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Monitoring forest attributes, C-fluxes, and C-stocks using the process-based model 3D-CMCC-FEM at the National level

Elia Vangi [a,b,*], Daniela Dalmonech [a,c,*], Giovanni d'Amico [b], Elisa Grieco [a], Mauro Morichetti [a], Paulina F. Puchi [a,e], Saverio Francini [d], Silvano Fares [a,c], Francesca Giannetti [b], Piermaria Corona [f], Roberto Barbetti [f], Gherardo Chirici [b,c,g], Alessio Collalti [a,c]

[a] Forest Modelling Laboratory, Institute for Agriculture and Forestry Systems in the Mediterranean, National Research Council of Italy (CNR-ISAFOM), Via Madonna Alta 128, 06128 Perugia, Italy

[b] geoLAB - Laboratory of Forest Geomatics, Dept. of Agriculture, Food, Environment and Forestry, Università degli Studi di Firenze, Via San Bonaventura 13, 50145 Firenze, Italy

[c] National Biodiversity Future Centre (NBFC), Piazza Marina 61, 90133 Palermo, Italy

[d] Department of Science and Technology of Agriculture and Environment (DISTAL), University of Bologna, 40126 Bologna, Italy

[e] Institute of Bioeconomy, Italian National Research Council (CNR-IBE), Via Madonna del Piano 10, 50019 Sesto Fiorentino, Italy

[f] CREA Research Centre for Forestry and Wood, Italy

[g] Fondazione per il Futuro delle Città, Firenze, Italy

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A B S T R A C T

Process-based forest models (PBFMs) are valuable tools for investigating the effects of climate change and alternative forest management strategies. However, they can also be considered a tool for monitoring forest conditions over short to extended periods, when ancillary data are scarce and continuous measurements are time-consuming. This study aims to evaluate the PBFM named '3D-CMCC-FEM' on its capacity to monitor Italian forests. We simulated 5135 plots, corresponding to ~83 % of the 6174 field plots included in the second Italian National Forest Inventory (NFI). The model was used to predict the carbon, nitrogen, and water cycles, including structural variables, and validated against observations from the third NFI. We also compared gross primary productivity (GPP) with two well-known remote sensing-based (RS) datasets. Overall, the model showed good performance in reproducing aboveground stocks and structural variables, with r^2 values ranging from 0.65 for diameter to 0.49 for height, and RMSE% ranging from 32 % for diameter and height to 46 % for volume. We aggregated and validated the simulation at the NUT2 level against the estimate of the third NFI, obtaining higher accuracy than the plot-level validation. Compared to RS–data the modeled GPP showed higher variability, with an overall RMSE% of 43 % and 41 % against the MODIS and GOSIF datasets, respectively. The 3D-CMCC-FEM model has consistently demonstrated reliability across multiple data sources and spatial scales, establishing it as a robust tool for forest monitoring, being, capable of delivering insights at daily, monthly, and annual resolutions over broad and heterogeneous areas. This approach offers innovative and promising improvements in the continuity of forest data, supporting more informed decision-making in climate policy and environmental management.

1. Introduction

International climate change negotiations have reached agreements and targets aimed at stabilizing atmospheric CO_2 concentrations and limiting the global temperature rise to below 2 °C compared to pre-industrial levels (Keith et al., 2024). For example, the New European Forest Strategy for 2030, a component of the European Green Deal, aims to achieve greenhouse gas emission neutrality by 2050 in the European Union. At least four of the 17 Sustainable Development Goals adopted by all United Nations Member States in 2015, as part of the 2030 Agenda, involve preserving, protecting, and restoring forest ecosystems as a fundamental climate action (UNCC, 2022). As part of the Paris

* Corresponding author at: Forest Modelling Laboratory, Institute for Agriculture and Forestry Systems in the Mediterranean, National Research Council of Italy (CNR-ISAFOM), Via Madonna Alta 128, 06128 Perugia, Italy.

E-mail addresses: elia.vangi@isafom.cnr.it (E. Vangi), daniela.dalmonech@cnr.it (D. Dalmonech).

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Agreement's enhanced transparency framework, Parties must biennially submit an inventory of their greenhouse gas (GHGI) emissions, categorized by sources and removals by sinks, following the Intergovernmental Panel on Climate Change (IPCC) guidelines and guidance. (IPCC et al., 2006; Vangi et al., 2023). In particular, the Land Use, Land-Use Change, and Forestry (LULUCF) sector is responsible for significant carbon stocks and emissions and can provide substantial benefits in mitigating climate change.

The LULUCF sector will be essential for achieving the EU's climate neutrality goal, as it may contribute to reducing net GHG emissions by 55 % by 2030, corresponding to 310 $MtCO_2e$ sequestered, and achieving carbon neutrality by 2050 (Korosuo et al., 2023; Di Lallo et al., 2023). However, assessing emissions and removals in the forest sector is particularly challenging due to the dynamic nature of carbon stocks, which are influenced not only by deforestation and forest degradation (Corona et al., 2023) but also by forest management. Furthermore, the uncertainty increases in the face of climate change. One of the primary ongoing debates focuses on whether the positive effects of atmospheric CO_2 fertilization on carbon storage and biomass production will persist or be offset by other limiting factors, such as climate extremes like heatwaves and dry spells. Recent studies suggest that in temperate forests, the impact of fertilization on forest growth may decline as the forests age, indicating that the positive effects cannot be sustained indefinitely (Bugmann and Bigler, 2011; Laffitte, 2022; Bian et al., 2023; Vangi et al., 2024a, 2024b). This adds complexity in understanding how forests respond to climate change. Unfortunately, there is currently no clear strategy to enhance the mitigation potential of forests, as the influencing factors are numerous and interconnected (Corona and Alivernini, 2024). Despite all uncertainties, the international community needs to accurately measure GHG emission trends for an effective climate mitigation strategy (Perugini et al., 2021), following the principle: "If you cannot measure it, you cannot improve it". Precise measurement and the development, calibration, and validation of reliable models are crucial for effectively quantifying these trends and planning near-term mitigation strategies.

Usually, in the context of international and national programs, forest data are collected using sample-based National Forest Inventories (NFIs), specifically designed to provide periodic aggregated estimates of several variables (e.g., forest area, growing stock volume, biomass, increments) at national and regional levels (Kangas et al., 2018; Chirici et al., 2020a, 2020b). Recently, traditional NFI integrated an advanced use of remote sensing (RS) technology to provide spatially continuous (also referred to as 'wall-to-wall' maps) and updated estimations of several forest variables (including the growing stock volumes [GSV], the aboveground biomass [AGB], aboveground carbon stock [CS], etc.; Nilsson et al., 2017; Vangi et al., 2021; Wulder et al., 2024). The transition to this so-called enhanced forest inventory (EFI) offers several benefits, enabling continuous mapping and improving the estimation of forest attributes, as well as optimizing the field campaign strategy through the integration of RS data (White et al., 2016). However, inventory survey campaigns are typically periodic, with temporal gaps often exceeding a decade in some national programs. Although data interpolation strategies that exploit integration with RS-data exist (Vangi et al., 2023), alternative approaches, such as process-based forest models (PBFMs), appear particularly promising.

PBFMs have shown to be essential tools for understanding and predicting forest growth, particularly in the context of climate change and forest management (Mäkelä et al., 2000; Maréchaux et al., 2021; Dalmonech et al., 2022). These models simulate the physiological processes from trees to stands at different spatial and temporal scales, such as photosynthesis, respiration, and water uptake, to predict growth and biomass accumulation under various environmental conditions and forest types, from monospecific and monolayer to complex mixed-species forests (Bohn and Huth, 2017; Collalti et al., 2016; De Wergifosse et al., 2022). However, accurate model predictions rely on careful calibration and species-specific parameterization. They also require extensive datasets for initialization, since they typically simulate real vegetation rather than potential vegetation, as is the case in many Dynamic Vegetation Models.. While techniques such as Bayesian inference (Forrester et al., 2021), machine learning algorithms (Hong et al., 2023; Yu et al., 2024), and the use of tree-ring data have been tested to refine model parameters and calibration (Yu et al., 2024), the large amount of data needed to initialize and run a simulation has resulted in models being moslty limited to stand and local-scale applications (Collalti et al., 2018; Suárez-Muñoz et al., 2023), where structural and meteorological data are usually available from in-situ measurement. Recent studies, however, have applied PBFMs over large scales (Ma et al., 2023; Miettinen et al., 2021), including stand-scale models (Dalmonech et al., 2024; Minunno et al., 2019), proving their ability to capture spatial and temporal carbon dynamics, in terms of fluxes and stocks, supporting national and regional monitoring efforts. It is worth noting that these models are not bookkeeping models or growth models but are based on the current understanding of the biogeochemical and biophysical processes and the ecophysiology of forest species, allowing for the simulation of both stocks and fluxes even in highly complex environments and under climate change conditions.

