CALiMERO

IMPROVING BIO-BASED INDUSTRIES LIFE CYCLE SUSTAINABILITY

D3.2
Ecosystem services methodology definition

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LIST OF ACRONYMS

$PM_{2.5}$	Particulate Matter with a diameter less than 2.5 micrometers
CF	Characterization Factor
$Q_{lu,current}$	Annual PM removal of the current land use
Q_{ref}	Average annual PM removal of the reference land use
LCA	Life Cycle Assessment
ES	Ecosystem Services
LANCA®	LANd use indicator value CAlculation model
PEF	Product Environmental Footprint
PNV	Potential Natural Vegetation
ILCD	International Life Cycle Data system
GEZ	Global Ecological Zone
LAI	Leaf Area Index
h	Canopy height
GEE	Google Earth Engine
EFISCEN	European Forest Information SCENario model
ERA5	Fifth generation of ECMWF atmospheric reanalysis of the global climate
T_{reg}	regeneration time
F_t	Net $PM_{2.5}$ flux at time t ($g \cdot m^{-2} \cdot h^{-1}$)
f_t	$PM_{2.5}$ flux at time t ($g \cdot m^{-2} \cdot h^{-1}$)
R_t	$PM_{2.5}$ flux resuspended to atmosphere at time t ($g \cdot m^{-2} \cdot h^{-1}$)
$V_{d,t}$	deposition velocity at time t ($m \cdot s^{-1}$)
C_t	pollutant concentration at time t ($g \cdot m^{-3}$)
A_t	accumulated $PM_{2.5}$ on leaves at time t ($g \cdot m^{-2} \cdot h^{-1}$)
rr_t	resuspension rate at time t (%)
V_g	gravitational settling velocity, 3.7×10^{-5}

R_a	aerodynamic resistance above the canopy
R_s	surface resistance
a_1	empirical constant dependent on land use category
u_*	friction velocity ($m \cdot s^{-1}$)
$u(z)$	Mean wind speed at height z ($m \cdot s^{-1}$)
k	von Karman constant (=0.41)
z	height of the weather station (m),10 m
d	displacement height (m)
z_0	roughness length (m)
ψ_M	stability function for momentum
L	Monin-Obuhkov stability length
C_{DN}	neutral drag coefficient (dimensionless)
β_m	dimensionless constant (4.7)
T	air temperature (K)
N	fraction of opaque cloud cover

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PROJECT INFORMATION

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Partner No.	PARTICIPANT ORGANIZATION | ACRONYM
1 (Coord.)	Contactica | CTA
2	WeLOOP | WELOOP
3	European Cellulose Insulation Association | ECIA
4	Swedish Environmental Research Institute | IVL
5	Neovili | NEOVILI
6	Cesefor | CESEFOR
7	Luxembourg Institute of Science and Technology | LIST
8	Technical University of Denmark | DTU
9	Techtera | TECHTERA
10	Essity | ESSITY
11	BIM Kemi AB | BIMKEMI
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Abstract:	Air pollution, particularly from fine particulate matter ($PM_{2.5}$), poses severe public health risks and is a major environmental concern across bio-based sectors. Forest ecosystems contribute to air quality regulation by removing $PM_{2.5}$ through canopy interception and deposition processes, yet this ecosystem service remains poorly represented in Life Cycle Assessment (LCA). The LANCA® model, recommended in Product Environmental Footprint (PEF), currently lacks characterization factors (CFs) for air purification, focusing instead on soil-related services. To address this gap, we develop a novel methodological framework for calculating spatially explicit CFs for $PM_{2.5}$ removal loss by forest land use. The approach integrates the land use CF framework (i.e., UNEP/SETAC LULCIA used in LANCA) with existing PM removal modeling (mainly the i-Tree model), which captures dynamic PM fluxes based on vegetation structure, meteorological conditions, and atmospheric pollutant concentrations. More specifically, PM removal loss CFs ($kg \cdot ha^{-1} \cdot yr^{-1}$) are derived as the difference between modelled PM removal of current vegetation and that of potential natural vegetation. The processes PM deposition and resuspension are modelled. The framework is implemented using open-access data to represent background CFs and is adaptable to data-rich foreground scenarios. It is illustrated for Sweden given its large forest area, big forestry industry and related case study in the CALIMERO project. The case study results reveal strong spatial and structural variation in CFs across ecological zones and forest types, with managed forests often exhibiting lower CFs (i.e., higher removal potential, around 0.1 kg·($kg \cdot ha^{-1} \cdot yr^{-1}$) than natural forests, an outcome explained by canopy structure and aerodynamic parameters used in the calculation, but also indicating an interest for further validation with local or European forest management data. The proposed framework enables the calculation of CFs for $PM_{2.5}$ removal using either global datasets or site-specific data, ensuring flexibility for both background and foreground LCA applications. The method can be extended beyond forestry to agricultural and urban land uses. Incorporating more PM-plant interaction processes, high-resolution spatial datasets and region-specific calibration would enhance accuracy.

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1 INTRODUCTION

1.1 Context

Air pollution poses critical health risks, being linked to more than 4 million premature deaths annually, and increased incidence of cardiovascular, respiratory, and neurological disorders (Rentschler & Leonova, 2023). The CALIMERO project explicitly highlights the impact of particulate matter (PM) emissions as a critical environmental hotspot, noting its high relevance across multiple bio-based sectors including biochemical production, pulp and paper industries, and construction activities. For example, PM emerged as an environmental hotspot for 35 out of 38 biochemical processes assessed, demonstrating the pervasive significance of addressing this pollutant category (Charpentier Poncelet et al, 2023). Forest ecosystems contribute significantly to air purification by absorbing gaseous pollutants such as sulfur dioxide (SO_2) and retaining particulate matter (PM) through canopy interception and surface adsorption, creating significant economic values linked with health damage alleviation (Xu et al., 2025).

Despite this recognition, the quantification of ecosystem services (ES), particularly those related to air purification, remains underdeveloped within Life Cycle Assessment (LCA). Currently, within the LCA community, the quantification of ES of different land uses remains limited and primarily relies on generalized or simplified assumptions (as stated in D1.3 of the CALIMERO project). The absence of standardized characterization factors (CFs) to quantify different changes in ES, as a result of land use (change), is one of the main reasons. LANCA® (LANd use indicator value CAlculation model) (Fischer, 2018) approach is recommended in EU guidelines of Product Environmental Footprint (PEF) to quantify land use impacts (Sala et al., 2019). PEF selected LANCA mainly because of its compatibility with LCA frameworks and its world-wide coverage of resulted CFs (Sala et al., 2019). However, the current development of LANCA focuses on soil-related ES, such as soil erosion resistance and mechanical filtration. Other critical ES from land use, including air purification through PM removal, are not considered. D1.3 of the CALIMERO project explicitly identifies these gaps, particularly highlighting insufficient coverage of impact pathways related to PM removal, and stresses the need for developing specific CFs, especially within the LANCA framework, to capture air quality services more effectively.

