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The impact of climate change on mango cultivation in southern Europe

Applying an Environmental niche model

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Abstract

The cultivation of mangoes (Mangifera indica L.) is gaining importance in Europe, especially in Southern regions, due to favourable climatic conditions. With the ongoing climate change, there is a potential for further improvement in these conditions, making southern Europe possibly more suitable for mango cultivation in the future. This study aims to assess the potential future impacts of climate change on mango cultivation suitability in southern Europe, focusing on Spain, Italy, Greece, south of France, Croatia, Montenegro & Albania.

Using Environmental Niche Modelling (ENM), this research integrates correlative and mechanistic approaches to evaluate current and future suitability scenarios. Key environmental variables, such as temperature, degree days, air humidity, cloud cover and soil factors, were analysed using Generalized Linear Models (GLM), Boosted Regression Trees (BRT), and Maximum Entropy Modelling (Maxent) with presence-only, randomly generated pseudo-absence observation data.

The performance of the algorithms was evaluated using metrics such as the Area Under the Receiver Operating Characteristic Curve (AUC) and the True Skill Statistic (TSS). All algorithms demonstrated high accuracy, with AUC values exceeding 0.8, but the difference in TSS values between calibration and validation suggests diminished model performance in new scenarios, highlighting the potential impact of overfitting due to limited observation points, emphasizing the need for cautious interpretation of the results. To ensure robustness and reduce uncertainty, an ensemble approach was adopted, averaging the results from GLM, BRT, and Maxent models.

Results from the mechanistic approach, which incorporates expert knowledge on physiological and morphological data, show a broader potential expansion of suitable areas compared to the correlative approach, which relies on observed relationships between species occurrence and environmental conditions. The mechanistic approach suggests that inland areas, particularly in Spain, might become more suitable due to projected increases in temperature. In contrast, the correlative approach indicates more conservative estimates of suitable areas, highlighting the importance of air humidity and specific microclimatic conditions. An combination of results reveal that while current suitable areas are concentrated along coastal regions of Spain and Italy, future projections extend these areas further inland and into new regions within Greece and Portugal.

The overall results indicate a significant expansion of suitable areas for mango cultivation under future climate scenarios. Both SSP1-2.6, which assumes lower greenhouse gas emissions, and SSP5-8.5, with higher emissions, project growth of suitable areas. However, water stress remains a limiting factor in both scenarios, particularly under SSP5-8.5. A spatial comparison reveal that while current suitable areas are concentrated along coastal regions of Spain and Italy, future projections extend these areas further inland and into new regions within Greece and Portugal. The analysis also highlights the critical role of irrigation and the need for adaptive agricultural practices, including efficient water management and strategic planning, to mitigate the adverse effects of climate change on mango production, as water scarcity remains a major constraint despite favourable temperature trends.

This research contributes to the growing body of knowledge on the impacts of (future) climate change on mango suitability in southern Europe and offers valuable insights for farmers, policymakers, and stakeholders in the agricultural sector. By anticipating changes in suitable cultivation areas, strategies can be developed to sustain and potentially expand mango production in Europe.

Table of contents

1. Introduction

The popularity of the mango (Mangifera indica L.) is on the rise globally, and notably within Europe. Presently, the mango stands as the sixth most consumed fruit worldwide, with a harvested area of 5.97 million hectares and a global production of 57 million metric tons per year, which is an increase of 35% from a decade ago (FAO, 2021). The major production region is Asia, accounting for 74.4% of the world's output. However, Europe, particularly Spain, has seen a rise in cultivating mangoes in the last 15 years, yielding 40,000 tons of mangoes in 2021 (FAO, 2021). This rise is attributed to favourable climatic conditions, characterized by warm sunny summers and frost in winters, which seem increasingly suitable due to ongoing climate change (del Pino et al., 2020). However, the rise of extreme drought in recent years has led to a 70% decrease in Spanish mango production in 2023, and water scarcity in the affected regions has resulted in reduced yields due to smaller mangoes (Trops, 2023). The impact and potential consequences of climate change on mango production in Spain, both now and in the future, remain unclear.

Climate change is ongoing and the effects are expected to be impacting land use systems across Europe (Aydinalp & Cresser, 2008). The impact varies by region, but generally more extreme weather events are the trend (Huber & Gulledge, 2011). It is likely to affect the suitability for cultivating mangoes in southern Europe as it is expected that the global temperature and rain falls less and more irregular (Legave, 2013).

Nevertheless, there is no unanimity on the exact changes per region when different scenarios are considered: from small to big changes. Using forecasts, it is possible to model how weather and environmental conditions may change based on assumptions of current developments. Effects on the potential growth areas of species can be evaluated by relating known occurrences to the change of climate data (Ramírez-Gil et al., 2019). This approach has been termed environmental niche modelling (ENM) and represents a powerful tool for characterising current and potential environmental and geographic distributions of species (Sillero et al., 2021; Peterson et al., 2018). The increasing interest in mangoes, both in consumption and European production, combined with climate change, presents uncertainties for farmers and exporters in the mango sector. Anticipating these changes by forecasting the environmentally suitable area of crops would help to reduce or mitigate negative impact and adapt ecological and economic strategies (Arenas-Castro & Gonçalves, 2021). An analysis is required to understand how the mango cultivation area in the Southern Europe might change due to climate change.

Mango is not a strictly tropical tree, as it also grows in areas with a subtropical and even mediterranean climate, such as in the Southern Europe. The overall climate conditions for mango production seem to be improving due to an increase of average temperature, which rises the number of degree-days, a decrease of cloud cover, and a longer dry period prior to flowering as a result of climate change (Legave, 2013; Geetha et al., 2016). Besides these positive changes, mango cultivation is affected by many other climatic factors that may change towards a negative influence, including maximum and minimum temperature, air humidity and rainfall (Cavalcante, 2022; Kumar et al., 2008; Parmar et al., 2012; Ramteke et al., 2022; Todorov & Bogsan, 2016; Van Zile, 2022; Zuazo et al., 2021). Additionally, topographical variables such as soil depth, soil texture, soil erodibility, elevation and slope steepness, while very slowly affected by climate change, also determine the potential growth area of mango trees (Elsheikh et al., 2013; Salunkhe et al., 2023; Todorov & Bogsan, 2016; Bally, 2006).

Currently, in southern Europe, water is being added artificially to mango orchards due to insufficient rainfall during certain periods (Zuazo et al., 2021). While already, one of the main challenges in semi-arid regions is the inconsistency of rainfall, combined with high temperatures, resulting in significant water shortages. Water consumption by human populations, agriculture, and ecosystems, cause conflicts over water usage, reduced agricultural productivity, and adverse effects on natural habitats (Schlosser et al., 2014). This condition, where the demand for water exceeds the available amount, is known as water stress. Climate change is expected to exacerbate this problem, with an increase in the frequency, magnitude, and impact of droughts and rising temperatures. Due to these developments, there will not be enough precipitation in the future, causing the necessity for irrigation to persist and the environmental variable of precipitation to be excluded from this study.