The first PBFM applied at the regional level in Italy was the 3D-CMCC-FEM (*Three-Dimensional – Coupled Model Carbon Cycle - Forest Ecosystem Module*) by Dalmonech et al. (2024). They applied the model in Basilicata, a southern Region in Italy, comparing the model predictions with RS-derived datasets and demonstrating the model's capabilities to capture the spatial-temporal trends in GPP and those in the RS-derived datasets. Building on these promising results, this study advances by evaluating the 3D-CMCC-FEM model's capability to simulate structural variables, carbon fluxes and stocks across pure and mixed forest stands at the national scale in Italy. Therefore, the primary objective of this study is to evaluate the effectiveness of the eco-physiological model as a comprehensive monitoring tool under current climatic conditions and a highly heterogeneous area, such as the ones in the Mediterranean basin in support of mandatory international reporting requirements. Notably, this represents the first Mediterranean large-scale application and evaluation of a PBFM over such a broad spectrum of species and climate conditions, including complex mixed forest stands. In this perspective, PBFMs can complement and integrate the scope of NFIs and GHG by addressing the inevitable limitations of conventional design-based approaches or bookkeeping models. The model was applied for the period 2005–2020 over the field plots from the second Italian NFI ('Inventario Nazionale delle Foreste e dei Serbatoi di Carbonio' – Gasparini and Tabacchi, 2011) and validated against the same plots re-measured between 2016 and 2020 in the field survey of the third Italian NFI. The dataset comprises a total of 5135 plots, 14 different forest categories, and two prevalent silvicultural systems (high forest and coppice) spanning a broad environmental gradient and heterogeneous landscape, thereby encompassing the spatial heterogeneity typical of the Mediterranean Basin. Simulation results were compared against multiple data sources at different spatial and temporal resolutions, including annual RS-based GPP datasets and the annual Italian GHGI, to assess the model's potential for national forest monitoring. This study advances forest modelling by evaluating the large-scale applicability of a PBFM within a national forest monitoring framework, integrating NFI- and RS-data to highlight the accuracy of large-scale forest carbon assessments.

2. Material and methods

2.1. Study area

The study area covers the entire territory of Italy (301,408 km^2, Fig. 1). The Italian peninsula spans over 11° of latitude and thus presents a wide range of climatic conditions, influenced by its proximity to seas and the presence of two prominent mountain chains with altitudes ranging from the sea level to 4000 m a.s.l. Italy has a predominantly

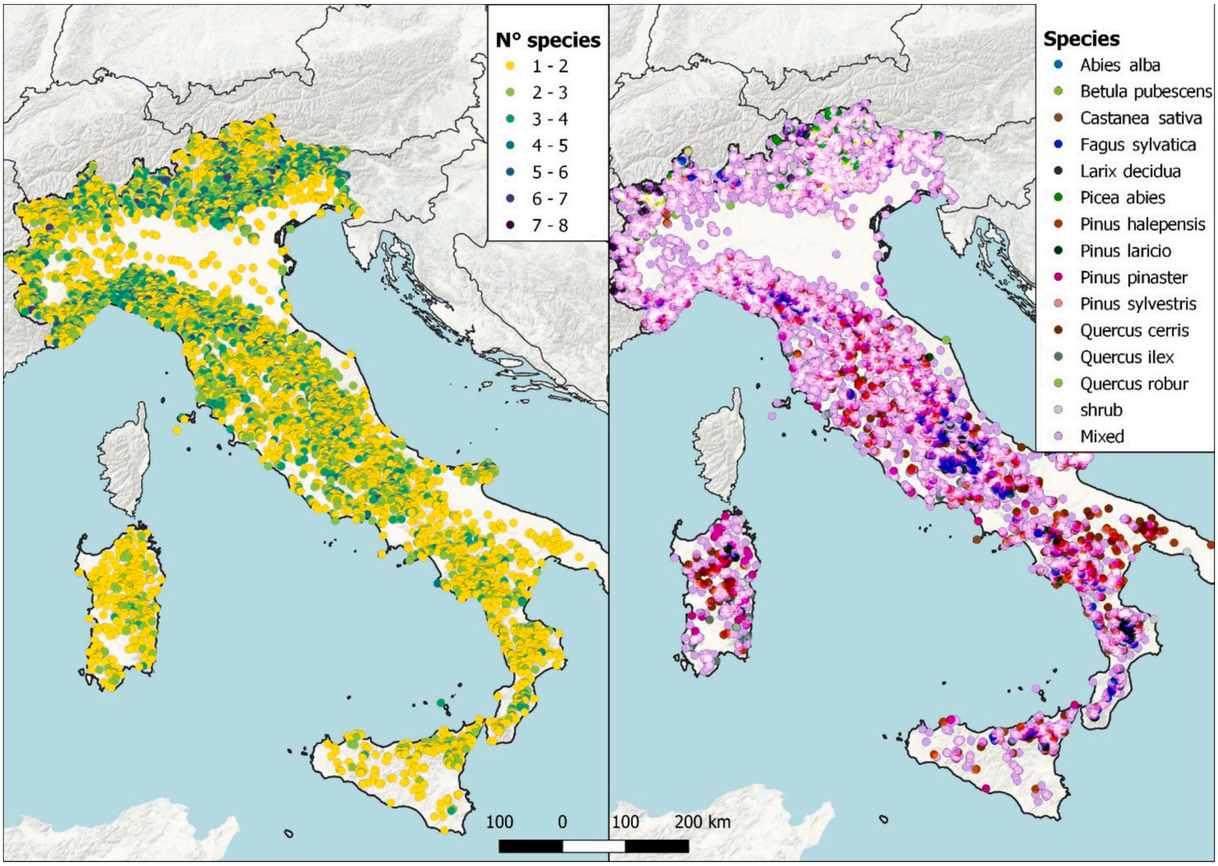

Fig. 1. The study area with the NFI plots' locations used to initialize the model simulations. On the left is the number of species for each plot; on the right is the dominant species for each plot. Multi-species plots were labeled as "mixed".

temperate Mediterranean climate. According to the 2015 Italian NFI (INFC, 2021), forest vegetation and other wooded lands occupy 11,054,458 ha (with a Standard Error of 0.3 %), about 36 % of the national territory. Deciduous species account for 68 % of forest area and are mainly represented by oaks (*Q. petraea* (Matt.) Liebl., *Q. pubescens* Willd., *Q. robur* L., *Q. cerris* L.) and European beech (*Fagus sylvatica* L.). Coniferous species, mainly spruce (*Picea abies* (L.) H. Karst.) and pines (*Pinus sylvestris* L., *P. nigra* J.F. Arnold, *P. pinae* L., *P. pinaster* Aiton) are the main plantation species, abundant along the seacoast and in northern areas. According to the European classification system (Barbati et al., 2014), 7 out of 14 European Forest Types occur in Italy. The two prevalent silvicultural systems are coppice and high forest, accounting for 42.3 % and 41.9 % of total forest area, respectively. The remaining 13.9 % of forests are characterized by structures that cannot be classified as canonical silvicultural systems (INFC, 2015). Most Italian forests (approximately 75 % of the area) can be classified as even-aged forests, primarily characterized by one-storied structures.

Italy is divided into 20 administrative regions (NUTS2, Fig. S1), for each of which the NFI provides estimates of forest area, total and mean GSV and CS, along with their standard errors.

2.2. The 3D-CMCC-FEM model

2.2.1. Main processes and allometries

The '*Three Dimensional – Coupled Model Carbon Cycle - Forest Ecosystem Module*' (3D-CMCC-FEM v 5.7) (Collalti et al., 2016, 2018, 2024; Dalmonech et al., 2022; Vangi et al., 2024a, 2024b) is a biogeochemical, biophysical, process-based forest model. The 3D-CMCC-FEM is designed to simulate carbon, nitrogen, and water cycles in forest ecosystems from the stand to the landscape level, spanning from one hectare to one square kilometer in size. The model represents the primary physiological processes underlying forest dynamics, including impacts of climate change and forest management. These processes are represented across different temporal and spatial scales, depending on the specific process to simulate, and are parameterized at the species level. Photosynthesis is modeled using the biogeochemical model of Farquhar, von Caemmerer, and Berry (Farquhar et al., 1980), parameterized as in Bernacchi et al. (2001, 2003). The Monsi–Saeki formulation of exponential light attenuation, coupled with the "Big-leaf" approach, is used to represent a multi-layered model and implemented for sun and shaded leaves (De Pury and Farquhar, 1997; Landsberg and Waring, 1997; Medlyn et al., 2002; Collalti et al., 2014). The acclimation of leaf photosynthesis to rising temperatures is considered according to Kattge and Knorr (2007). Autotrophic respiration (R_A) follows the so-called '*Growth-and-Maintenance-Respiration-Paradigm*' (Collalti et al., 2020), in which R_A is mechanistically divided into maintaining the already existing tissues ('maintenance respiration', R_M) and the cost of synthesizing new ones ('growth respiration', R_G). While a fixed fraction of newly produced tissues controls R_G, temperature, and nitrogen content (a stoichiometrically fixed fraction of carbon in live tissues) controls R_M. Temperature also affects enzyme kinetics via a standard Arrhenius relationship, but is adjusted for thermal acclimation as described in Collalti et al. (2018, 2024). The net primary productivity (NPP) is computed by subtracting R_A from the gross primary productivity (GPP). The model considers a seventh C-pool of non-structural carbon (NSC), which includes starch and sugars (undistinguished) to buffer periods when respiration exceeds assimilation (i.e., $R_A > GPP$). For this reason, not all the annual NPP is allocated to biomass production; instead, it can be used to replenish the NSC pool and sustain tree respiration (or leaf development during spring) during a period of negative carbon balance. In the extreme case of total NSC depletion, when current photosynthates cannot replenish the NSC pool, the model predicts stand mortality based on the carbon starvation hypothesis (Collalti et al., 2017; McDowell and Sevanto, 2010; Rowland et al., 2015), one of the various mortality mechanisms accounted for by the model. The model accounts for six primary carbon (C) and nitrogen (N) structural biomass pools: leaves, stems, branches, fine roots, coarse roots, and fruits, as well as the NSC pool. Additionally, the model considers various C and N sub-pools, such as sapwood versus heartwood and live versus deadwood. All these pools are initialized at the simulation's start and updated daily, monthly, or annually, depending on the process, differently for evergreen and deciduous species.