1.2 Aim and objectives

Addressing these identified gaps, **this study aims to develop a novel methodological framework to calculate CF specifically designed to quantify $PM_{2.5}$ (particulate matter with a diameter of less than 2.5 micrometers) removal resulting from different forest occupations**.

Given the spatially explicit and temporally dynamic nature of PM removal process, the proposed approach is designed to be scalable to global implementation, yet computationally feasible. As a demonstration case, the methodology is implemented in Sweden, with the intention to generalize it for global applications. Sweden was selected because it has a major forested area, related forestry & wood industry and is a case study within the CALIMERO project.

This work focuses primarily on background CF development, leveraging only open-access global datasets to ensure broad applicability and reproducibility. However, we also provide recommendations for more data-rich foreground assessments, where detailed site-specific information is available. The framework is designed to be modular and flexible, supporting both high-resolution applications and broader land use categories beyond forestry, such as agriculture and urban systems, through integration with land cover and ecological zone data.

The following sections present the modeling framework, data sources, and analytical steps, followed by a case study implementation in Sweden. The results are then analyzed to assess spatial and structural trends in $PM_{2.5}$ removal, and implications are discussed for expanding the approach to other land use types and integrating it with regionalized Life Cycle Inventory datasets (with land use elementary flows per region) and LCA tools.

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2 METHODOLOGY & DATA

In this work, the CF for $PM_{2.5}$ removal associated with forest land use was calculated using a spatially explicit and temporally dynamic modeling approach integrating remote sensing data, meteorological conditions, and land-specific parameters. The analysis involved a comparative evaluation between current land use scenarios (i.e., PM removal of current forest land use activities) and a reference land use scenario (potential PM removal if the current forest land use activities do not occur, but a natural scenario of an ecological zone prevails), integrating two distinct methodologies: LANCA (Land Use Indicator Calculation Model) and particulate matter removal modelling, mainly based on the i-Tree model (Hirabayashi et al., 2015) and the framework considered by Zhang and He (2014). LANCA is used to guide CF development for land use of current forest land use (hereafter CF), while i-Tree model is used for dynamic $PM_{2.5}$ removal calculation. In this section, LANCA and i-Tree model are described first, followed by data sources and spatial data processing for current and reference land use situation.

2.1 Land use characterization factors – LANCA framework

LANCA® was developed tailored to the guidelines of the UNEP SETAC framework (Koellner et al., 2013), calculating CFs at country level, for the elementary land flows that are fully compatible with the International Life Cycle Data System (ILCD) land use classification (Fischer, 2018). It assesses land use impacts due to occupation and transformation by quantifying deviations from the reference situation. The reference situation represents a situation where land use activity would not happen, i.e., potential natural vegetation (PNV). Using the same framework as LANCA, the CF for PM removal loss is calculated as:

$$\mathrm{CF} = -(Q_{LU,current} - Q_{ref}) \quad (1)$$

Where:

- $Q_{lu,current}$: Annual PM removal of the current land use (in our case, specific forest types with management or degradation).
- Q_{ref}: Average annual PM removal of the reference land use (typically natural or undisturbed forest, defined by ecological zones)
- CF: Characterization factor ($kg \cdot ha^{-1} \cdot year^{-1}$)

A positive CF means that the current land use quality is worse than the reference situation, while negative CF indicates better performance. As such, the CF should be labelled as particulate matter removal loss. Both $Q_{LU,current}$ and Q_{ref} are based on i-Tree model and study of Zhang and He (2014), with different vegetation-specific spatial parameters.

2.2 Particulate matter removal modelling

Prior to specifying the model, we shortly list the processes involved in particulate matter removal: (1) deposition of particulate matter on vegetation, (2) resuspension in the air from the vegetation surface, (3) wash off by precipitation, with PM landing on the ground surface (clotting together with other particles), (4) dissolution in water & (5) plant uptake and/or encapsulation into the wax layer (Schaubroeck et al., 2014). We will not quantify all these processes, but restrict particulate matter removal modelling based on established models considering data availability at large scale, which leads to mainly considering the processes of (1) deposition and (2) resuspension. For quantification of forest PM removal, the i-Tree model has been widely used, especially at larger scales (Cimburova & Barton, 2020; Hirabayashi et al., 2015; Pace et al., 2021; Pace & Grote, 2020; Tiwari et al., 2019). It integrates vegetation structure, meteorological conditions, and pollutant concentrations to estimate pollutant removal rates. The model calculates downward pollutant flux based on vegetation parameters (e.g., roughness length) and atmospheric conditions (e.g., wind speed), offering a spatially explicit and temporally dynamic assessment. The general dynamic calculations are as follows:

$$F_t = f_t - R_t \tag{2}$$

$$f_t = V_{d,t} \cdot C_t \cdot 3600 \tag{3}$$

$$R_t = (A_{t-1} + f_t) \cdot \frac{rr_t}{100} \tag{4}$$

$$A_t = (A_{t-1} + f_t) - R_t \tag{5}$$

Where:

- F_t is net $PM_{2.5}$ flux at time t ($g \cdot m^{-2} \cdot h^{-1}$)
- f_t is $PM_{2.5}$ flux at time t ($g \cdot m^{-2} \cdot h^{-1}$)
- R_t is $PM_{2.5}$ flux resuspended to atmosphere at time t ($g \cdot m^{-2} \cdot h^{-1}$)
- $V_{d,t}$ is deposition velocity at time t ($m \cdot s^{-1}$)
- C_t is pollutant concentration at time t ($g \cdot m^{-3}$)
- A_t is accumulated $PM_{2.5}$ on leaves at time t ($g \cdot m^{-2} \cdot h^{-1}$)
- rr_t is the resuspension rate at time t (%)

rr_t depends on the wind speed according to i-Tree model, and values for these were retrieved from it (Hirabayashi et al., 2015).

When it comes to the calculation of the deposition velocity ($V_{d,t}$), two approaches can be found in literature: (a) based on the species-specific parameters of deposition velocity per leaf area index (LAI) for different conditions, namely wind speed, obtained from test such as wind tunnel tests (notably in the i-Tree model for $PM_{2.5}$) or (b) based on the roughness length. Our selection is due to limitation of data availability on these parameters, here, restricted to the latter. Hereto, we mainly worked further on the calculation framework presented by Zhang and He (2014) based on roughness length.

