

Spatiotemporal variability and uncertainty in wood decay estimates across Europe and Scandinavia using a data-driven moisture content model with multi-scale weather datasets

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ARTICLE INFO

Keywords:

Wood
Durability
Numerical
Gridded weather data
Spatiotemporal uncertainty

ABSTRACT

The use of remote sensing and reanalysis weather data has not been adequately acknowledged for large-scale built environment applications, primarily regarding engineering analyses that traditionally rely on computationally expensive numerical models. This study employs a parsimonious data-driven approach concerning service life assessment of rain-exposed wooden components, enabling mapping and assessment of related risks across Europe and Scandinavia from gridded data. Wood moisture content is the primary vector for fungal decay and accurate modeling is essential for the design of wooden commodities. Numerical models of moisture flow within woody material provide accuracy but are impractically slow for large-scale applications. We explore high-resolution decay risk assessments using a neural network trained on existing numerical predictions of moisture content. Specifically, the model used time-lagged gridded weather data as inputs to calculate moisture content at grids of 5.5 (1.0) km resolution over 21–36 (6) years across Europe (Scandinavia), compared with similar calculations from 890 weather stations. The moisture data were subsequently used to predict decay rates and quantify uncertainties stemming from temporal and spatial variation in weather. The results present high-resolution decay hazard maps alongside the associated spatiotemporal variations. Both spatial and temporal variations were identified as significant contributors to uncertainty in decay assessments, with their impacts varying considerably across regions in Europe. The study is part of an effort to integrate uncertainty propagation in service life prediction of wood, to enhance the resilience and reliability of wood in outdoor applications and to optimize its potential for sustainable and enduring construction solutions.

1. Introduction

Wood elements used in exposed above-ground applications are subject to a variety of biotic and abiotic deteriorating mechanisms, such as superficial weathering, cracking, and fungal decay [1,2]. Among the deteriorating mechanisms, fungal decay is particularly harmful as it breaks down the lignocellulose, substantially reducing the strength of the affected biomass. Decay fungi require free water to deteriorate wood, and the rate of deterioration generally increases with increasing temperature [3]. Consequently, the development of fungal decay and the service life of wood in outdoor applications depend on temporal variations in wood moisture content and temperature [3,4]. Assessment

of deterioration by fungal decay is essential for several engineering applications, including life-cycle planning, maintenance decision-making, and structural safety assessments (e.g., [5–7]).

Service-life assessment of wood components commonly relies on factorized frameworks, see e.g., [8–10]. This type of assessment is based on the principles of ISO 15686 [11] where the expected deterioration is obtained by adjusting a reference case using quantifiable factors representing the influence of climate, detailing, geometry, and material properties. This approach is practical because it separates the different drivers of decay, allowing each to be represented by dedicated models or datasets. Among these factors, climate exposure plays a central role, as it governs the wetting and drying dynamics that ultimately control fungal

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<https://doi.org/10.1016/j.rineng.2026.108983>

Received 21 October 2025; Received in revised form 26 December 2025; Accepted 3 January 2026

Available online 5 January 2026

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activity.

The effect of climate on the fungal decay hazard has been widely studied. The Scheffer Climate Index (SCI) remains the most widely used metric to define decay hazard [12]. The SCI estimates the decay hazard as a function of monthly aggregates of precipitation and temperature, but a modified version considering relative humidity has later been proposed [13]. The Moisture Index developed by the NRC-IRC considers both wetting and drying processes and has likewise been applied to decay assessment [14,15]. Like the SCI, the MI is derived entirely from climatic variables, combining annual rainfall with the evaporative drying potential determined by temperature and relative humidity. An alternative to these climate-index approaches is to explicitly model the causal relationships between climate variables, material climate and fungal decay for a reference, thereby considering the underlying processes and dynamics [16,17]. Wood moisture data can here be obtained from numerical models considering free water [18–21], and by processing the simulated moisture content through a decay model, previous studies have been able to estimate the relative decay risk in different climates [4,16,17].

Within factorized decay assessment, the climate factor is influenced by two key sources of uncertainty in the underlying climate data. First, analyses are typically based on a “representative” or average annual climate, which may fail to capture the full inter-annual variability of weather conditions and can introduce application-specific bias when used as a substitute for long-term records [22,23]. Second, assessments rely on measurements from weather stations that may be located far from the site of interest. This spatial mismatch is particularly problematic in topographically complex regions and urban environments, where climatic conditions can vary substantially over short distances at the meso-scale [24,25].

With advancements in remote sensing, satellite sensors, and algorithms for integration of multi-source weather observations with numerical weather prediction models, reanalysis datasets have become increasingly valuable for spatially complete and physically consistent applications [26–28]. Copernicus (the Earth observation component of the European Union’s Space program) provides such datasets globally and across Europe, currently with higher resolution for the latter. These spatially and temporally consistent datasets are ideal for analyzing the geographical variation of fungal decay at a highly granular level over long timespans. In doing so, they enable detailed assessment of spatiotemporal uncertainties relating to weather in decay prediction.

In this study, we apply a numerically informed metamodel together with multi-year gridded weather datasets to estimate decay hazards and associated spatiotemporal uncertainties for a reference case of Norway spruce (*Picea abies*) sapwood board. The metamodel is used to predict moisture-content variations at the wood surface, forming the basis for calculating annual decay dose across Europe (1985–2020) at 5.5 km resolution using the Copernicus European Regional ReAnalysis (CERRA) dataset [29], and across Scandinavia (2018–2023) at 1 km resolution using the MET Nordic dataset [30]. For the Scandinavian region, wind speed and orientation are additionally incorporated to consider wind-driven rain. To ensure the suitability of the gridded weather input, the predictions were evaluated against those derived from long-term weather station records from the European Climate Assessment and Dataset (ECAD).

The primary aim of this work is to quantify the spatiotemporal variability of climate-driven decay risk to enable more informed predictions within factorized design frameworks. Temporal uncertainty denotes the year-to-year variability in decay-relevant climatic exposure, which is typically condensed into a single average climate factor in factorized design. Spatial uncertainty arises from the mismatch between weather-station location and the actual site conditions due to geographical distance and local climatic variation. The horizontal reference configuration corresponds to the baseline exposure case used in factorized service-life design frameworks [31,32]. By mapping decay dose and its variation over space and time, the study clarifies how

uncertainty in climatic exposure affects the reference case used in factorized service-life design. The resulting uncertainty information (e.g. mean values and variation) is intended as input to existing service-life frameworks, enabling them to better represent real climatic variability. The other factors required for predicting the service life of actual structures, such as detailing, geometry, and material choice, are not considered here.

2. Methods and data

This section describes the procedure of modelling temporal variation of wood moisture content, including both numerical analysis and the metamodel, and the mechanistic decay model used for post-processing this data for decay assessment. It then goes on to describe the different weather datasets used in the analysis. Finally, the methods for the statistical comparison of grid and point decay values, as well as for the spatiotemporal uncertainty analyses, are presented.

2.1. Moisture content model

The moisture content model uses a metamodel derived from an artificial neural network (ANN) trained on reference moisture data generated by finite-element simulations. These simulations represent a wooden reference board made of Norway spruce (*Picea abies*) sapwood, with a thickness of 22 mm and sealed short sides (hereafter referred to as *reference board*). One face of the reference board is exposed to precipitation, while the opposite face is sheltered from precipitation but open to the air. This setup forms the reference case in the factorized service life prediction framework described by Meyer-Veltrup et al. [32], based on the principles of ISO-15686-1 [11]. Any variations in species, exposure conditions, or other parameters are accounted for by adjusting the service life derived from this reference case.

The process for building the metamodel is shown, conceptually, in Fig. 1. The process for generating the dataset as well as the process for training and validating the ANN are briefly described in the following sections.

2.1.1. Numerical model

The metamodel is trained on a dataset used by [17] where hourly climate data were used as input to a numerical model to obtain temporal variations in moisture content (u) of the horizontal reference board. Input to the numerical model was obtained from the Meteorological database [33], and included hourly values of relative humidity (RH), temperature (T), and precipitation (p) over one year per location. Rather than corresponding to any specific historical year, this dataset is a synthetic construct designed to mirror a typical year at selected locations. The typical year is generated from monthly averaged climate data between (2000–2019) using a parameter-specific stochastic procedure. A total of 551 European locations with nearby weather stations were used.