The phenological and allocation schemes are all described in Collalti et al. (2016, 2024) and Merganičová et al. (2019). The 3D-CMCC-FEM incorporates the 'age effect' through various mechanisms. Ecological theories from the 1960s outline the dynamics of this effect (Kira and Shidei, 1967; Odum, 1969). At the same time, historical and contemporary evidence hints that forest productivity initially experiences a stepwise increase, followed by stabilization and a subsequent minor decline. The underlying factors contributing to this decline remain a topic of discussion, with hypotheses suggesting a reduction in GPP due to hydraulic constraints (Ryan et al., 1997; Tang et al., 2014) or an increase in R_A linked to an increase in biomass undergoing respiration. The 3D-CMCC-FEM addresses both factors by integrating an age modifier (Landsberg and Waring, 1997), which lowers the maximum stomatal conductance (and consequently, GPP) within the Jarvis model for stomatal conductance (Jarvis, 1976). Additionally, it enhances R_A due to biomass accumulation and increased respiring tissues (Collalti et al., 2020).

The tree height is computed by the model through the Chapman-Richards allometric equations (Von Bertalanffy, 1957):

$$H = 1.3 + CR_a\left(1 - e^{-(CR_b DBH)}\right)^{CR_c} \tag{1}$$

where H is the stem height (in m) of the average tree in the forest stand and DBH is the diameter at breast height (in cm).

Similarly, following Cannell (1984) and Landsberg and Waring (1997), stem biomass (in dry matter) is computed as follows:

$$W = a \cdot DBH^b \tag{2}$$

where W is the stem biomass (in kg of dry matter) of the average stand tree.

The coefficients CR_a, CR_b, CR_c, a, and b of Eqs. (1) and (2) are species-specific parameters estimated through non-linear regression fitted on the tree-level data from the second NFI, for each combination of species and silvicultural system. This accounts for different growth patterns between coppice and high forest stands.

2.2.2. Input and output model data

The 3D-CMCC-FEM model relies on input data that define the initial forest stand conditions at the beginning of simulations. This includes species composition, DBH, H, stand age, tree density (number of trees per hectare, which represents the dimension of the grid cell in this simulations), the silvicultural system (coppice or high forest), and soil characteristics (soil depth and soil texture). The model requires daily weather input data, including the following variables: maximum (Tmax, °C) and minimum air temperature (Tmin, °C), vapor pressure deficit (VPD, hPa), shortwave solar radiation (MJ$\cdot$m$^{-2}\cdot$d^{-1}), precipitation (mm day^{-1}), and annual atmospheric CO_2concentration (ppmv, parts per million by volume). The 3D-CMCC-FEM model incorporates about 55 species-specific, time-independent parameters related to ecophysiology, biophysics, biogeochemistry, and structural traits of the tree species (Collalti et al., 2019). Most parameter values were derived from existing literature and prior model calibration, optimization, and validation efforts (e.g.,Collalti et al., 2016, 2018; De Pury and Farquhar, 1997; Marconi et al., 2017; Dalmonech et al., 2022; Testolin et al., 2023; Morichetti et al., 2024; Saponaro et al., 2025), with an intentional focus on avoiding the use of site-specific measurements to enhance the model's general applicability (see Mahnken et al., 2022).

As output data, 3D-CMCC-FEM produces a range of output data at daily, monthly, or annual time scales, depending on the process simulated. Key outputs include GPP, NPP, and several state variables, such as evapotranspiration, Leaf Area Index (LAI), rainfall interception, and carbon and nitrogen stocks to cite a few. These stocks encompass metrics such as stem biomass, branch and bark biomass, fine and coarse root biomass, fruit production, and above and below-ground biomass. Additionally, the 3D-CMCC-FEM outputs include numerous variables representing the overall C- and N-cycles, energy and water cycles, and forest stand attributes. The 3D-CMCC-FEM model provides information to support decision-making in forest management planning, such as current annual volume increment (CAI), CS, GSV, and stand basal area (BA). Collalti et al. (2023); Collalti et al., 2024) provide a comprehensive list of output variables and an in-depth description of the model's theoretical bases.

2.3. Climate data

The model requires daily climate data covering the whole simulation period for each plot location. Climate data were retrieved from the dynamically downscaled ERA5 reanalysis for Italy (Raffa et al., 2021). The downscaling was performed through the Regional Climate Model COSMO5.0_CLM9 and INT2LM 2.06 (Rockel and Geyer, 2008) on the ERA5 global reanalysis from the Copernicus Climate Change Service (C3S) (Hersbach et al., 2020) at the original hourly temporal scale, increasing the spatial resolution from 31 km to 2.2 km pixels.

The variables needed for model initialization and simulation were downloaded in NetCDF format for the period 2005–2020 and consisted of minimum, maximum, and average temperatures (Tmin, Tmax, Tav, in °C), total precipitation amount (Pr in mm h^{-1}), averaged surface net downward shortwave radiation (Rg, in MJ m^{-2} h^{-1}) and dew point temperature (Td, in °C) at hourly time scale. From Tav and Td, the relative humidity (RH, in %), another climatic input for the model, was computed via the Humidity R package (Cai, 2019). Hourly data were aggregated daily by calculating the mean value, except for Pr, for which the daily sum was computed. All climate data needed for running the model were extracted at each plot location.

2.4. Soil data

Soil depth and texture (as percentages of clay, silt, and sand) are essential information to perform the model simulations. We retrieved such soil properties from the national raster maps developed at the Soil Cartography Laboratory of the Council for Agricultural Research and Economics (CREA) (Corona et al., 2023; Costantini and Dazzi, 2013). These maps comprise four layers at 250 m spatial resolution, representing Italy's soil depth (in cm) and the weighted average content of silt, sand, and clay (in %) in the top meter of depth. As for the climate data, soil data were extracted at each plot location.

2.5. NFI data, model runs, and validation

The field reference data for initializing and validating the 3D-CMCC-FEM were acquired in the second and third Italian NFI frameworks with reference years 2005 and 2015, respectively (INFC, 2007, 2021). Both NFI cycles followed a closely aligned strategy, based on a three-phase, systematic, and unaligned sampling design with 1 km × 1 km grid cells (Fattorini et al., 2006). In the first phase, the land use of each sampling point was classified using aerial orthophotos. In the second phase, qualitative information, such as forest type, management, and property, was collected in the field from a sub-sample of the first-phase points, stratified by Italian administrative regions and land use and land cover classes. Finally, in the third phase, quantitative information was measured in the field using circular plots of 13 m radius for a second-phase sub-sample of points stratified by Italian administrative regions and forest types. All tree stems with a DBH greater than 2.5 cm were callipered, and a subsample of height was measured. Plot-level and per-hectare GSV were estimated via allometric equations conceived explicitly in the framework of the NFI (Tabacchi et al., 2011). For more information on Italian NFI, please refer to Chirici et al. (2020a, 2020b) and Vangi et al. (2021).

The simulations were performed over the geo-referenced locations of the Italian NFI plots. The stand characteristics required to initialize the model at the start of 2005 were obtained from tree-level information collected during the second NFI field campaign. The plot-level data from the third cycle were used to validate the simulations. Both initialization and validation datasets from the Italian NFI are available at a hectare-level resolution. Therefore, all the output variables are referred to the simulation grid cell, set in this simulation to 1 ha. Since the field survey of the third cycle spanned four years (2016–2020), the validation was performed against the actual measurement year for each plot. As a result, the simulation spanned a total of 15 years, from 2005 to 2020. Based on the plot-level data from both NFI cycles (i.e., plots that were measured in both 2005 and 2015 and are present in both databases), we select all plots that were not affected by natural or anthropogenic disturbances during the 15-year simulation period that can have caused changes in land cover or species composition and for which species-specific parameterizations were available. Disturbances within the simulation period (2005–2020) were detected using the 3I3D algorithm (Francini et al., 2021), an unsupervised change detection algorithm that analyzes the trajectory of three vegetation indices over three consecutive years. The algorithm enables the detection of disturbances such as late frost, heat waves, pest outbreaks, fire, windthrow, thinning, harvesting, and clear-cutting as long as they cause a detectable reduction in photosynthetic activities. 3I3D is an open-access tool (Francini et al., 2022a, 2022b) originally designed for use with Sentinel-2 imagery (Francini and Chirici, 2022). However, as done in this study, 3I3D

