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**FRAMING THE FOREST: ASSESSING CARBON STORAGE
AND SEQUESTRATION USING FOREST SPECIES
EXTRACTION METHODS**

Dissertation supervised by
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DECLARATION OF ORIGINALITY

I declare that the work described in this document is my own and not from someone else. All the assistance I have received from other people is duly acknowledged, and all the sources (published or not published) are referenced.

This work has not been previously evaluated or submitted to NOVA Information Management School or elsewhere.

Prague, November 22, 2023

Luís Monteiro

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RESUMO

As florestas são importantes ecossistemas que oferecem múltiplos serviços de ecossistemas. Desta forma, classificar com precisão espécies florestais é crucial para uma gestão e conservação eficaz das florestas. Este estudo apresenta uma extensa análise dos ecossistemas florestais de Portugal. Inicialmente, foi avaliado o desempenho de diferentes classificadores do Google Earth Engine, utilizando vários algoritmos para extrair espécies e grupos de espécies florestais. O estudo destacou a importância da seleção de algoritmos, enfatizando a eficácia do classificador Support Vector Machine. Posteriormente, foi realizada uma classificação a nível nacional para os períodos de 2018 e 2022, revelando alterações significativas a nível das áreas florestais. Portugal registou uma redução da área florestal total, com uma diminuição de 131,940 hectares. Em 2018, a área florestal total era de 2 711,395 hectares e em 2022 diminuiu para 2,579,455 hectares. Por último, os efeitos espaciais do armazenamento e sequestro de carbono foram investigados. Os resultados mostraram uma diminuição notável de 220 kg/ha na captura de carbono a nível nacional, enquanto que ao nível do NUTS III, as sub-regiões sequestraram uma média de 130 kg/ha. Este estudo contribui com dados importantes para apoiar processos de tomada de decisão, colmatando a lacuna entre a classificação de espécies florestais e a avaliação precisa do seu carbono sequestrado, tendo implicações práticas para a gestão florestal, a conservação da natureza e a avaliação de créditos de carbono.

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ABSTRACT

Forests are critical ecosystems providing multiple ecological services; therefore, accurate species classification is crucial for effective forest management and conservation. This study conducted a comprehensive analysis of Portugal's forest ecosystems. First, the performance of Google Earth Engine classifiers was assessed, employing various algorithms and input configurations to extract main forest species. The study highlighted the importance of algorithm selection, particularly emphasizing the efficacy of the Support Vector Machine classifier. Second, a national-level classification for 2018 to 2022 revealed significant changes in forested areas. Portugal experienced a considerable reduction in total forested area, decreasing by 131,940 hectares. In 2018, the total forested area with the selected species and species groups was 2,711,395 hectares. By 2022, it had diminished to 2,579,455 hectares. The spatial effects of carbon storage and sequestration within these forests were investigated in the third phase. Results showed a notable decrease of 220 kg/ha in carbon capture at the national level. At NUTS III, subregions sequestered an average of 130 kg/ha. This research contributes valuable data for informed decision-making processes, bridging the gap between accurate species classification and precise carbon assessment, having practical implications for forest management strategies, conservation efforts, and carbon credit evaluations.

PALAVRAS-CHAVE

Observação da Terra

Machine-Learning

Espécies florestais

Mapeamento de vegetação

Sequestro de carbono

Serviços de ecossistemas

SDG 12: Consumo e Produção Responsáveis

SDG 13: Ação Contra a Mudança Global do Clima

SDG 15: Vida Terrestre

KEYWORDS

Earth Observation

Machine-Learning

Forest Species

Vegetation Mapping

Carbon Sequestration

Ecosystem Services

SDG 12: Responsible Consumption and Production

SDG 13: Climate Action

SDG 15: Life on Land

ACRONYMS

AGB – Aboveground biomass

ALOS-3 – Global Digital Surface Model dataset - Advanced Land Observing Satellite-3

CART – Classification and Regression Trees

COS18 – Portuguese land use, land cover map for 2018

EO – Earth observation

ES – Ecosystem services

EVI – Enhanced Vegetation Index

GBT – Gradient Boosting Trees

GEE – Google Earth Engine

InVest CSS – InVEST Carbon Storage and Sequestration

K – Kappa coefficient

ML – Machine learning

LULC – Land use and land cover

NDVI – Normalized Difference Vegetation Index

MMU – Minimum mapping unit

MMW – Minimum mapping width

NFI – National Forestry Inventory

NOVA IMS – Nova Information Management School

NUTS – Nomenclature of Territorial Units for Statistics

OA – Overall accuracy

PA – Producer accuracy

RF – Random Forest

ROI – Region of Interest

RS – Remote sensing

S2 – Sentinel-2

SAVI – Soil Adjusted Vegetation Index

SVM – Support Vector Machine

UA – User Accuracy

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1. INTRODUCTION

Forests cover about 4.06 billion ha, encompassing roughly 31% of the world's land surface (FAO, 2022). They are critical ecosystems that provide an array of essential ecological services that contribute to societal well-being, such as carbon sequestration, biodiversity conservation, and water regulation (Anon, 2005; Friedlingstein et al., 2022). Their significance goes beyond their physical expanse and intricate ecological networks. Forests play a pivotal role in sequestering and storing carbon, making their contribution paramount in the fight against climate change (Palmer, 2021). This role has become increasingly crucial as rising global temperatures, extreme weather events, and shifting climate patterns pose significant risks to ecosystems and societies worldwide (Calvin et al., 2023; Pan et al., 2013).

The transition from forests to alternative land uses, primarily propelled by increasing human population and urban sprawl, poses a significant threat nowadays (Fitts et al., 2021). Globally, this issue is of great importance, as data indicates that these land use changes have consistently resulted in higher carbon inputs than corresponding carbon sinks (Houghton, Hall, and Goetz, 2009). Therefore, apprehending the intricate interplay between a forest's carbon content and the accurate delineation of carbon pools stands as a compelling global mandate (Jiang et al., 2022). An urgency pointed out by international commitments, such as the sustainable development objectives posited by the United Nations (Cao et al., 2023). This imperative task emphasizes the necessity for a deeper understanding of the interrelation between carbon cycles and land use changes through comprehensive mapping and monitoring of these intricate dynamics (Mahowald et al., 2017). These efforts are crucial for preserving this vital ecosystem and their significant implications on global climate initiatives.

Carbon accounting studies have assumed a fundamental role in quantifying sequestered carbon over time, offering indispensable insights for policy formulation concerning human-environmental interfaces and adaptive methodologies (Giri et al., 2011). These studies meticulously assess areas where specific land use practices warrant preservation to maintain carbon

reservoirs. Additionally, they discern locales where land use alterations hold the potential to curtail carbon emissions, thereby serving as invaluable tools in strategic environmental planning and management (Narine, Popescu, and Malambo, 2019).

In recent years, the advancement of remote sensing (RS) technology has remarkably bolstered these endeavors. Researchers have leveraged satellite imagery to study forests at various temporal and spatial scales (Calders et al., 2020; Hansen et al., 2013). This approach enhances our understanding of carbon dynamics and provides a comprehensive view of ecosystem changes, allowing for more informed and effective conservation strategies. RS technologies enable the construction of enduring observational datasets, facilitating the assessment of environmental changes over prolonged temporal scales (Tyler et al., 2016). This capability allows for deriving ecologically meaningful information tailored explicitly for monitoring vegetation characteristics and related ecosystem services (ES), such as carbon sequestration, biodiversity conservation, soil erosion prevention, water purification, and recreational opportunities (Holzwarth et al., 2020).

A big challenge in classifying vegetation and forest species from satellite imagery resides in the intricate characteristics of forest ecosystems, the vast diversity of species, and the inherent variability in spectral signatures (Lausch et al., 2018). However, recent technological developments have been helping to extract valuable information related to ecosystem services from forest vegetation. Recent advances in Earth Observation (EO) technologies, such as satellite imaging, LiDAR systems mounted on airborne platforms, and unmanned aerial vehicles (UAVs), coupled with cloud computing platforms, machine learning algorithms (ML), and big data analytics, have offered a wide range of spectral, spatial, and multi-temporal information (Ustin and Middleton, 2021). These cutting-edge technologies allow for the precise extraction of vegetation and forest characteristics, including species composition, canopy structure, aboveground biomass (AGB) estimation, and biodiversity assessment (Lechner, Foody, and Boyd, 2020; Pu, 2021). In fact, by leveraging ML algorithms and cloud-based platforms, researchers can process vast amounts of remotely sensed data quickly and accurately, which

not only facilitates real-time monitoring of forest ecosystems but also provides valuable insights into the vital ecosystem services (Nitoslawski et al., 2021; Scowen et al., 2021).

Within the realm of EO tools, Google Earth Engine (GEE) has emerged as a powerful platform for analyzing and processing extensive satellite datasets (Gorelick et al., 2017). This platform facilitates cloud-based image classifications, enabling the integration of ML algorithms into the classification process. Specifically, GEE's ML-based classification system offers diverse algorithms, serving as the cornerstone for mapping various land covers, including intricate forest areas. ML is a computer-based approach widely used for developing systems capable of learning and solving problems automatically (Mitchell, 1997). Supervised classification employs machine learning methods as alternative algorithms for classifying large-dimensional input data (Hastie, Tibshirani, and Friedman, 2009). These methods utilize training data to instruct the algorithm in object recognition while testing data assesses algorithm performance (Bishop, 2006). Within the GEE platform, a diverse selection of ML algorithms is available, including decision trees, support vector machines, random forests, and deep learning models. These algorithms can categorize pixels to distinguish specific land use and land cover (LULC) classes based on their unique spectral characteristics (Gorelick et al., 2017; Jin et al., 2013). However, it is crucial to acknowledge that each algorithm has strengths and limitations, and the choice of algorithm can significantly influence the accuracy of species classification (Adugna, Xu, and, Fan 2022).

Integrating satellite-derived products with change detection algorithms enhances the precision of environmental monitoring and plays a pivotal role in developing timely and accurate monitoring systems for ES (De Araujo Barbosa, Atkinson, and Dearing, 2015). This integrated approach is critical when estimating the amount of carbon in a landscape related to forest species, offering a comprehensive understanding of how this ES is strongly affected by LULC changes (Cai and Peng, 2021). Moreover, these estimations are vital in the context of social values related to carbon neutralization, underlining the intricate balance between human activities and

environmental sustainability. This progress paves the way for more informed decision-making in environmental protection and sustainable resource management (Han et al., 2022).

Understanding the composition and distribution of forest species is fundamental for effective forest management, conservation planning, and ecosystem health monitoring (White et al., 2016). A rapid and efficient method for precisely mapping and monitoring changes in forest cover over time is crucial to support these management and conservation efforts. Significantly, this process extends to estimating the carbon storage within these forests and assessing the carbon capture potential of a reforestation project (Lefebvre et al., 2021). Accurate assessment of carbon storage not only provides essential data for climate change mitigation strategies and enables the implementation of targeted conservation actions by comprehensively understanding the complex relationship between forest species and carbon dynamics. Advanced modeling tools like the InVEST Carbon Storage and Sequestration (CSS) model (Natural Capital Project, n.d.), with insights into forest composition, empower us to make well-informed decisions. Based on precise carbon estimation, these decisions are central to sustainable land use practices, biodiversity conservation, and environmental resilience (Marvin et al., 2023). Thus, integrating technological innovation and ecological understanding becomes instrumental in preserving our ecosystems and ensuring a sustainable future.

In addressing these challenges, the present study employs a comprehensive approach that uses satellite data and cutting-edge technologies with traditional forestry inventory information. Using the power of cloud computing through GEE and the sophisticated algorithms within the InVEST CSS model, the study explores the intricate spatial patterns of AGB sequestered and stored within Portugal's mainland forest species. The initial phase of the research was dedicated to a systematic comparison and evaluation of various Google Earth Engine (GEE) classifiers. This phase was presented as a paper at the 3rd International Conference on Geospatial Information Sciences (iGISc2023) and is scheduled for publication in Springer's Lecture Notes in Geoinformation and Cartography (LNG&C) series.

In the second phase, the study broadened its scope to cover the entire country, involving mapping diverse forest landscapes and documenting variations in associated species over two distinct periods. This extensive mapping process provided essential input data for the InVEST CSS model, which was utilized in the final part of the study. The second and third parts of the study have been submitted to an international scientific journal for further evaluation and dissemination.