$V_{d,t}$ at each time t (hereafter as V_d) was calculated using following equations:

$$V_d = V_g + \frac{1}{R_a + R_s} \tag{6}$$

Where:

- V_g is the gravitational settling velocity, 3.7×10^{-5} ($m \cdot s^{-1}$) (Zhang & He, 2014)
- R_a is the aerodynamic resistance above the canopy ($s \cdot m^{-1}$)
- R_s is the surface resistance ($s \cdot m^{-1}$)

$$R_a = \frac{u(z)}{u_*^2} \tag{7}$$

$$R_s = \frac{1}{V_{ds}} = \frac{1}{a_1 u_*} \tag{8}$$

Where:

- a_1 is empirical constant dependent on land use category and provided by Zhang and He (2014)
- u_* is friction velocity ($m \cdot s^{-1}$), calculated in equation 9-22.

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- $u(z)$ Mean wind speed at height z (m·s^{-1})
- Vds is surface deposition velocity (m·s^{-1})

For the neutral atmosphere (L=0):

$$u_* = \frac{k \cdot u(z-d)}{\ln\left(\frac{z-d}{z_0}\right)} \tag{9}$$

Where:

- k is von Karman constant (=0.41)
- z is the height of the weather station (m),10 m
- d is the displacement height (m)
- z_0 is the roughness length (m)

For unstable atmosphere (L<0):

$$u_* = \frac{k \cdot u(z-d)}{\ln\left(\frac{z-d}{z_0}\right) - \psi_M\left(\frac{z-d}{L}\right) + \psi_M\left(\frac{z_0}{L}\right)} \tag{10}$$

Where:

- ψ_M is stability function for momentum
- L is Monin-Obuhkov stability length (m)

ψ_M is calculated as below:

$$\psi_M = 2\ln\left(\frac{1+x}{2}\right) + \ln\left(\frac{1+x^2}{2}\right) - 2tan^{-1}(x) + \frac{\pi}{2} \tag{11}$$

$$x = \frac{1}{(1-28\frac{z}{L})^{0.25}} \tag{12}$$

For stable atmosphere (L>0):

$$u_* = C_{DN} \cdot u(z)\left[\frac{1}{2} + \frac{1}{2}\sqrt{1-\left(\frac{2u_0}{\sqrt{C_{DN} \cdot u(z)}}\right)^2}\right] \tag{13}$$

$$C_{DN} = \frac{k}{\ln\left(\frac{z}{z_0}\right)} \tag{14}$$

$$u_0 = \sqrt{\frac{\beta_m z g \theta_*}{T}} \tag{15}$$

$$\theta_* = 0.09(1-0.5NN^2) \tag{16}$$

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Where:

- C_{DN} is neutral drag coefficient (dimensionless)
- β_m is dimensionless constant (4.7)
- g is acceleration due to gravity (=9.81 m·s^{-2})
- T is air temperature (K)
- N is fraction of opaque cloud cover

To calculate the stability length, L, Pasquill stability class (A, B, C, D, E, F) and roughness length (z_0) are used (Equation 17-22). Pasquill stability class is determined by daytime insolation, surface wind speed, and cloud cover (Pasquil, 1961).

$$\text{Pasquill = A : } \frac{1}{L} = -0.0875 \cdot z_0^{-0.1029} \tag{17}$$

$$\text{Pasquill = B : } \frac{1}{L} = -0.03849 \cdot z_0^{-0.1714} \tag{18}$$

$$\text{Pasquill = C : } \frac{1}{L} = -0.0807 \cdot z_0^{-0.3049} \tag{19}$$

$$\text{Pasquill = D : } \frac{1}{L} = 0 \cdot z_0^{-0} \tag{20}$$

$$\text{Pasquill = E : } \frac{1}{L} = 0.0807 \cdot z_0^{-0.3049} \tag{21}$$

$$\text{Pasquill = F : } \frac{1}{L} = -0.03849 \cdot z_0^{-0.1714} \tag{22}$$

2.3 Novel integrated methodology for CF on PM removal per land use

To obtain PM removal loss CF for land use, we integrate the PM removal calculations with the land use CF framework, as considered in LANCA, the total net PM flux of each year (F) was used as the annual indicator of land use performance (i.e., Q_{ref} for reference land use or $Q_{LU,current}$ for current land use) in Equation 1, integrating both deposition and resuspension processes. To obtain a representative value, the annual F_t values were averaged over a 5-year period, providing a more stable estimation of long-term $PM_{2.5}$ removal capacity. The accumulated $PM_{2.5}$ removal (A_0) was initialized to zero. At each time step, the function updated A_t by adding the current deposition flux while accounting for resuspension losses (R_t), thereby reflecting the net deposition at each iteration.

To this end, V_d depends on satellite parameters and vegetation structures. While the same meteorological data and treatment over studying times are used for both Q_{ref} and $Q_{lu,current}$, vegetation structure is key to differentiating them, thus determining CF. More specifically, the displacement height (m), d, the roughness length (m), z_0, are calculated differently for reference and current situation (section 2.4.2.1 and 2.4.2.2). In the following section, we describe the spatial data processing for both meteorological data (section 2.4.1) and vegetation-specific parameters for both $Q_{lu,current}$ (section 2.4.2.1) and Q_{ref} (section 2.4.2.2).

2.4 Coding, Spatial Data & Data Processing

Code, based on above methodological framework, to run was newly written and implemented in Google Earth Engine (GEE) using an iterative function that sequentially processed each image in the $PM_{2.5}$ flux time series. The analysis focused on a specified country boundary using Large Scale International Boundary (LSIB) dataset (United States Department of State, Office of the Geographer, 2017). All data were spatially clipped to match the analysis region (in this case, Sweden). The temporal range is 2018-2022.

2.4.1 Meteorological data

To support the estimation of PM removal and its related meteorological dependencies, multiple satellite and reanalysis datasets were harmonized and processed in GEE. These datasets are publicly available at a global level.

Three primary datasets were utilized:

1. **$PM_{2.5}$ Concentration**: The $PM_{2.5}$ concentration data were sourced from the work of Wei et al. (2023), providing globally gridded pollution levels. The images were rescaled to convert raw values into standard concentration units (μg·m^{-3}) in i-Tree model using a scalar transformation.
2. **Cloud Cover**: Cloud fraction data were obtained from the Earth Engine Data Catalog (Kanamitsu et al., 2002). The original percentage values were normalized to fractional.
3. **ERA5 Land Meteorological Data**: ERA5 hourly land reanalysis data provided key meteorological variables (Copernicus Climate Change Service, 2019), including horizontal wind components (eastward and northward component at 10 m), surface net solar radiation, and near-surface air temperature (2 m). Only four snapshots per day (0h, 6h, 12h, 18h) were retained to reduce data volume. These time points were selected as they represent nighttime, early morning, midday, and late afternoon conditions, effectively capturing diurnal variability while significantly reducing data volume. In addition, as cloud cover dataset has a cadence of six hours, our snapshots selection is also temporally aligned with it.