The numerical model was based on Fick’s second law of diffusion, with model parameters and assumptions from Niklewski and Fredriksson [20]. The model output describes the variation in moisture content of the reference case, i.e. a wooden board with a thickness of 22 mm produced from Norway spruce (*Picea abies*) with sealed short sides and one face exposed to precipitation. The problem can be described in one dimension, with the equation governing change in moisture content as follows:

$$\frac{du}{dt} = \frac{d}{dx} \left(D \frac{du}{dx} \right) \quad (1)$$

where u (%) is the moisture content, D (m^2/s) is the transport coefficient and x is the coordinate along the thickness of the board (with $x = 0$ on the face exposed to precipitation). The transport coefficient is dependent on both moisture content and temperature. In the absence of

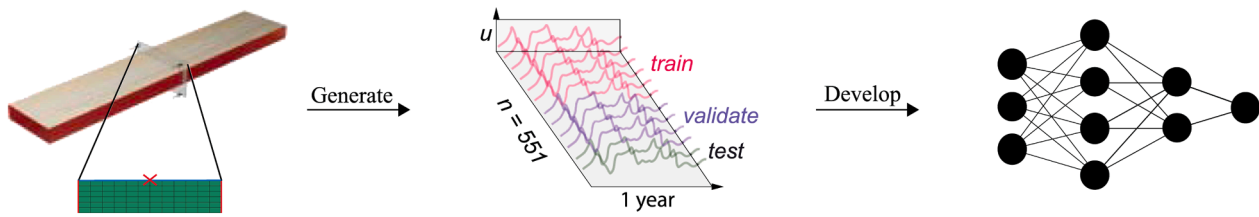


Fig. 1. Schematic of the ANN model and its training using the finite element based simulated data. The model was trained on about 551 time-series, each consisting daily moisture content values over a year.

precipitation, both boundary conditions were described as a surface flux:

$$q_n = k_p(p_{vs} - p_{va}) \quad (2)$$

where q_n ($\text{kg}/\text{m}^2\text{s}$) is the moisture flux, k_p ($\text{kg}/\text{m}^2\text{sPa}$) is the mass transfer coefficient, p_{va} (Pa) is the vapor pressure of the ambient air and p_{vs} (Pa) is the vapor pressure at the wood surface. The rate of change in moisture content at the boundary is then obtained by dividing the flux by the dry wood density. A density of $350 \text{ kg}/\text{m}^3$ is used. The vapor pressure of the air, p_{va} , is calculated from the relative humidity and temperature, and the vapor pressure at the wood surface is calculated from the moisture content via the sorption isotherm, which describes the relationship between the equilibrium moisture content in wood and the relative humidity of the surrounding air [34]. The mass transfer coefficient is set to $k_p = 30 \cdot 10^{-9} \text{ kg}/\text{m}^2\text{sPa}$. It is assumed that the temperature at the wood surface is equal to that of the air, thereby neglecting the influence of radiative heating and cooling. Fig. 2a shows the diffusion coefficient and Fig. 2b shows the sorption isotherm, as well as how it relates to the vapor pressure. In the case of wetting of the top face, the moisture content on the boundary is set to a maximum value of 120 %. The duration of wetting is estimated from the hourly precipitation.

For an in-depth discussion and rationale of the model parameters, the reader is referred to the original works by Niklewski et al. [35] and Niklewski and Fredriksson [20]. The model represents a simplified description of moisture dynamics and does not account for radiative heating or cooling. Nevertheless, validation under both laboratory and outdoor conditions has shown satisfactory agreement with measurements at multiple depths, including near-surface or on-surface moisture readings, core measurements, and gravimetric data [20,36]. This level of agreement indicates that the model is adequately accurate for applications in decay prediction.

2.1.2. Metamodel

The metamodel is constructed using an artificial neural network approach, employing time-lagged weather variables as inputs and

trained on simulated daily moisture content data, as detailed in the previous section. Daily values were obtained by averaging sub-hourly (10 values per hour) moisture outputs generated by the numerical model.

An ANN is comprised of a set of fully connected nodes (or neurons) over a few layers. The schematic in Fig. 1 shows a generic ANN with three nodes in the first (left) layer (input layer), 4 and 2 nodes in the second and third layers, respectively (hidden layers), and a single node in the final layer (output layer). The number of nodes on the input (output) layer is equivalent to the number of predictor (predictand) variables. The information flowing forward through the connections (feed forward ANN) is mathematically manipulated through linear and non-linear operations applied to the nodes on the input and hidden layers to estimate the output variable. Finding the appropriate ANN architecture is a trial-and-error problem. Under each architecture, the model is parameterized (calibrated) based on a set of corresponding input-output dataset (usually called training dataset) by minimizing a loss function (a measure of modeling error). The dataset is usually divided into three portions: training, validation, and testing. Training data are necessary for the parameterization while validation data are used only for the so-called “stopping rule” of the parameterization process, based on an in-process evaluation of the ANN performance at every epoch of the optimization (minimization of loss function). Finally, testing data are completely new data used for the post-process evaluation of the ANN performance after it is developed.

The ANN architecture in this study was first developed by Hosseini et al. [37]. The present model used up to two hidden layers (HLs) with 4–20 neurons in each layer and between 2 and 10 output nodes representing moisture content at different depths of the horizontal reference board. After many repeats of the training-validation process as described below, a hybrid of three most satisfactory candidate models is combined to reduce noisy outcomes for the final metamodel and produce robust predictions. All models include an output node representing the moisture content at a depth of 1 mm, which is where decay is assessed. Each input node layer included an array of data of the predictor variables, i.e.,

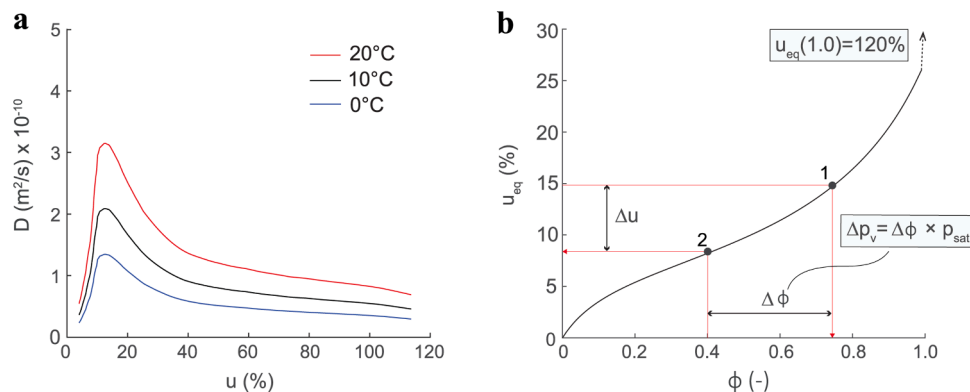


Fig. 2. Panel (a) shows the diffusion coefficient at three different temperatures and panel (b) shows the sorption isotherm. The annotations in (b) show how the difference in vapor pressure (Δp_v) is calculated for a wood surface at 15% moisture content and the ambient air at 40% relative humidity, as well as the change in moisture content, Δu , after equilibrium is attained.

the equivalent time series of daily average relative humidity (RH), and daily average temperature (T), and total daily precipitation (p), and their time lagged versions. After a set of cross-validation and ANN model analyses based on a wide range of assumptions, a maximum lag $L = 11$ days is assumed to capture satisfactorily the memory of the system. In other words, the moisture content on each day is assumed to be affected by the weather up to 11 days prior, while most of the moisture variations are explained by the most recent weather. In total, this results in a total of 36 predictors consisting of present and lagged RH, T and p. Consequently, in each node of the first HL, the inputs are multiplied by individual scalar weights w , summed up, and added to a scalar bias b . This can be mathematically expressed as follows:

$$n_{j,h=1} = \sum_{i=1}^{36} (X_i \times w_{i,j,h=1}) + b_{j,h=1} \quad (3)$$

where j is the index of neuron ($j = 1, 2, \dots$ for the first hidden layer, so $h = 1$), X_i is the input data vector and $w_{i,j}$ is the scalar weight of the i th input variable for the j th neuron. The resulting scalar, n , is processed through a scaled hyperbolic tangent (tanh) transfer function, $f(n)$, defined as:

$$f(n) = \frac{e^{2n} - 1}{e^{2n} + 1} \quad (4)$$

Generally, a neuron on the second HL considers the results of the neurons on the first HL as input variables, and so forth for the output layer. While the transfer function for both HLs is tanh, no transfer function is applied to the output layer, i.e., $f(n)=n$.

The full dataset ($n = 551$ typical climates) was divided into training, validation, and testing subsets, where the training ($n = 469$) and validation ($n = 41$) portions were used for ANN parameterization and the remaining climates ($n = 41$) were reserved exclusively for testing, as detailed later. To calibrate the parameters of ANN (w and b), an iterative optimization problem is solved to minimize the mean squared error (MSE) between the estimated and reference moisture u for the training dataset. The process starts with random initial parameters (variable between -1 and 1 , similar range as the normalized input variables), which were updated based on the Levenberg-Marquardt back-propagation algorithm at multiple iterations until a minimum MSE is achieved. This requires that $f(n)$, and, thus, MSE, have a mathematical equation differentiable with respect to the parameters w and b .

The ANN models are usually prone to overfitting due to the use of many parameters (i.e., perfect fit to the data used for training, but noisy for new data). To prevent this, a stopping rule is defined based on a part of the data (validation portion), separate to the training data portion. This study uses a so-called, "maximum validation fail (MVF)" criterion, which monitors MSE for the validation portion (validation MSE) at each iteration of the optimization. As a result, when the validation MSE increases for 10 consecutive iterations (regardless of possible continuation of decrease in training MSE), the training process stops, and the ANN parameters are fixed based on the iteration that resulted in minimum validation MSE (rather than minimum training MSE). The length of useful data for input variables in this study is approximately two hundred thousand, i.e., $551 \times (365 - L)$, which is much larger than the number of ANN parameters, making overfitting less likely. However, the MVF criterion is still useful to address the possible issue of ANN converging at a local minimum. To clarify, it is favorable to stop an ANN parameterization based on the MVF criterion and repeat it with new random initial parameters that are likely to end at a new final parameterization and exit potential local minima. The resulting ANNs from the repeats are, then, ranked by minimum validation MSE. Finally, a hybrid model giving an arithmetic average of the outputs from the three top-ranked ANNs is used. Two of the selected ANNs have multiple outputs, which could additionally mitigate overfitting towards certain wood depth. The combined scheme (rather than individual ANN) is shown useful for generalization of the ANN outputs for other problems

(see e.g., [38]).