This study contributes to three United Nations Sustainable Development Goals (SDGs). Firstly, in alignment with SDG 15: Life on Land, the research employs advanced technologies such as remote sensing, machine learning algorithms, and cloud computing to map and monitor forest landscapes, providing valuable insights into the composition and distribution of forest species. Secondly, the study addresses SDG 13: Climate Action by emphasizing the pivotal role of forests in carbon sequestration and storage. Using the InVEST Carbon Storage and Sequestration (CSS) model and satellite-derived products, the research enhances the precision of environmental monitoring, offering crucial data for climate change mitigation strategies and supporting informed decision-making in sustainable land use practices. Lastly, about SDG 12: Responsible Consumption and Production, the accurate estimation of carbon storage within Portugal's forest species contributes to responsible consumption and production practices. The study's insights, derived from mapping and monitoring forest dynamics, provide a foundation for sustainable resource management, helping to balance human activities with environmental sustainability and supporting targeted conservation actions.

By combining the strengths of GEE cloud computing capabilities, its embedded classifiers, and the analytical precision of the InVEST CSS model, this study aims to increase our understanding of carbon storage within Portuguese forest key species. Through this multifaceted approach that integrates advanced technology with traditional forestry knowledge, the present study aims to pave the way for informed conservation strategies, sustainable resource management, and a more resilient future for Portugal's forests.

2. MATERIALS AND METHODS

2.1. Study Area

For the present research, the study area corresponds to Portugal's mainland, encompassing nearly 90,000 km² within the Iberian Peninsula in southwestern Europe (Figure 1). Portugal's climate exhibits temperate characteristics influenced by the Atlantic and Mediterranean regions, resulting in cold and wet winters and hot and dry summers.

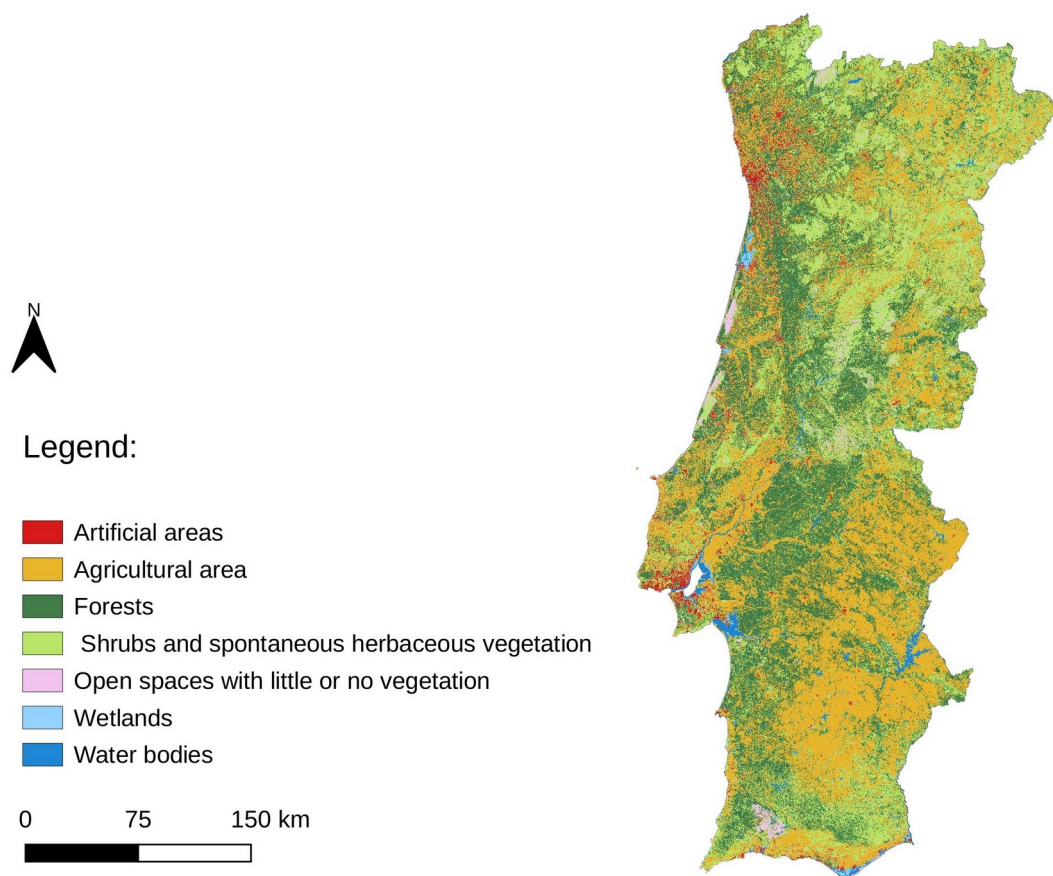


Figure 1: Location of the study area - Land Cover Map of 2018. Source: Direção-Geral do Território (DGT), 2019.

The country's landscape demonstrates notable diversity; the southern region, characterized by water scarcity and higher temperatures, exhibits less exuberant vegetation, contrasting with the more pronounced Atlantic and

Mediterranean climates prevalent in the central and northern regions (Ribeiro, 1998).

The flat terrains of the southern regions accommodate extensive agricultural activities and pastures in agro-forestry systems, featuring sparse evergreen oak trees such as Cork oak (*Quercus suber*) and Holm oak (*Quercus ilex*). Conversely, the central and northern regions, characterized by higher elevations, are marked by smaller landholdings, family-based agriculture, and forests dominated by Stone pine (*Pinus pinea*) and Maritime pine (*Pinus pinaster*) and eucalyptus trees (Cabral and Telles, 2022). Significant disparities in human geography are also present, with notable human settlements concentrated predominantly along the coastal areas, particularly from the capital city of Lisbon and extending northward (Ribeiro, 1998).

Regarding the Nomenclature of Territorial Units for Statistics (NUTS), Portugal mainland is subdivided into 23 subregions that, from 2015, represent the two metropolitan areas, and 19 intermunicipal communities.

2.2. Materials

2.2.1 Satellite Data

Available Sentinel-2 (S2) imagery from 2018 and 2022 was accessed using the GEE platform, filtered by cloud cover, and composited into a single cloud-free to capture the typical annual cycle of natural vegetation and agriculture observed in the study area. The data went through several steps to create high-quality multitemporal composites. First, pixels from images with a reported cloud cover of less than 10%, which are not flagged as cloud or cirrus in the quality assessment band, were chosen, followed by a calculation of the median value of valid observations to generate yearly composites. All bands from S2 imagery were used along with various vegetation/spectral indices and topographic characteristics in datastacks.

The inclusion of spectral indices for classifying forest species was considered highly appropriate to improve the efficiency of image classification tasks due to their established effectiveness in characterizing vegetation in various other

studies (Likó et al., 2022; Montero et al., 2023; Quan et al., 2023). In the present study, the spectral indices employed included the Normalized Difference Vegetation Index (NDVI) (Rouse et al., 1974)) and Enhanced Vegetation Index (EVI) (Huete, Liu, and van Leeuwen, 1997), used to highlight and distinguish vegetation of different types and at various stages of its evolutionary seasonal cycle. Additionally, the Soil Adjusted Vegetation Index (SAVI) (Huete, 1988) was utilized to reduce the impact of soil reflectance and enhance vegetation response. Further, topographic characteristics such as slope and elevation were derived from the Global Digital Surface Model dataset - Advanced Land Observing Satellite-3 (ALOS-3) with a horizontal mesh resolution of approximately 30 meters. The final datastack was composed of 17 bands and used as input features in the supervised image classification process outlined in Part 2.3.

The NDVI was also employed as ground truth data and was independently utilized to restrict the training data on the map, serving as samples in the classification process.

2.2.1 Auxiliary Data

Auxiliary data in the form of reference points representing forest classes were derived from the Portuguese land use and land cover map for 2018 (COS2018), a product developed by the Directorate General for Territory to enhance the accuracy of the classification process. This dataset is available in vector format with a minimum mapping unit (MMU) of 1 ha and a minimum width of linear elements (MMW) of 20 m, and its nomenclature includes more than 80 classes. Therefore, to ensure the compatibility of the map and achieve the study's specific goal of focusing on the most representative forest species, it was necessary to reclassify into seven classes, encompassing both individual species and groups of species.

COS18 served as ground truth data for a stratified sampling approach, and the training samples collected on the 2018 S2 composite were then migrated and employed to classify the 2022 S2 composite. For this, a spectral distance measure was applied to discard samples that exhibited significant changes

between the target (2022) and reference (2018) years to ensure the accuracy of the classification. The classification algorithm benefited from knowing LULC patterns in 2018 with this approach. It applied it to the 2022 imagery, allowing for a robust assessment of land cover changes over time.

Furthermore, carbon density values for AGB within each forest class were extracted from the 6th Portuguese National Forestry Inventory (NFI) (ICNF, 2019). This data served as an essential input for the InVEST CSS Model. Table 1 outlines the seven assessed classes representing mainland Portugal's most prominent forest species, along with their corresponding carbon density values measured in tons per hectare (t/ha).

Forest class name	Description of the class	Carbon density (t/ha)
Cork oak forests	Cork oak including trees in agroforestry systems and other non-forest areas.	89.65
Holm oak forests	Holm oak forest, including trees in agroforestry systems and other non-forest areas.	53.67
Eucalyptus forests	Forests where the dominant species is eucalyptus (<i>Eucalyptus</i> spp.).	83.55
Forests of other broad-leaved	Areas comprising broadleaf tree species, including chestnut tree, carob tree, acacias, and various oak species, excluding cork and holm oaks.	175.08
Maritime pine forests	Forests where the dominant species is maritime pine (<i>Pinus pinaster</i>).	137.56
Stone pine forests	Forests where the dominant species is stone pine (<i>Pinus pinea</i>).	85.71
Forests of other coniferous	Forests are dominated by species of resinous trees that do not belong to the maritime pine class and stone pine.	147.73

Table 1: Name, description, and carbon density of forest classes scheme.

Table 2 provides a concise overview of the datasets details used in the study, listing their names, type of data, sources, and resolution or MMU.

Name	Type	Sources	Resolution/MMU
S2 imagery 2018 – single bands	Raster	European Space Agency (ESA) - GEE	10m
S2 imagery 2018 – spectral indices	Raster	European Space Agency (ESA) - GEE	10m
S2 imagery 2022 – single bands	Raster	European Space Agency (ESA) - GEE	10m
S2 imagery 2022 – spectral indices	Raster	European Space Agency (ESA) - GEE	10m
Global Digital Surface Model (DSM)	Raster	Earth Observation Research Center Japan Aerospace Exploration Agency (JAXA EORC) - GEE	30m
COS2018	Vector	Direção-Geral do Território	1ha
CAOP2022	Vector	Direção-Geral do Território	-

Table 2: Description of datasets utilized in the study.

2.3. Methods

2.3.1 Overview

The methodology is summarized in Figure 2, outlining the comprehensive three-part study. Detailed flowcharts of each phase of the study are presented in Annex B.

During the initial part, a systematic comparison and evaluation of four GEE classifiers, Classification and Regression Trees (CART), Gradient Boosting Trees (GBT), Random Forest (RF), and Support Vector Machine (SVM), was conducted. Using the default GEE parameters, these machine learning algorithms assessed their suitability and accuracy in mapping forest species within a specific Region of Interest (ROI) inside the study area. This analysis aimed to provide invaluable insights into the ML algorithms' strengths, weaknesses, and applicability within the GEE platform. The resulting insights served as the foundation for the second phase of the research, guiding the subsequent investigations.