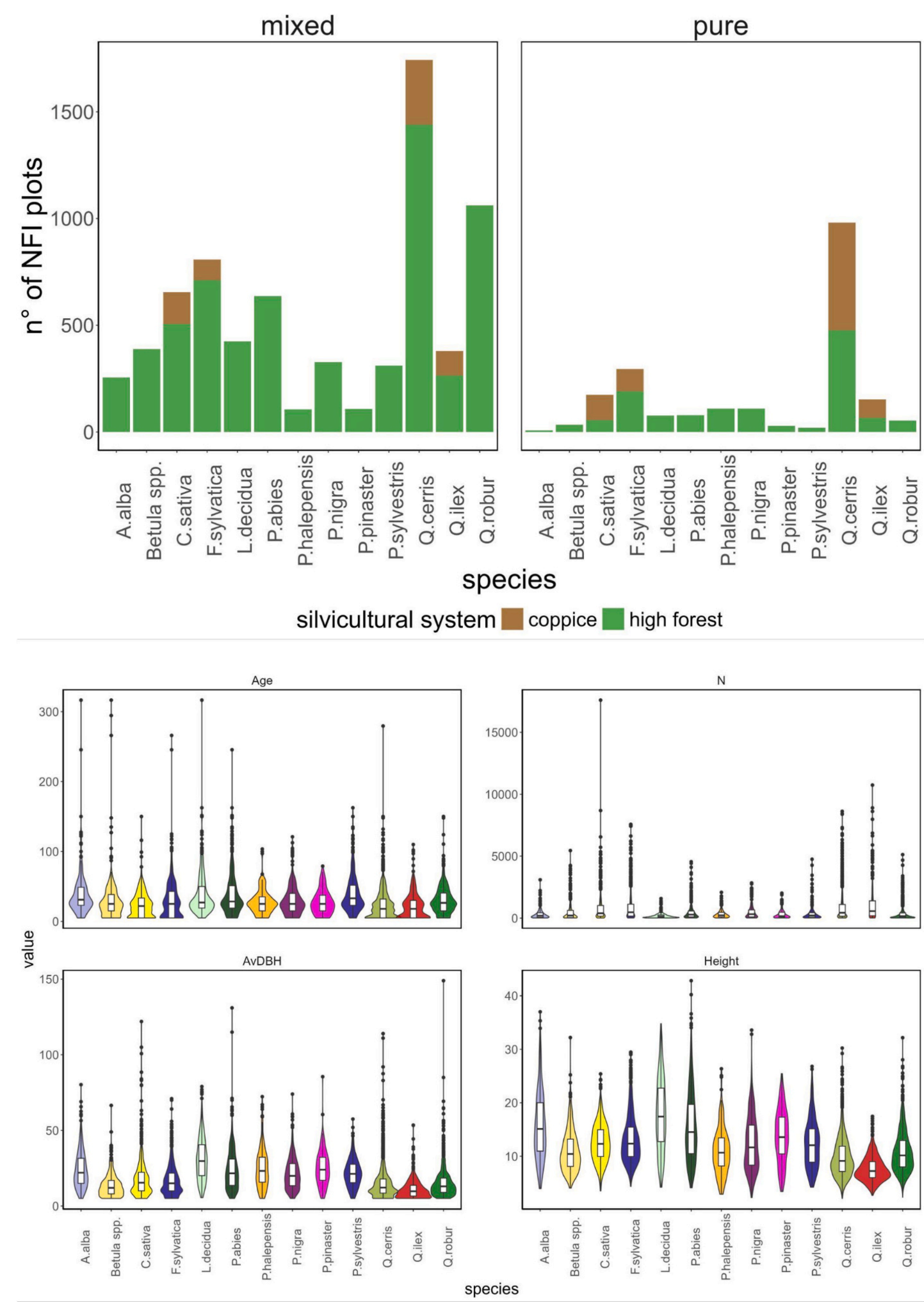

Fig. 2. Top) Species distributions by composition and silvicultural system; Bottom) age, number of trees per hectare, DBH, and H distribution by species.

provides reliable results also using Landsat imagery as input (Francini et al., 2022b), especially in the Mediterranean context (Chirici et al., 2020) and compared to other algorithms (Palahí et al., 2021).

Overall, a total of 5135 out of 6174 plots representing ~83 % of the plots and including 14 of the most common Italian species (*Q. cerris* L., *Q. ilex* L., *Q. robur* L., *F. sylvatica* L., *C. sativa* Mill., *P. halepensis* Mill., *P. pinaster* Aiton, *P. nigra* J. F. Arnold, *P. sylvestris* L., *L. decidua* Mill., *P. abies* (L.) H. Karst, *A. alba* Mill., *B. pubescens* Ehrh.). Out of the dropped plots, only 55 were affected by disturbance during the study period. A species-specific parameterization has not yet been determined for the remaining ones, which are primarily composed of azonal formations, hornbeam forests, and mixed broadleaf forests.

From the selected plots, the ones in which more than one species was present, regardless of the basal area share, were labeled as "mixed" and initialized with tree-level disaggregated data by species, including a maximum of four species. Fig. 2 illustrates an overview of the plot's composition and structure. All the simulations were performed using the R3DFEM R-package (Vangi et al., 2025).

We computed RMSE, RMSE%, and r^2 between observed and simulated values for the plot-level DBH, H, GSV, and CS. The RMSE was calculated for each variable of interest as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}\left(y_i - \underline{y_i}\right)^2}{N}} \tag{3}$$

where N is the number of NFI field plots (i.e., 5135), y_i is the value of the variable considered for the i-th plot, $\underline{y_i}$ and is the value predicted by 3D-CMCC-FEM for the same variable for the same plot. The RMSE% was calculated as the ratio of RMSE for the given variable to its average value across all NFI plots.

Model results for GSV and CS were aggregated at the NUT2 to validate them against the official, design-based NFI estimates of mean GSV and CS at the national and NUT2 levels (https://www.inventarioforestale.org/it/statistiche_infc/; accessed on 24 September 2024) for the reference year 2015. Since the simulation setup was designed to exclude forest management and, thus, harvesting, we account for the possible mismatch between model results and the actual NFI official estimates by adding the estimates of mean GSV and CS harvested (https://www.inventarioforestale.org/it/statistiche_infc/; accessed on 24 September 2024) to their respective stocks (mean GSV and mean CS), both at the national and regional level. We did not compare total values because the number of simulated plots differed from those measured in the NFI.

With the same aggregation methods, we compared the model results for GSV and CS with the estimates produced in the framework of the GHGI for the period 2006–2018 for the Land Use, Land Use Change and Forest (LULUCF) sector, comparing the category "forest land remaining forest land" (ISPRA, 2021). In both the NFI design-based validation and the GHGI comparison, we computed the RMSE% and r^2.

2.6. RS-based GPP dataset

RS-based datasets have continuous spatial and temporal coverage, making them suitable candidates for assessing the overall model's capability for reproducing GPP flux. We used two widely used RS GPP datasets from two independent sources to compare the model GPP results at the plot level. The temporal agreement between the model and the two RS datasets was assessed by computing the r^2 and RMSE% for each plot and year, considering the entire simulation period (2005–2020). The overall agreement of the model with the RS dataset was computed by averaging the plot-level RMSE%. The two RS datasets are briefly described below:

2.6.1. GOSIF-GPP

The GOSIF GPP dataset (Li and Xiao, 2019a) combines RS sun-induced fluorescence (SIF) observed by the Orbiting Carbon Observatory-2 (OCO-2), the enhanced vegetation index (EVI) from the Moderate Resolution Imaging Spectroradiometer (MODIS) satellite data, meteorological data, i.e., photosynthetically active radiation (PAR), vapor pressure deficit (VPD), and air temperature obtained from the NASA reanalysis MERRA-2 data set to return a spatial SIF dataset (Li and Xiao, 2019b). Established relationships between the original OCO-2 SIF and flux tower GPP were then used to provide the final GPP product. For the comparison in this study, we used the annually aggregated ensemble mean of eight different GPP estimates, resulting from various GPP-SIF relationships (http://globalecology.unhedu), from 2005 to 2020. The dataset provides annual GPP estimates at 0.05 degrees (approximately ~5 km at the Italian latitude) spatial resolution. This product is hereinafter referred to as "GOSIF".

2.6.2. MODIS-GPP

The MODIS GPP product is designed to provide an accurate, regular measure of terrestrial vegetation growth. GPP is determined by first computing a daily net photosynthesis value, which is then composited over an 8-day observation interval. The product is a cumulative composite of GPP values based on the radiation use efficiency concept (Running et al., 2021).

For comparison, we aggregate the 8-day Terra and Aqua GPP products at 500 m resolution composite (Running et al., 2021) from the cloud computing platform Google Earth Engine into an annual composite for each simulation year (2005–2020). For each year, we selected only the image that met the top-quality specifications (QC_bit = 0, SCF_QC (000,001)) from the product documentation. This product is hereinafter referred to as "MODIS".

3. Results

3.1. Model evaluation

Annual model outputs at the plot level were evaluated against the third Italian NFI field data for each plot's actual measurement year (from 2017 to 2020). The simulations yielded RMSE% values of 32, 36, 46, and 46 %, along with r^2 values of 0.65, 0.49, 0.61, and 0.53 for DBH, H, GSV, and CS, respectively (Fig. 3).