Currently, mangoes are only commercially grown on a small extent in Italy (mostly Sicilia), Greece (Crete), Corsica and Spain (Andalucia) while there may be suitable production areas in other southern European regions within Italy, Spain, Portugal, France, Croatia, Albania, Montenegro and Greece. Thus, this study tries to analyse the impact of climate change on the suitability for mango cultivation in Southern Europe, and compare this with the current crop extent, to see how climate change may expand or contract the existing cultivation area.

1.2 Research Objective

This study aims to clarify the future uncertainties surrounding mango production in Southern Europe. This objective will be achieved by utilizing an Environmental Niche Model.

The following research question has been set up to reach the objective of this research:

Will climate change cause an expansion or contraction of the suitable area for mango production in southern Europe?

The following guiding questions have been established in order to find an answer to the main research question:

- *Q1: Which environmental variables positively (or negatively) contribute to the suitable area of mango cultivation?*
- *Q2: How are some of these environmental conditions changing as a result of climate change?*
- Q3: *Which areas in southern Europe are currently suitable for growing mangoes?*
- *Q4: Under different climate scenarios, how would suitable areas for mango growth in southern Europe expand or contract in the future?*
- *Q5: To what extent is water stress a factor in an environmentally suitable area for mangoes?*

First, it is essential to determine the key environmental variables that influence mango growth and identify the conditions under which mango trees are present. Subsequently, this study will compare how changes in climate, as expected according to different IPCC scenario’s, will impact the suitability for mango growth in different parts of Europe. These environmental variables will then be integrated with suitability for mango growth in an Environmental Niche Model (ENM) using various machine learning algorithms and expert knowledge. Estimates will be done by statistical analysis on how much the suitable extent of mango areas will expand or contract under the different scenario's, compared to the currently suitable mango cultivation areas. Next, the outcomes will subsequently be visualized using maps for various scenarios and show which areas in the southern Europe become suitable and unsuitable for growing mangoes in the future. The final step is to include the water component and check if suitable mango areas are situated in regions without water stress.

1.3 Relevance

In terms of tropical fruits, mango is the most interesting to investigate in terms of cultivation in Europe for a few reasons. The production of this fruit in Europe is the most upcoming compared to other tropical fruits such as avocados and bananas (FAO, 2021; Perez, 2023). Mangos are often compared to avocados since their production areas are similar. However, mangoes have a higher potential than avocados because they require less water (Frankowska et al., 2019), which is already scarce in southern Europe.

There is uncertainty about the potential for mango production in Europe's future. Commercial organizations, such as Trops, that produce mangoes warn of their dependency on water, fearing that future supplies may be insufficient to sustain their production (Trops, 2023). The results of this study will help mango farmers and governments of southern European countries with their management and choices of starting or sustaining a mango farm, by clarifying the future impact for mangoes as a result of the environmental changes. Incorporating both current and future climate change projections is crucial for sustainable agriculture (Akpoti et al., 2019) and it is imperative to inform these stakeholders about the inevitable impacts of climate change, allowing them to adequately prepare by reducing or mitigating the impact and adapt their ecological and economic strategies.

In addition, the global shipping of mangoes carries numerous environmental drawbacks. While container ship transport is relatively efficient compared to other means, it still poses a considerable environmental burden due to emissions of NOx, SO2, CO, and CO2. Furthermore, mangoes are often transported in refrigerated containers and occasionally by air, which has an even higher carbon footprint. The transportation emission accounts for 32% to their overall carbon footprint. Shortening the distance between production and consumption can reduce up to 3.2 kg CO_2 per ton of mangoes (Mersereau, 2023). However, any increase in water usage for cultivation must also be considered. Additionally, shortening the distance from farmer to the consumer, resulting in a more local transportation cycle, can lower transport costs. This reduction can either lead to decreased consumer prices or increased profit margins for farmers. Besides, a more localized supply chain ensures that a larger portion of funds remains within the European Union (Huang, 2004).

The food and agriculture organisation of the United Nations (FAO) has developed a data portal for suitable growing areas of agricultural crops in Europe. However, it lacks information on the mango that stakeholders in mango field need. This study will fill this information gap.

1.4 Research Structure

The study is divided into several steps, as illustrated in Figure 1.

- Chapter 2: The first step is done by conducting a preliminary literature review of relevant concepts and theories from scientific literature on environmental niche modelling (ENM) in relation to crop suitability area assessments and climate change scenarios. This provides information about existing studies on this topic and which climate scenarios, ENM algorithms, methods, and environmental variables are valuable to incorporate for mangoes.

- Chapter 3: From there, the study area and parameters of environmental variables are determined, together with suitable datasets that can serve as input for the ENM which are identified and obtained from research organisations. This data is described and prepared as input for the ENM model by addressing errors and ensuring uniform size and spatial scale. The data is then processed in the model using various algorithms and expert knowledge, after which the results of these models are compared and validated for accuracy.

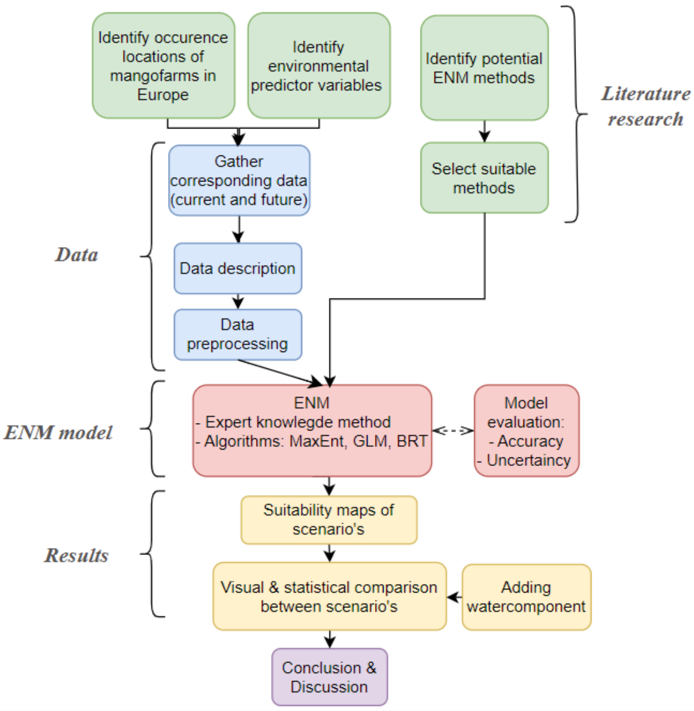

Figure 1: Flowchart research structure

- Chapter 4: The results can then be analysed and presented. This can be done through a visual and statistical comparison between future climate scenarios and the current situation. Additionally, the water component is added.

- Chapter 5 & 6: In these chapters the results are interpreted, placed within context of existing knowledge and outlined significance to the broader scientific community. Besides, the limitations and suggestions for future research are discussed. The final step involves drawing a conclusion that answers the main question '*Will climate change cause an expansion of contraction of the suitable area for mango production in southern Europe?*'

2. Theoretical background

This chapter provides a theoretical background of the previously described context and problem statement by comparing and analysing various relevant scientific literature. The concept of ENM is first presented, followed by an outline of several techniques, an explanation of climate change models, and an examination of mango growth characteristics.