The performance of the developed metamodel based on the above process has been tested against the generated data from numerical modelling at 41 unique typical-year climate data locations, comprising the testing dataset, neither used in training nor in validation as defined earlier [37]. As the metamodel successfully reproduced numerical results, it can be employed for rapid, large-scale, and high-resolution decay hazard mapping for the first time in this study. It should be noted, however, that the range of climates in which the underlying numerical model has been validated is limited, and its performance under very hot or cold conditions is therefore subject to increased uncertainty.

2.2. Decay model

For predicting the development of fungal decay, we post-process the moisture content at the wood surface (depth 1 mm) in a mechanistic dose-response model from [3]. The model combines the daily averages of wood moisture content and temperature to a daily dose, which is a relative value describing the growth conditions for fungal decay. The following equations are used to calculate the moisture induced dose, d_u , and the temperature induced dose, d_T :

$$\begin{aligned} d_u &= c_1 u^5 + c_2 u^4 + c_3 u^3 + c_4 u^2 + c_5 u + c_6 \\ d_T &= c_7 T^4 + c_8 T^3 + c_9 T^2 + c_{10} T \end{aligned} \quad (5)$$

where u (%) is the moisture content, T (°C) is the temperature and c_1 - c_{10} are constants ($c_1=6.75 \cdot 10^{-10}$; $c_2=-3.5 \cdot 10^{-7}$; $c_3=7.18 \cdot 10^{-5}$; $c_4=-7.22 \cdot 10^{-3}$; $c_5=0.34$; $c_6=-4.98$; $c_7=-1.8 \cdot 10^{-6}$; $c_8=9.57 \cdot 10^{-5}$; $c_9=-1.55 \cdot 10^{-3}$; $c_{10}=4.17 \cdot 10^{-2}$). The moisture- and temperature-induced doses are then combined to a total dose, d , through the following equation:

$$d = \frac{(3.2d_T + d_u)}{4.2} \quad (6)$$

where, $d_T = 0$ for days with sub-zero minimum daily temperature ($T_{\min} < 0$ °C), or with temperatures exceeding 40 °C ($T_{\max} > 40$ °C). Similarly, $d_u = 0$ for $u < 25$ %.

The daily dose accumulates over time and converts to wood decay rating via the response-function, where decay rating is measured on the following scale describing the severity of decay: 0 (sound), 1 (slight attack), 2 (moderate attack), 3 (severe attack), and 4 (failure) according to EN 252 [39]. The service life of a member ends when the cumulative dose exceeds a value corresponding to a specific decay rating. In this study we used cumulative annual dose, d_{year} , to quantify spatiotemporal variations, as this period captures the full weather cycle. The annual dose averaged over multiple years is denoted $\bar{d}_{year}$.

It should be noted that the dose-response concept and Eq. (5)–6 apply to multiple wood species. However, the target dose at which decay begins depends on the biocidal components specific to each wood type [40]. Even wood species with similar biocidal properties can decay at different rates; for example, more permeable species like pine sapwood retain higher moisture content and therefore accumulate a higher dose compared to Norway spruce. In the factorized service life design framework, where Norway spruce serves as the reference case, differences in moisture dynamics and biocidal composition are accounted for when determining the target dose for decay initiation [41].

2.3. Model validation

The modeling approach used here builds on previously validated components. Specifically, the numerical moisture model that provided training data for the ANN has been validated against field measurements of wood moisture in multiple studies [20,36]. Likewise, the fungal decay dose model [3] was derived from field decay experiments performed at multiple locations in Europe, ensuring that the dose metric correlates

with actual decay development. However, these models have not previously been used with gridded data. Since gridded data are fundamentally different from weather stations, in particular concerning precipitation, this integration required further validation. This was done by comparing model predictions using reanalysis grid data to those using observed weather data at 890 locations across Europe.

2.4. Weather datasets

The study used three different weather datasets, including CERRA [29], MET Nordic [30] and ECAD [42], provided by Copernicus Climate Change Service, Norwegian Meteorological Institute, and European Climate Assessment and Dataset, respectively. The CERRA and MET Nordic data are based on reanalysis, which is the process of using data assimilation to combine observations and models to reconstruct a complete dataset with spatial and temporal consistency. They include sub-daily reanalyses at grid sizes of 5.5 km and 1 km for Europe and Scandinavia, respectively, whereas the ECAD data are quality-controlled/improved collection of daily weather measurements from meteorological stations scattered over Europe. The spatial coverage (distribution) of the grid (point) data used in this study is shown in Fig. 3. Considering the direct in-situ measurements by the ECAD data, they were used as a reference for the evaluations of decay calculated based on the CERRA reanalysis.

The metamodel takes daily values of relative humidity, temperature and precipitation as input. Therefore, only stations with long and reliable data of these variables were included for the ECAD- and CERRA-calculated decay data comparisons, which were performed for the horizontal reference board. In addition to the three primary variables, the exposure of the vertical reference board to precipitation also depends on wind velocity and orientation, both of which can be highly variable. Consequently, only the MET Nordic dataset was deemed suitable for this analysis, and thus the analysis of the vertical reference board is limited to the Scandinavian region. Detailed descriptions of all datasets are provided in the following sections.

2.4.1. CERRA and CERRA-Land

The Copernicus European Regional ReAnalysis (CERRA) sub-daily gridded datasets offer historical reconstructions of weather variables in the atmosphere, and at the surface at a horizontal resolution of $5.5 \text{ km} \times 5.5 \text{ km}$ [29]. There are four subsets for CERRA including: single levels (atmospheric and surface data), height levels (levels up to 500 m), pressure levels (levels up to 1 hPa), and model levels (native model levels). In addition, CERRA-Land [43] dataset provides reconstruction of surface and soil variables at the same resolution as the CERRA

reanalysis.

In this study, we specifically used 2 m temperature and 2 m relative humidity (as a recommended height for related sensors in usual weather stations) from CERRA sub-daily (3 h) reanalysis data on single levels [44] and daily (24 h) total precipitation at the surface from CERRA-Land sub-daily reanalysis data. For consistency, the variables' data of both datasets were downloaded from the analysis (rather than forecast) product type. All downloads were available between August 1984 and June 2021 (roughly 36 years). However, we studied the data for the 36 complete years of 1985–2020, unless otherwise stated, to calculate annual doses of decay for each grid. As described earlier, the moisture content metamodel is based on the daily weather data as input variables. With the choice of analysis data product, the CERRA-Land precipitation data are directly equivalent to p. However, the RH and T input data were prepared by aggregating the 3 h data from CERRA on single levels to a 24 h average starting at 06:00, for consistency with the time of the daily precipitation data from CERRA-Land. The average daily T was calculated in the same way, but in the case of temperature the minimum, $T_{\min}$, and maximum, $T_{\max}$, within the same period were stored as well for use in Eq. (6).

2.4.2. MET Nordic

The MET Nordic dataset offers current and past weather analyses and forecast for northern Europe. Data is provided by the Meteorological Cooperation on Operational Numerical Weather Prediction (MetCoOp), through the MetCoOp Ensemble Prediction System (MEPS). The raw model output has a spatial resolution of 2.5 km, which is then down-scaled to 1 km. Data used in the present study includes hourly values of wind speed and orientation at 10 m, T and RH at 2 m, and surface precipitation. This data was downloaded from the third rerun (2017–2022), for a total of 6 years [30]. It can be noted that the precipitation has been bias-corrected using in-situ observations and national weather radar data, allowing direct consideration of some parameters such as precipitation at high original resolution. As with all reanalysis products, some degree of bias may remain. Nevertheless, the data provide spatially and temporally consistent representations of weather variability that are appropriate for assessing relative differences and spatiotemporal patterns.

The MET Nordic data is used to calculate wind driven rain intensity, R_{wdr} , by combining hourly wind speed and orientation by precipitation through the following equation:

$$R_{\text{wdr}} = R_h \frac{U}{V_t} \cos(\varphi), \quad (7)$$

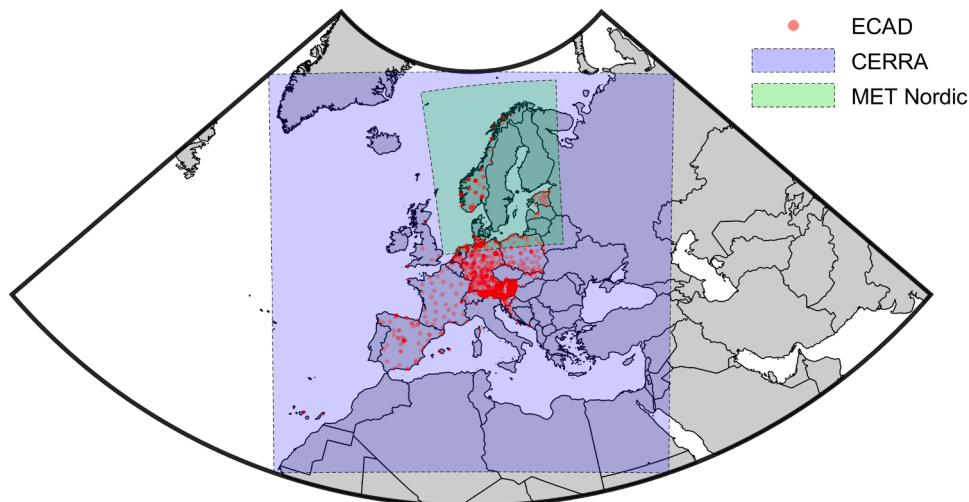


Fig. 3. The full coverage domains for CERRA (purple box) and MET Nordic (green box), and the areal distribution of the studied ECAD weather stations (red dots).

where R_h is the amount of precipitation passing through a horizontal plane, U is the wind speed (m/s), φ is the angle between the wind direction and the normal of the wood surface in question and V_t is the terminal velocity of the droplets, which for light to moderate rain spells can be set to 4.5 m/s [45]. The dataset does not distinguish between liquid and solid precipitation, and solid precipitation is generally not included in driving rain estimates. As a simplification, precipitation at air temperatures below 0 °C was therefore excluded. While this method is approximate, its influence on decay estimates is limited, as contributions to the cumulative dose are generally small at temperatures near freezing.