The mixed category consistently achieved the best performance in terms of RMSE% for all variables considered (DBH: 31 %, H: 34 %, GSV: 43 %, CS: 47 %). At the same time, at the species level, *C. sativa*, *L. decidua*, *P. abies*, *A. alba*, *B.* ssp., and *F. sylvatica* outperformed the other species. The highest RMSE% for GSV and CS was obtained by *P. nigra* sp. (GSV = 66 %, CS = 73 %). Results grouped by species and NUT2 Regions are reported in the Supplementary Materials for GSV and CS (Figures from S2 to S5).

Plot-level simulations for the same year of the third NFI field survey were aggregated for NUT1 (national) and NUT2 (regional) administrative levels and compared with the official third NFI estimates (INFC, 2021). We obtained a mean GSV and CS at the national level of 162.3 m^3 ha^{-1} and 57.6 MgC ha^{-1}, compared to the official estimates of 167.8 m^3 ha^{-1} and 58.4 MgC ha^{-1}, respectively. We obtained an RMSE% of 10.1 % and 10.5 % at the regional level, and r^2 values of 0.95 and 0.86 for GSV and CS, respectively (Figs. 4 and 5). The same validation is presented in the Supplementary Materials for BA and CAI (Figs. S6 and S7, respectively).

Finally, following the same aggregation procedure, modeled GSV predictions at the NUT2 level were compared against official estimates from the Italian GHGI for 2006–2018 (LULUCF sector, forest land remaining forest land category), yielding a mean RMSE% and r^2 of 18.8 % and 0.82, respectively, over the years (Table 1, Fig. S9). The region with the lowest RMSE% was Lombardia (7.5 %), while the highest RMSE % was reached in the Marche (47.3 %). Year-wise, the RMSE% ranged from 22.2 % in 2006 to 17 % in 2013, increasing again to 20 % in 2018 (Table 1).

The carbon stock was also compared against the official Italian GHGI

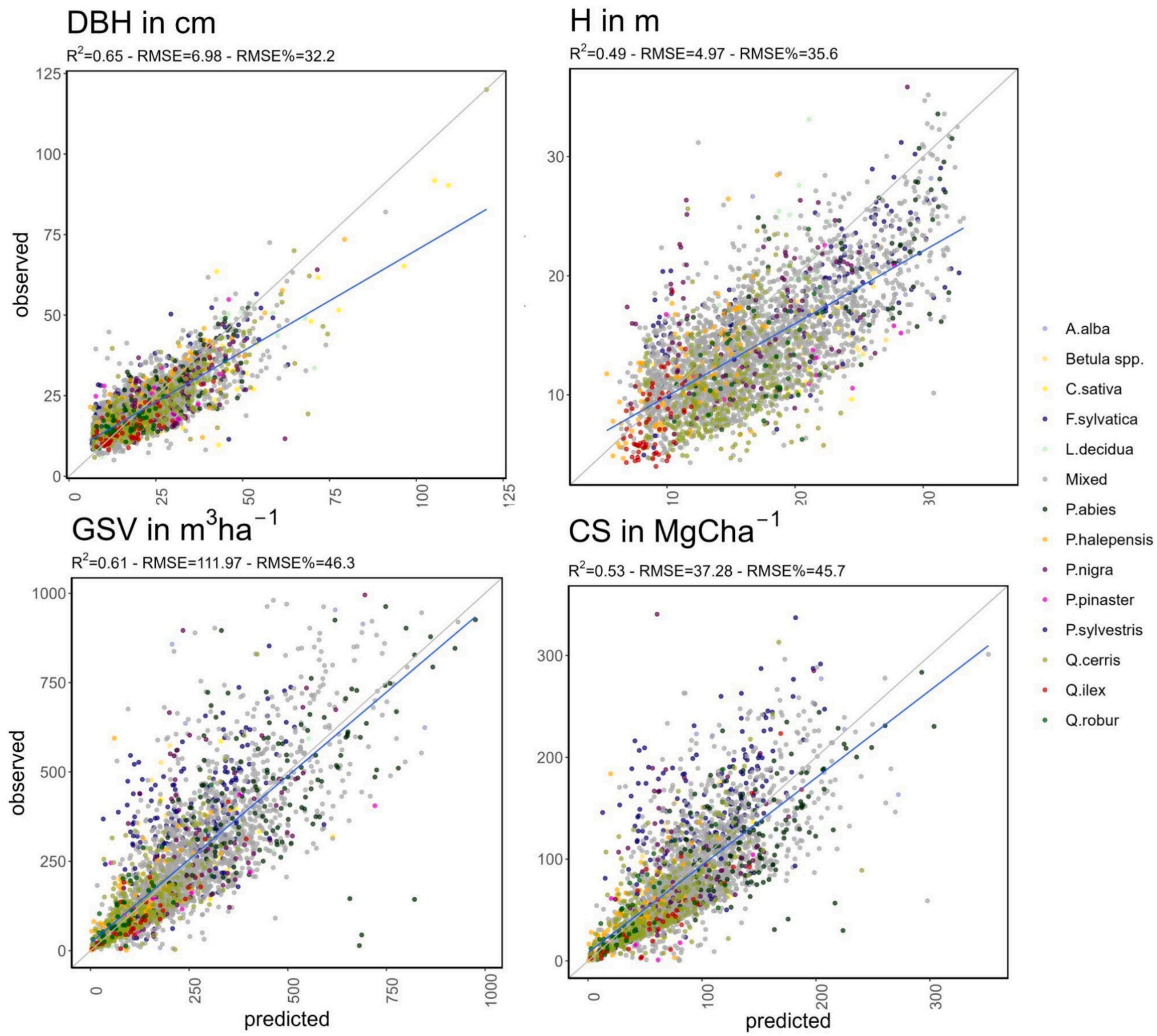

Fig. 3. Single-plot level validation of the 3D-CMCC-FEM simulation against the field-measured values of the third Italian NFI. DBH, H, GSV, and CS are the diameter at breast height, tree height, growing stock volume, and aboveground carbon stock, respectively. The grey line is the y = x line, and the blue one is the regression line between predicted and observed values. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

for the same period (Fig. S10), yielding an overall RMSE of 19.2 % and an r^2 of 0.65, respectively. Similar to the GSV, the CS RMSE% reached the minimum in Piemonte (5.7 %) and the maximum in the Marche (54 %). The yearly RMSE% follows the same pattern as the GSV RMSE%, starting in 2006 at 22 %, decreasing to a minimum in 2011 (17.4 %), and then increasing again up to 2018 (21.2 %) (Table 1). Figs. S9 and S10 show the regional comparison between the simulation's results and the official estimates from the national GHGI for GSV and CS.

3.2. Model comparison against RS datasets

Due to the very different spatial resolution between the model simulation and the RS-based dataset, the comparison is shown at the national level. The 3D-CMCC-FEM simulated average annual GPP for 2005–2019 is shown in Fig. 6, with overall values ranging from ~600 up to ~3000 gC m^{-2} yr^{-1}. The years with the highest and lowest GPP mean values were 2020 and 2005, with approximately 1300 and 720 gC m^{-2} yr^{-1}, respectively. All three GPP datasets (3D-CMCC-FEM, GOSIF, and MODIS) exhibit a positive trend in productivity over time, with the 3D-CMCC-FEM results aligning more closely with GOSIF than with MODIS dataset, as reflected in the higher overall performance (GOSIF RMSE% = 43; MODIS RMSE% = 46). At the plot-level, the lowest performance against both datasets (reflected in higher RMSE% values) was found in the northern regions and the main islands, in particular in Trentino-Alto Adige, Valle d'Aosta, and Sardegna, with RMSE% over 100 % for a few dozen plots (Fig. S8 in Supplementary Materials).