Each dataset was independently filtered by date according to the defined temporal range (2018-2022). To ensure consistent spatiotemporal resolution and alignment of all input variables necessary for the considered PM removal modeling, temporal joins were implemented to synchronize the datasets at the image level. A hierarchical joining strategy was used: ERA5 data were first matched with cloud cover using a ±3-hour window, which is sufficient to capture near-simultaneous atmospheric states given the high temporal resolution of both datasets and the relatively slow variability of cloud cover within a short time span. A subsequent join with $PM_{2.5}$ data was performed using a ±12-hour window, which allows a matching with $PM_{2.5}$ dataset that have lower temporal resolution (daily). This step ensures that for each ERA5 observation, the temporally closest cloud and $PM_{2.5}$ images are attached as properties, enabling coherent multi-variable analysis.

2.4.2 Vegetation structure data

The vegetation structure related parameters are empirical constant for land use category provided by Zhang and He (2014) (a_1), roughness length (z_0) and displacement height (d).

2.4.2.1 Current Land Use ($Q_{lu,current}$)

$a_1$value depends on the current forest types. According to Zhang and He (2014), there are two possibilities for a_1 values for forest, 3.4 × 10^{-3} (tropical broadleaf trees) or 4. 3 × 10^{-3} (all the other types of trees). u_* is calculated according to Equation (9-22), which depends on two land-specific parameters: z_0, and d. They can be calculated with satellite data of LAI and canopy height (h) according to the Raupach model. Empirical evidence-based parameters, $C_S = 0.003$, $C_R = 0.3$, $\psi_h = 0.193$ were used according to the suggestion of Raupach (Floors et al., 2021).

$$\lambda = 0.5LAI \tag{23}$$

$$\frac{d}{h} = 1 - b \tag{26}$$

$$b = 1 - \frac{\exp(-a)}{a} \tag{27}$$

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$$a = \sqrt{2c_{d1}\lambda} \tag{28}$$

$$\frac{z_0}{h} = b \exp\left(\frac{-\kappa}{\min\left(\sqrt{C_S + C_R\lambda}, c_{max}\right)} - \psi_h\right) \tag{29}$$

To align with the land use classification scheme proposed by Koellner et al. (2013) for LCA land use elementary flows (Table 1, forest related land use), we introduced a forest management layer that distinguishes between natural forests (i.e., primary and secondary) and used forests (including both extensive and intensive used forest) in the current land use context. Since this layer of data is lacking of explicit management intensity (i.e., no differentiation on intensive or extensive forest), we adopted an indirect classification approach based on structural canopy parameters.

Table 1. Land use and cover classification for LCA according to Koellner et al. (2013).

ID use	Land use/cover class	Descriptions
1.	Forest	Areas with tree cover >15%
1.1	Forest, natural	Forest not used by humans
1.1.1	Forest, natural, primary	Forests minimally disturbed by human impact, where flora and fauna species abundance are near pristine
1.1.2	Forest, natural, secondary	Areas originally covered with forest or woodlands, where vegetation has been removed, forest is re-growing and is no longer in use
1.2	Forest, used	Forests used by humans
1.2.1	Forest, used, extensive	Forests with extractive use and associated disturbance like hunting, and selective logging, where timber extraction is followed by re-growth including at least three naturally occurring tree species
1.2.2	Forest, used, intensive	Forests with extractive use, with either even-aged stands and clear-cut patches, or less than three naturally occurring species at planting/seeding

Following the findings of Floors et al. (2021), dense forests typically exhibit smoother aerodynamic profiles. Accordingly, we used z_0 as a proxy for forest management intensity, under the assumption that denser, more uniform forests (with lower-than-average z_0 within an ecological zone) are extensive, while forests with higher-than-average z_0 are intensive. This zonal mean-based thresholding approach provides an approximation of forest management levels in the absence of harmonized field data. The resulting classification and its structural validation using z_0 and d distributions are presented in section 3.1.

2.4.2.2 Reference Land Use (Q_{ref})

Global Ecological Zone (GEZ) classification system developed by FAO was used as reference situation, as proposed by De Laurentiis et al., (2019), which categories divide the globe into five major domains, including tropical, subtropical, temperate, boreal and polar (FAO, 2010). Similar to the calculation for Q_{lu}, three land specific parameters are required for Q_{ref} calculation. a_1 values were obtained by matching GEZ with land cover categories available in Zhang and He (2014) (Table 2).

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Table 2. matching of global ecological zone (GEZ) classification with land cover categories in Zhang and He (2014).

GEZ code	GEZ	Land Cover Categories in Zhang and He (2014)
41	Boreal coniferous forest	Evergreen needleleaf trees
43	Boreal mountain system	Evergreen/deciduous needleleaf trees, mixed wood forest
42	Boreal tundra woodland	Tundra
50	Polar	Ice
24	Subtropical desert	Desert
22	Subtropical dry forest	Deciduous broadleaf trees
21	Subtropical humid forest	Deciduous/Evergreen broadleaf trees
25	Subtropical mountain system	Deciduous/Evergreen broadleaf/needleleaf trees, mixed wood and transitional forests
23	Subtropical steppe	Short grass and forbs
32	Temperate continental forest	Deciduous broadleaf trees
34	Temperate desert	Desert
35	Temperate mountain system	Evergreen needleleaf trees
31	Temperate oceanic forest	Deciduous broadleaf trees
33	Temperate steppe	Short grass and forbs
15	Tropical desert	Desert
13	Tropical dry forest	Drought deciduous trees
12	Tropical moist forest	Tropical broadleaf trees
16	Tropical mountain system	Deciduous/Evergreen broadleaf trees
11	Tropical rainforest	Tropical broadleaf trees
14	Tropical shrubland	Deciduous shrubs/evergreen broadleaf shrub
90	Water	Water

2.4.2.3 Specific data for Sweden case

To demonstrate the practical application of the proposed CF modeling of land use PM removal ES framework, a case study was conducted for Sweden (i.e., global available dataset clipped to Sweden). This region was selected due to its extensive forest coverage, active forest and wood-processing sectors, and its key role as a designated case study region within the CALIMERO project.