2.1 Definition of Environmental niche modelling (ENM)

Land suitability analysis plays a crucial role informing decision-making and sustainable land management across various sectors. It helps optimize land use, minimize environmental impacts, and to ensure the efficient allocation of resources (Malczewski, 2004). Land suitability analysis, such as Environmental niche modelling (ENM), in agriculture is a process that assesses the suitability of specific parcels of land for various agricultural purposes (Akpoti et al., 2020).

ENM falls under the overarching concept of Species Distribution Modelling (SDM). Both methods primarily aim to understand and predict species' habitats based on specific factors, however, SDM captures the entirety of an organism's ecological needs such as predation, competition and symbiosis, while ENM emphasizes environmental constraints more explicitly (Sillero et al., 2021).

In order to describe, comprehend, and/or forecast the distribution of species, ENMs use statistical techniques or theoretically developed response surfaces to link physiological or chorological data to environmental variables (Sillero et al., 2021). The mathematical output of ENMs can be an equation relating the expected distribution of the species (the dependent variable) to a set of environmental predictors (the independent variables). This mathematical model can be spatialised into a cartographic model, i.e. a map representing habitat suitability or the probability of the species occurrence (Sillero et al., 2021).

Environmental niche modelling (ENM) is a suitable approach for the aim of this research as it can predict how suitable a new area is for cultivation of the a particular fruit based on occurrence data and environmental variables. It is in line with the research objective by not integrating biotic factors.

2.2 ENM in crop suitability studies

There are numerous general studies, such as Halder & Hasan (2020) and Legave et al. (2023), that describe the general negative global effects of climate change on mango cultivation areas, instead of the specific statistical use of Environmental Niche Modelling (ENM).

In recent years, the use of ENM to explore these patterns and processes of species distribution has significantly increased (Melo-Merino et al., 2020) especially in crop suitability analysis (Akpoti et al., 2022; et al., 2023; Ramirez-Cabral et al., 2016). One such study predicts the impact of climate change on suitable areas for a similar fruit, avocado, in the Americas (Ramírez-Gil et al. 2019). Eitzinger et al. (2013) conducted a study about the suitability area of mangoes in relation to climate change in Haiti & Akhter et al., (2017) used the same MaxEnt algorithm to check for future potential of mango distribution in Bangladesh.

Taken the large amount of similar studies on the impact of climate change on crops using ENM, it can be said that the ENM method seems appropriate to apply for this study. Yet these studies make many different choices regarding spatial resolution, temporal extent, ENM method, number of variables and climate change scenarios (Table 1). The outcome of these choices can serve as a basis for this study.

Table 1: Characteristics of different scientific studies that use ENM

Name researchers	Subject	Study area	Temporal extent (year)	Spatial resolution	ENM method	Nmbr. Of variables	Climate model	CC scenario	Nmbr of suit. classes
Ramirez-Cabral et al., (2016)	Common bean	World	Current, 2050 2100	111 km^2	CLIMEX	17	2 GCM's	A2, A1B	4
Akpoti et al., (2022)	Rice	West-Africa	2030 2050 2070 2080	1km^2	BRT, GLM, MaxEnt, RF	24	Avg. of 32 GCM	RCP2.6, RCP4.5, RCP6.0, RCP8,5	3
Ramírez-Gil et al. (2019)	Avocado	Americas	Current 2050	4km^2	MaxEnt	11	Avg. Of 22 GCM	RCP4.5 RCP8.5	Scale 0-100
Appelt et al., (2023)	Coconut, Oil palms & rubber	Southeast Asia	1981-2010 2041-2070	10km^2 10m^2 231m^2	EcoCrop	2	5 GCM's	SSPS2.6 SSPS8.5	Scale 0-100
Akhter et al., (2017)	Mango	Bangladesh	Current 2050 2070	1km^2	MaxEnt	19	1 GCM	RCP4,5 RCP8.5	4
Eitzinger et al. (2013)	Mango & Coffee	Haiti	2013 2020 2030 2050	1km^2	MaxEnt	19	Avg. Of 19 GCM	SRES-A2	5

2.3 Correlative and mechanistic models

As shown in table 1, there are many different methods within ENM to differentiate the crop suitability of an area with regard to climate change. Sillero et al. (2021) suggest that ENMs can be divided into 2 main categories, namely: mechanistic and correlative models:

- Mechanistic models typically incorporate physiological, morphological, and behavioural data and have more explanatory purposes, while correlative models use geographical occurrence data and have a more predictive purpose (Sillero et al., 2021; Elith et al., 2006;). Mechanistical models are grounded in a comprehensive understanding of the biological processes and mechanisms that dictate a species' distribution. They explicitly integrate the physiological limitations of a species to its environmental constraints (Melo-Merino et al., 2020).

- Correlative models are rooted in the observed relationship between species occurrence (presence/absence) and the environmental conditions of those locations. They correlate the current distribution of a species with environmental factors to project its distribution in different regions or under altered circumstances (Evans et al., 2015).

As a result, there is no hard dividing line between mechanistic models and correlative models but rather a spectrum of purely based regression on presences (correlative) and models that include some kind of expert knowledge on the relations between environmental factors and the crop, such as Climex (Ramirez-Cabral et al., 2016) and EcoCrop (Appelt et al., 2023).

In current literature, correlative models are the most commonly applied but the approach has been criticized for their inability to consider the full range of processes shaping species ranges and the uncertainty in predicting events in the near future (Evans et al., 2015). Compared to correlative models, mechanistic models may excel in these certain aspects but come with their own set of disadvantages such as the need for extensive and sometimes unavailable detailed data, validation challenges and generalizability of results to other regions (Evans et al., 2015). Ideally, the choice for a modelling algorithm should be driven by the research question rather than being solely dictated by the available data (Sillero et al., 2021). Because the outcomes of the methods can differ greatly and the research objective does not lend itself specifically to one method, both methods are used.

2.3.1 Mechanistic approach (Expert knowledge approach)

In this approach, environmental variable parameters established by experts are plotted over a spatial area, where crop-specific thresholds differentiate regions as suitable or unsuitable for cultivation. In this method, occurrence data is not considered; instead, thresholds for various variables define the areas suitable for mango cultivation. This study describes this niche-based mechanistic model as the 'expert knowledge approach'.

2.3.2 Correlative approach (Algorithmic approach)

Correlative models use the algorithmic approach to describe the relationship between a response variable (e.g., the presence or absence of mango farms) and explanatory variables (e.g., environmental conditions) based on observational data to predict the distribution of mango farms. Correlative methods can be divided into three main categories based on the type of data about species' occurrences they rely on: presence-absence, pseudo-absence, and presence-only methods (Sillero et al., 2021).

In this context, 'presence' indicates that a species was observed at a specific location when the data was collected, while 'absence' means that the species was not observed at that location during data collection. However, it's important to note that the absence of a species in recorded data doesn't always mean the species is completely absent from the area as detection issues, seasonal behaviour or sampling efforts can result in undetected presences (Graham et al., 2004).

Some ENM methods only require data on where a species was observed ('presence' records), while presence-absence methods additionally require data on where a species was not observed ('absence' records). When 'absence' records are not available but are necessary for modelling, 'pseudo-absence' records can be generated. These can be created by selecting random locations within the dataset where the species was not recorded, by choosing locations in areas that don't match the expected habitat for the species, or by randomly selecting locations in the study area while excluding places where the species was observed (Graham et al., 2004). This pseudo-absence method is most suitable for this research as only presence records of mango farms are available, and creating absence records improves the reliability of results. The chosen 'pseudo-absence' modelling algorithms are shortly described below.