Due to splash, it is assumed that only 70 % of the wind-driven rain will be retained on the vertical surface and be available for absorption, following common practice in hygrothermal simulations [46]. The daily amount of water that is retained on the vertical surface is then used as input for the metamodel (p). As such, the horizontal and vertical reference boards differ only in the amount of water that strikes the surface, which is a simplification neglecting potential standing water on the horizontal face.

2.4.3. ECAD

The European Climate Assessment & Dataset (ECAD) offers daily observations in Europe and contains various meteorological measurements, such as temperature, relative humidity, and precipitation, among others [47]. The ECAD dataset is comprised of weather station data, sourced from locations scattered over Europe. The dataset includes *blended* and *non-blended* data. The blended sets have been made near-complete by substituting missing data from nearby stations or synoptic data [48]. A nearby station is used to infill data if the distance to the station in question is <12.5 km and the difference in elevation is <25 m. If no station satisfies these requirements, then a different dataset is used.

Such curated “point-type” measurements-based weather data could provide reference observations to calculate bias in gridded data from remote sensing or modelling. The other two datasets of this study (CERRA and MET Nordic) are gridded sets based on reanalysis. Naturally, local variation within grid cells poses a challenge for grid-to-point data comparisons. However, the ECAD dataset is used as a benchmark to investigate to what extent the gridded data are biased for decay analyses that are normally used at a building scale.

To evaluate error and bias in the use of CERRA dataset, this study used a subset of blended data series from 890 ECAD sites located within the domain of CERRA. The series were selected for having minimal missing or suspicious data (<0.5 % of time) and at least 21 recent years of continuous data during the 36 complete years of CERRA, i.e., 1985–2020. Thus, the shortest period for the grid-point (i.e., CERRA-ECAD) data comparison was 2000–2020, while most series had the full-length record of 36 years. The missing and suspicious data were based on the available labels with the blended data, and no further data quality control was sought.

2.5. Grid to point decay comparison

The use of long and recent blended weather data series from ECAD with minimal missing or suspicious data provides a reliable set of reference weather data series at the weather station points across Europe. Each of these reference sites is encompassed by a 5.5-km grid of CERRA. By comparing the corresponding annual decay time series for the point-grid pairs, we can investigate the magnitude and direction of the spatiotemporal biases in using CERRA relative to ECAD. We use graphical and statistical analyses based on the scatter and quantile-quantile plots, and a relative bias criterion as defined below for any given point-grid pair:

$$rBIAS = \frac{\sum_{y=1}^N (d_{year,y,CERRA} - d_{year,y,ECAD})}{\sum_{y=1}^N d_{year,y,ECAD}} \quad (8)$$

where, $d_{year,y}$ is annual dose of decay in year y with indices corresponding to each of the two datasets, and N is number of years that, as described earlier, could vary between 21 and 36 for different ECAD sites. Thus, $rBIAS$ could indicate both negative and positive values. The best agreement between ECAD and CERRA for decay analyses at a given location (point/grid) is achieved when $rBIAS$ is closer to zero (e.g., ± 0.1 or ± 0.2). Larger positive (negative) $rBIAS$ indicates significant over-estimation (underestimation) of annual decay based on CERRA in relation to ECAD. Some biases are inevitable due to, e.g., different spatial scales (grid vs. point) of the two datasets and may not necessarily be a signature of erroneous data, and could simply be a consequence of natural spatial variability. However, a larger magnitude of $rBIAS$ might be additionally attributed to the uncertainties of remote sensing measurements (e.g., attenuation of signals) and of reanalysis processes underlying CERRA, as well as the errors in the weather station measurements (e.g., wind-induced rainfall under catch) in the gap filling processes in the blended ECAD data. In addition to analyzing $rBIAS$, quantile-quantile plots allowed us to illustrate the range of percentiles of decay dose corresponding to any obvious over- or under-estimation. Finally, since the aggregated doses of decay will reach a critical level (a high decay rating) only after several years, a scatter plot of the average annual doses over the N years (rather than individual yearly doses) were analyzed as a more suitable graphical criteria for the comparison of general agreement between the two datasets in the context of wood decay.

2.6. Measures of uncertainty and variability

The primary aim of this study is to investigate spatiotemporal dispersion in decay data. For the temporal analysis, we calculate the standard deviation and the corresponding coefficient of variation. Standard deviation gives a measure of the absolute variation of the parameter in question whereas the coefficient of variation, CV, gives the same value relative to the mean. The standard deviation, σ , is calculated as follows for temporal analyses at a given grid cell for any of the given data sets:

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^N (d_{year,i} - \bar{d}_{year})^2} \quad (9)$$

where, N is the number of years (for which measurements are available at the grid cell), $d_{year,i}$ is the annual dose accumulated over year i and $\bar{d}_{year}$ is the mean annual dose of all years. The corresponding coefficient of variation (CV) is then calculated as follows:

$$CV = \frac{\sigma}{\bar{d}_{year}} \quad (10)$$

For the spatial analysis, we compared the fungal dose in each grid cell with the doses in surrounding cells using concentric distance bands (e.g., 20–30 km). For each band, we calculated the average absolute relative deviation (RMD) between the dose of the central grid cell and the doses of all other grid cells within that band. The RMD for a single grid cell is defined using the following equation:

$$RMD = \frac{1}{M} \sum_{j=1}^M \frac{|\bar{d}_{year,j} - \bar{d}_{year}|}{\bar{d}_{year}} \quad (11)$$

where, $\bar{d}_{year}$ is the mean annual dose at the reference grid cell, M is the number of grid cells within a specified distance band (excluding ocean and large bodies of water) and $\bar{d}_{year,j}$ is the mean annual dose for grid cell j within this band. Note that the mean annual dose is the average over six

years. This calculation was performed across several distance bands with radii ranging from 10 to 100 km, each band spanning 10 km (0–10 km, 10–20 km... 90–100 km). These results quantify the average error associated with using a single point estimate to represent areas at increasing distances.

3. Results and discussion

3.1. Point-to-grid validation

To verify the model's performance with gridded inputs, the decay dose outputs from CERRA were compared to those from 890 ECAD weather stations using three different metrics shown in Fig. 4:

1. relative bias ($rBIAS$) in annual doses of decay (the map and the histogram above it on the left)
2. quantile-quantile plot of all annual doses (the top right plot)
3. scatter plot of the average annual doses (the bottom right plot)

In total, there were 890 ECAD sites meeting the selection criteria for being included in the grid-point data comparison, i.e., having at least 21 recent years of continuous daily precipitation, temperature, and relative humidity data within the period 1985–2020, and, at max, 0.5 % of the time (at daily scale) missing or suspicious data. The majority of these 890 sites, i.e., 819 sites, had a full-length record of 36 years, and the remaining sites, i.e., only 71 sites, had variable lengths uniformly between 21 and 35 years.

On the top left in Fig. 4a, the bell-shaped histogram indicates an almost normal distribution of the $rBIAS$ values that are centered at around +0.1. Most of the $rBIAS$ values are within the range of -0.05 and 0.25 , while the overall range is between -0.45 and 0.95 (excluding 3 values above 1 which are assumed to be outliers). Thus, for a large portion of the locations there are relatively small differences between annual doses calculated from CERRA and ECAD data. Also, the fact that the mean of the $rBIAS$ is positive (around +0.1) indicates that, on average, the CERRA data tends to predict higher doses than the ECAD data. Conversely, the map in Fig. 4b illustrates the spatial distribution of $rBIAS$, where this tendency is confirmed by the larger number of blue

dots (CERRA prediction higher than ECAD prediction) compared to the number of red dots (CERRA prediction lower than ECAD prediction).

The map additionally shows that the density of the 890 sites was highest in central and western Europe, predominantly in Germany, the Netherlands, and Austria, followed by France and Spain in the west and southwest, and Norway and Estonia in the north and northeast. There were fewer number of sites from Slovakia, Poland, Slovenia, Croatia, Latvia, and Switzerland. From the consistent colors in the map and histogram in Fig. 4a and b, a few general trends can be discussed. For example, there is no location with a negative $rBIAS$ in the coastal regions of the Netherlands, France, and Spain, and south and southwest coasts of Norway, and the overestimations via CERRA are not typically very high. As will be discussed in the following sections, these regions generally showed the highest decay hazards due to receiving high moisture loads from the Atlantic Ocean and North Sea. The overestimation of higher doses is generally shown by the quantile-quantile and the scatter plots in Fig. 4c and d. Particularly in the quantile-quantile plot, the deviations start above the 50th percentile, equivalent to the annual dose of around 40. The deviations were still minimal up to the 75th percentile but increased considerably towards the 99th percentile, where the equivalent annual doses were near 95 and 75 for CERRA and ECAD, respectively. The labels on the quantile-quantile plot also shows the distribution of extreme annual doses. For example, the 99.9 percentile of around 120 (90) for CERRA (ECAD) indicates that only 0.1 % of the annual doses (across years and sites), were higher than 120 (90).