As explained above, only three land-specific parameters, a_1, z_0 and d are needed to determine PM removal of current land use. For a_1, in total only two possible values for forest-related land use (see section 2.4.2.2), for tropical broadleaf trees or the rest. In Sweden, only four ecological zone are available (no tropical broadleaf

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trees system) and they share the same a_1 values according to the matching with Zhang and He (2014) (Table 3). z_0 and d for each ecological zone adopts the mean values from natural forests as reference surface parameters (see results section 3.2).

3 RESULTS AND DISCUSSION

3.1 Vegetation parameters in Sweden – Current vegetation

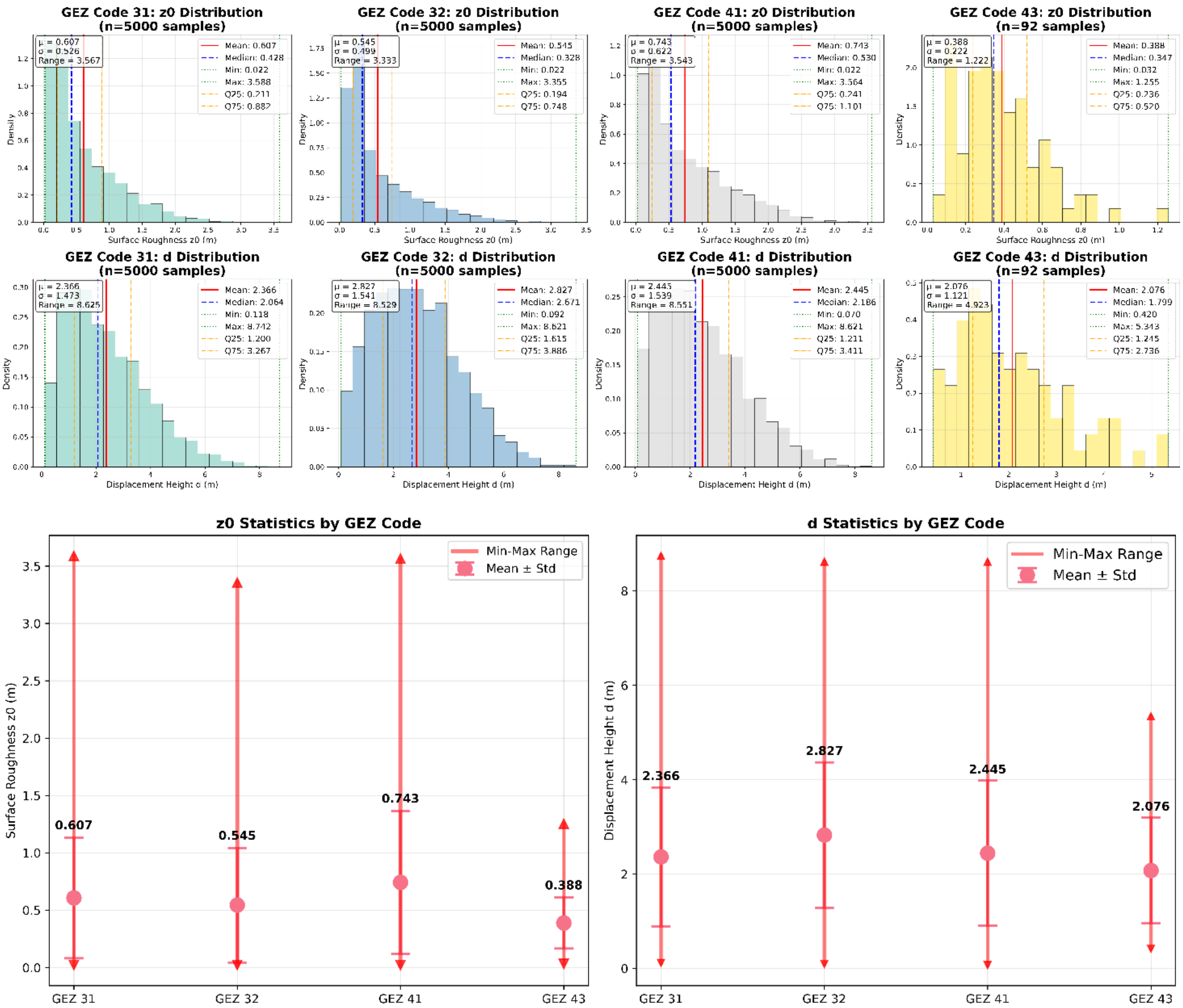

Figure 1. Distribution and summary mean and min-max range of roughness length (z0, m) and displacement height (d, m) of used forest type in each ecological zone in Sweden.

Figure 1 illustrates the statistical distributions (top two rows) and summary mean and min-max range (last row) of z_0 and d for four ecological zones (temperate oceanic (GEZ 31), temperate continental (GEZ 32), boreal coniferous (GEZ 41), and boreal mountain systems (GEZ 43)), each sampled from maximum 5,000 instances. GEZ 43 (Boreal mountain system) contains only 92 instances of used forest.

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3.2 Reference Vegetation Parameters in Sweden – used versus natural forests