In this study, three modelling methods were used, Maxent, GLM, and BRT, as they are the main ENM methods. It is prudent to employ multiple algorithms for a more dependable result as Akpoti et al. (2022) concludes that algorithms yield highly divergent results.

Maxent

Since its introduction in 2006 by Phillips et al. (2006), the Maximum Entropy Modelling (Maxent) software has become highly popular as a modelling tool. Maxent has proven to be highly accurate in making predictions, even when working with small amounts of only presence data (Sillero et al., 2021; Phillips et al., 2006). Ørsted & Ørsted (2019) assert that MaxEnt demonstrates superior accuracy compared to other species distribution models. The Maximum Entropy (MaxEnt) approach estimates probability density, treating presence data as samples drawn from a distribution across a study region.

GLM

Generalized linear models have been extensively applied in ecological research and a great number of published studies have used this method for predictive species distribution. Generalized linear models are mathematical extensions of linear regression models (Guisan et al., 2002). GLM assume that there is a relationship between the mean of the response variable (the occurrence data for ENMs) and the linear combination of the explanatory variables (the environmental predictors for ENMs).

BRT

Boosted Regression Trees (BRT), also known as stochastic gradient boosting, is an algorithm that can be ran based on pseudo-absence data, just like MaxEnt and GLM. But unlike GLM and MaxEnt, this is a tree-based model rather than a regression-based model, which adds to the reliability of this study by using different approaches. BRT uses a form of forward stage-wise regression to construct a sum of regression trees. Each stage consists of a gradient-descent step, in which a regression tree is fitted to the derivatives of the loss function (Phillips et al., 2009).

2.4 Climate change models

As previously stated, the effects of climate change (CC) are anticipated to influence ranges of various crops (Arenas-Castro & Gonçalves, 2021). This is particularly relevant for mango production areas in Europe as it is predicted that climate change would impact this region a lot (European Commission, 2020).

2.4.1 Climate change scenarios

Climate change projections are subdivided into various scenarios, ranging from extreme high negative human impact to low negative human impact. Within ENM studies, various classifications of scenarios are made, including Shared Socioeconomic Pathways (SSPs) (Table 1).

A method, with an increasing degree of practical use, to split up climate change scenario's is that of the SSP narratives describing alternative socio-economic developments as summed up below (Riahi et al., 2017). SSP scenarios are fundamentally determined by quantitative descriptions of key scenario drivers, such as population, economic growth, and urbanization. However, it is important to note that SSPs are solely socio-economic scenarios. They are linked with RCPs, which are climate scenarios describing greenhouse gas concentration trajectories based on varying levels of policy ambition, as SSPs were developed based on the framework provided by RCPs. Lower RCPs represents stringent mitigation scenarios, where greenhouse gas emissions are significantly reduced to keep global temperature rise low while in contrast higher RCPs represent the opposite (Meinshausen et al., 2011). The SSP1.26 means SSP1 in combination with RCP2.6. Appelt et al. (2023) chooses to incorporate the two most extreme SSP scenarios in their research while in many other studies predictions from different SSP scenarios are employed. The scenarios are described below with a display of projections (Figure 2).

SSP1: Sustainability – Taking the green road, (Low challenges to mitigation and adaptation)
SSP2: Middle of the road, (Medium challenges to mitigation and adaptation)
SSP3: Regional Rivalry, (High challenges to mitigation and adaptation)
SSP4: Inequality – A road divided, (Low challenges to mitigation, high challenges to adaptation)
SSP5: Fossil-fueled development, (High challenges to mitigation, low challenges to adaptation)

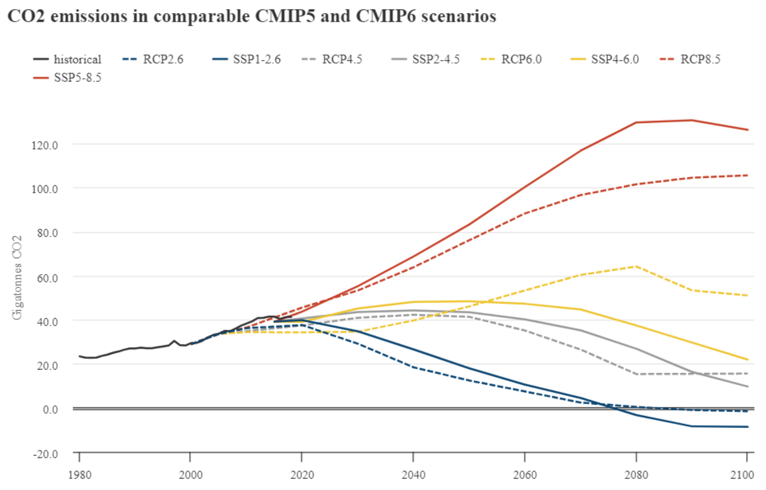

Figure 2: Comparison of SSP Scenario projections (Harrisson, 2021)

2.5 Current growing regions of mango trees

The prevailing climate determines the growing areas of mangoes, which is spread across the world. In 2021, a global production of 57 million tons of mangoes was harvested. The majority of this production, specifically 25 million tons, took place in India (Mango Production by Country, n.d.). As previously mentioned, Spain accounts for a minor share in mango production with 40,000 ton (FAO, 2021), which is so little that the country doesn't appear on the world map of mango production per country (Figure 3). When zooming in on climate zones and latitudes, it can be concluded that mangoes primarily occur in tropical and subtropical climates. However, the mango tree can also thrive in Mediterranean climates with the provision of irrigated water.

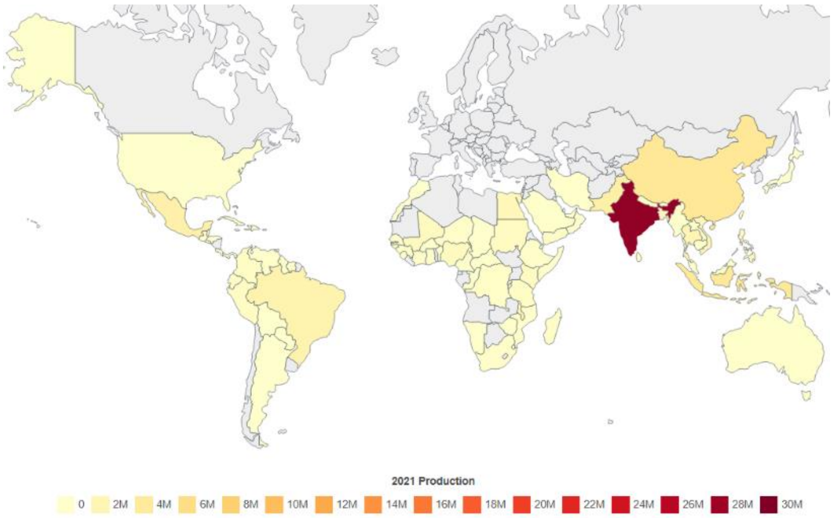

Figure 3: Mango production per country in 2021 in millions (Mango Production by Country, n.d.)