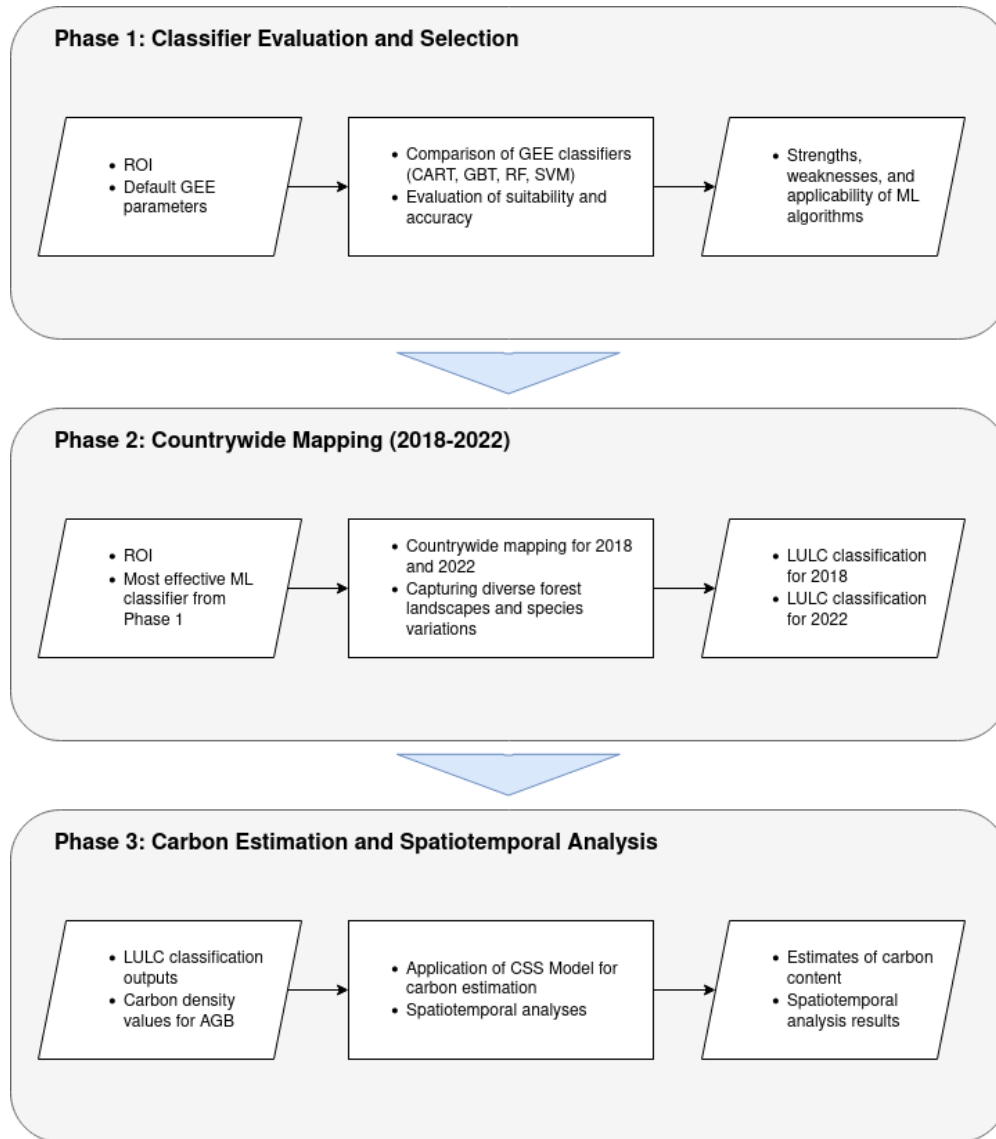


Figure 2: Methodological approach for forest species mapping

In the second phase, an exhaustive mapping of the entire country was performed for 2018 and 2022. This mapping effort meticulously captured the diverse forest landscapes and the corresponding variations in associated species during these two periods. The most effective ML classifier identified in the previous phase was utilized for the classification process. The resulting LULC classification outputs served as crucial input data for the subsequent step, involving the application of the CSS Model.

In the final stage, the study estimated the carbon content sequestered and stored within the Aboveground Biomass (AGB) of the country's forests for the specified periods, employing the CSS Model. Additionally, spatiotemporal

analyses were conducted to ascertain the net change in mean AGB carbon storage and sequestration, analyze the distribution frequency of tree species, and explore potential relationships between carbon storage and tree species.

2.3.2 Spatial Stratification

The Portuguese landscape is a central component of the nation's natural, cultural, and scientific heritage, forming the base of its territorial identity. As a result, the government agency responsible for territorial planning has identified and characterized several landscape units (LU), grouped into categories, based on similar a set of physical characteristics, such as geology, geomorphology, soils, and climate, but also with standard features regarding human occupation (d'Abreu, 2004). Therefore, a spatial stratification procedure was implemented to account for the diverse landscape of Portugal (Figure 3).

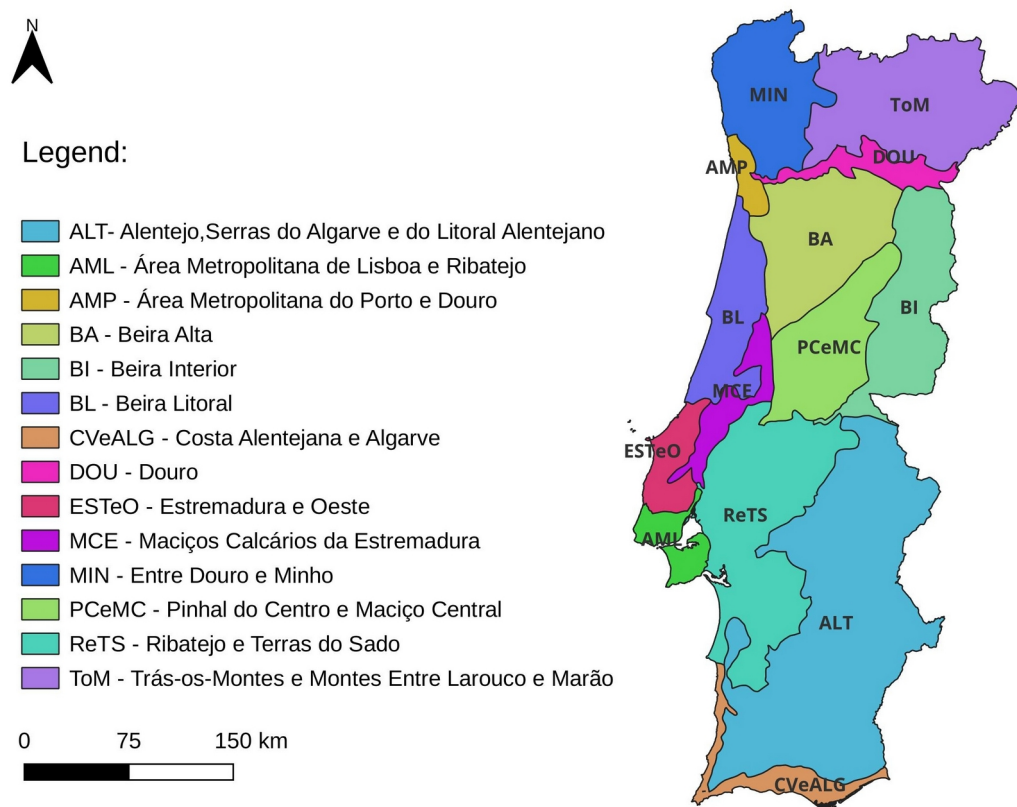


Figure 3: Mapping zones identified by acronyms after spatial stratification. Source: d'Abreu, 2004.

This process involved reclassifying the original landscape units into 14 larger mapping zones created based on environmental factors that influence the distribution of the target forest species. Grouping landscape units into a more extensive zone allows for more effective and efficient image classification processes, as the original landscape units are relatively small (Annex A). Also, the division into a mapping zone concentrated the sampling effort in areas with a higher likelihood of the forest species, leading to a more efficient and accurate national image classification (Cano et al., 2017).

2.3.3 Comparative Analysis of GEE Classifiers for Forest Species Extraction

The choice of employing the four ML learning algorithms - CART, GBT, RF, and SVM - was mainly driven by their diverse capabilities in ensuring accurate forest species classification and addressing the unique challenges of RS data.

- CART is a classification algorithm that utilizes entropy structure, represented by a decision tree, to classify objects based on their inherent characteristics within a given class (Berk, 2016).
- GBT is an ensemble learning algorithm that combines multiple weak prediction models, typically decision trees, to create a robust predictive model. It works by sequentially adding new models that correct the mistakes made by previous models, leading to a highly accurate final prediction. GBT captures complex relationships between features and the target variable (Friedman, 2001).
- RF is a classifier derived from a decision tree that enables multi-classification or regression using an ensemble of multiple decision tree models and is nowadays one of the most used algorithms (Jin et al., 2013). It addresses the limitations of the decision tree algorithm, particularly its sensitivity to training data, by constructing a statistical data ensemble (Breiman, 2001).
- SVM formulates a classification function that successfully separates classes by optimizing a hyperplane based on training data. Critical parameters such as kernel functions, cost parameters, and gamma are crucial in determining the optimal hyperplane for accurate classification (Talukdar et al., 2020).

In GEE, a two-phase approach was developed to improve the accuracy of forest species mapping by filtering out non-forest areas and enabling a more focused analysis of the relevant features.

The initial phase involved a binary classification to distinguish the forest from non-forest pixels, which served as a mask layer for the second phase classification. However, being the main focus of this part solely on the classifiers, an ROI was selected corresponding to the landscape units of Montes entre Larouco e Marão, and Trás-os-Montes, merged into a larger mapping zone (Figure 4). Limiting the research scope to a specific (and smaller) geographic context allowed it to streamline the analysis, ensuring a more targeted and detailed examination of the chosen algorithms' performance.

The first phase employed a binary-class, index-driven, pixel-based classification to detect pixels corresponding to the forest class. Areas identified with relevant vegetation cover, the NDVI were used as a basis for photo interpretation, with pixels values of NDVI greater than 0,6 were selected as representative of vegetated areas, and training points were manually marked on the map (García Del Toro and Más-López, 2019).

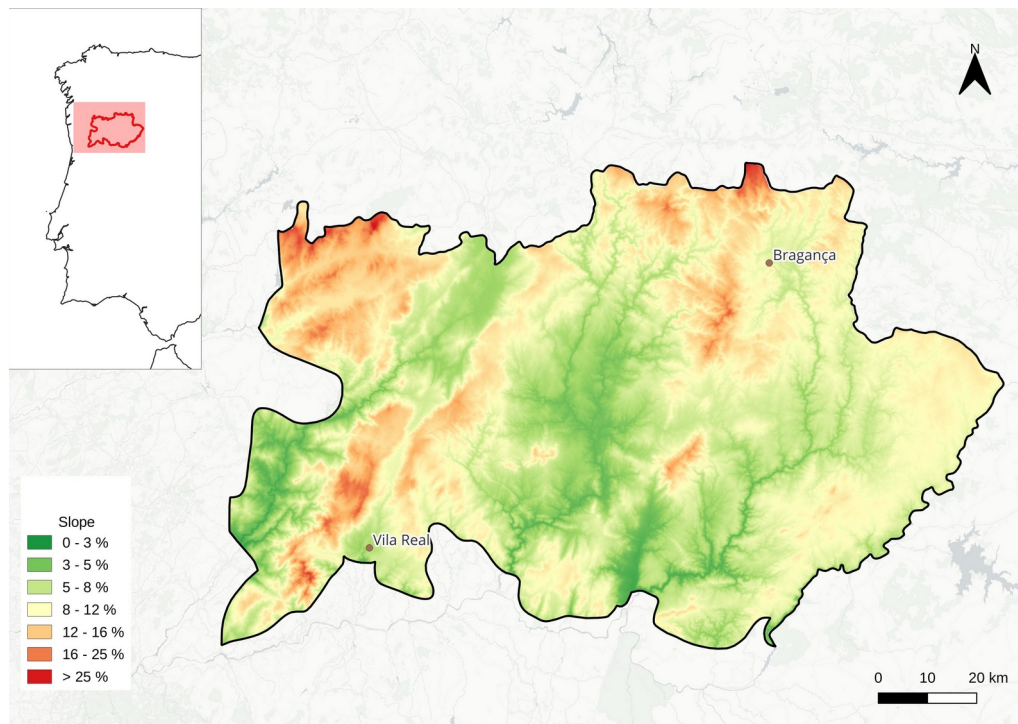


Figure 4: ROI of Montes entre Larouco e Marão, and Trás-os-Montes

One hundred randomly and evenly distributed reference points were placed throughout the map for each class. The drawn points were divided randomly for each class, into 70% for training the classifiers and 30% for map validation.

Lastly, a classification was performed using the data stack, which included bands, indices, and topographic factors, to generate the final map, and the pixels were then classified into either forest or non-forest classes. The output forest layer was then exported from the final map to be used in the second phase of the research of the input features.

In the second stage, a data-driven, pixel-based classification was employed to detect seven forest species classes. The classification was performed only on the pixels of the forest layer identified in the first stage. Also, in this phase,

the mapped forest species reference points were randomly divided into 70% and 30%, respectively, to train and validate the classifiers for each class. The training points were marked on the map over areas corresponding to these classes from the COS2018 dataset. A total of 30 reference points per forest species class were considered, resulting in 210 reference points.

The resulting land cover map was then post-processed to eliminate small, isolated pixels and noise. The necessary accuracy assessments were conducted for each classifier using a stratified random sampling protocol. Validation samples were composed of randomly located points or pixels as sampling units and assessed in GEE. The classification result was then subjected to an accuracy assessment procedure, encompassing the calculation of various metrics such as overall accuracy, confusion matrix, kappa coefficient, and producer and user accuracies for each class.

2.3.4 Nationwide Forest Mapping (2018 and 2022)

The same two-classification-step method was applied for the national forest species mapping - the first phase employed binary classification to map the presence or absence of vegetation in each pixel. By effectively filtering out forests from non-forest areas, the subsequent analysis intended to be better targeted, concentrating solely on the relevant features essential for accurate mapping.

A consistent two-step classification methodology was employed for the national forest species mapping. In the initial phase, binary classification was used to discern the presence or absence of vegetation within each pixel. By meticulously distinguishing forested regions from non-forest areas, this step aimed to create a filtered dataset, concentrating exclusively on pertinent features crucial for precise mapping.