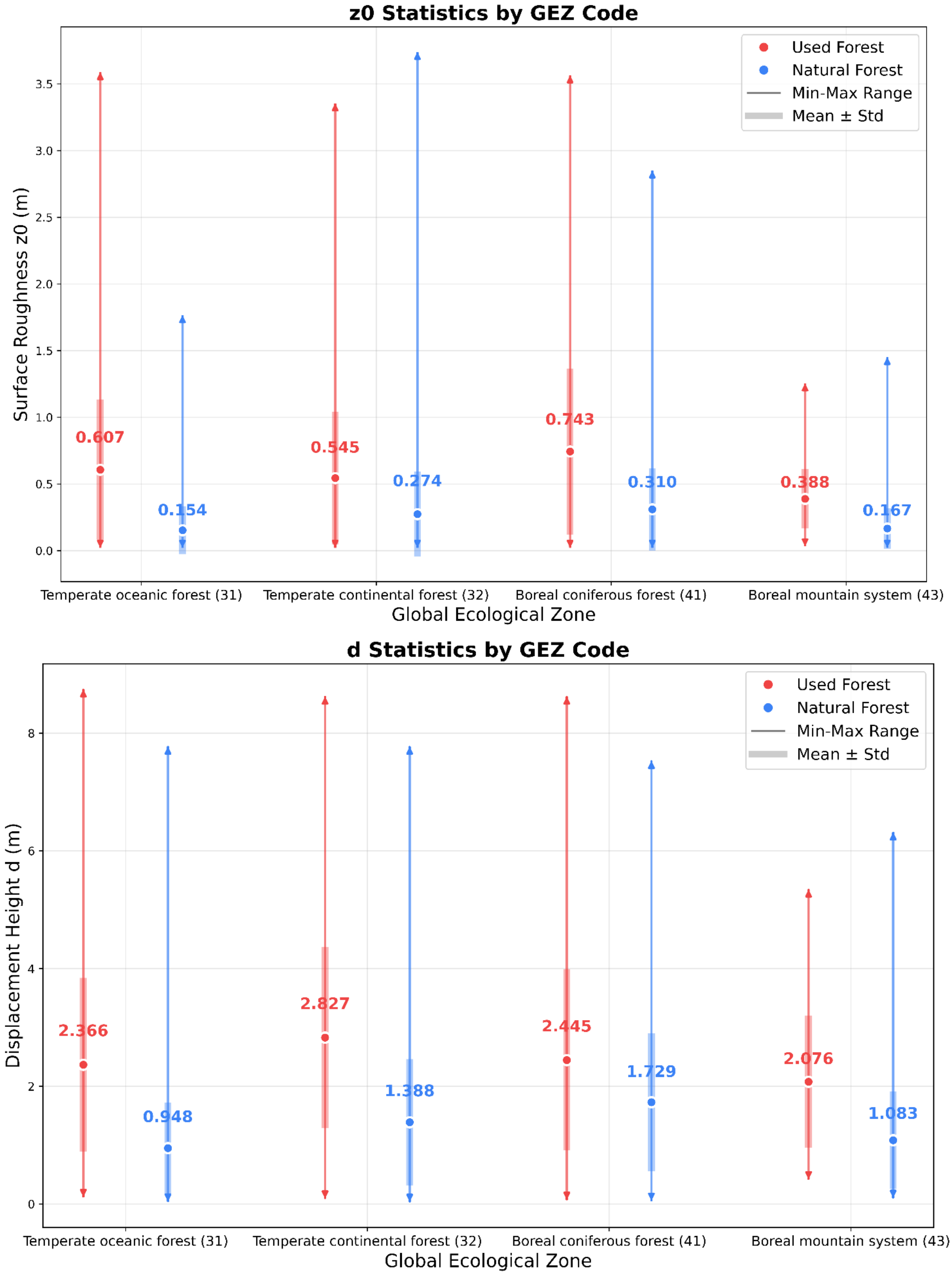

Figure 2. Comparing statistics of roughness length (z0) and displacement height (d) of natural and used forest type in each global ecological zone (GEZ).

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Figure 2 presents the statistical distributions of z_0 and d across four GEZs, comparing used forests and natural forests. Consistently across all zones, natural forests exhibit lower mean z_0 and lower d values compared to used forests in Sweden. This consistent divergence in both z_0 and d between land-use types justifies using the mean values from natural forests as a reference baseline in land surface modeling and land use impact assessments (Table 3).

Table 3. z_0, d, and a_1 value for reference land use in Sweden.

GEZ code	GEZ	z_0	d	$a1$
31	Temperate oceanic forest	0.154	0.948	0.0043
32	Temperate continental forest	0.274	1.388	0.0043
41	Boreal coniferous forest	0.310	1.729	0.0043
43	Boreal mountain system	0.167	1.083	0.0043

3.3 Land-use PM removal loss CF in Sweden and Statistic Analysis

PM-removal loss CFs were obtained for all datapoints in Sweden through equation 1, considering the data obtained in the previous section on current and reference land uses. Results map of Sweden (Figure 3), including CF ($kg \cdot ha^{-1}$), forest types, and ecological zones can be found in this link below: https://code.earthengine.google.com/716c19657c84f02647ab3f474297b4e9. The results show that current forest occupation leads to greater losses in PM removal in the central and northern regions, while exhibiting a net beneficial effect predominantly in the southern region.

The statistical analysis of the developed CFs (Figure 4) provides useful insights into the relationship between CF values and the four ecological zones and forest types present in Sweden. The CF distribution is left-skewed with some extreme values, as shown in the histogram and Q-Q plot, where a few low values extend the distribution's tail to the left. Negative CF values indicate that current land use (i.e., used forest) performs better in terms of $PM_{2.5}$ removal than the reference (natural forest). This situation might be raised when the displacement height (d) of the used forest is higher than that of reference, leading to enhanced vertical mixing and increased PM removal by the vegetation canopy. As d is a key parameter influencing aerodynamic resistance, a higher value reduces resistance and increases deposition flux. In Sweden, some managed forests may be denser or structurally taller than natural reference conditions, thereby generating negative CFs, and thus performing better in PM removal. Additionally, the CF values are centered around zero, suggesting that, on average, forest land use has only a limited impact—either positive or negative—on $PM_{2.5}$ removal compared to the reference state. This reflects the relatively subtle differences in vegetation structure and function between current forest types and the potential natural vegetation in the studied zones. Sweden is also a case where the natural vegetation mainly consists of forests. Yet, the picture will be very different when performing afforestation of desert area.

The boxplots analysis of CFs across ecological zones and forest types (Figure 4) highlights distinct spatial and structural trends in $PM_{2.5}$ removal effectiveness. Current forests occupying in ecological zones 31.0 (Temperate Oceanic Forest) and 32.0 (Temperate Continental Forest) exhibit lower median CF values—indicating more effective $PM_{2.5}$ removal—compared to boreal zones 41.0 (Coniferous Forest) and 43.0 (Mountain System), where CFs are generally higher. In addition, occupying natural forest at each ecological zone is not zero stems from the methodological choice to use the mean values of surface roughness length (z0) and displacement height (d) derived from natural forests within each ecological zone to define the reference land surface conditions. As a result, the CFs associated with these types reflect a near-zero or minimal deviation from the reference case, rather than implying any actual degradation or management impacts.