2.6 Environmental variables

There are various environmental variables crucial for the growth of mango trees and its fruits, which can be categorized into climate variables and topographic variables (Miller, 2010). Climate variables describe the weather conditions such as temperature, and can change due to changes in the climate. On the other hand, topographic variables are static relative to the rates of change in climate variables and consist of variables specific to a topographic location, such as elevation, slope and soil (Miller, 2010).

The climate variables in this study will mostly be based on the study by Eitzinger et al. (2009) & Akther et al. (2017) which studied annual trends, seasonality and extreme or limiting climate factors. However, those studies use the mean, max and min of the hottest, coldest, driest and wettest quarter/month which is not done in this study because the growing period of mangoes within southern Europe is already known and thus environmental values for specific months within the growing process are included.

For the growth process to progress optimally, several variables are crucial based on previous studies (Table 4). Certain choices regarding crucial parameters thresholds of variables for mango growth in the expert knowledge approach are clarified either because various sources provide conflicting information or because these parameters significantly influence the final outcome. According to Van Zile (2022), Cavalante (2022) and Bally (2006) other environmental variables like air humidity, hours of sun & elevation also play a crucial role in the suitable area for growing mango trees but don’t need extra explanation as these variables are less conflicted in multiple sources.

2.6.1 Climate variables

Temperature

Mangoes are originally tropical fruits and thus thrive best under stable, high-temperature conditions. However, the fruit is adaptable, with temperature not being the sole critical factor for its growth. Intriguingly, a cooler winter, with temperatures between 10-15.7°C, promotes flowering, encourages earlier fruiting in younger trees, and supports lower annual growth rates in densely populated plants (Zuazo et al., 2021; Núñez-Elisea & Davenport, 1994). Based on the findings of Geetha et al. (2016), Carella et al. (2021) & Makhmale et al. (2016), considering varieties similar to those of Osteen, specific temperature guidelines for different growth periods are:

First month of flowering (April): Av. Min. temp. of 15°C and an av. Max. temp. of 30°C
Second month of flowering (May): 17.5°C and 30°C, respectively
Third month of flowering (June): 21°C and 30°C, respectively
Rest of growing period (July – September): 23°C and 30°C, respectively

It's also important to note that temperatures rising above 48°C can inhibit mango growth and even kill the tree. Besides, it's vital that temperatures do not drop below 0°C, as this can harm the flowers (Todorov & Bogsan, 2016).

Degree days

It is common to indicate the number of degree days of different growth periods of a mango. Growing Degree Days (GDDs) represent the accumulated warmth required for a specific organism, like a plant, to progress through its life cycle of fruit growth, for which the formula is given (Kanzaria et al.,2015):

GDD = (daily max temp + daily min temp/2)−base temp

However, the number of Degree-Days of mangoes varies by growth stage and growth area. For example, Mosqueda-Vázquez et al. (1992) found that 2293 degree-days were needed for fruit maturity to be reached with a base temperature of 12 °C degrees, while Ramteke et al. (2022) concludes that 1660 degree-days were required for fruit maturity to be reached in the case of comparable mango varieties, with a base temperature of 10 °C degrees. Moore (2010) concludes between 1600-1800 degree-days for fruit maturity to be reached, with a base temperature of 12 °C degrees. The base temperatures are the minimum temperatures per growing month as indicated under the variable temperature. Thus, there is no correspondence between studies of base temperature and amount of degree-days. A combination of studies yielded 1660 degree-days with a base temperature of 12 °C degrees taken for this study.

2.6.2 Topographic variables

Soil

The soil plays an important role in mango cultivation and can be segmented into different categories of characteristics, each influencing mango growth in a different degree. Because of the extent of this study, the soil characteristics of saturation, well-drainage, nutrient availability, nutrient retention, oxygen soil, drainage class, carbon organic matter were not included as this can mostly by fixed by artificial agriculture. The soil characteristics that can't be easily changed and are thus taken into account in this study are:

- *Soil texture:* Mango trees are commercially cultivated in loamy sandy soils, which are deemed highly suitable (fine surface texture), while sandy loam and sandy clay loam are moderately suitable (medium surface texture). Conversely, lowland soils prone to soaking, as well as stony and sandy terrains, should be avoided (coarse surface texture)(Todorov & Bogsan, 2016; Salunkhe et al., 2023).

- *Soil depth:* Furthermore, it is essential that the soil is deep enough so that the roots can grow deep and thus get enough nutrients from their surroundings. Elsheikh et al (2013) suggests that the depth of suitable soil should be at least 75 cm, with preference to more depth to impermeable layers because mango trees have deeply rooted roots.

- *Soil erosion:* Accelerated soil erosion is a major environmental issue, leading to significant losses of soil organic carbon. Mango trees degrade the structure of the soil, reduce its water retention capability, decrease soil nutrients, and reduce soil depth, all of which diminish the soil's productivity if the soil is susceptible to erosion (Salunkhe et al., 2023). Thus, areas with very weak to weak erodibility soils are not suitable for growing mango trees.

2.6.3 Water component

One of the main challenges in semi-arid regions is the inconsistency of rainfall, combined with high temperatures, resulting in significant water shortages. Currently, in southern Europe, water is already being irrigated to mango orchards due to insufficient rainfall during certain periods (Zuazo et al., 2021). Water consumption by human populations, agriculture, and ecosystems, cause conflicts over water usage, reduced agricultural productivity, and adverse effects on natural habitats (Schlosser et al., 2014). This condition, where the demand for water exceeds the available amount, is known as water stress.

The average water consumption of a mango tree varies by growth period but is generally between 2 and 3 mm rainfall per day (De Souza et al., 2016; Duran et al., 2019; de Azevedo et al., 2003), which is considerably more than what consistently falls in southern Europe. Because mango farms in southern Europe are already supplied with water by artificial irrigation, precipitation is not a determining environmental factor and because suitable precipitation will only decrease in the future, the necessity for artificial irrigation will persist. This leads to the exclusion of precipitation as environmental variable in the modelling phase, but the degree of water stress in the region is included afterwards allowing the water component to be incorporated into the overall analysis.

3. Method

3.1 Study area

Currently, mainland Spain, particularly the region of Andalucia, is the area with the largest commercial cultivation of mangoes (Zuazo et al., 2019). This is due to the prevailing climate in this region, which is characterized as a Mediterranean climate based on the European Köppen Climate Classification (Wikipedia contributors, 2023). However, mango cultivation is emerging in other Southern European countries. For instance, Italy and Greece are currently experimenting with mango cultivation in Sicily and Crete (Jonico, 2021). But also other regions around the Mediterranean Sea possess a similar Mediterranean climate as the area of Andalucia. With potential climate changes, it might become feasible in the future to cultivate mangoes in other areas with the similar climate zone or perhaps even other climate zone. Therefore, as an initial study area, all of Southern European countries with a Mediterranean climate were included because it is expected that, due to climate change, areas suitable for mango production within these boundaries might be changing. This means that the countries Portugal, Spain, Italy, Greece, (southern) France, Croatia, Montenegro and Albania are included as study area (Figure 4). France's dividing line is determined by the expectation that no suitable future temperature for mango growth will be present above this altitude. Cyprus is excluded because information of topographical variables and some climate variables are missing for this area.