Modeled GPP follows altitudinal and latitudinal species-specific gradients, with higher productivity between 1000 and 1500 m a.s.l., corresponding to the beech-dominated areas. Near the seaside, in plain zones where Mediterranean species dominate, GPP exhibits the lowest values, increasing as elevation increases. On the contrary, species such as *F. sylvatica*, *P. abies*, and L. *decidua* all exhibit an opposite trend in mountainous areas, with GPP values decreasing with increasing elevation. Generally, the highest GPP values were found in older forest stands,

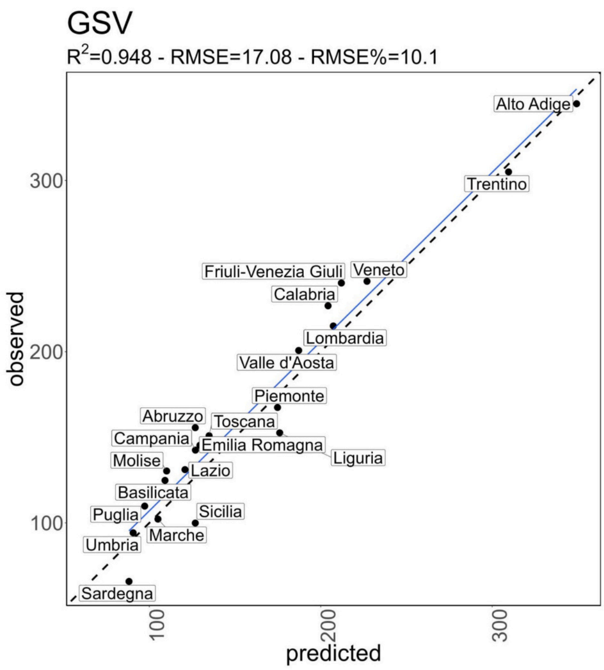

Fig. 4. NUT2 INFC, 2015 GSV against modeled GSV ($m^3\ ha^{-1}$); The dotted line is the y = x line, and the blue is the regression line. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

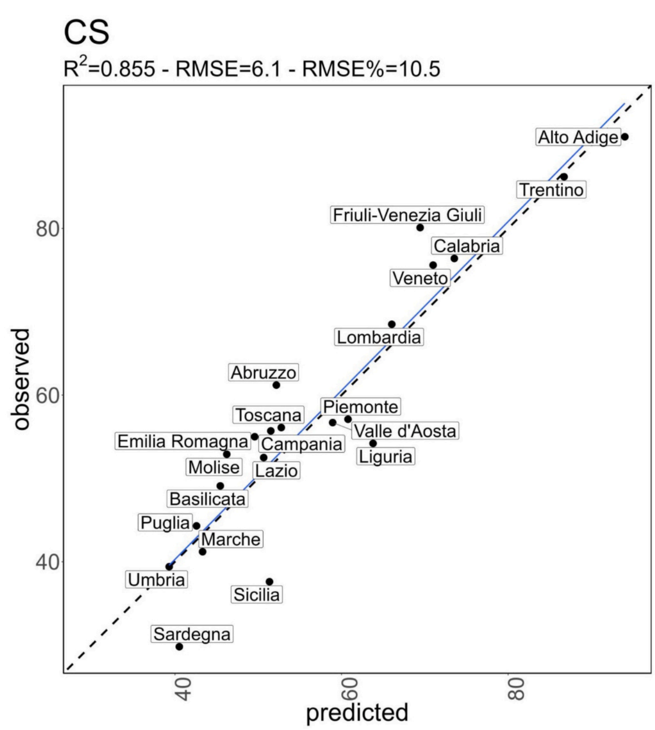

Fig. 5. NUT2 INFC, 2015 CS against modeled CS (MgC ha^{-1}); The dotted line is the y = x line, and the blue is the regression line. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

and for the same species, productivity is usually higher in coppice than in high forests. Productivity also increases with the number of species in the plot, up to a maximum of three species (data not shown).

Table 1
Performance of the model against the GHGI values, both for GSV and CS, for each year.

	GSV		CS	
YEAR	RMSE%	r^2	RMSE%	r^2
2006	22.20	0.87	21.63	0.73
2007	20.80	0.86	20.25	0.74
2008	20.01	0.86	19.53	0.73
2009	19.40	0.85	19.01	0.73
2010	18.36	0.85	18.12	0.73
2011	17.33	0.85	17.47	0.73
2012	17.41	0.84	17.92	0.72
2013	17.05	0.84	17.94	0.72
2014	17.14	0.84	18.34	0.72
2015	17.35	0.84	18.65	0.72
2016	17.79	0.83	19.01	0.72
2017	18.94	0.83	20.40	0.71
2018	20.00	0.82	21.21	0.70

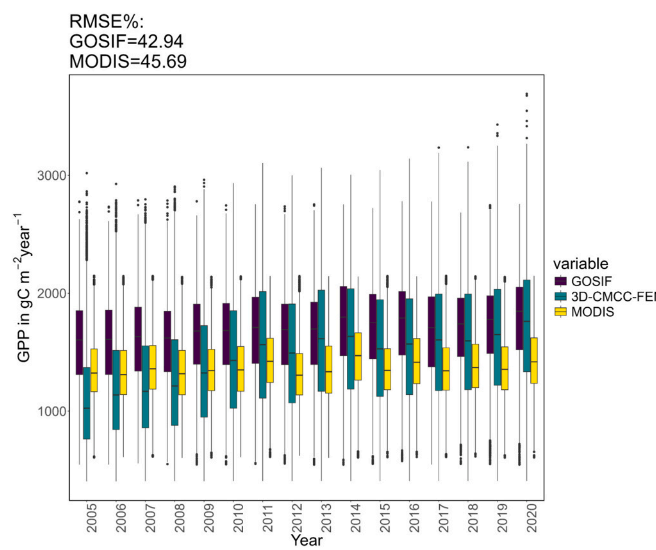

Fig. 6. GPP (in gC $m^{-2}y^{-1}$) distribution for each simulated year from the RS-based dataset (GOSIF in dark violet, MODIS in yellow) and the 3D-CMCC-FEM model results (in light green).

4. Discussion

In this study, we evaluated the performance of the process-based forest model 3D-CMCC-FEM in predicting and reproducing important forest structural and stock variables, as well as key carbon fluxes, at the national level, using consecutive NFI data, demonstrating the model's capability to simulate complex forests on a large spatialscale. To date, and to the best of our knowledge, this represents the most extensive application and validation of a process-based eco-physiological forest model ever conducted in Italy and the Mediterranean Basin. The findings highlight the model's potential as a valuable tool for monitoring operational forestry tasks and international reporting initiatives, showing results comparable to currently used methods, with the potential to track many more variables at a significantly finer temporal resolution and under climate change conditions.

Empirical interpolation methods between successive NFIs are commonly employed to estimate key forest variables that are not assessed annually. For example, the one used by the Italian Ministry of Environment, Land and Sea (2019, section 3.3; ISPRA, 2021) for reporting GHG for the LULUCF compartment under the UNFCCC, adopts a bookkeeping model that annually updates the CS in the LULUCF sector by adding the current stock increment to the net of losses caused by disturbances and mortality (derived from underestimated statistics at the national level, as already acknowledged by Federici et al., 2008). This approach only considers soil properties and climatic variability indirectly and is thus unsuitable for extended periods, which can be characterized by climate extreme and, thus, unstable and unmeasured growth conditions. Furthermore, in such interpolation approaches, forest age often drives structural variables without considering species-specific adaptation to local environmental conditions. The 3D-CMCC-FEM model, on the other hand, describes forest dynamics by integrating biogeochemical and biophysical processes at different temporal and spatial scales, such as photosynthesis, respiration, transpiration, competition for resources, and natural mortality, considering the vertical structure and age- and climate-related changes in physiological traits.

While PBFMs often accurately represent forest processes (Collalti et al., 2016; Wramneby et al., 2008), they typically perform poorly outside their calibration domain (Mahnken et al., 2022; Prentice et al., 2015). To address this limitation, we rigorously assess the model's performance at a large spatial scale. This involved comparing model outputs with multiple sources and types of data across different spatial and temporal resolutions, including a large set of NFI plots measured between 2017 and 2020; national and regional design-based NFI estimates for the reference year 2015; regional GHGI estimates for the relevant sector from 2006 to 2018; and RS-based GPP data from 2005 to 2020. The model was tested using a parameterization approach that was general enough (i.e., not site-specific) to allow application at the national level, while still maintaining a sufficient level of accuracy and realism for reliable simulation results (sensu Mahnken et al., 2022). Therefore, we simulated all plots along the extensive Italian environmental and climatic gradient, using a general set of species-specific parameters to avoid site-specific calibrations, thereby testing the suitability of the 3D-CMCC-FEM model as a forest monitoring tool over vast areas. Our results demonstrate the applicability of the model for national and international reporting purposes.

4.1. NFI plot-level validation

The model effectively reproduced structural and stock variables at the plot level, though it exhibited a slight tendency to overestimate certain variables, particularly DBH. The 3D-CMCC-FEM estimates DBH annually using inverse allometry, which links stem volume and DBH through two fixed, species-specific parameters (see Eq. 1). Mean tree height (H) is similarly updated each year, resulting in comparable overestimations. However, GSV and CS aligned more closely with observed data, indicating the model's capacity to mitigate systematic errors stemming from species-specific growth parameters. For example, in this national-scale simulation, the 3D-CMCC-FEM accurately replicated BA despite overestimating DBH, likely due to a slight underestimation of stand density in plots with lower DBH. This compensation effect has been noted in other RS-based approaches (e.g., Vangi et al., 2023) and PBFMs (e.g., Dalmonech et al., 2024), while other studies (e.g., Minunno et al., 2019, 2025) reported better performance for a different model for structural variables (DBH, H, BA) than for stock variables (GSV, CS), likely because they calibrated multiple model parameters directly using NFI data.

Most overestimations occurred in cases with high structural variable values, which are relatively rare in Italy. Structural and stock variables are highly sensitive to stand density and mortality processes, which are more challenging to simulate, especially in old and mature forests, characterized by high wood volume and carbon content. Another source of potential uncertainty was the identification of forest disturbances within the NFI plots. Although the 3I3D algorithm has been shown to perform better than other change detection algorithms in Mediterranean areas (Francini et al., 2021), continuous forest cover management and biotic and abiotic disturbances that do not sufficiently open the canopy are extremely challenging to detect from RS, which may result in substantial discrepancies between observed and simulated values. The most critical factors influencing forest disturbance detection are spatial resolution, cloud presence, and disturbance dimension. This study used the Landsat dataset in the 3I3D algorithm due to the simulation period (2005–2020). The coarse 30 m spatial resolution, in combination with the typically small disturbance sizes found in Italy (Chirici et al., 2020a, 2020b), may have led to an underestimation of both disturbance presence and size (Francini et al., 2021), which could be reflected in the more extreme bias observed in some plots.