The second phase of the classification focused on a multi-class problem by discriminating between the seven different classes. Both classification steps utilized the pre-prepared datastacks comprising all S2 bands, the spectral indices NDVI, EVI, and SAVI, and the topographic characteristics like slope

and elevation. This comprehensive set of data layers ensured a robust and detailed analysis for accurate classification. These species were identified within the forest pixels recognized during the initial phase of the classification task. For this, the COS2018 dataset was used as ground truth data to define 100 points per class for each of the 14 mapping zones. Then, training points collected for 2018 were used to migrate to the 2022 classification, employing a spectral distance measurement.

In both phases of the research, the SVM algorithm was consistently employed for classification. This choice was informed by the results of the preceding part of the study and the algorithm's ability to effectively handle intricate datasets, especially in distinguishing complex forest features (Ghosh et al., 2014; Shao and Lunetta, 2012; Suess et al., 2015). Furthermore, feature importance and hyperparameter tuning were analyzed to optimize the model and enhance its accuracy. This analysis was pivotal in identifying the most influential features and fine-tuning the classifier parameters for precise classification.

After generating the land cover maps for 2018 and 2022, a post-processing phase was initiated to eliminate small, isolated pixels and noise, enhancing the accuracy and clarity of the output maps.

Lastly, accuracy assessments were conducted, involving the calculation of several key metrics. These metrics included Overall Accuracy (OA), which provides a class-independent measure of accuracy, indicating the general precision of the algorithm. Producer Accuracy (PA) represented how accurately reference sample units were classified. At the same time, User Accuracy (UA) denoted the likelihood that a sample unit assigned to a specific class corresponded to that class on the ground. The Kappa coefficient (K) was also calculated, serving as a statistical measure of agreement and providing an overall evaluation of accuracy.

2.3.4 Assessment of Forest Species Carbon Storage and Sequestered

In the final phase of the study, the resulting land cover maps served as crucial inputs for the InVEST CSS model, allowing for the estimation of carbon storage by forest classes and the amount of carbon sequestered between

2018 and 2022. The model focused entirely on AGB-related carbon values in this study due to data limitations. The model generated detailed carbon storage raster maps for each year, illustrating the carbon sequestered and stored in each pixel. Positive values denoted carbon sequestration, indicating the absorbed carbon amount, while negative values represented carbon loss, signifying the released carbon quantity.

All spatial analyses were meticulously conducted at the NUTS III level to yield valuable insights into carbon dynamics within each subregion. This approach allows for cross-border comparability, enhancing understanding of the ecosystem's carbon balance over time.

3. RESULTS

3.1. Comparative Analysis of GEE Classifiers for Forest Species Extraction

Among the compared classification results, the SVM classifier exhibited the highest overall classification accuracy at 69%, outperforming RF at 63%, GBT at 60%, and CART at 56% (Table 3). Similarly, when considering the kappa coefficient, SVM attained the highest value of 0.62, while RF and GBT achieved 0.54 and 0.52 kappa, respectively, followed by CART with 0.43.

Classifier	OA	PA	UA	Kappa
CART	0.56	0.59	0.59	0.47
GBT	0.60	0.63	0.62	0.53
RF	0.63	0.65	0.63	0.55
SVM	0.69	0.71	0.71	0.62

Table 3: Overall accuracy and kappa coefficient for CART, GBT, RF, and SVM classifiers.

Analysis of producer and user accuracies highlighted the varying performance of different classes across different classifiers, with certain classes exhibiting high accuracy rates. In contrast, others show variations depending on the classifier used. Among all the classified classes, the Other Broadleaved class consistently achieved the highest user accuracy across most classifiers. Specifically, CART yielded a user accuracy of 73%, GBT achieved 69%, and SVM achieved 91%. However, the RF classifier showed a slightly different pattern, with the highest user accuracy of 80% observed for the Cork and Holm oak classes. On the other hand, the Eucalyptus class performed consistently poorly across all classification algorithms, with the lowest user accuracy (CART – 48%, GBT – 53%, RF – 53%, SVM – 56%).

When considering the producer accuracy, the distribution of high and low accuracy rates across classes showed more dispersion. Specifically, for both CART and SVM classifiers, the Other coniferous class showcased the highest producer accuracy, reaching 83%. The GBT classifier achieved a slightly

lower producer accuracy of 79% for the other broadleaves class. In the case of RF, the Cork and Holm oak classes demonstrated a producer accuracy of 75% and 73%, respectively. The classes with the lowest producer accuracy were stone pine for GBT (37%) and SVM (53%) and maritime pine for CART (33%) and RF SVM (47%).

Compared with other outputs, the CART classifier tended to overestimate the number of pixels classified as maritime pine in the northwest region of the image, which predominantly consisted of eucalyptus and other broadleaves with scattered beech stands. The classification images also exhibited a minor salt-and-pepper effect attributed to the shadows of trees within the forest (Figure 5).

Table 4 showcases the estimated abundances of classified forest species in the study area derived from the outputs of the evaluated classification algorithms.

Class	CART (ha)	GBT (ha)	RF (ha)	SVM (ha)
Eucalyptus	45.03	66.76	68.12	72.64
Other broadleaves	7.63	7.53	8.40	3.79
Cork oak	18.95	8.58	8.02	9.36
Holm oak	17.80	8.95	8.25	9.10
Other coniferous	6.32	3.23	3.35	3.10
Maritime Pine	16.64	9.75	9.42	8.45
Stone Pine	5.42	4.16	2.70	2.67

Table 4: Forest species classes extent based on CART, GBT, RF, and SVM classification

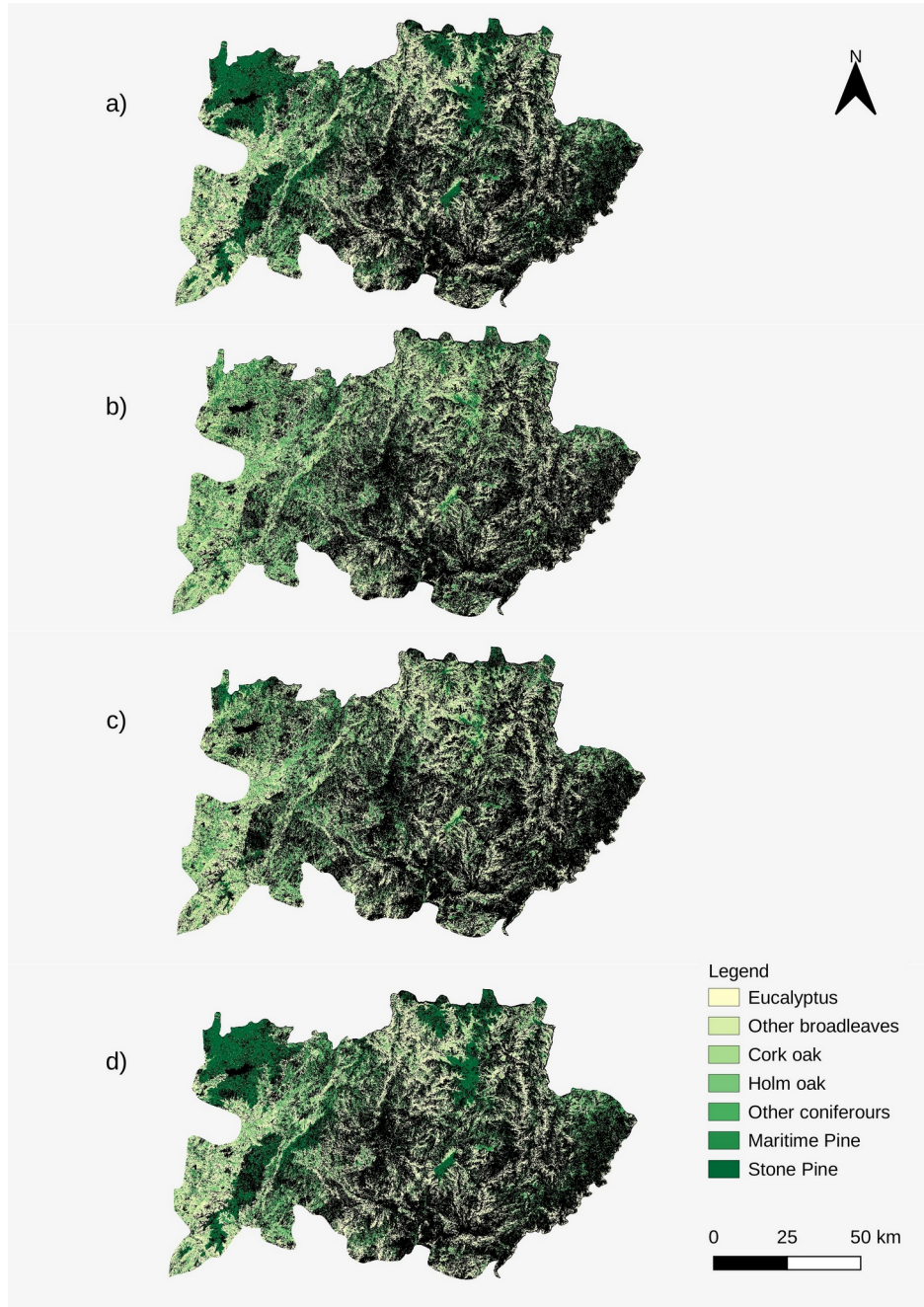


Figure 5: Figure 5: Classification of output images using CART (a), GBT (b), RF (c), and SVM (d) classifiers. (Color black symbolizes masked areas – non-forest vegetation).

3.2. Nationwide Forest Mapping (2018 and 2022)

For the national-level forest species classification, the composite for the year 2018 was derived from 1183 images. By 2022, 1175 images precisely met the filter criteria for the analysis.

Changes in forest land cover classes from 2018 to 2022 are meticulously detailed in Table 5. In 2018, the total forested area with the selected species and groups of species on Portugal's mainland was 2,711,395 hectares. By 2022, this area had decreased to 2,579,455 hectares, reducing the total forested area by 131,940. These results translate to a loss change rate of approximately 32,985 hectares annually. The classified LULC maps for forest species in 2018 and 2019 can be located in Annex C.

Cork oak forest exhibited a marginal decrease from 15.98% to 16.65%, accompanied by a corresponding reduction in area measurements. Conversely, the Holm oak class displayed a slight increase from 16.14% to 16.96%, with minimal changes in its spatial extent. While experiencing an increase in annual percentage change, the eucalyptus class witnessed a notable change in its area from 2018 to 2022, with a reduction in both hectares. The forests of other Broad-leaved showcased a modest alteration from 16.15% to 16.39%, reflective of changes in the landscape composition. Notably, the Stone Pine and Maritime Pine classes both underwent considerable transformations, with Stone Pine declining from 16.54% to 14.92% (accompanied by an annual change of -14.14%) and Maritime Pine from 5.06% to 4.72% (with an annual change of -11.30%), each marked by substantial decreases in their spatial extent.

The Other Coniferous class also demonstrated a marginal change from 0.72% to 0.67%, emphasizing the nuanced shifts in land cover dynamics, resulting in an annual change of -11.21%.

Forest class name	Area (ha) 2018	Area (ha) 2022	Percentage 2018	Percentage 2022	Annual % Change
Cork oak forests	433231.32	429610.63	15.98	16.65	-0.84
Holm oak forests	437560.20	437390.29	16.14	16.96	-0.04
Eucalyptus forests	797594.71	765556.04	29.42	29.68	-4.02
Forests of other broad-leaved	437810.10	422818.67	16.15	16.39	-3.42
Maritime pine forests	448391.12	384968.93	16.54	14.92	-14.14
Stone pine forests	137233.69	121730.14	5.06	4.72	-11.30
Forests of other coniferous	19608.96	17410.81	0.72	0.67	-11.21
Total	271143.01	257948.55	100.00	100.00	-

Table 5: Land Cover Changes and Dynamics of Forest Classes (2018 and 2022).

As for the accuracy assessment, results for classifying forest species in 2018 and 2022 provide valuable insights into the classifier's performance (Table 6). In 2018, the overall accuracy stood at 71.01%, with Producers Accuracy at 68.61% and Users Accuracy at 70.21%, resulting in a Kappa coefficient of 0.68. Regarding 2022, the classification maintained a high overall accuracy of 72.23%, while Producers Accuracy slightly decreased to 67.21%, Users Accuracy to 69.85%, and the Kappa coefficient to 0.67.

LULC	Overall accuracy (%)	Producers accuracy (%)	Users accuracy (%)	Kappa
2018	71.01	68.61	70.21	0.68
2022	72.23	67.21	69.85	0.67

Table 6: Comparison of Land Use and Land Cover Classification Accuracy (2018 and 2022) - Overall Accuracy (OA)%, User's Accuracy (UA)%, Producer's Accuracy (PA)%.