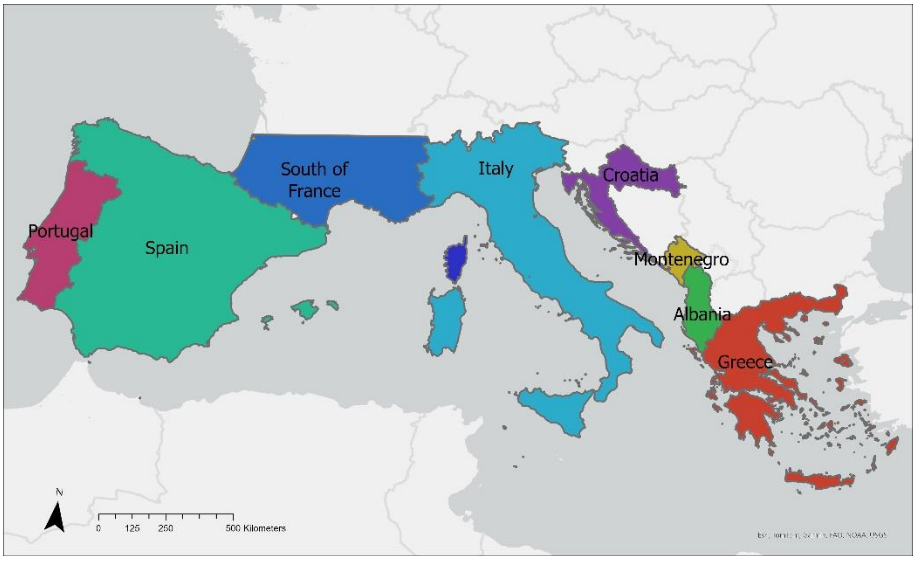

Figure 4: Study area of this research

3.2 Workflow

Within the method, a number of key steps are taken to achieve the desired result (Figure 5):

- <u>Data collection & description</u> of occurrence locations of mango farms and environmental predictor variables
- <u>Data preprocessing</u> such as aligning spatial resolution, checking multicollinearity and checking Spatial autocorrelation (SAC)
- <u>Combine presence/absence layer and predictor layer</u> in algorithmic and expert knowledge approach
- <u>Evaluate and combine model algorithms parameters</u>
- <u>Create variables maps</u> of different (future) scenarios
- <u>Combining variables</u> in total suitability maps of different future scenarios
- Do a <u>statistical and spatial comparison</u> of the results

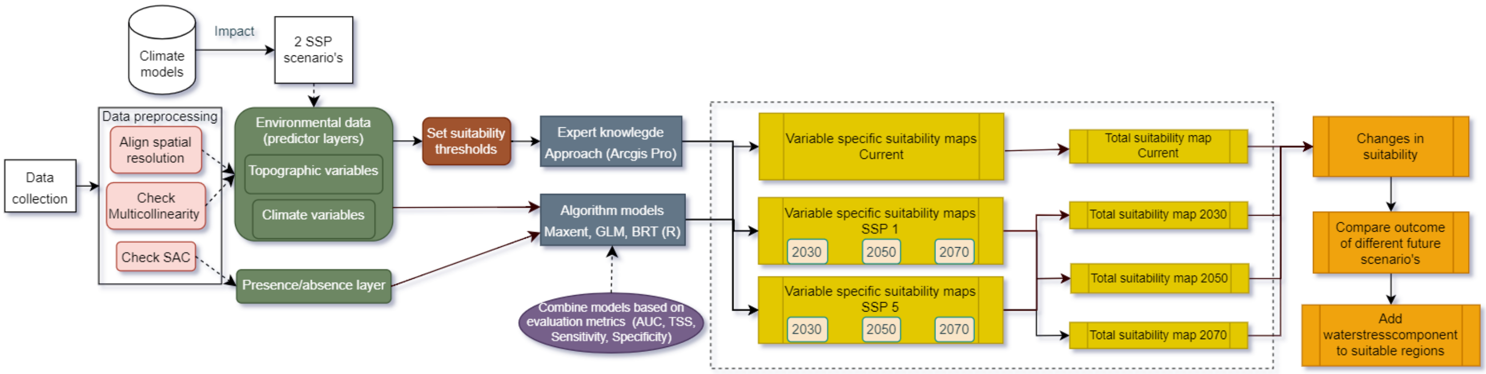

Figure 5: Flowchart of key steps in method

3.3 Two different approaches

The scientific literature describes several approaches that appear suitable for this study. To achieve reliable results, it has been decided to compare two approaches: one more mechanistic in nature and the other correlative in nature (See Chapter 2.3 for an extensive explanation). Uncertainty associated with all types of ENM's has prompted calls for a comparison of modelling approaches. Calls for more comparison have been echoed by agricultural impact modellers, who are concerned about bias introduced by model-specific representations of key physiological processes (Estes et al., 2013). Correlative models have been criticized for their lack of mechanistic representation of abiotic or biotic interactions while for mechanistic models the necessary physiological information is rarely available or trustworthy (Estes et al., 2013). Different correlative algorithms have been selected for application because comparisons between algorithms using the same input data can yield highly divergent results (Akpoti et al., 2022). The following algorithms were chosen for their excellence in handling pseudo-absence data (Table 2):

Table 2: justification algorithms correlative and mechanistic approach

Approach	Justification of choice
MaxEnt algorithm	- Highly accurate predictions with small amounts of data (Sillero et al., 2021; Phillips et al., 2006) - Superior accuracy and precision compared to other SDM (Ørsted & Ørsted, 2019) - Most commonly used in ENM
GLM algorithm	- Straightforward and logical results that can serve as baseline (Guisan et al., 2002) - Widely used in ENM
BRT algorithm	- Tree based model and thus different than MaxEnt and GLM which serves as a good comparison - Most accurate model for climate-based forecasts in SDM (Schatz et al., 2019)
Expert knowlegde approach	- Good by forecasting fundamental niche - Check whether current mango cultivation areas are logically located - Suitable for comparison with correlative approach - Can use more environmental variables

Correlative models use the algorithmic approach to describe the relationship between a response variable (e.g., the presence or absence of mango farms) and explanatory variables (e.g., environmental conditions) based on observational data. These models predict the distribution of mangoes by assuming that observed presence locations are fully suitable and that pseudo-absence locations are not suitable, scaling the suitability of other locations between these extremes (Sillero et al., 2021; Elith et al., 2006).

On the other hand, mechanistic models incorporate expert knowledge on physiological and morphological data to provide a more detailed understanding of the environmental constraints on species distribution (Melo-Merino et al., 2020). Thus in comparison to correlative models the mechanistic models integrate expert knowledge to define the physiological limits and requirements of a species in relation to environmental variables by settings predefined thresholds for various environmental variables. By summing the times an area is deemed suitable according to each variable, the overall suitability for mango cultivation can be determined.

3.4 Data collection and description

To model the predictive distribution of mangoes (dependent variable), ENMs (Ecological Niche Models) require two types of input data. The first type is occurrence data, which represents the species found within the sampled area. The second type of data essential for ENMs is environmental data (independent variables).