In contrast, the few red circles on the scatter plot, equivalent to negative $rBIAS$, are predominantly scattered in regions with lower decay doses. Accordingly, the average annual doses based on the CERRA (ECAD) data for the sites that showed underestimation was up to around 50 (60), versus 100 (80) for the sites with overestimation. The sites associated with negative $rBIAS$ were typically associated either with the drier climates such as in the western Mediterranean regions of south France and east Spain, or colder climates such as in Alpine regions of south Germany, north Switzerland, and west and central Austria, as well as the most mountainous parts of Norway.

However, negative and positive $rBIAS$ sites often appear in proximity. Fig. 5 shows typical cases, indicating that these variations are generally related to microclimate variations due to urban meso-climates

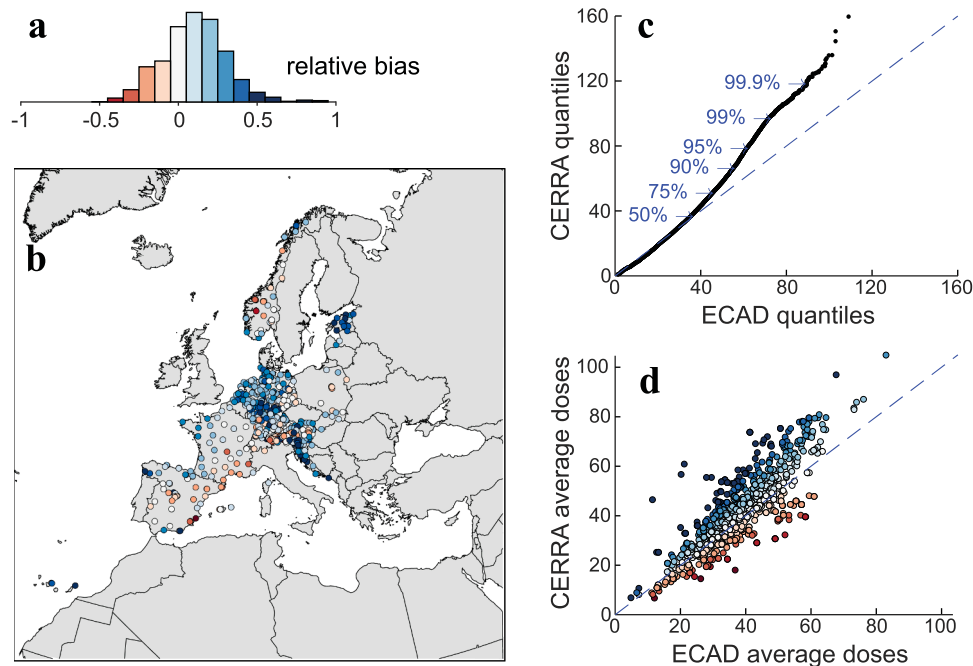


Fig. 4. Comparing annual doses of decay calculated based on the CERRA and ECAD weather data for 890 ECAD sites. The subplots show the relative bias in annual dose ($rBIAS$) by distribution (a) and location (b), a quantile-quantile plot of annual doses (c), and a scatter plot of average annual doses (d).

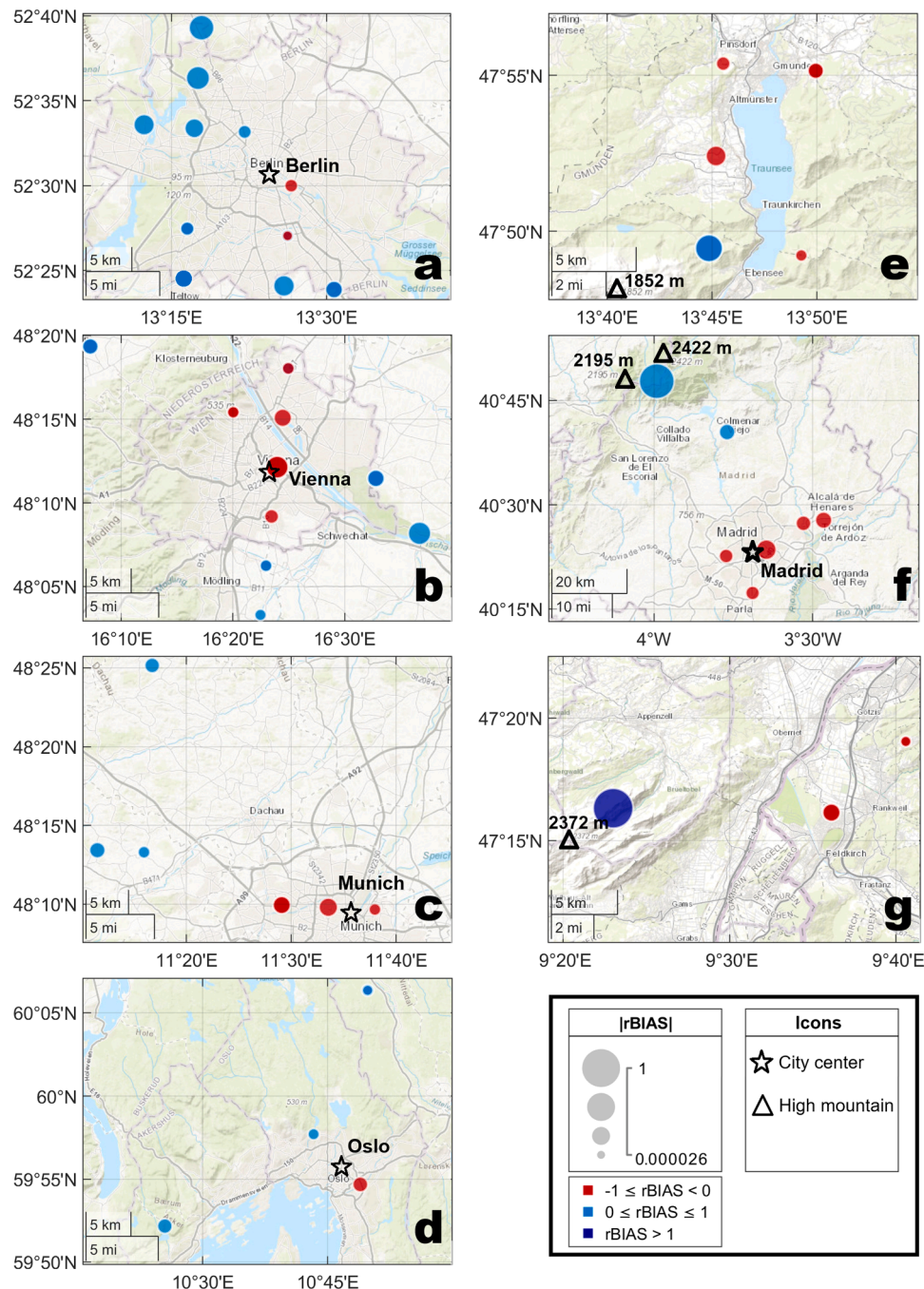


Fig. 5. Proximity of locations with both positive and negative $rBIAS$: in and out of the cities Berlin, Germany (a), Vienna, Austria (b), Munich, Germany (c), Oslo, Norway (d), around Lake Traun, Austria (e), Madrid city and Guadarrama mountains, Spain (f), and Alpstein mountains, Switzerland (g).

[25] and topography [24]. One example is Berlin (Fig. 5a): of 11 ECAD sites in or near the city, only two show negative $rBIAS$ near to central areas, while positive $rBIAS$ generally increases outward. The three closest sites to the center had a $rBIAS$ within ± 0.05 , and the three most extreme positive $rBIAS$ values of 0.22, 0.29, and 0.35 appear 15–20 km away in the south and north boundaries of the city. Likewise, in Vienna (Fig. 5b), the two most significant negative $rBIAS$ occur at most central sites, possibly due to the additional impacts from the Danube River passing through the city, which moderates local temperatures and tends to increase humidity. Generally, similar impacts appear in Munich (Fig. 5c), Oslo (Fig. 5d) and, for example, Warsaw (Poland), Basel and Geneva (Switzerland), Braunschweig, Konstanz, Fürth, Erlangen, Stuttgart, Magdeburg, Leipzig and Regensburg (Germany), Graz and

Dornbirn (Austria), and Valladolid (Spain) (not shown). Conversely, high positive $rBIAS$ values often occur near mountains (Fig. 5e–g). Among five sites around the Traunsee lake, Austria (Fig. 5e), the southwestern site in the slopes of the Salzkammergut Mountains is the only one indicating a high positive $rBIAS = 0.43$, while three of the remaining sites with highest negative $rBIAS$ were in urban areas of the northern parts. More significant differences are observed between the negative $rBIAS$ for Madrid in Spain and the high positive $rBIAS = 0.76$ for the Guadarrama mountains, northwest of the city (Fig. 5f). A few extraordinarily high $rBIAS$ (> 1 , not shown in the histogram in Fig. 5) are observed near the mountains Alpstein (Fig. 5g), Wetterstein (not shown), and Triglav (not shown) in Switzerland, Germany, and Slovenia, respectively.

