, Seidl R, Potapov P, Gardiner B, Hetemäki L, Chirici G (2021) Concerns about reported harvests in European forests. Nature 592: E15–E17. https://doi.org/10.1038/s41586-021-03292-x.

Paquette A, Messier C (2011) The effect of biodiversity on tree productivity: from temperate to boreal forests. Global Ecol Biogeogr 20: 170–180. https://doi.org/10.1111/j.1466-8238.2010.00592.x.

Pickering J, Tyukavina A, Khan A, Potapov P, Adusei B, Hansen M, Lima A (2021) Using multi-resolution satellite data to quantify land dynamics: applications of PlanetScope imagery for cropland and tree-cover loss area estimation. Remote Sens 13, article id 2191. https://doi.org/10.3390/rs13112191.

Ramezani H, Lister A (2023) Effects of cluster plot design parameters on landscape fragmentation estimates: a case study using data from the Swedish national forest inventory. Appl Geogr 158, article id 103045. https://doi.org/10.1016/j.apgeog.2023.103045.

Riva F, Nielson S (2021) A functional perspective on the analysis of land use and land cover data in ecology. Ambio 50: 1089–1100. https://doi.org/10.1007/s13280-020-01434-5.

Roos A, Eggers J, Mark-Herbert C, Lindhagen A (2018) Using von Thünen rings and service-dominant logic in balancing forest ecosystem services. Land Use Policy 79: 622–632. https://doi.org/10.1016/j.landusepol.2018.08.046.

Senf C, Seidl R (2021) Mapping the forest disturbance regimes of Europe. Nat Sustain 4: 63–70. https://doi.org/10.1038/s41893-020-00609-y.

Sjølie H, Latta G, Solberg B (2013) Potential impact of albedo incorporation in boreal forest sector climate change policy effectiveness. Clim Policy 13: 665–679. https://doi.org/10.1080/14693062.2013.786302.

Sokolik I, Soja A, DeMott P, Winker D (2019) Progress and challenges in quantifying wildfire smoke emissions, their properties, transport, and atmospheric impacts. J Geophys Res-Atmos

124: 13005–13025. https://doi.org/10.1029/2018JD029878.

Stein A, Gerstner A, Kreft H (2014) Environmental heterogeneity as a universal driver of species richness across taxa, biomes and spatial scales. Ecol Lett 17: 866–880. https://doi.org/10.1111/ele.12277.

Tanhuanpää T, Mikkonen N, Kujala H, Heinaro E, Mäyrä M, Kumpula T (2023) Input data resolution affects the conservation prioritization outcome of spatially sparse biodiversity features. Ambio 52: 1793–1803. https://doi.org/10.1007/s13280-023-01885-6.

Tomppo E, Schadauer K (2012) Harmonization of National Forest Inventories in Europe: advances under COST Action E43. Forest Sci 58: 191–200. https://doi.org/10.5849/forsci.10-091.

US Department of Agriculture (2024) Forest Inventory and Analysis program. https://research.fs.usda.gov/programs/fia. Accessed 11 October 2024.

Villalobos L, Coria J, Nordén L (2018) Has forest certification reduced forest degradation in Sweden? Land Econ 93: 220–238. https://doi.org/10.3368/le.94.2.220.

Winkel G, Sotirov M, Moseley C (2021) Forest environmental frontiers around the globe: old patterns and new trends in forest governance. Ambio 50: 2129–2137. https://doi.org/10.1007/s13280-021-01647-2.

Wolf J, Asch J, Tian F, Georgiou K, Ahlström A (2023) Canopy responses of Swedish primary and secondary forests to the 2018 drought. Environ Res Lett 18, article id 064044. https://doi.org/10.1088/1748-9326/acd6a8.

Total of 62 references.