3.4.1 Occurrence data

Mangoes are already being commercially cultivated in southern Europe in the regions Andalucia, Murcia, Sicilia, Calabria, Basilicata & Crete. Most of the production occurs in areas near the coast around Malaga and Almeria (Figure 6).

At present, this information is only broadly available by region, and detailed data on specific mango-producing areas is scarce. Information from local web pages with manual research on Google Maps and contact with mango export companies is combined to pinpoint mango production areas on a high spatial resolution (Appendix B, Table 15), which was the most reliable and feasible method for collecting occurrence data As a result, it is only known where mango farms are present and knowledge of locations where they do not grow is unclear. Thus, the data only consists of presence data and no absence data is available, which is taken into account while conducting the ENM algorithms. The location of mango farms are shown in figure 6 with a distinction between locations not included as a result of spatial autocorrelation (SAC).

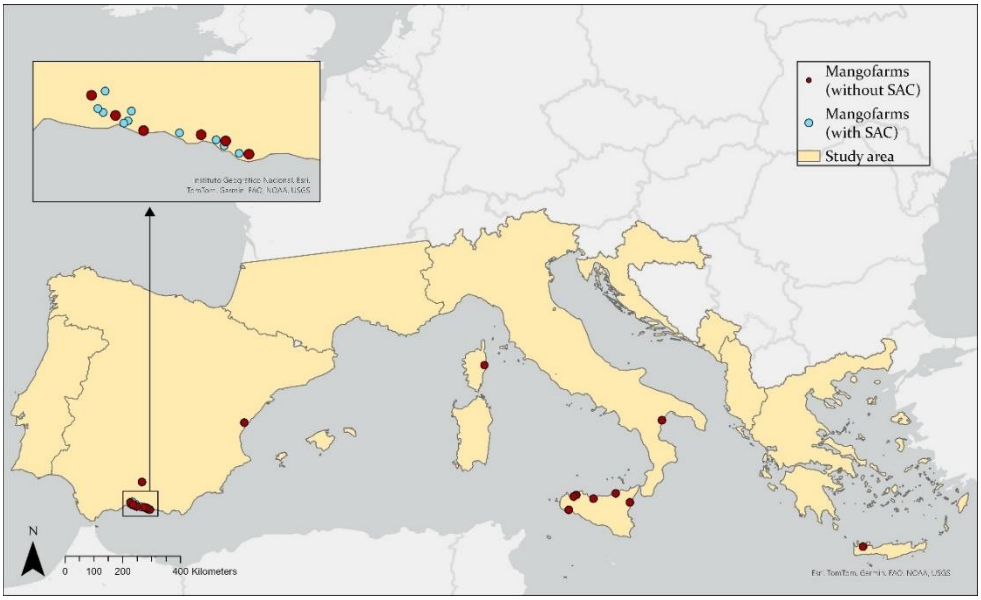

Figure 6: Locations of mango farms in study area

3.4.2 Environmental predictor variables of mangoes

In the theoretical background, a justification is provided for the chosen environmental variables and its parameters. Table 3 presents an overview of these variables, along with the corresponding parameters, references, data sources, selected climate models, temporal resolution, and spatial resolution.

All datasets have complete geographical coverage as they span across the whole of Europe. When combining the datasets a 30 arc-second spatial resolution, commonly referred to as '1-km' resolution, was chosen because most variables were available at this scale or could be converted to this resolution. Some suitability thresholds of environmental variables change at this resolution, making this accuracy essential for mapping out small suitable areas for mango cultivation.

Within the variables, several key decisions were made that are crucial in creating a suitable area. Based on preliminary analysis of two different time periods, it has been determined that a growing season from April up to and including September, rather than March up to and including August, is more suitable for mangoes in terms of temperature and degree-days across southern Europe. Therefore, the decision was made to base the suitability analysis for mango cultivation on data from April through September, as these months are most conducive to mango growth.

Additionally, for the expert knowledge approach, the hours of sun were determined by the average monthly cloud cover during the growing period from April through September . The average day length in southern Europe is 13,8 hours, which implies that the maximum cloud cover is 5,8 hours per day if the hours of sun should be above 8 hours (Calculated from; Times for sunrise and sunset in Spain, (n.d.)). If this is proportionally recalculated to a 24-hour period, assuming an equal distribution of cloud cover between day and night, the maximum cloud cover is 10 hours (42%). Slope steepness was excluded because, despite its significance for mango growth, it was too complex and imprecise to convert to a 1-km resolution.

3.4.3 Climate change models

Ten suitable GCMs (Global Climate Change models) were satisfactory for predicting the climate factor temperature in the Mediterranean based on a conducted performance-based CMIP6 model assessment for each region of Europe by Palmer et al., (2022). Out of the ten suitable GCMs, four of them were shown, downscaled, and calibrated by WorldClim v2.1 as baseline climate data (Table 4*). These four GCMs were selected for inclusion in this study due to the ease of data extraction and the reliability and completeness of the data provided by WorldClim. The current and future water availability is based on the data of the organisation Aqueduct, which predicts the impacts of climate change based on an average of five GCMs (Table 4**). As for air humidity and cloud cover, there is only one GCM completely available for the time period and horizontal resolution of this study, being HadGEM3-GC31-LL.

The values were averages over three future periods including 2030: 2021-2040, 2050: 2041-2060, and 2070; 2061-2080.

As narratives, the SSPs 1 and SSP 5 were chosen to be included because future socio-economic development is uncertain and outcomes between these scenarios differ significantly. These SSP narratives are paired with the extreme low-emission RCP 2.6 and high-emission RCP 8.5 scenarios, forming the combinations SSP1.26 and SSP5.85. By selecting these two extremes, this study allows for the assessment of the impacts of both low and high-end climate outcomes on mango cultivation, providing a robust analysis of potential future conditions.