In view of the above, a reanalysis grid in a geographically diverse climate, e.g., including mountains and adjacent valley/plains with urban/rural areas and water bodies, presents an approximate climate for the grid. Thus, the accuracy of the reanalysis data depends, among others, on the local and regional climate variation forces. The evidence discussed above about the local variations of climate is, of course, limited and needs extensive evaluations. However, the results indicate the need for high-resolution weather observations for annual wood decay variations in certain geographical locations and local circumstances.

Despite the significant deviations at higher percentiles of annual doses in the quantile-quantile plot, the scatter plot in Fig. 4 shows most of the average annual doses near the dashed (45-degree) line, indicating a generally good agreement between the two datasets (CERRA and ECAD) for decay analyses aggregated over long periods (over two decades in this case) which is usually needed for the service life assessments. Hence, the next section is devoted to large scale mapping and evaluations of average decay doses over the entire domain (i.e., all grids) of the CERRA dataset. In addition, availability of the high-resolution (1-km) weather data over Scandinavia from the MET Nordic dataset let us investigate the uncertainties based on this resolution and region as well. As mentioned earlier, the 1-km resolution MET Nordic data was quite useful to calculate wind-driven rain, and thus, the doses of decay for vertical reference boards. The vertical reference boards are used to analyze the decay risk for buildings with timber cladding, which are exposed to wind-driven rain.

3.2. Horizontal reference board

Fig. 6 shows the mean annual dose of horizontal reference board over Europe between 1985 and 2020 (a) and Scandinavia between 2017 and 2022 (b). Regions with the higher annual dose are found in western parts bordering the Atlantic Sea, including the Spanish, French, British and Irish coastlines among others. This could be attributed to the maritime climate, where the proximity to the Atlantic Ocean fosters a wetter environment conducive to fungal growth. While the annual dose is in general lower in the Scandinavian countries, the same effect is clearly seen along the western coast of Norway, Sweden, and Denmark in both datasets, regardless of their variable data length and resolution. The coastal region of Norway is known for its great amounts of precipitation. In contrast, the Alps as well as the Norwegian mountains exhibit a markedly lower dose, which could be due to the region's altitude and

lower temperatures, factors known to impede fungal growth.

On a continental scale, the general trends correspond rather well to similar maps produced from sparse weather station data and interpolation [16,17]. However, the detailed maps presented in Fig. 6 reveal significant variability within localized areas, particularly on scales of 100 to 200 km. This fine-scale variation underscores the limitations of previous decay hazard maps while highlighting that the granularity provided by high-resolution gridded datasets enables a more nuanced understanding of environmental trends.

3.2.1. Temporal variation

Temporal analyses for the annual dose on horizontal reference boards were based on the CERRA dataset. Fig. 7 compares the array of annual doses based on the reanalysis data (the 20th and 80th percentiles, and average annual doses on the left plot) by the corresponding results from a previous study [17], where a 'typical' year was used to develop decay maps. For consistency, the dose values were recalculated for the 'typical year' data with the metamodel presented in this paper, rather than with the numerical model. Thereby, any bias between the two studies due to different moisture models was eliminated. In almost all cases, the dose calculated by the 'typical year' falls within the range of values produced from the reanalysis data, however the difference to the average value varies between locations. Some of the horizontal lines in the left plot of Fig. 7a, showing the interval between the 20th and 80th percentiles, do not cross the 45-degree line, meaning that the 'typical year' represented rather an extreme climate year in the context of decay assessment (i.e., with a significantly higher or lower than average dose). To illustrate better the variable differences between the 'typical year' and reanalysis results, cumulative distribution of the annual doses was crossed with the vertical lines corresponding to the 'typical year' value for three examples, see Fig. 7b. The difference can be attributed to natural variability across years, as well as spatial variability due to uncertainties related to comparing grids to points.

Fig. 8 illustrates the temporal dispersion of the annual decay dose, expressed as the coefficient of variation (CV), calculated using Eqs. (9)–(10) across the CERRA reanalysis region. The range of CV values indicates considerable variation in annual dose between years. As a relative measure, the CV is particularly sensitive in regions where absolute decay rates are low, resulting in disproportionately high values despite minimal absolute variation. This phenomenon is evident in the arid and cold climate zones, such as parts of Africa and Greenland, respectively (darkest areas in Fig. 8).

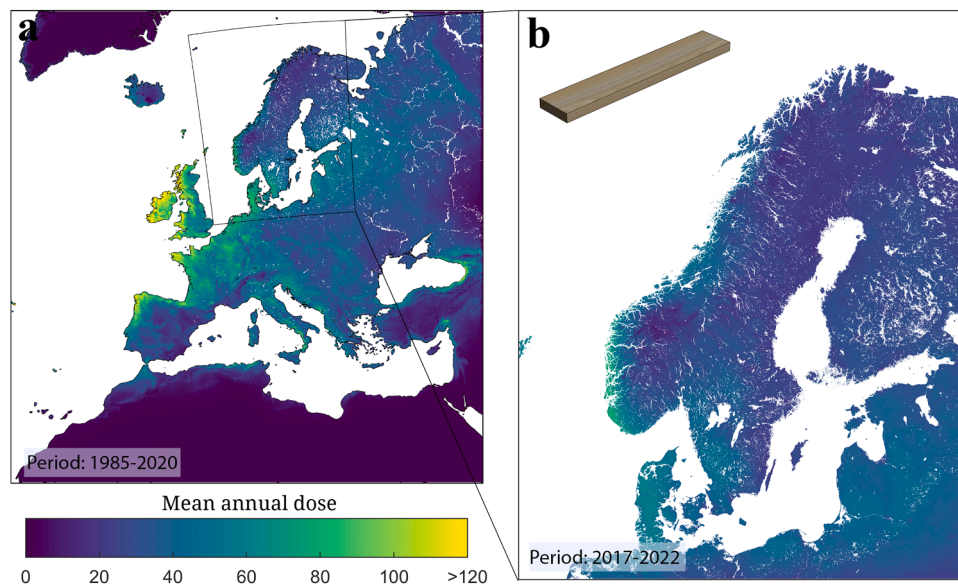


Fig. 6. Average annual decay hazard based on the CERRA (a) and MET Nordic (b) datasets, respectively.

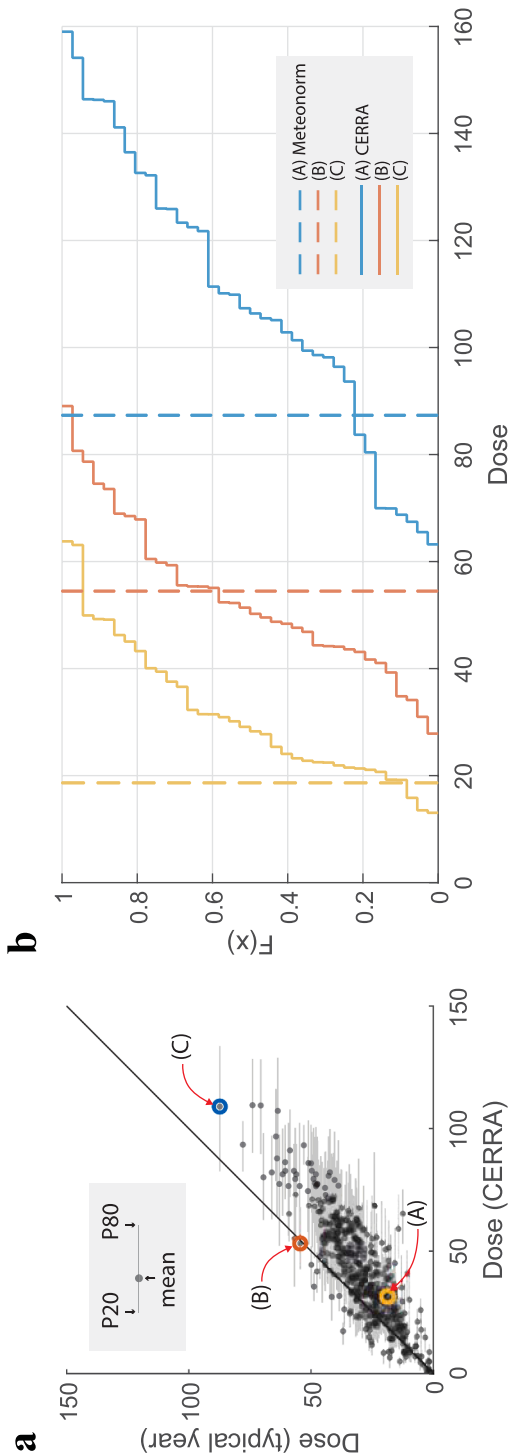


Fig. 7. Comparison between the annual dose calculated based on the 'typical year' and the annual doses calculated based on 36 years of reanalysis (CERRA) data for each location. Subfigure (a) compares annual dose from the 'typical year' and average annual dose from multi-year reanalysis, while the corresponding horizontal lines extend to the 20th and 80th percentiles over multiple years. Subfigure (b) shows the cumulative distribution of annual doses for three examples over multiple years compared with vertical dashed lines showing the dose based on the typical year.