3.3. Assessment of Forest Species Carbon Storage and Sequestered

Due to the decrease in the total forested area from 2018 to 2022, there has been a reduction in the Aboveground Biomass (AGB) stock, impacting the amount of carbon sequestered and stored. Nationally, between 2018 and 2022, Portugal experienced a decline in the carbon captured by forest ecosystems, amounting to 0.22 tons per hectare (220 kilograms per hectare). This decline in biological carbon is attributed to the diminishing AGB density, manifested through negative net changes in the total forest area over time.

Detailed maps for 2018 and 2022, depicting the outputs of the InVEST Carbon model, can be found in Annex D. These maps provide a comprehensive visual representation of the carbon dynamics, offering valuable insights into the changes in carbon sequestration patterns over the specified period.

When examining the results at the NUTS III level, it was found that Portugal sequestered an average of 0.13 tons per hectare (130 kg/ha) of carbon within each subregion. This output implies an increase in mean AGB stock estimated by the subregion at 32.5 kg/ha per year. Figure 6 illustrates the net changes (in tons per hectare) of mean AGB carbon sequestered by forest ecosystems in each subregion. These subregions are identified by their respective NUTS III codes (Annex F). Out of the 23 subregions analyzed, six experienced a decline in captured carbon, whereas 17 demonstrated positive carbon sequestration between the study years. The subregions that witnessed a decline in carbon capture over time include 184 (Baixo Alentejo), 150 (Algarve), 187 (Alentejo Central), 16H (Beira Baixa), 186 (Alto Alentejo), and 181 (Alentejo Litoral).

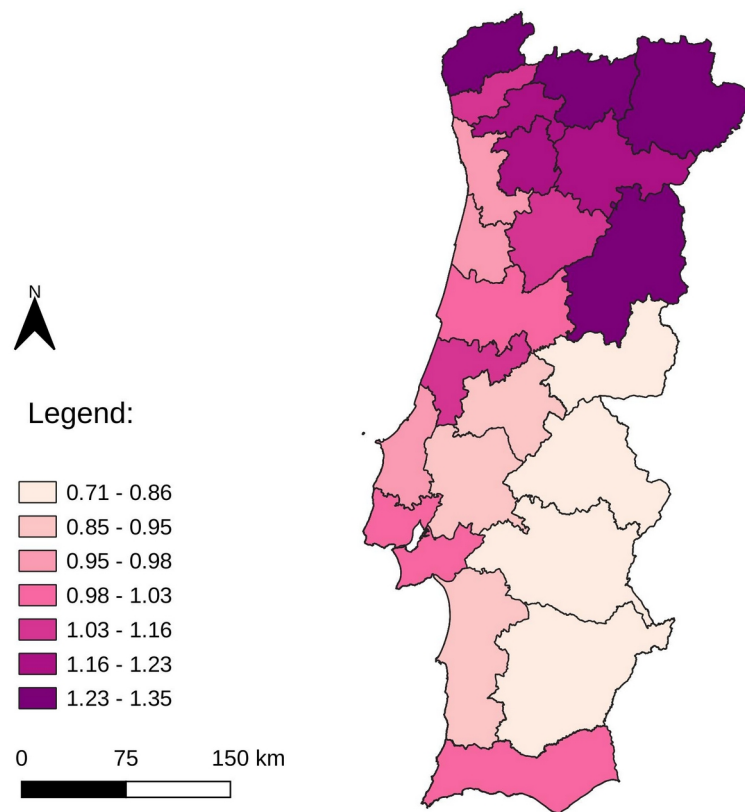


Figure 6: Average AGB carbon sequestration across NUTS III subregions (2018 and 2022).

The sequestration and storage of biological carbon are intricately linked to the frequency distribution of tree species within each subregion, as illustrated in Figure 7. By meticulously comparing this data with the six flagged subregions that demonstrated a lack of carbon sequestration between 2018 and 2022, it becomes feasible to discern the specific tree species accountable for this observed decline. This analysis delves into the nuanced interplay between regional vegetation dynamics and carbon sequestration patterns, shedding light on the pivotal role of tree-species composition in shaping carbon balance within diverse ecosystems Annex F.

The analysis shows that the distribution of Stone pine, Maritime pine, and Other coniferous Forests declined, while Holm oak increased across these six subregions.

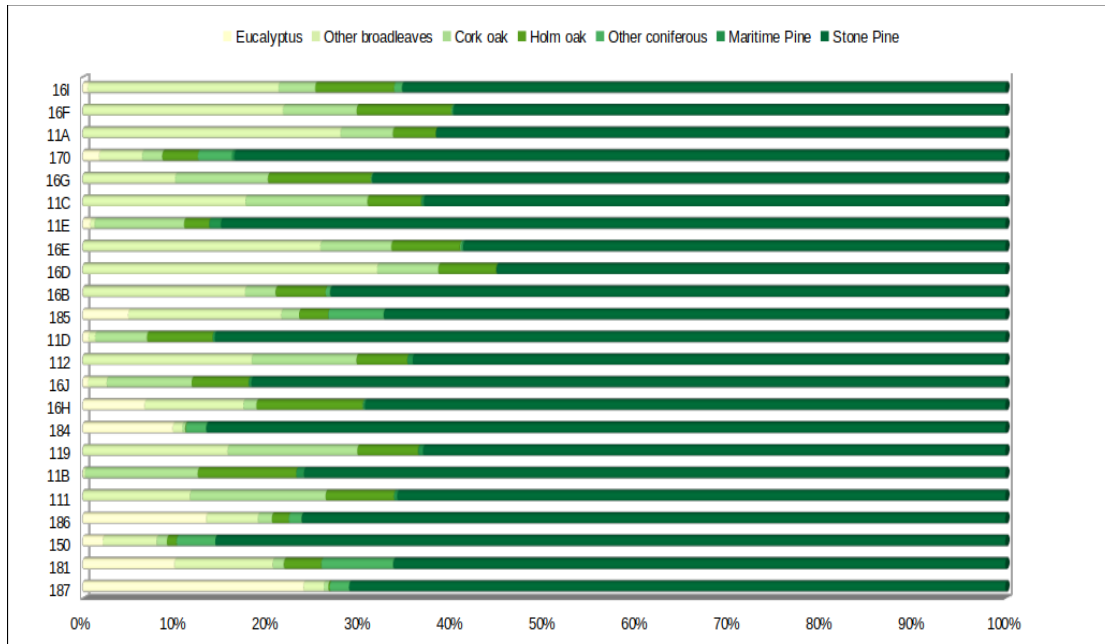


Figure 7: Average tree species frequency distribution across NUTS III subregions (2018 and 2022).

Other Broadleaves Forests expanded in all subregions except in Algarve and Alentejo Litoral. Eucalyptus Forests decreased across all subregions except in Algarve and Beira Baixa. A Pearson correlation was computed for the study years to demonstrate the relationship between the captured and stored carbon amounts and tree species at the NUTS III level, as illustrated in Figure 8.

The analysis revealed a robust positive correlation between carbon storage and Other Broadleaves and a similarly strong positive correlation with Other Coniferous and Stone Pine Forests. Conversely, there is a significant negative correlation with Holm oak, and negative correlations are observed for Cork oak and Maritime Pine, while Eucalyptus exhibits a comparatively lower correlation. Notably, the relationship between carbon storage and tree species evolved over the studied period.

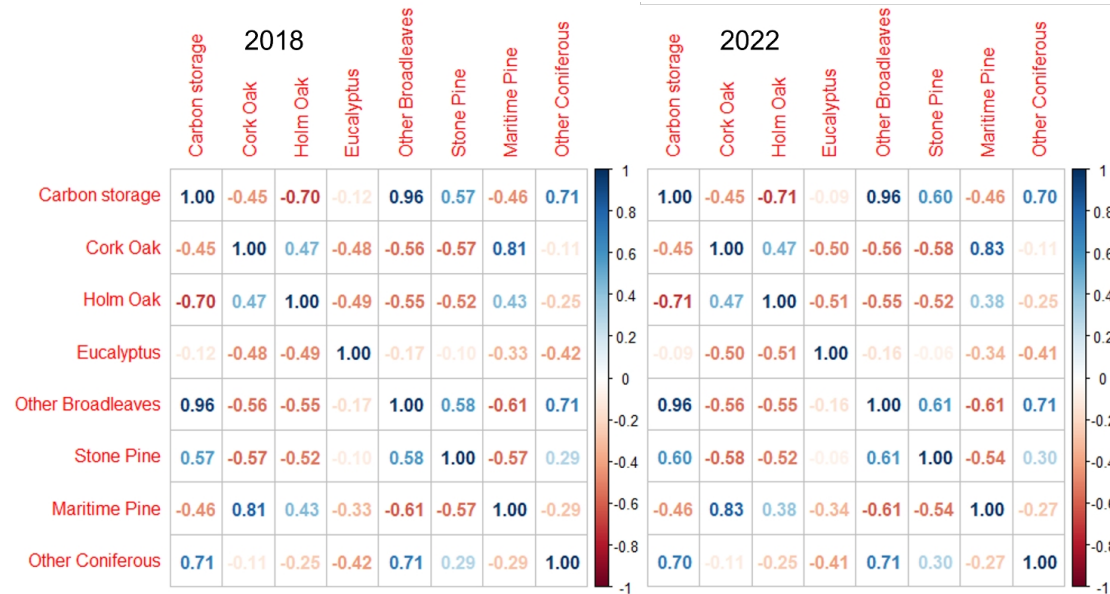


Figure 8: Pearson's correlation analysis (2018 and 2022) between carbon storage and tree species distribution at NUTS III level.

Between 2018 and 2022, positive associations strengthened for Holm oak and Stone pine, whereas they weakened for Eucalyptus and Other Coniferous species. Within specific species, Cork Oak demonstrated a notable correlation with Maritime Pine Forests, and Other Broadleaves exhibited a strong correlation with Other Coniferous Forests.

4. DISCUSSION

Forests play a vital role in providing multiple ES, highlighting the significance of accurate classification for effective forest management and conservation. Recent advances in RS, advanced decision systems, and geoinformation technologies are transforming the assessment of forest species, enhancing the ability to evaluate and manage environmental resources more effectively (Pandey and Arellano, 2022).

In the contemporary landscape of geospatial research, GEE stands as a prominent cloud-based analysis and modeling platform, assuming a pivotal role, especially in the domain of LULC classification. Its capabilities empower researchers by providing a vital tool for conducting intricate and precise geospatial analyses, pushing the boundaries of scientific understanding (Tamiminia et al., 2020). As an initial step, this study aimed to demonstrate the platform's effectiveness in accurately mapping and classifying forest species in Portugal, focusing on its classifiers.

Four distinct algorithms were evaluated, leveraging a combination of S2 bands, specific vegetation indices, and topographic characteristics as input features. Identical training and testing datasets were utilized across all classifiers to ensure unbiased evaluations. Among these algorithms, SVM emerged as the standout performer, consistently achieving the highest accuracies. This outcome not only corroborates earlier research but also underscores SVM's prowess in effectively tackling intricate challenges related to the classification of complex forest species (Ghosh et al., 2014; Shao and Lunetta, 2012; Suess et al., 2015).

Previous research has shown similar performance levels between SVM and RF classifiers (Ballanti et al., 2016). While both classifiers have displayed high accuracy in various studies, our research yielded superior results with the SVM classifier. This discrepancy might be attributed to the fact that RF classifiers typically excel when provided with many instances, enabling them to effectively utilize their randomization concept and generalize well to new data (Raczko and Zagajewski, 2017). Given our emphasis on multispectral

data and limited sample size per class in this study, the SVM classifier demonstrated superior performance.

The lower accuracies observed for CART and GBT classifications can be attributed to their sensitivity to variations or outliers in the data, leading to decreased accuracy compared to SVM and RF classifiers (Breiman, 2001). In this study, special attention was given to the quality and relevance of input features, employing meticulous feature selection and engineering techniques to enhance the attributes' discriminative power. These efforts aimed to ensure a more accurate representation of the underlying patterns in the data, potentially contributing to the superior performance of SVM and RF classifiers.

The relatively lower accuracies observed in CART and GBT classifications can be attributed to their heightened sensitivity to data variations and outliers. This sensitivity often leads to decreased accuracy compared to the more robust SVM and RF classifiers (Breiman, 2001). SVM and RF classifiers are recognized for their resilience in overcoming these challenges, exhibiting lower sensitivity in the face of data variations. While RF demonstrates impressive parameter resilience, SVM is slightly more sensitive to hyperparameters (Basheer et al., 2022). Moreover, the specific distribution and characteristics of the dataset used in this study might have favored SVM and RF classifiers. These classifiers excel in scenarios with non-linear or complex decision boundaries, allowing them to adapt more effectively to the inherent complexities of the data (Mitchell, 1997).