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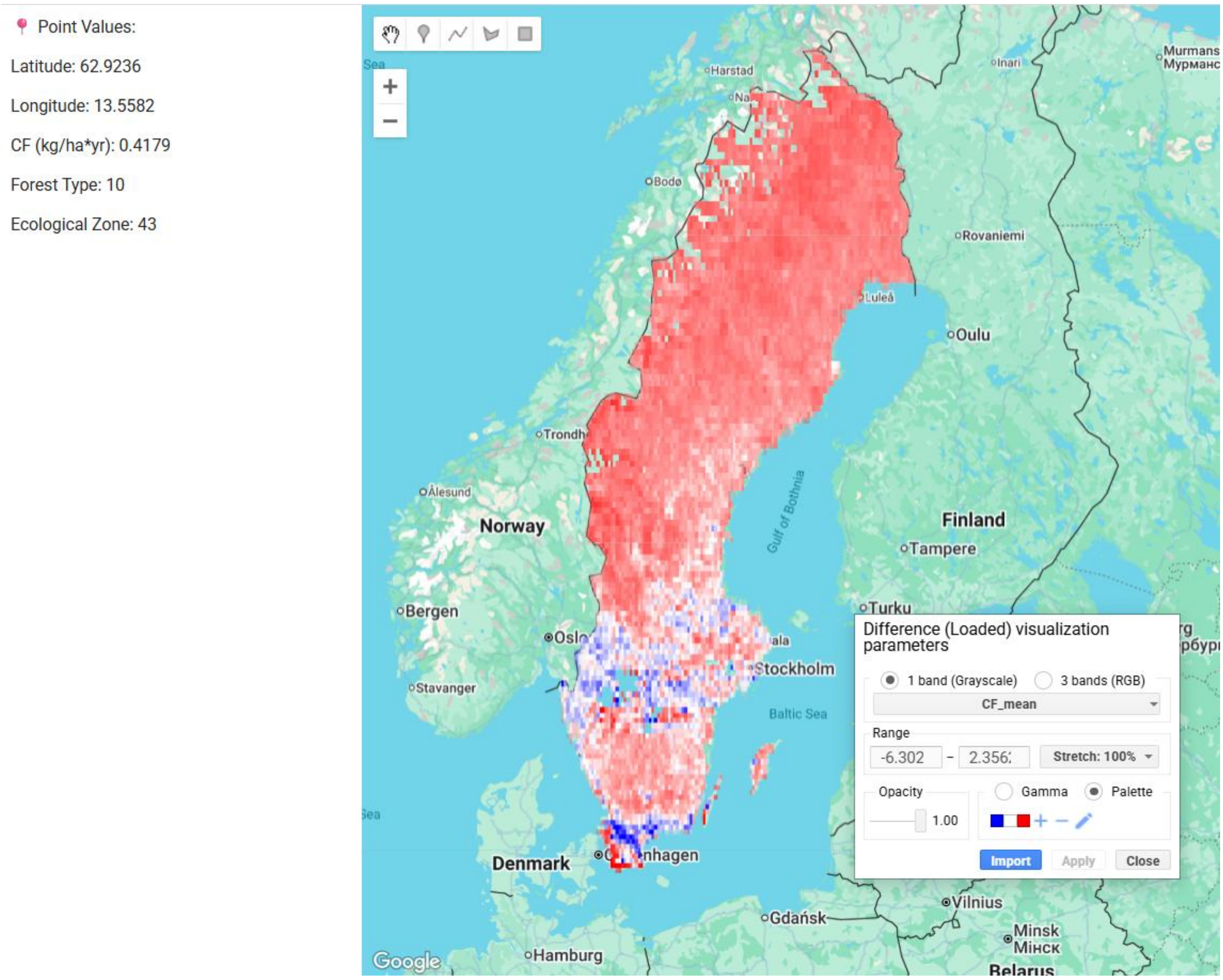

Figure 3. Screen shot of the CF map in Sweden (blue means negative CF, meaning current land use performs better in terms of $PM_{2.5}$ removal than the reference, red means positive CF, meaning current land use perform worse than reference).

In our results, forest Types 21 (extensive) and 22 (intensive) consistently exhibit lower CFs (and thus stronger $PM_{2.5}$ removal) particularly in temperate zones 31.0 and 32.0. In contrast, forest Type 1 (naturally regenerating forest) and 10 (primary forest), representing minimally managed or natural forests, shows higher CFs across all zones, indicating lower removal potential. These observations appear counterintuitive, as natural forests are typically assumed to provide greater ES. A plausible explanation may lie in the forest type data that were used to calculate z_0 and d which are two critical parameters for CF calculation. Based on our calculation and analysis in Figure 2, Swedish used forest tends to have higher z_0 and larger d than natural forest, suggesting that they may have more fragmented canopies or structural heterogeneity (such as clearings, gaps, or variable stand heights). These structural features likely enhance turbulent mixing near the surface, thereby increasing deposition velocity and net $PM_{2.5}$ removal, ultimately leading to lower CFs. However, such counterintuitive results call for results verification by using other forest management data. For example, the management intensity model available from EFISCEN Space (Schelhaas et al., 2022) provides another possibility to further differentiate land use classes into intensity levels (e.g., intensive, extensive, semi-natural) specific in Europe. Incorporating this data could support a more nuanced assessment of the influence of management practices on PM removal potential and validate our results in this work.

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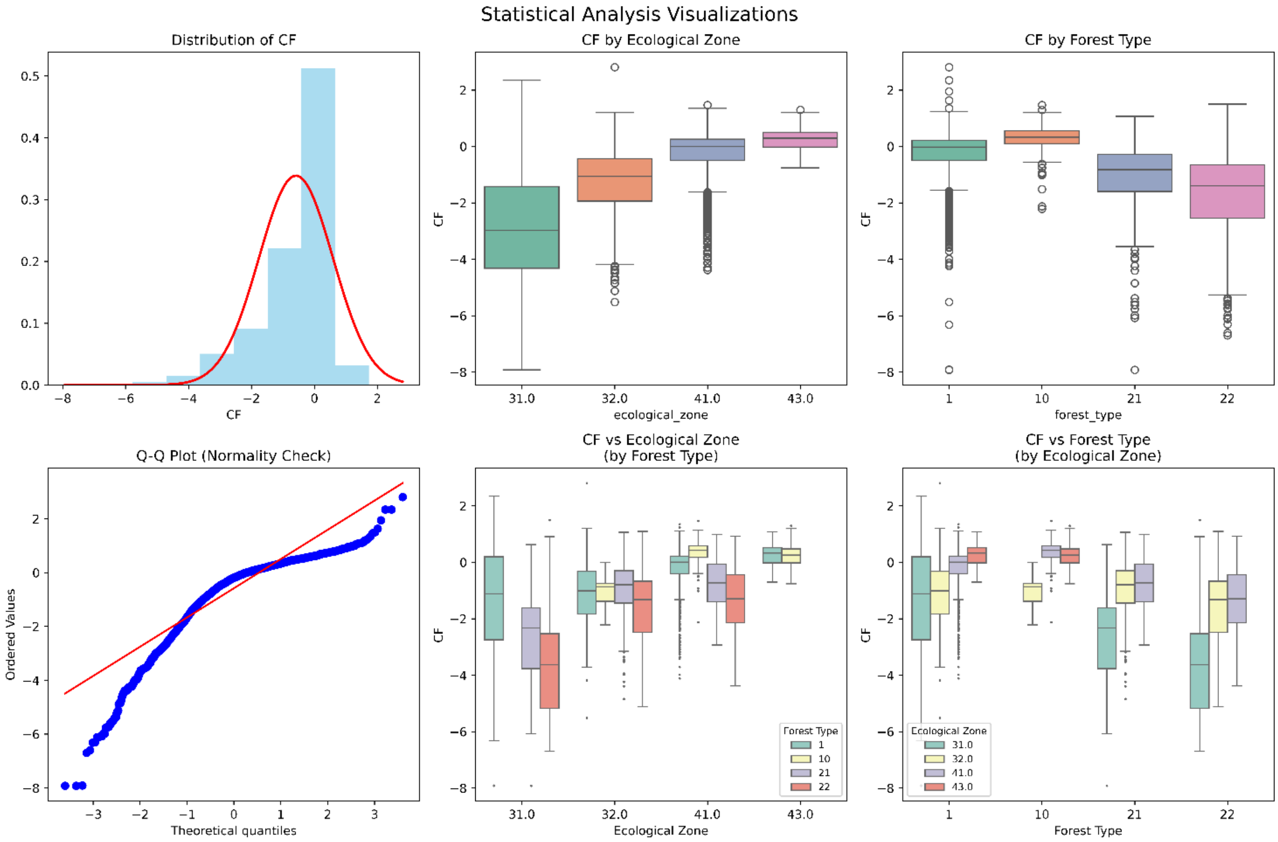