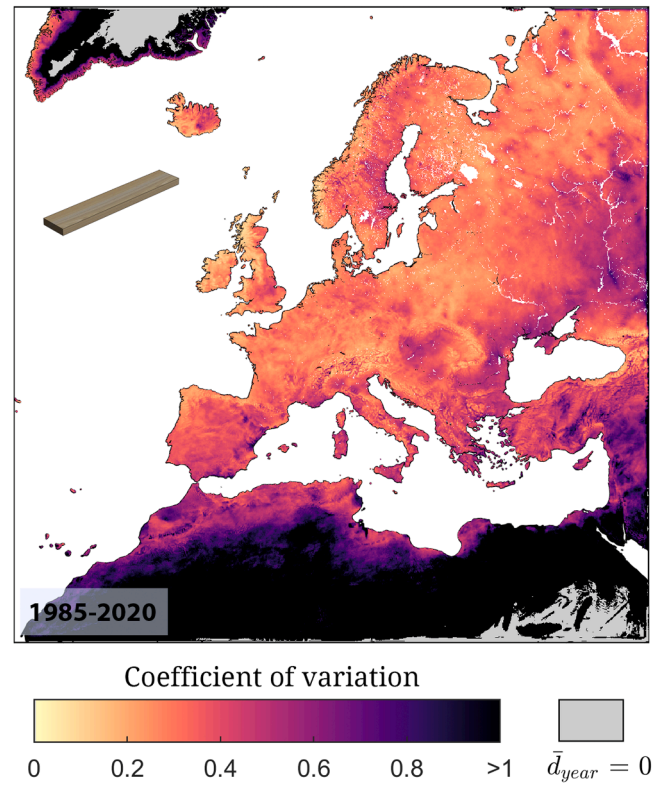


Fig. 8. Temporal coefficient of variation (CV) of annual dose, calculated over 36 years. The grey colour shows areas with a mean annual dose of zero.

Combining the mean annual decay dose (Fig. 6) and the CV (Fig. 8) enables more comprehensive assessment of service life, incorporating uncertainty stemming from temporal variation. Unlike deterministic analysis based on a single 'typical year', this approach captures the stochastic nature of weather patterns and their cumulative impact on decay processes. This is important not only for prediction of service life in a design context, but also for validating existing deterministic models against real data on decay progression.

For components with relatively short service lives, the temporal variation in annual dose can introduce significant biases in service life predictions. This is because, over shorter periods, the variability between years is less likely to average out, leading to larger relative deviations from the predicted service life. Conversely, for components with longer service lives, the cumulative effect of annual variability tends to stabilize due to the law of large numbers. This reduces the impact of individual extreme years as their effects are diluted by more typical years, resulting in a lower coefficient of variation relative to the mean.

It should be noted that the coefficient of variation (CV) is purely a measure of dispersion and does not account for potential non-stationarity caused by climate change. Previous studies comparing contemporary and projected 'typical years' indicate that climate change generally creates more favorable conditions for fungal decay. For example, the annual fungal dose in Europe is projected to increase by 0 to 5 units across most of the continent under two different RCP scenarios [17]. Although this projected increase is significant, it remains relatively small compared to the year-to-year variability observed in Fig. 8.

We also note that the temporal variability of the dose obtained in this paper originates from the temporal variability in the input parameters used in the metamodel (e.g., precipitation, temperature, and relative humidity). In practice, there could be additional variability due, for example to parameters not considered (e.g., wind and sunlight affecting drying conditions) and inherent randomness in the decay process of wood (i.e., even under the same external conditions, different boards

may display different moisture contents). Physics-based stochastic models could be developed to explicitly incorporate all potential sources of variability, supporting a more robust Life-Cycle Analysis. They could also serve prognostic purposes, with the intent of predicting the Remaining Useful Life (RUL) of boards subject to given external conditions [49,50]. The analyses presented here could serve as a foundation for such models. Stochastic formulations for deterioration modeling have already been implemented successfully for other materials and degradation processes, like chloride-induced deterioration in concrete, but the literature on wood is scarce on this aspect.

3.2.2. Spatial variation

The spatial analysis was conducted to understand how the distance from a hypothetical weather station affects the error in fungal dose estimation. Fig. 9a illustrates these values in annual fungal dose across Scandinavia for the 50–60 km distance band. In other words, if a hypothetical weather station is placed in a cell, the value of that cell represents the relative mean deviation (RMD) when using the station's data to estimate the dose in another cell located at distance of 50–60 km. The map shows that regions with significant topographical variation, such as the Norwegian mountains, have high spatial uncertainty, as previously noted in [24]. In contrast, coastal areas exhibit lower-than-expected variability. It should be noted that we do not explore the variability within the bands, which could potentially be high.

Fig. 9b shows spatial variability across 10 distance bands at four representative locations. The four locations were selected to highlight certain trends. In the Norwegian mountains, the RMD start at 80 % in the first distance band (<10 km) and increase consistently across all bands up to about 200 % in the outermost band, reflecting the complex terrain. In Bergen, spatial variability is relatively low at smaller distance bands (e.g. RMD < 10 % at 10–20 km) but rises steadily as more topographical diversity is captured within the bands. Oslo demonstrates low and stable spatial variability with an RMD of 10–15 % across all distance bands, suggesting homogeneity in climatic conditions. In contrast, Gothenburg exhibits an early increase to an RMD of 40 % at the distance band of 10–20 km followed by a plateau. The examples of Gothenburg can be explained by the fact that the city is in a small region with higher fungal dose values compared to the surroundings, which is lower and relatively uniform.

The spatial variation in dose can be attributed to several weather-influencing factors. Since dose is greatly influenced by precipitation, it is likely that much of the spatial variation in dose is also linked to variations in precipitation. Mountains play a significant role as moist air is subject to orographic lift leading to cooling and condensation. The windward side tends to receive greater amounts of precipitation. Very local effects, such as urban heat islands, have also been shown to affect precipitation patterns, although this effect was not explored in this study. Distance to ocean can also influence precipitation amounts, with increasing distance being associated with reduced precipitation, but the significance of this effect is limited in forested regions [51].

Again, we note that the uncertainties obtained in this study are a direct result of the spatial variability of the input parameters used in the metamodel. A proper analysis accounting for all sources of spatial variability should be based on random field models [52]. A random field model could be decomposed into three parts: (i) a mean field, quantifying the spatial variability in the dose due to the underlying average conditions at each location, (ii) a zero-mean non-stationary field, quantifying the correlation among the dose in different points as a function of their reciprocal distance, and (iii) a white noise component, accounting the inherent randomness of the process and possibly including micro-climate effects that cannot explicitly modeled. Each of these components can be formulated in terms of the external conditions [53], i.e., the input parameters used for the calibration of the metamodel in this paper. Finally, combining both the spatial and temporal aspects could lead to spatiotemporal random fields, which could be used to quantify the probability of exceeding pre-specified dose amounts at any given location. Such sophisticated models are beyond the scope of the analyses presented here, but the results of this study could serve as a foundation for their development.

3.3. Vertical reference board

Fig. 10a illustrates the wall orientation receiving the most wind-driven rain over the six-year period. The map of dominant wind-driven rain orientation generally aligns with previous research. For instance, along the Norwegian coast, south and south-west orientations are most exposed, while in the southern inland regions, exposure varies more significantly [54]. Similarly, in southern Sweden, the map is

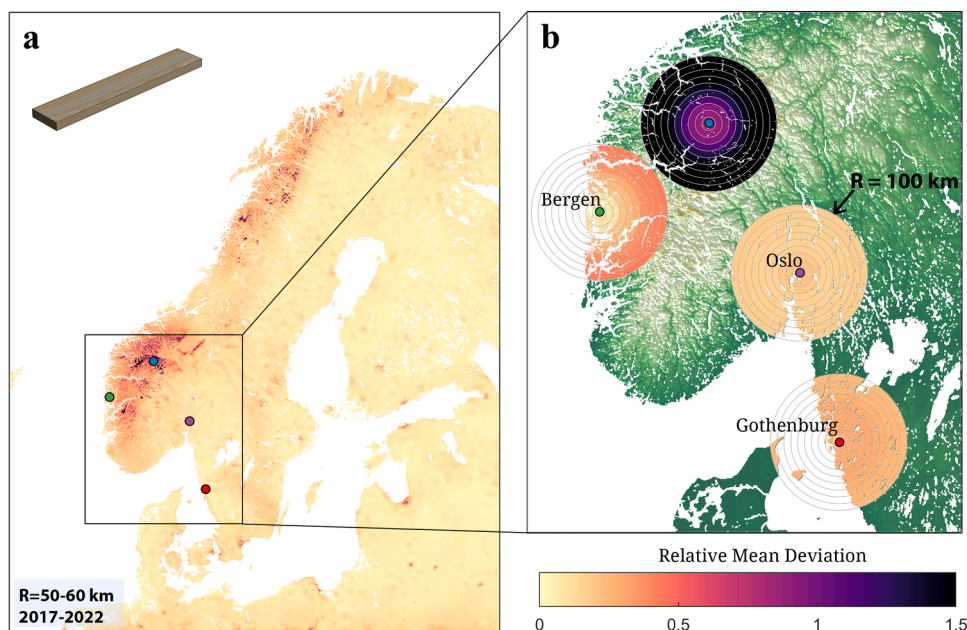


Fig. 9. The Relative Mean Deviation (RMD) annual dose within a single distance band of 50–60 km (a) as well as in a varying radius distance bands (0–10, 10–20... 90–100 km) (b). Grid cells in ocean and water bodies were excluded.