The relevance of selected features cannot be overstated, as it profoundly impacts the outcomes of the classifier. In this study, there may have been better choices than the 18-band data stack for CART and GBT algorithms. It is possible that this number of input bands failed to capture crucial spectral information necessary for the algorithms to differentiate between classes effectively. This insight underscores the significance of thoughtful feature selection, aligning with the findings of Zhang and Roy (2017), who emphasized the importance of carefully selecting relevant bands tailored specifically for classification purposes. Therefore, future research efforts should prioritize the refinement of feature selection processes. Ensuring the inclusion of pertinent spectral information is essential, as it enhances the

classifiers' capacity to make precise distinctions between diverse classes. These investigations are pivotal in guiding more informed decisions when selecting the optimal platform and algorithm combinations.

When analyzing the national-level classification results from 2018 to 2022, Portugal experienced a significant reduction in total forested area, decreasing by 131,940 hectares. In 2018, the total forested area with the selected species and species groups was 2,711,395 hectares; by 2022, it had diminished to 2,579,455 hectares. These findings align closely with those reported in various studies, despite a slight underestimation by the GEE classification compared to the data published by the Global Forest Watch (Hansen et al., 2013). This discrepancy can be attributed to the rich diversity within the Portuguese forest landscape, extending beyond the specific forest species chosen for this study. These key species were selected based on the available data in the Portuguese National Forestry Inventory. While the study did not aim to encompass the entire forest diversity, incorporating a more comprehensive range of species in future assessments is crucial for accurately representing the nation's forest resources. Expanding species selection in future studies can enable a more nuanced and precise understanding of Portugal's forests. This enhanced insight can facilitate more informed decision-making in forestry management and environmental conservation and contribute significantly to our understanding of the dynamic nature of forest ecosystems.

The relatively high accuracy achieved in forest species classification demonstrates the effectiveness of combining multispectral images with other auxiliary data, presenting a novel approach significantly enhancing tree species classification accuracy. This finding is further supported by the study conducted by You et al. (2022). The authors used S2 images to extract spectral reflectance, indices, texture, phenological data, and additional variables like topography, precipitation, air temperature, ultraviolet aerosol index, and NO₂ concentration. Employing feature combination and optimization techniques, the authors developed forest tree species classification maps utilizing various GEE algorithms.

An essential factor contributing to the high-quality results of the classifications was spatial stratification, involving mapping zone definitions and multiple stages of analysis and mapping. This approach, tailored to the diverse Portuguese landscape, facilitated the implementation of customized procedures, including specific training datasets. Such methods have demonstrated significantly improved classification accuracy in numerous studies incorporating spatial domain divisions (Cano et al., 2017; Inglada et al., 2017).

Implementing a two-stage procedure for forest species mapping also aimed to enhance the quality of classification outputs. Initially, a binary and a multi-class approach were tested and compared in the first stage of the method to extract the forest layer. The comparison revealed slight differences, with the multi-class classifier showing lower accuracy and more misclassifications. A similar approach was employed by Tarantino et al. (2021), who used an intra-annual time series of S2 and embedded phenology in the first stage to extract the grassland layer as a pre-filter. In the second stage, the focus shifted to specific grassland habitats.

At the national scale, there was a decline in Portugal's forest ecosystems' carbon capture, dropping by 220 kg/ha between 2018 and 2022. The average carbon sequestration within the NUTS III regions was 130 kg/ha. However, these figures are likely underestimated due to classification inaccuracies, a concern illuminated by Cunha et al. (2021). Their analysis of intervention scenarios using the InVEST Carbon Model underscored the limitations of the CSS model in simplifying the earth's carbon cycle and assuming a linear change in carbon storage over time. Consequently, the precision of the outputs is intricately linked to the accuracy of the LULC classification and the supplied carbon pool values, both of which exhibit variations within the data source.

Regarding the complex interplay between tree species and carbon storage, there was a robust positive correlation between carbon storage and Other Broadleaves and Other Coniferous and Stone Pine Forests. It is worth mentioning that the high carbon storage observed in Other Broadleaves can be linked to the elevated carbon values found in chestnut trees and acacias

within this forest class (ICNF, 2019). This finding aligns with the concept that the composition of tree species within a forest type significantly influences its carbon storage potential, highlighting the need for a nuanced understanding of species-specific contributions to carbon sequestration. Similar patterns have been observed in related studies, underscoring the intricate interplay between tree species composition and carbon storage dynamics in forest ecosystems (Gebrewahid and Meressa, 2020; Hüblová, 2021; Sun and Liu, 2020). Research by Hüblová and Frouz (2021) emphasized the influence of tree diversity on carbon sequestration, highlighting similar positive correlations with specific broadleaves and coniferous species. Additionally, Chen et al. (2019) discussed the spatial-temporal variability in carbon storage patterns in forest ecosystems, mirroring our observation of evolving associations over time.

5. CONCLUSIONS

This extensive research endeavor developed an innovative methodology to create a comprehensive land cover map of varied forest species across mainland Portugal and evaluate their carbon storage capacity. The study focused on seven distinct forest species categories in 2018 and 2022. It involved several stages, including evaluating GEE classifiers, national forest classification for specific years, and using the InVEST Carbon Model.

Foundational to the entire study, high-resolution imagery captured at a 10-meter resolution from the S2 sensor, auxiliary datasets, supervised image classification, and post-classification analysis were employed. Spatial stratification into mapping zones and subzones, coupled with knowledge-based rules, enhanced the map's accuracy, overcoming challenges faced in previous studies related to mapping complex landscapes like Portugal.

The study's evaluation of classifiers underscored the performance of the SVM algorithm in classifying complex forest species. Despite comparable performance levels between SVM and RF classifiers reported in previous research, this study's emphasis on multispectral data and the limited sample size per class favored SVM, highlighting its effectiveness in this specific context. The results obtained with SVM have led to its consideration for the next phase of the national forest classification.

Furthermore, the national forest classification from 2018 to 2022 unveiled a significant reduction in Portugal's total forested area, declining by 131,940 hectares. The study produced a highly detailed land cover map, exhibiting accuracy rates of 71.01% for the 2018 classification and 72.23% for 2022. This thematic classification is crucial for applications requiring high thematic precision, and the map's versatility was evident with high accuracy when considering a reduced number of land cover classes.

Furthermore, this study integrated the InVEST Carbon Model, enabling a nuanced exploration of the relationship between tree species composition and carbon storage within Portugal's forest ecosystems. Despite limitations, the analysis revealed some correlations between carbon storage and specific

forest classes such as Other Broadleaves, Other Coniferous, and Stone Pine Forests. Significant trends emerged at the national level, indicating a decline of 220 kg/ha in carbon capture by Portugal's forest ecosystems between 2018 and 2022. At the subregion level (NUTS III), each area sequestered an average of 130 kg/ha, highlighting regional disparities.

The implications of this study extend beyond scientific understanding, with potential applications in crucial areas such as wildfire prevention, nature conservation, and water management. By leveraging innovative remote sensing techniques, advanced modeling approaches, and local expertise, this research significantly contributes to the knowledge base of Portugal's land cover and forest dynamics. The study's methodology, designed to be flexible and adaptable, can serve as a blueprint for mapping land cover in other countries, provided the local landscape structure and dynamics are accurately reflected in mapping zones and subzones. Through this holistic approach, the study not only enriches our comprehension of Portugal's natural landscapes but also offers valuable insights into sustainable environmental management practices worldwide.

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ANNEXES

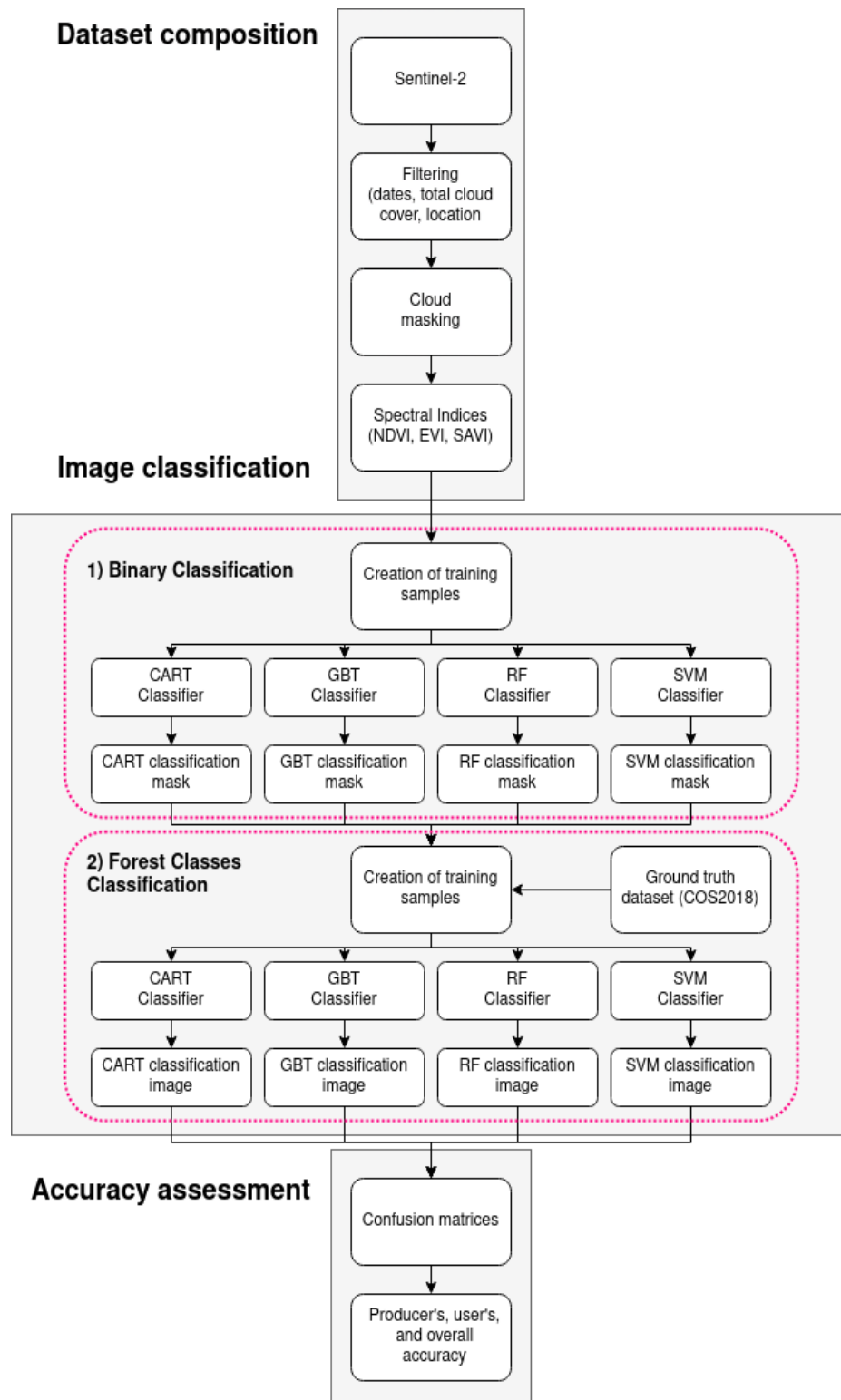
Annex A – Reclassification of Landscape Units

Name	Area (m)	Area (ha)	UniPais. reclassified
Trás-os-Montes	8313709787	831370.98	1
Montes Entre Larouco e Marão	4144120580	414412.06	1
Entre Douro e Minho	7316759775	731675.98	2
Douro	7209537984	720953.80	3
Área Metropolitana do Porto	1932991887	193299.19	4
Área Metropolitana do Porto + Douro	6358080635	635808.06	4
Beira Litoral	1639876111	163987.61	5
Beira Alta	58009052.46	5800.91	6
Beira Interior	7922052499	792205.25	7
Pinhal do Centro	4014795065	401479.51	8
Maciço Central	2075111413	207511.14	9
Maciços Calcários da Estremadura	2089380541	208938.05	9
Ribatejo	6370834863	637083.49	10
Terras do Sado	7428701023	742870.10	11
Alto Alentejo	4812673811	481267.38	11
Baixo Alentejo	5310504072	531050.41	12
Alentejo Central	846221499	84622.15	12
Serras do Algarve e do Litoral Alentejano; Baixo Alentejo	34463633	3446.36	12
Serras do Algarve e do Litoral Alentejano	2178733659	217873.37	12
Costa Alentejana e Sudoeste Vicentino	4445727518	444572.75	12
Costa Alentejana e Sudoeste Vicentino; Algarve	553849099.2	55384.91	13
Algarve	57590170.7	5759.02	13
Ribatejo; Área Metropolitana de Lisboa - Norte	86256055.67	8625.61	13
Área Metropolitana de Lisboa - Sul	786354327.9	78635.43	15