Figure 4. Statistical analysis visualization of characterization factors (kg·ha⁻¹yr⁻¹) in Sweden over ecological zone and forest types (1 (naturally regenerating forest), 10 (natural primary forest), 21 (extensive used), and 22 (intensive used)).

3.4 Potential Application for Background and Foreground Calculation

The present work provides a general framework and the possibility to calculate PM removal loss CFs with or without site-specific information. The use of globally available datasets, such as for LAI, h, and forest type, enable a consistent parameterization of vegetation structure at large spatial scales for background assessment. In addition, the use of the a_1 values provided by Zhang & He (2014), which cover 26 distinct land use types, allows for extending the calculation of CFs for $PM_{2.5}$ removal from forest ecosystems to a broader set of land use categories, including agricultural systems (e.g. croplands, maize, sugar cane) and urban areas into the CF framework. To establish the reference situation, we propose a preliminary matching scheme (Table 2) that links each GEZ with a corresponding a_1 value derived from Zhang and He's land cover classification.

However, this alignment remains subject to refinement, as discrepancies between classification systems may compromise the ecological representativeness of CFs. To address these limitations, future work should prioritize the harmonization of land use typologies between global ecological datasets and the Zhang & He (2014) framework. This may involve developing a translation layer that accounts for biophysical parameters (e.g., LAI, canopy height, vegetation cover) and management intensity, thereby improving the accuracy of land use attribution within each GEZ. Additionally, region-specific calibration of a_1 values may be necessary to reflect local vegetative conditions, especially in regions with dynamic land conversion or mixed land management regimes. Incorporating high-resolution spatial datasets (e.g., Sentinel-derived land cover maps or country-level land use inventories) could further refine CF estimation.

Furthermore, our study highlights the importance of spatial heterogeneity and forest structural characteristics in determining the $PM_{2.5}$ removal potential of forest ecosystems, as reflected in the variability of CFs across

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ecological zones and forest types. The development of such spatially explicit CFs opens up new opportunities for improving the regional accuracy of Life Cycle Impact Assessment (LCIA). Emerging regionalized tools/datasets such as *RegioInvent* (Maxime Agez & Matthieu Soultre, 2025) and the Sphera database, which have already country-specific land use flows, provide promising pathways for incorporating geospatially explicit CF, notably at country-level, and inventory information into LCA systematically and at background level. More precisely, we foresee the derivation of such country/region-level CF which can thus then readily be coupled.

4 Conclusion

This study presents a novel and spatially explicit framework for developing characterization factors (CFs) for particular matter removal of less than 2.5 micrometers (i.e. $PM_{2.5}$) associated with forest land use, addressing a key methodological gap identified in current Life Cycle Assessment (LCA) practices. We integrated PM removal modelling (mainly i-Tree model) into land use CF (considered in the LANCA framework used in the PEF) to compute CFs based on dynamic PM flux calculations and vegetation-specific structural parameters. More specifically, PM removal loss CF ($kg \cdot ha^{-1} \cdot yr^{-1}$) are derived as the difference between modelled PM removal of current vegetation and that of potential natural vegetation. Code was written in Google Earth Engine (GEE) to execute that, considering global data. We illustrated the framework for Sweden given its abundant forest and forestry sector, and because it constitutes a selected case study in the CALIMERO project. Our preliminary findings reveal spatial variability in CFs across ecological zones and forest types, driven largely by forest structural heterogeneity. Notably, managed forests, classified as extensive and intensive, often exhibit lower CFs, indicating higher $PM_{2.5}$ removal compared to natural or minimally managed forests. This counterintuitive result is likely due to enhanced turbulent mixing associated with greater z_0 and d values in used forests, as well as their structural discontinuities that may promote deposition efficiency.

The methodological flexibility of our framework—allowing CF estimation based on globally available datasets while also supporting more accurate foreground assessments with high-resolution local data—enables its applicability across a wide range of land use types and geographic regions. Additionally, our approach is scalable and adaptable to agricultural and urban systems by leveraging the a_1 parameter typology proposed by Zhang and He (2014), thus broadening its potential for integrated land use impact modeling.

Importantly, such potentially resulting CFs (notably country-based) are well-suited for integration into emerging regionalized LCA platforms such as RegioInvent, which spatially links life cycle inventory flows to trade-adjusted consumption markets and regionalized LCIA methods. Incorporating our CFs into such tools can significantly enhance the geographic specificity and relevance of air quality-related impact assessments in LCA, enabling a more realistic reflection of land use-based ecosystem services. In fact, the loss in PM removal could be readily translated in human health loss (Disability Adjusted Life Years), by using the mid-to-endpoint factor already used for the PM midpoint category, as for example used in the ReCiPe method.

Future research should focus on improving the ecological representativeness of land use classifications by harmonizing typologies across datasets, refining regional a_1 values, and validating forest management categories using alternative sources such as the EFISCEN Space model. Additionally, more types of PM-vegetation interaction processes should be modelled (PM wash off, dissolution, encapsulation etc.), as e.g., done by Schaubroeck et al. (2014) for wash off. Finally, the complexity of these interactions is still being and should still be further unraveled. Recent empirical and advanced modelling of two forest stands provides some interesting alternative insights (Bignotti et al., 2022). Through these advances, both in modelling, data and understanding, the robustness and policy relevance of CFs for $PM_{2.5}$ removal—and their integration into global sustainability assessments—can be further enhanced.

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