We found significant variability in structural variables predicted at the plot level. Water availability and carbon allocation processes drive the growth of structural variables, such as DBH and H (see Collalti et al., 2024), which, in turn, influence BA, CAI, GSV, CS, and mortality dynamics, thereby regulating stand density. These processes are influenced by a subset of parameters that determine, for example, the length of the growing season, the latitudinal (acclimation) differences in thermal range for photosynthesis, and the overall shape of the allometric relations between variables (DBH, H, and GSV in particular). These individual characteristics are primarily inherited from the oroclimatic conditions in which the species live and grow, in addition to genetic factors also inherited from previous generations living under the same conditions (Johnstone et al., 2016; Vangi et al., 2024b). At the species level, we found the same general overestimation trend, driven mainly by a few outlier plots, for which the model predicts a higher growth rate than the one observed in the field (Figs. S4-S5 in Supplementary Materials). This is especially true for widely distributed species, such as beech, silver fir, and European black pine, as well as mixed plots where the total stocks, for example, depend on those of individual species. This also applies if we group NFI plots at the regional level for all investigated variables (Figs. S2-S3 in Supplementary Materials). A few outliers tend to create an overestimation pattern in the regression line between predicted and observed values. However, we did not find any latitudinal pattern in the plot-level observed versus predicted values, indicating that the species parameters used were suitable for representing the species' structural and stock variables across all their latitudinal and altitudinal distributions.

4.2. NFI regional-level validation

Despite the general (i.e., not site-specific) parameterization employed in this application, the 3D-CMCC-FEM's predictive performance showed robust and reliable results, effectively capturing a diverse range of individual characteristics typically shaped by intra-specific variability. The model accurately replicated national and regional spatial trends in GSV and CS relative to official NFI estimates, demonstrating its capacity to simulate forest growth reliably also at large spatial scales.

The model outputs closely match the official NFI values at the NUT2, while exhibiting a slight but systematic tendency to underestimate stocks. The major discrepancies were found in southern regions and islands, particularly Sardegna and Sicilia, where the mean GSV and CS were slightly overestimated. This can be attributed to the specific forest types found in these regions. In particular, forests on the main island of Italy are typically multi-species, multi-layered, characterized by low GSV and sparse vegetation, as well as other wooded and bush lands, for which species-specific parameterizations are lacking in the literature. Approximately 30 % of the total NFI plots were discarded in these regions, primarily due to the lack of species-specific parameterization. As a result, the simulations reflect generally more productive plots, leading to an overestimation of mean stock values. Although the regional mean harvested volume was accounted for, it is worth mentioning that the impact of harvested volume on average stocks is almost negligible at the plot level. For instance, according to NFI estimates, the regions with the highest percentage of harvested volume per hectare are Umbria and Marche, with 1.7 % and 1.5 % of the mean GSV per hectare, respectively. Puglia and Molise reported a 0 % harvest volume per hectare. The Italian 13 m radius plot-level survey is likely unable to capture rare phenomena (both in space and time), such as disturbances, thereby failing to accurately represent the national harvesting regime. This is also reflected in the standard error associated with the estimated mean harvested volume, which exceeds 50 % for most regions, with a mean value of 54 %. Other data sources in Italy are known to underestimate forest harvesting (Chirici et al., 2011; Corona et al., 2007). With more recent RS-based approaches, such as the 3I3D method, other studies found up to a 40 % higher harvesting rate at the regional level (Francini et al., 2021; Francini et al., 2022a, 2022b). However, paradoxically, these studies confirm the low levels of harvesting in Italy, which, according to official reports (RAF, 2019), do not exceed 24 % of the total CAI, making Italy one of the European countries with the lowest levels of wood production (Madrid, 2015; Bleu, 2019). Another international source (Joint Forest Sector Questionnaire) estimates that, for 2016–2017, Italy had approximately 13 million cubic meters of harvested wood, corresponding to approximately 0.9 % of the total national wood stock. The FAOSTAT (2025) and EUROSTAT (2025) services made a similar estimate for the same period. Despite the uncertainty surrounding these estimates, Italian wood production is significantly lower than its potential. It remains lower than in other European countries, underscoring the limited impact of forest management on the total wood stock. This is the main reason to not include forest management and disturbances in the simulation setup for this work. However, incorporating the NFI harvesting estimation into our validation confirms that the 3D-CMCC-FEM model correctly reproduces wood and carbon stocks at both regional and national levels. Pilli et al. (2013) applied the yield curve–based Carbon Budget Model of the Canadian Forest Sector (CBM-CFS3) to Italian forests for the period 1995–2009 and projected the national forest carbon budget through 2020. Due to the differences in the output between CBM-CFS3 and the NFI, the comparison required several assumptions regarding forest area expansion and contraction, species composition, disturbance and harvesting regimes, and current increment ratios for both even-aged and uneven-aged forests. The CBM-CFS3 model consistently overestimated the different C pools compared to other reference sources, including NFI, national reports, and GHGI. In contrast, the 3D-CMCC-FEM output is consistent and directly comparable with the NFI results, showing a conservative trend in estimating C pools. In addition, incorporating the non-parameterized species in the future will enable the simulation of the discarded plots and, consequently, the application of the NFI estimators, thereby coupling the simulation estimates with their respective standard errors.

4.3. GHGI regional-level validation

Model results, when compared with the GHGI at both national and regional levels, show an upward trend in mean aboveground carbon pools (Table 1, Fig. S8). This increase reflects the accumulation of GSV as forest stands age. During the study period, the relatively low disturbance rates were indeed insufficient to produce any noticeable decline in GSV or carbon stocks. However, model predictions initially underestimated the reference values, but after 2013, for both stocks, the model predictions overestimated the official measures. This trend can be attributed to the different drivers of forest growth in the two approaches (PBFM vs GHGI). In particular, the GHGI uses the *For-est* model for the Forest Land sector (Federici et al., 2008), which assumes constant area increase in the period from 2006 to 2019, while our simulation is plot-based and does not consider forest area changes, despite it can be indirectly considered (as in the NFI methodology) by simulating the field plots measured in the third survey of the NFI which were not present in the second survey. These plots were added to account for the forest expansion between consecutive survey campaigns. However, since it would be impossible to validate these plots until the next NFI cycle, this exercise fell outside the scope of the present study. However, as new NFI data becomes available, the forest area change could be taken into account as well. Another crucial methodological difference between the two approaches is the source data used for CAI estimation, which is the primary driver of forest growth. Both models used a Chapman-Richard function to model the CAI as a function of GSV (*For-est*) or age (3D-CMCC-FEM). In the *For-est* model, CAI is estimated from an outdated national collection of yield tables, which has been found not to accurately represent today's growth rates (see Federici et al., 2008; Vangi et al., 2023). Other studies involving PBFMs have reached the same conclusion: yield tables have too many limitations for calibrating growth curves (see for example: Henttonen et al., 2017; Minunno et al., 2019). On the other hand, the Chapman-Richard function in the 3D-CMCC-FEM model was calibrated for each species, using field measurements from the second NFI. This enables continuous calibration updates and improvements as new field data becomes available. However, the limitation of using yield tables for parameterization purposes was already acknowledged in the paper describing the *For-est* model (Federici et al., 2008), in which an underestimation of the CAI was observed compared to the second Italian NFI. This may be another cause for miscorrelation and the overestimation of GSV and CS by the 3D-CMCC-FEM model compared to GHGI after 2013. However, it is worth noting that the drift in the estimation concerning GHGI is relatively small and could be accounted for by using the third Italian NFI data to initialize the simulations. Another interesting feature of our PBFM approach is the possibility of monitoring other C compartments, including litter and soil, which make part of the model's output. Although the validation of other C pools is outside the scope of this study, the comprehensive list of variables simulated by the model makes it an ideal tool for international reporting, enabling monitoring and addressing all five C pools listed by the IPCC (2006). In this sense, the use of a PBFM in the Italian case, but also in countries with comparable data availability, could be effectively integrated in reporting activities, overcoming the known limitations of other approaches and allowing the monitoring of variables that would otherwise be difficult to measure and monitor (Valentini and Miglietta, 2015). As pointed out by a recent review by Leoni et al. (2025), there is no silver bullet in carbon monitoring, and each approach has its own advantages and limitations. In the authors' opinion, this timely study further emphasizes the need to explore new solutions and combine techniques and knowledge to set up a reliable monitoring system capable of responding promptly to the needs of the national and international community.