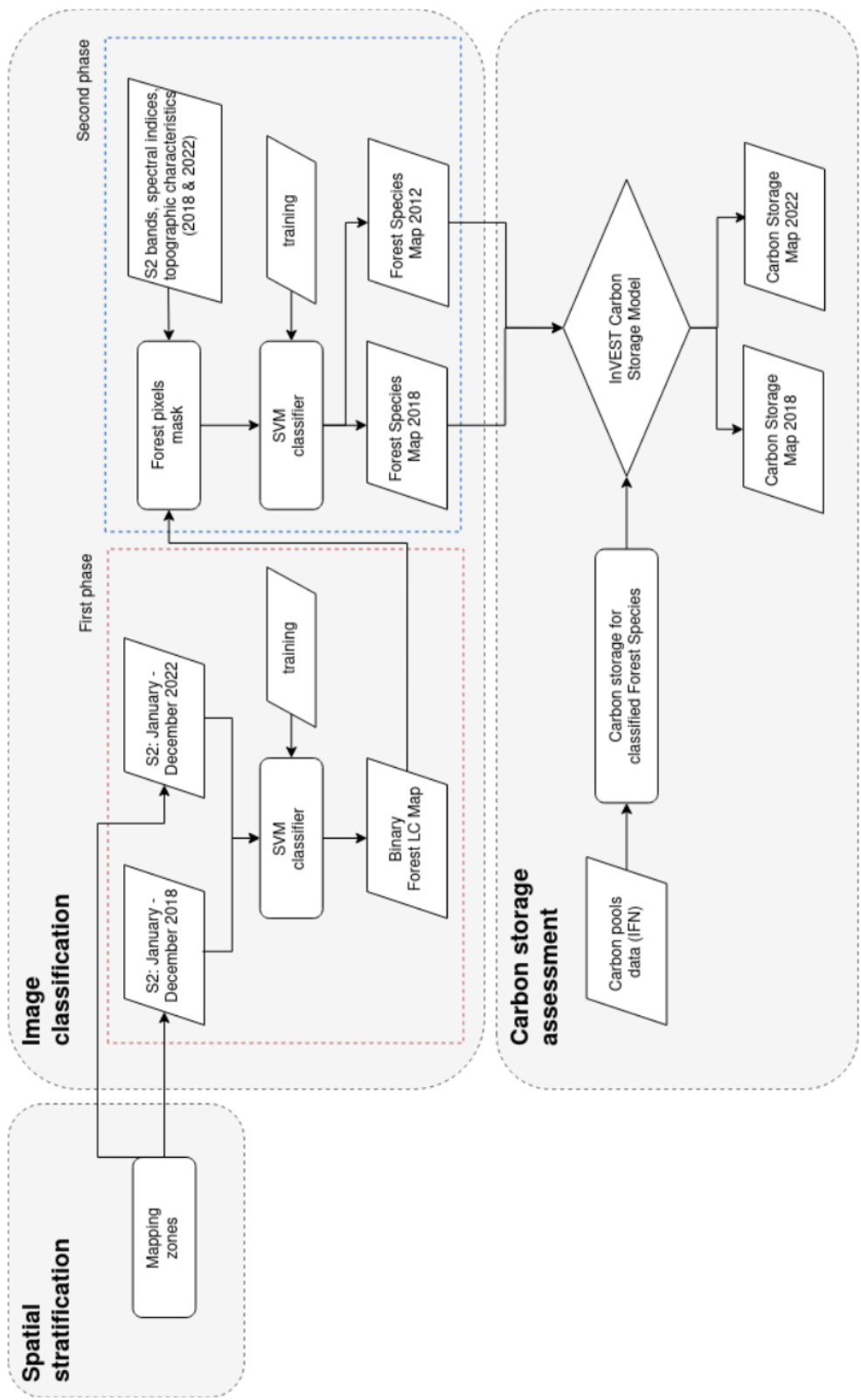
Área Metropolitana de Lisboa - Norte	2159386032	215938.60	15
Estremadura - Oeste; Área Metropolitana de Lisboa - Norte	644287548.6	64428.75	15
Estremadura - Oeste	109864587.4	10986.46	14

Annex B – Research flowcharts

Flochart of comparative analysis of GEE classifiers for forest species extraction

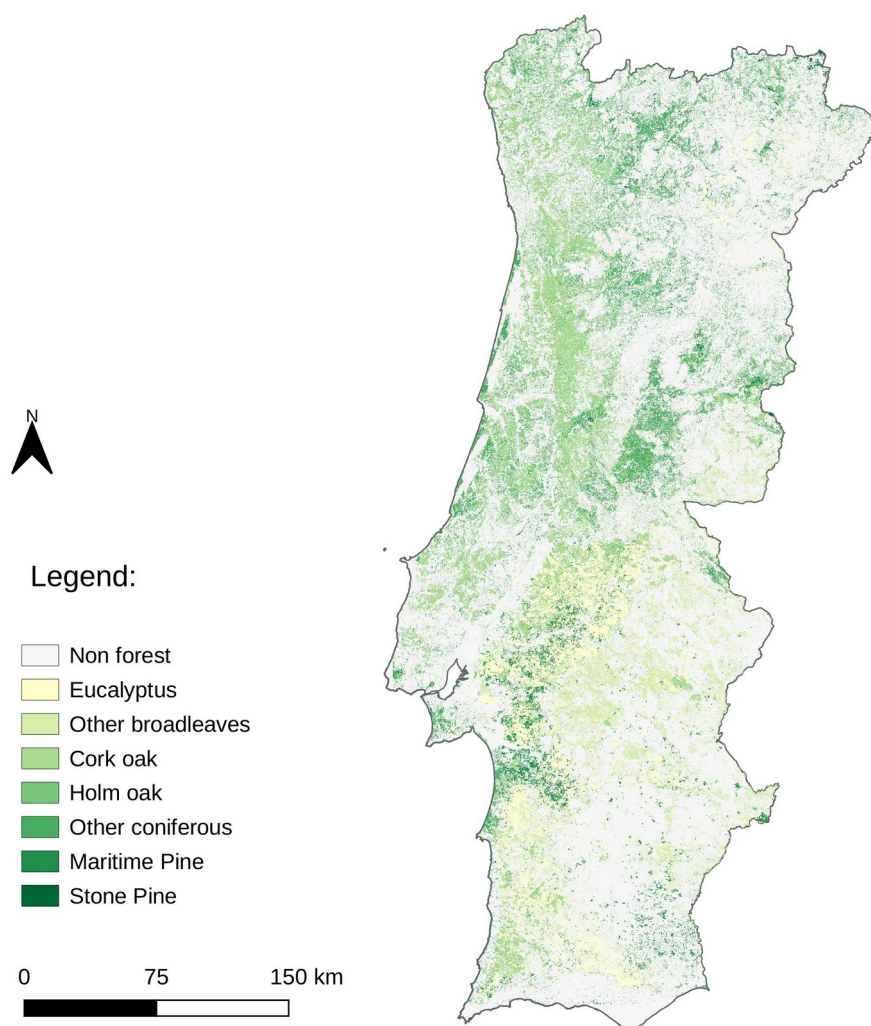


Flochart of Nationwide Forest Mapping (2018 and 2022) and InVEST Carbon Model

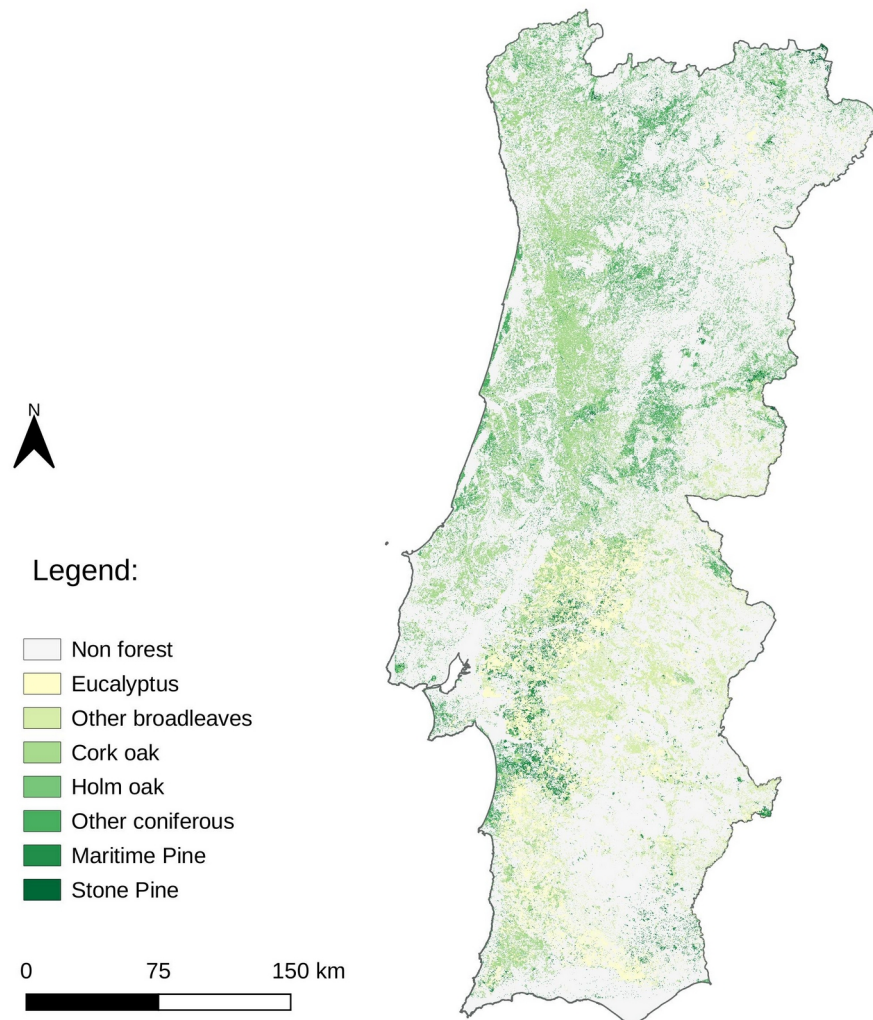


Annex C – Nationwide Forest Mapping Map (2018 and 2022)