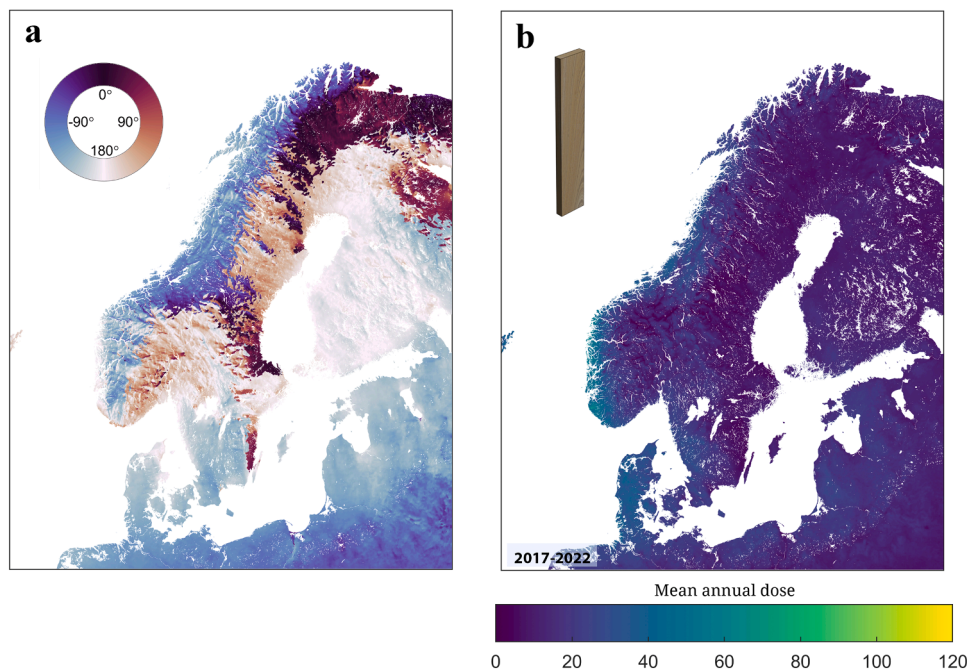


Fig. 10. Panel (a) shows the wall orientations receiving the highest amounts of driving rain. Note that the orientation follows the convention for wind direction, with 0° and 90° indicating driving rain coming from north and east, respectively. Panel (b) shows the corresponding annual dose of a vertical reference board.

consistent with studies on wind-driven rain in Gothenburg [55], Lund and Norrköping [56].

Fig. 10b shows the annual dose in the wall orientation that receives the most driving rain. Since fungal decay is heavily dependent on water exposure, the wall orientation receiving the most driving rain was considered critical, as supported by monitoring data reported by Brischke et al. [57]. Therefore, the decay risk for the vertical reference board was assessed exclusively for this orientation to accurately reflect the highest potential for deterioration. As expected, a comparison between Fig. 10b and Fig. 6b shows that the dose is generally much lower on a vertical face than on a horizontal one. The relative difference between the two configurations is however highly variable, with 80 % of the cells ranging between 0.3–0.6. This variation highlights the problem of using a single factor to accommodate differences between horizontal and vertical surfaces, a standard approach in factorized design guidelines [9].

It should be noted that the wall orientation was chosen based on the amount of wind-driven rain retained on the surface, which is a reasonable assumption under equal conditions. While this approach simplifies the analysis by not considering the impact of shading, it's important to note that orientations receiving less sunlight may have different moisture content when subject to similar amounts of driving rain. However, assessing the impact of shading falls outside the scope of this study.

Fig. 11 shows the spatial variation of the vertical reference boards, as quantified by the Relative Mean Deviation (RMD). The RMD is significantly higher for the vertical case compared to the horizontal one. This difference can be attributed to the influence of wind speed and orientation on the exposure to precipitation, which introduces additional variability in moisture exposure. Wind speed, direction, and precipitation can all vary significantly over short distances, causing localized differences in driving rain impact. As these additional influences only affect vertical surfaces, it is expected that the resulting uncertainty in fungal decay risk will increase.

4. Conclusions

This study used a metamodel, trained with a numerical model for moisture transport of a specific type of reference board and combined

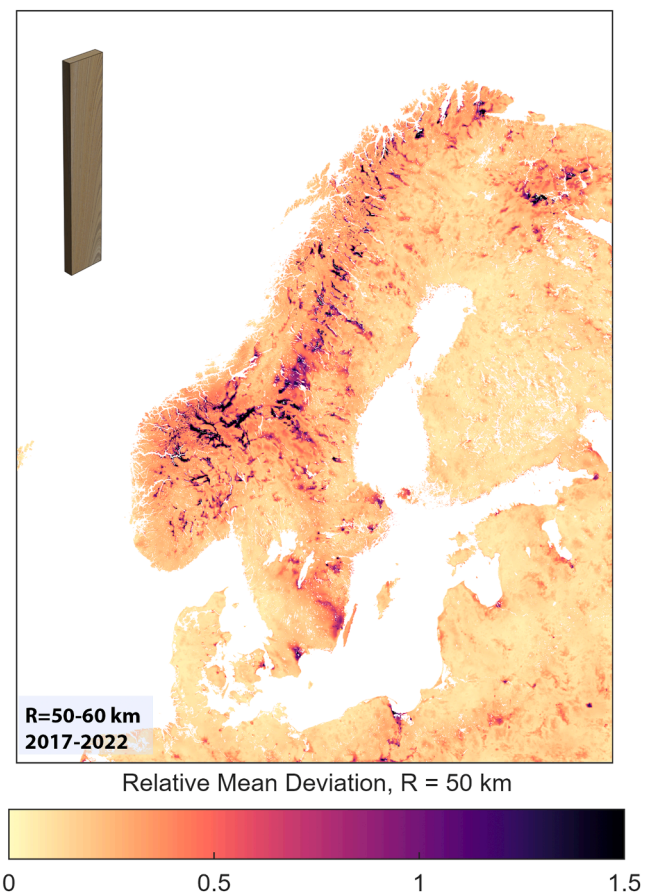


Fig. 11. The spatial variation of annual dose quantified through the relative mean deviation (RMD) in a distance band of 50-60 km.

with multiscale reanalysis datasets, to explore the spatial and temporal patterns of wood decay across Europe and Scandinavia. We performed a

point-to-grid comparison between annual decay values derived from weather station data (ECAD) with those from reanalysis data (CERRA) and then applied reanalysis data (CERRA and MET Nordic) to assess spatiotemporal uncertainties. Key conclusions from the point-to-grid comparison are as follows:

- Relative biases typically vary between -0.05 and 0.25 and rarely exceeded -0.25 and 0.35 , where negative/positive values show underestimation/overestimation by CERRA compared to ECAD.
- Overestimations by CERRA compared to ECAD were prevalent across most of Europe, except in specific regions such as the western Mediterranean (France and Spain), colder climates in the Alps and Norway, and urban areas (compared to their surrounding environments).
- Detailed analyses of the adjacent locations with positive and negative biases were associated well to local climate variations due to urbanization, hydrological and topographic features.
- Annual decay patterns based on reanalysis data generally agreed with those from weather stations, but future research could focus on bias correction methods that account for both general patterns (e.g., latitude and longitude) and specific conditions (e.g., proximity to water, mountains, and cities).

Key conclusions from the analysis of spatiotemporal variability include:

- The temporal variation, quantified via the coefficient of variation, generally varied between 20 % and 40 % over Europe, with higher values being correlated to lower annual dose. This highlights the importance of considering annual dose as a random variable in service life estimation.
- Spatial variation, quantified via the relative mean deviation, was strongly influenced by topography. The results emphasize the need to use weather data from nearby stations in regions with diverse topography. For instance, using data from a station 50–60 km away could introduce significant errors in mountainous areas, whereas in flat terrain, errors rarely exceeded 20 %.
- The vertical reference board subjected to wind-driven rain exhibited a much lower rate of decay. The relative mean deviation increased significantly in the vertical case, as variations in wind speed and orientation contribute to greater uncertainties compared to the horizontal scenario which is only affected by precipitation.

The results of the present study offer deeper insight into uncertainties stemming from variations in climate. The findings can be used with probabilistic techniques to propagate climate-driven uncertainties in service life modelling, providing critical information for service life planning. By quantifying climate uncertainties, this research represents an initial step to transition from deterministic to probabilistic models, incorporating uncertainties in service life prediction. Additionally, the study outlines a general methodology for similar applications in moisture modelling where precipitation data is decisive, starting with a bias evaluation against weather station data before using reanalysis data for further analysis.

Funding

This study was carried out in the project WoodLCC which is supported under the umbrella of ERA-NET Cofund ForestValue by the Ministry of Education, Science and Sport (MIZS) - Slovenia; The Ministry of the Environment (YM) - Finland; Research Council of Norway (RCN) - Norway; The Swedish Research Council for Environment, Agricultural Sciences and Spatial Planning (FORMAS), Swedish Energy Agency (SWEA), Swedish Governmental Agency for Innovation Systems (Vinnova) - Sweden; Estonian Ministry of the Environment; Estonian Research Council; Federal Ministry of Food and Agriculture (BMEL) and

Agency for Renewable Resources (FNR) - Germany. ForestValue has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 773324.

CRediT authorship contribution statement

Hasan Hosseini: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Leandro Iannacone:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Conceptualization, Formal analysis. **Christian Brischke:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Funding acquisition, Conceptualization. **Jonas Niklewski:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization, Formal analysis.

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.

Acknowledgements

We acknowledge the data providers in the ECA&D project, as well as all other data providers for the datasets used in this study, as described and cited with appropriate references in the paper.

Data availability

Data will be made available on request.

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