4.4. RS-based GPP dataset comparison

Overall, the model demonstrated satisfactory performance in simulating GPP compared to large-scale and independent RS-based datasets, which aligns with the results of a different study using the same model (Dalmonech et al., 2024; Mahnken et al., 2022). As pointed out in Zhang and Ye (2021) differences between the modeled and the RS-based GPP can be attributable to several sources of uncertainty. Besides the differences in spatial resolution, the underlying algorithm and approaches even between the two RS-based datasets, as between the RS-based and the model, differ substantially, making the comparison challenging from the outset (e.g., Dunkl et al., 2023; Wang et al., 2025). In this context, it is important to note that while RS-based datasets are used as references for performance metrics, they are not direct GPP measurements but model-derived estimates based on different methodologies. For example, GOSIF GPP is based on SIF and EVI, while MODIS GPP uses a LUE model driven by NDVI. These approaches have inherent limitations compared to the biogeochemical model of Farquhar et al. (1980) implemented in 3D-CMCC-FEM. Notably, SIF better reflects photosynthetic activity, whereas NDVI is more closely tied to canopy greenness. At the same time, different satellite-derived datasets targeting the same variable, such as greenness and, by extension, forest structural attributes (e.g., NDVI and LAI), have been shown to produce significantly different estimates of GPP (Xie et al., 2019). Moreover, while the Light Use Efficiency (LUE) model does not account for saturation effects caused by increasing solar radiation, these effects are explicitly simulated in the biogeochemical photosynthesis model of Farquhar et al. (1980)

implemented in the 3D-CMCC-FEM. This distinction is crucial for interpreting GPP trends, especially under high-radiation conditions, as it underscores the need to consider the assumptions behind each modelling approach when assessing ecosystem productivity. However, although RS products such as GOSIF and MODIS are model-derived and therefore subject to inherent uncertainties, they represent well-established and widely used datasets for global GPP monitoring in many studies. As such, they provide a valuable and independent reference for evaluating model performance at different spatial and time scales, across a wide range of ecosystems and potentially at the global level.

Discrepancies between RS-based and PBFMs datasets often stem from differences in spatial and temporal resolution, requiring aggregation of fine-scale model outputs to align with coarser RS products. This can reduce model performance in complex landscapes like maquis ecosystems, particularly in the Mediterranean, where high heterogeneity challenges both accurate simulation and alignment with satellite data (Dalmonech et al., 2024; Teijido-Murias et al., 2025; Vaglio Laurin et al., 2025). Furthermore, discrepancies in phenological timing, such as the onset and cessation of the growing season, between remote sensing data and PBFMs outputs (as even between RS products) remain a well-recognized and widely documented issue in the scientific literature (see, for example, Peano et al., 2019). These yet-not-resolved mismatches can arise from differences in how phenological transitions are defined and detected by satellite observations versus model simulations, as well as from limitations in model parameterization or input data resolution, and, therefore, generate uncertainty in model outputs (Dunkl et al., 2023).

Additionally, this comparison analysis highlighted some critical challenges in applying the 3D-CMCC-FEM at the national level, pinpointing other sources of uncertainties that can explain the differences across model results and RS-based datasets. Compared to the previous application of the model at a gridded level in Dalmonech et al. (2024), which focused on GPP fluxes alone, in this study, a higher resolution climate forcing was used, and simulations started from observed forest structure. This allowed for a more consistent representation and more accurate simulations of growth-related variables and GPP fluxes, as the accuracy of meteorological forcing is pivotal to correctly simulate GPP (e.g., Zhang et al., 2022). Yet, the residual spatial mismatch between the exact forest structural information at the plot level and the climate resolution at 2.2 km could partially explain the differences in the GPP trends in the first years of model runs, where simulations are affected by the initial conditions (Hurtt et al., 2010), and could have contributed to the lower performances in the northern regions of Italy, characterized by the typical alpine orography and meteorological heterogeneity.

5. Challenges and limitations

This study provides the first national-scale assessment of 3D-CMCC-FEM simulations. To evaluate the model's effectiveness as a monitoring tool, we compare its primary outputs with data from various independent sources, addressing several challenges and limitations. PBFMs are inherently complex, requiring initial forest conditions, extensive parameterization, and calibration to simulate forest dynamics accurately. The substantial number of model parameters, coupled with the limited availability of independent calibration data, complicates the achievement of accurate simulations across diverse environmental conditions, particularly for tree species with limited eco-physiological data in the literature. To mitigate these uncertainties, we opted to simulate a maximum of four species per plot, thereby reducing potential errors associated with species-specific parameters.

Furthermore, calibration and parameterization must strike a careful balance to avoid overfitting the model (through excessive tuning) and relying on overly generalized parameters that fail to capture eco-physiological differences between species, or within the same species across varying environmental conditions. On the other hand, parameters that are too specific can lead to overfitting and extrapolation errors (Barry and Elith, 2006; Getz et al., 2018). The parameterization challenge underscores the difficulty of balancing scalability and resolution in simulations. Simulating fine-scale, stand-level processes while maintaining feasibility at large scales requires aggregating the diverse forest tree species in Italy into a smaller set for which the model has been tested, and reliable parameter data are available from the literature. This approach potentially enhances the robustness and reliability of the simulation framework. However, representing small-scale variability within broader scales and coarser model resolutions remains challenging. Additionally, accurately capturing the impacts of wildfire events, which operate at distinct spatial and temporal scales, and human-driven forest cover changes, such as land abandonment leading to forest expansion, further complicates the simulation of all effect and their interactions.

It is worth noting that we did not account for significant biotic disturbances such as pest outbreaks and diseases, nor abiotic disturbances like windthrow, late frosts, and fires (which is the most significant source of carbon loss in Italian forests, RAF, 2019). The latter, in particular, is challenging to capture in observation-based meteorological gridded datasets due to the spatial resolution of currently available datasets, making it difficult to simulate forest growth accurately. These factors could significantly alter carbon fluxes and stocks and, in turn, strongly influence the long-term carbon dynamics. In this regard, it is also important to note that forest disturbances (whether abiotic or not) that do not significantly alter the canopy structure are often invisible to medium-resolution optical sensors, such as Landsat and Sentinel-2, making their detection through unsupervised algorithms nearly impossible to date (Mitchell et al., 2017). Ultimately, we want to stress a final yet important consideration regarding harvesting level and forest disturbances in Italy: at the national level, harvest and disturbance statistics are missing or inconsistent. No single data source can track disturbance regimes over time, either at the national or regional level, highlighting the urgent need for a standard and continuous monitoring framework that integrates the potential while minimizing the weaknesses of each single approach.

Finally, extreme climatic events are assumed to be already embedded in the climate datasets used to drive the 3D-CMCC-FEM. They are therefore implicitly represented in the model outputs. However, we acknowledge the uncertainties associated with the dataset and the possible misrepresentation of such events due to the coarse spatial resolution of climate data with respect to other inputs. We also did not consider species migration within the plots, since a period of 15 years represents a relatively short timescale in the context of forest species migration, as the dispersal, establishment, and expansion of tree populations typically occur over decades to centuries. On the other hand, changes in basal area share among species within plots can be attributed to disturbances that were excluded for reasons explained in paragraph 4.2. Furthermore, this affected 55 plots out of the whole NFI database.

6. Conclusions

While often regarded solely as predictive tools, PBFMs can also serve as practical instruments for forest monitoring. These models can generate a comprehensive set of variables that would otherwise require significant time and financial investment to measure directly, provided they are rigorously validated against empirical data.

The 3D-CMCC-FEM model demonstrated consistent reliability across diverse data sources, and multiple spatial and temporal scales, and for different forest species, establishing itself as a robust tool for large-scale forest monitoring with temporal resolutions ranging from daily to annual. This approach mirrors the performance of RS-based methods while offering the added advantage of more continuous temporal data. Moreover, the model effectively tracks changes in GSV and CS between NFI surveys at both local and national scales, potentially reducing costs associated with field surveys.

This capability lays the groundwork for a forest monitoring framework that addresses both governmental needs for updated GHG emissions data and private sector interests in carbon offset investments. Overall, this integrated approach introduces promising advancements in the accuracy and continuity of forest data, enhancing decision-making for climate policy and environmental and forest management, highlighting the potential for integrating new, previously underappreciated tools into the mandatory reporting processes required to track carbon dynamics and climate change.

CRediT authorship contribution statement

Elia Vangi: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Daniela Dalmonech:** Writing – review & editing, Writing – original draft, Software, Data curation. **Giovanni d'Amico:** Writing – review & editing, Data curation. **Elisa Grieco:** Writing – review & editing. **Mauro Morichetti:** Writing – review & editing. **Paulina F. Puchi:** Writing – review & editing. **Saverio Francini:** Writing – review & editing, Data curation. **Silvano Fares:** Writing – review & editing. **Francesca Giannetti:** Writing – review & editing. **Piermaria Corona:** Writing – review & editing. **Roberto Barbetti:** Writing – review & editing, Data curation. **Gherardo Chirici:** Writing – review & editing. **Alessio Collalti:** Writing – review & editing, Writing – original draft, Software, Project administration, 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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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecoinf.2025.103489.

Data availability

The 3D-CMCC-FEM model code (https://github.com/Forest-Modelling-Lab/3D-CMCC-FEM) and the R package R3DFEM (https://github.com/Forest-Modelling-Lab/R3DFEM) are freely available. Remote sensing data are freely available at the original sources. All other data and codes are available via the Zenodo repository: doi:10.5281/zenodo.17405619.

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