Forest map for 2018

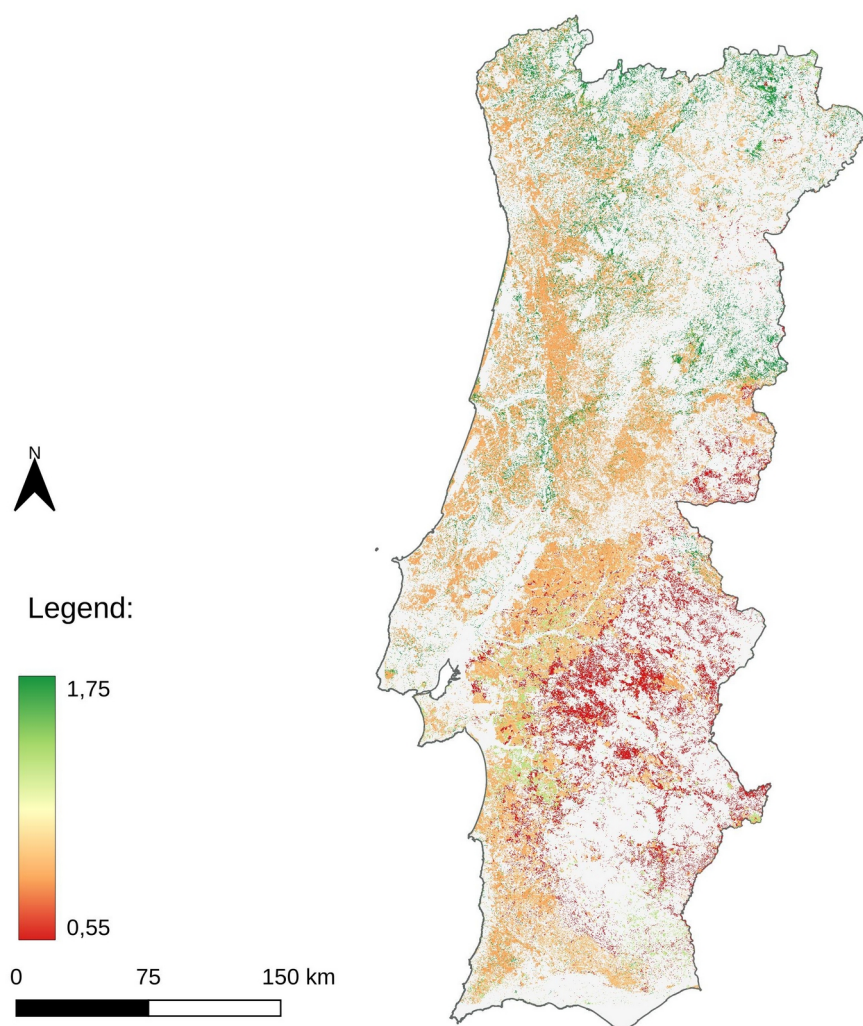


Forest map for 2022

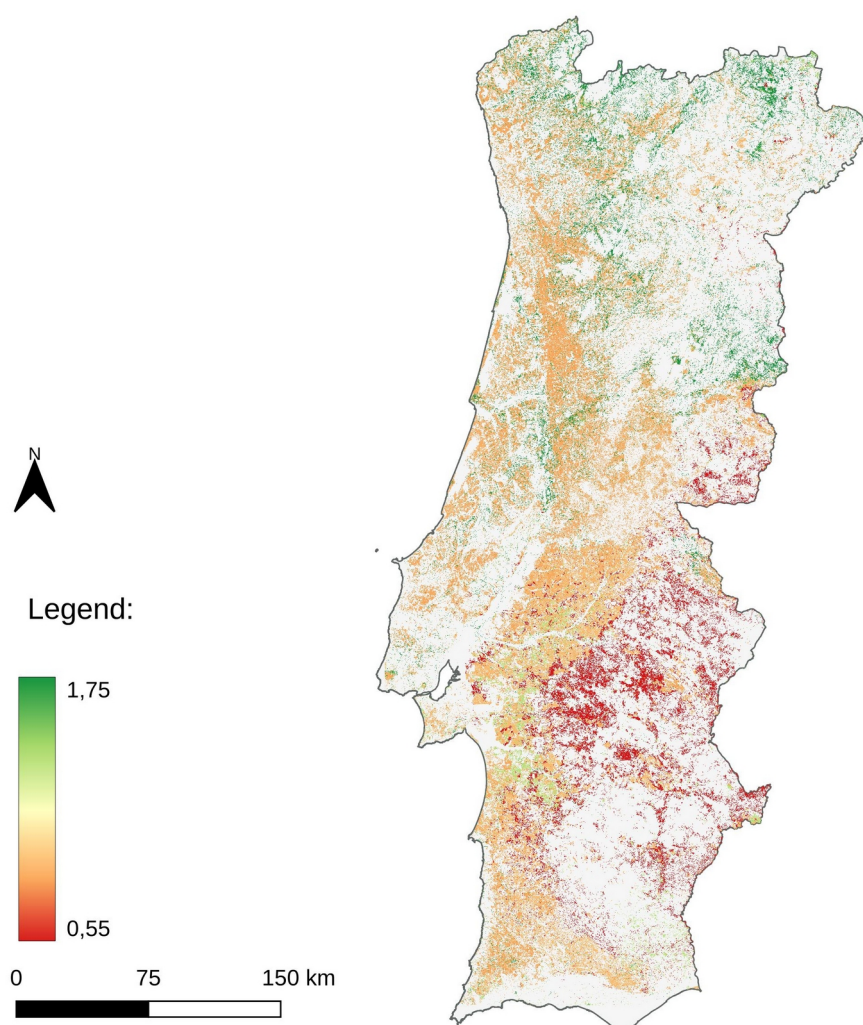


Annex D – InVEST Carbon Model Maps (2018 and 2022)

Carbon model map for 2018



Carbon model map for 2022



Annex E – InVEST Carbon Model Outputs per NUTS III

Carbon model outputs for 2018

Code	Name	Area (ha)	Mean	Median	StDev
187	Alentejo Central	739346.410	0.707	0.550	0.259
181	Alentejo Litoral	530940.570	0.909	0.900	0.261
150	Algarve	499679.490	0.981	0.900	0.287
186	Alto Alentejo	608433.570	0.814	0.840	0.280
111	Alto Minho	221884.160	1.241	0.860	0.445
11B	Alto Tâmega	292190.840	1.322	1.480	0.438
119	Ave	145136.480	1.196	0.860	0.438
184	Baixo Alentejo	854272.340	0.788	0.550	0.321
16H	Beira Baixa	461463.790	0.837	0.840	0.238
16J	Beiras e Serra da Estrela	630494.820	1.290	1.380	0.455
112	Cávado	124579.070	1.142	0.840	0.422
11D	Douro	403157.670	1.161	0.860	0.431
185	Lezíria do Tejo	427497.180	0.931	0.900	0.251
16B	Oeste	222015.510	0.963	0.840	0.300
16D	Região de Aveiro	169285.940	0.976	0.840	0.320
16E	Região de Coimbra	433556.770	1.016	0.840	0.353
11E	Terras de Trás-os-Montes	554359.660	1.351	1.750	0.441
11C	Tâmega e Sousa	183151.520	1.173	0.860	0.433
16G	Viseu Dão Lafões	323774.070	1.140	0.860	0.419
170	Área Metropolitana de Lisboa	301523.860	1.025	0.900	0.333
11A	Área Metropolitana do Porto	204126.920	0.977	0.840	0.322
16F	Região de Leiria	244912.730	1.027	0.840	0.360
16I	Médio Tejo	334430.930	0.950	0.840	0.279

Carbon model outputs for 2022

Code	Name	Area (ha)	Mean	Median	StDev
187	Alentejo Central	739346.410	0.700	0.550	0.255
181	Alentejo Litoral	530940.570	0.907	0.900	0.262
150	Algarve	499679.490	0.970	0.900	0.282
186	Alto Alentejo	608433.570	0.810	0.840	0.281
111	Alto Minho	221884.160	1.246	0.860	0.446
11B	Alto Tâmega	292190.840	1.345	1.750	0.437
119	Ave	145136.480	1.202	0.860	0.439
184	Baixo Alentejo	854272.340	0.758	0.550	0.302
16H	Beira Baixa	461463.790	0.831	0.840	0.242
16J	Beiras e Serra da Estrela	630494.820	1.302	1.750	0.458
112	Cávado	124579.070	1.143	0.840	0.422
11D	Douro	403157.670	1.174	0.860	0.437
185	Lezíria do Tejo	427497.180	0.932	0.900	0.254
16B	Oeste	222015.510	0.967	0.840	0.304
16D	Região de Aveiro	169285.940	0.978	0.840	0.323
16E	Região de Coimbra	433556.770	1.020	0.840	0.356
11E	Terras de Trás-os-Montes	554359.660	1.357	1.750	0.441
11C	Tâmega e Sousa	183151.520	1.174	0.860	0.434
16G	Viseu Dão Lafões	323774.070	1.142	0.860	0.421
170	Área Metropolitana de Lisboa	301523.860	1.028	0.900	0.338
11A	Área Metropolitana do Porto	204126.920	0.979	0.840	0.324
16F	Região de Leiria	244912.730	1.031	0.840	0.363
16I	Médio Tejo	334430.930	0.952	0.840	0.282

Net exchange in carbon model outputs (2018-2022)

Code	Name	Area (ha)	Mean Net Ex.	StDev Net Ex.
187	Alentejo Central	739346.41	-0.007	-0.004
181	Alentejo Litoral	530940.57	-0.002	0.001
150	Algarve	499679.49	-0.011	-0.005
186	Alto Alentejo	608433.57	-0.004	0.001
111	Alto Minho	221884.16	0.005	0.001
11B	Alto Tâmega	292190.84	0.023	-0.001
119	Ave	145136.48	0.006	0.001
184	Baixo Alentejo	854272.34	0.030	-0.019
16H	Beira Baixa	461463.79	-0.006	0.004
16J	Beiras e Serra da Estrela	630494.82	0.012	0.003
112	Cávado	124579.07	0.001	0.000
11D	Douro	403157.67	0.013	0.006
185	Lezíria do Tejo	427497.18	0.001	0.003
16B	Oeste	222015.51	0.004	0.004
16D	Região de Aveiro	169285.94	0.002	0.003
16E	Região de Coimbra	433556.77	0.004	0.003
11E	Terras de Trás-os-Montes	554359.66	0.006	0.000
11C	Tâmega e Sousa	183151.52	0.001	0.001
16G	Viseu Dão Lafões	323774.07	0.002	0.002
170	Área Metropolitana de Lisboa	301523.86	0.003	0.005
11A	Área Metropolitana do Porto	204126.92	0.002	0.002
16F	Região de Leiria	244912.73	0.004	0.002
16I	Médio Tejo	334430.93	0.002	0.003

Annex F – Tree Frequency per NUTS III

Tree frequency outputs for 2018

Code	Name	Eucalyptus	Other broadleaves	Cork oak	Holm oak	Other coniferous	Maritime Pine	Stone Pine
187	Alentejo Central	23.94	2.57	0.49	0.17	2.22	0	70.61
181	Alentejo Litoral	9.98	11.34	1.23	4.23	7.99	0.01	65.22
150	Algarve	2.2	5.63	1.15	1.12	4.47	0	85.43
186	Alto Alentejo	13.41	6.1	1.53	1.92	1.44	0.02	75.58
111	Alto Minho	0	11.68	14.8 2	7.78	0	0.37	65.34
11B	Alto Tâmega	0	0.27	12.6 1	11.61	0.01	0.87	74.62
119	Ave	0	16.07	14.2 9	6.99	0.01	0.54	62.1
184	Baixo Alentejo	9.79	1.15	0.32	0.07	2.61	0	86.05
16H	Beira Baixa	6.73	10.83	1.47	12.87	0.08	0.21	67.82
16J	Beiras e Serra da Estrela	0.61	2.12	9.65	6.85	0.02	0.35	80.41
112	Cávado	0	18.5	11.5 1	5.75	0.01	0.58	63.65
11D	Douro	0.66	0.74	5.76	7.66	0.01	0.26	84.91
185	Lezíria do Tejo	4.98	17.74	1.95	3.44	6.19	0.06	65.64
16B	Oeste	0.08	18.12	3.35	5.64	0.48	0.09	72.24
16D	Região de Aveiro	0	32.76	6.73	6.59	0.04	0.02	53.87
16E	Região de Coimbra	0	25.18	7.5	7.76	0.18	0.2	59.18
11E	Terras de Trás-os-Montes	0.84	0.52	9.86	2.95	0.02	1.32	84.49
11C	Tâmega e Sousa	0	17.85	13.4 6	6.14	0.01	0.3	62.24
16G	Viseu Dão Lafões	0	9.37	9.85	11.53	0.09	0.06	69.09
170	Área Metropolitana de Lisboa	1.82	5.13	2.23	4.1	3.88	0.29	82.56

11A	Área Metropolit ana do Porto	0	28.3	5.73	4.86	0.01	0.01	61.08
16F	Região de Leiria	0.01	22.11	8.16	11	0.11	0.12	58.48
16I	Médio Tejo	0.58	20.7	4.07	9.7	0.88	0.06	64.02

Tree frequency outputs for 2022

Code	Name	Eucalyptus	Other broadleaves	Cork oak	Holm oak	Other coniferous	Maritime Pine	Stone Pine
187	Alentejo Central	23.94	1.85	0.48	0.13	2.01	0	71.59
181	Alentejo Litoral	9.97	9.93	1.18	3.88	7.58	0.01	67.45
150	Algarve	2.19	6.04	1.08	0.98	3.93	0	85.77
186	Alto Alentejo	13.4	5.11	1.48	1.76	1.33	0.02	76.9
111	Alto Minho	0	11.62	14.56	7.03	0	0.35	66.43
11B	Alto Tâmega	0	0.26	11.82	9.75	0.01	0.79	77.37
119	Ave	0	15.4	13.79	6.19	0.01	0.51	64.12
184	Baixo Alentejo	9.79	0.91	0.31	0.06	1.81	0	87.11
16H	Beira Baixa	6.73	10.57	1.36	10.13	0.07	0.18	70.97
16J	Beiras e Serra da Estrela	0.6	1.95	8.71	5.5	0.01	0.24	82.98
112	Cávado	0	18.14	11.2	5.29	0	0.56	64.79
11D	Douro	0.65	0.72	5.45	6.57	0.01	0.22	86.39
185	Lezíria do Tejo	4.98	15.39	1.9	2.84	5.81	0.05	69.02
16B	Oeste	0.08	16.94	3.26	5.21	0.43	0.08	74.01
16D	Região de Aveiro	0	31.11	6.48	5.97	0.03	0.01	56.4
16E	Região de Coimbra	0	26.39	7.85	7.14	0.18	0.18	58.27
11E	Terras de Trás-os-Montes	0.84	0.43	9.53	2.5	0.01	1.2	85.5
11C	Tâmega e Sousa	0	17.46	12.97	5.49	0.01	0.28	63.8
16G	Viseu Dão Lafões	0	10.71	10.26	10.75	0.08	0.06	68.14
170	Área Metropolitana de Lisboa	1.82	4.15	2.14	3.61	3.49	0.28	84.51
11A	Área Metropolitana do Porto	0	27.59	5.63	4.46	0.01	0.01	62.29
16F	Região de Leiria	0.01	21.31	7.8	9.49	0.11	0.11	61.16

16l	Médio Tejo	0.58	20.6	3.9	7.38	0.82	0.06	66.66
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2015	Título Subtítulo	Nome completo do candidato	
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