Table 3: Environmental parameter variables information

Parameter	Unsuitable	Suitable	Reference	Datasource	Climate model	Temporal resolution	Horizontal resolution
Climate variables							
Mean temperature before flowering season (Jan-March)	<10°C or >15.7°C	10-15.7°C	Zuazo et al., 2021 Bally, 2006 Geetha et al., 2016 Galan Sauco et al., 2014	Worldclim	Av.of *	1970-2000 (current) 2021-2040 (2030) 2041-2060 (2050) 2061-2080 (2070)	1 km²
Mean temperature first month flowering season (April)	<15°C or >30°C	15-30°C	Geetha et al., 2016 Carella et al., 2021	Worldclim	Av.of *	"	1 km²
Mean temperature second month flowering season (May)	<17.5°C or > 30°C	17.5-30°C	Geetha et al., 2016 Carella et al., 2021	Worldclim	Av.of *	"	1 km²
Mean temperature third month flowering season (June)	<21 or >30c°C	21-30°C	Geetha et al., 2016 Carella et al., 2021	Worldclim	Av.of *	"	1 km²
Mean temperature of growing period of mangoes (July-September)	<23 or >30°C	23-30°C	Geetha et al., 2016 Carella et al., 2021	Worldclim	Av.of *	"	1 km²
Minimum temperature in growing period	*<0°C for 4 hours*	*No <0°C for 4 hours*	Zuazo et al., 2021 Bally, 2006	Worldclim	HadGEM2-ES; KNMI-RSCMO22E	2017-2021	1 km²
Maximum temperature in growing period	*>45°C for 4 hours*	*No >45°C for 4 hours*	Todorov & Bogsan, 2016	Worldclim	HadGEM2-ES; KNMI-RSCMO22E	2017-2021 (current) 2028-2032 (2030) 2048-2052 (2050) 2068-2072 (2070)	1 km²
Degree days - Total growing period mango (April till September)	*<1660 degree days*	*>1660 degree days*	Ramteke et al., 2022 Amaral et al., 2023	Worldclim	Av.of *	1970-2000 (current) 2021-2040 (2030) 2041-2060 (2050) 2061-2080 (2070)	1 km²
(Relative) Air humidity	<50% and >75%	>50-75%	Van Zile, 2022 Kumar et al., 2008	Copernicus	HadGEM2-ES; KNMI-RSCMO22E	2017-2021 (current) 2028-2032 (2030) 2048-2052 (2050) 2068-2072 (2070)	12.5 km²
Hours of sun within growing season (Cloud cover)(March-October)	<8 hours (>42%cc in 24 hours)	>8 hours (42%cc in 24 hours)	Parmar et al., 2012 Cavalcante, 2022	Copernicus	HadGEM2-ES; KNMI-RSCMO22E	2017-2021 (current) 2028-2032 (2030) 2048-2052 (2050) 2068-2072 (2070)	12.5 km²
Water Stress***	High	Medium/Low	Hofste et al., 2019	Aqueduct	Av. of **	1960-2014 (current) 2030, 2050, 2080	Vector area
Topographical variables							
Elevation	>1200m	0-1200m	Bally, 2006	EU-DEM	x	2016	1 km²
Soiltexture	Coarse (clay < 18 % and sand > 65 %)	Medium (18% < clay < 35% and sand > 15%,\or clay < 18% and 15% < sand < 65%) Medium fine (clay < 35 % and sand < 15 %) Fine (35 % < clay < 60 %) Very fine (clay > 60 %)	Todorov & Bogsan, 2016 Salunkhe et al., 2023	ESDAC European Soil Database	x	2006	1 km²
Soilerodibility	Very weak Weak	Moderate Strong Very strong	Salunkhe et al., 2023	ESDAC European Soil Database	x	2006	1 km²
Soildepth (to impermeable layer)	<75cm (shallow)	>75cm (deep)	Elsheikh et al., 2013	ESDAC European Soil Database	x	2006	1 km²

*= CMCC-ESM2, GISS-E2-1-G, HadGEM3-GC31-LL, MRI-ESM2-0
** = GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0, UKESM1-0-LL
*** = Used after running approaches

3.5 Data Preprocessing

Once the data is collected and checked for correctness, it must be prepared for processing in a model (Figure 7). To examine whether the Environmental Niche Model can predict the suitable areas correctly when using presence-only data two types of input data are needed for the model: occurrence data of mango farms and relevant environmental predictor variables. This raw data requires several adjustments before it can be incorporated into the model. These steps are explained in the following paragraphs.

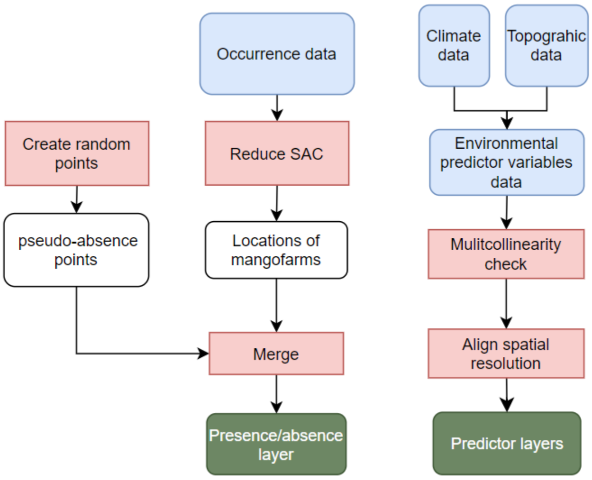

Figure 7: Flowchart of data preprocessing

3.5.1 Preprocessing of occurrence data

<u>SAC</u>

Spatial autocorrelation problems (SAC) can be defined as the fact that things being close-by are more related to each other than things that are further away (Tobler, 1970). SAC is able to amplify the significance of correlations between environmental and occurrence data when non-spatial models are used (Mauricio Bini et al., 2009). In order to avoid developing inaccurate models that lead to false conclusions about how environmental variables affect species distribution, SAC should be reduced. Checking for SAC is done by assessing the value of Moran's I from the auto covariate spatial regression with the 'Spatial autocorrelation' tool in ArcGIS Pro based on degree days as a variable (Dormann et al., 2007).

The analysis yielded a Moran's Index suggesting that the spatial distribution of the dataset is not significantly different from random (Appendix C.1, Figure 29). However, the Average Nearest Neighbour analysis revealed a different aspect of spatial structure, indicating a tendency towards clustering of the points (Appendix C.1, Figure 30).

To reduce the clustering in the presence points and thereby minimize the spatial autocorrelation in the explanatory variables used in the modelling, occurrence points within a 10-kilometer radius were removed. The nearest neighbour analysis after this adjustment yielded a significant result suggesting a tendency towards a random distribution of points (Appendix C.1, Figure 31). Consequently, the cluster of points in southern Spain was greatly reduced, making this area less dominant in the model (Figure 6). This adjustment left 17 presence points.

<u>Creating pseudo-absence</u>

Barbet-Massin et al., (2012) suggest the use of randomly selected pseudo-absences across space, as this approach consistently yields the highest accuracy for each algorithm. Moreover, they conclude that the recommended number of pseudo-absences and presence points varies per algorithm. In cases with few presence points, in this case only 17, it is advised to generate fewer pseudo-absences for BRT, while for GLM and MaxEnt, a higher number of pseudo-absences is recommended (Barbet-Massin et al., 2012). However, it is also stated that this varies by model and doesn't have such a big impact the result (Čengić et al., 2020; Lobo & Tognelli., 2011).

The ratio between presences and (pseudo)absences determines the optimal threshold above which predicted probabilities can be considered as suitable for a modelled species, which can be estimated making use of various quality indicators. Various models were created with pseudo-absence numbers of 170 (x10), 1700 (x100), and 10,000. It was found that for GLM and BRT, 170 pseudo-absence points provide the most accurate result, while for MaxEnt, 1700 pseudo-absences points are optimal (Appendix D.2, Table 16). To improve the distribution across space, a minimum distance of 500 meters was maintained between points. Additionally, two random distributions of pseudo-absences were used to train the models, thereby reducing uncertainty and improving the robustness of the model.

3.5.2 Preprocessing of environmental variable data

Excluding precipitation

The preliminary analysis of climate and topographic variables reveals that precipitation in areas where current mango farms are located do not align with the minimum precipitation required for mango growth of generally 2 and 3 mm per day (De Souza et al., 2016; Duran et al., 2019; de Azevedo et al., 2003)(Figure 8). Since precipitation is not expected to significantly increase in future climate projections, mango will continue to be an irrigated-fed crop (Maselli et al., 2020). Therefore, precipitation is not a variable to include when predicting suitable mango cultivation areas with environmental variables.

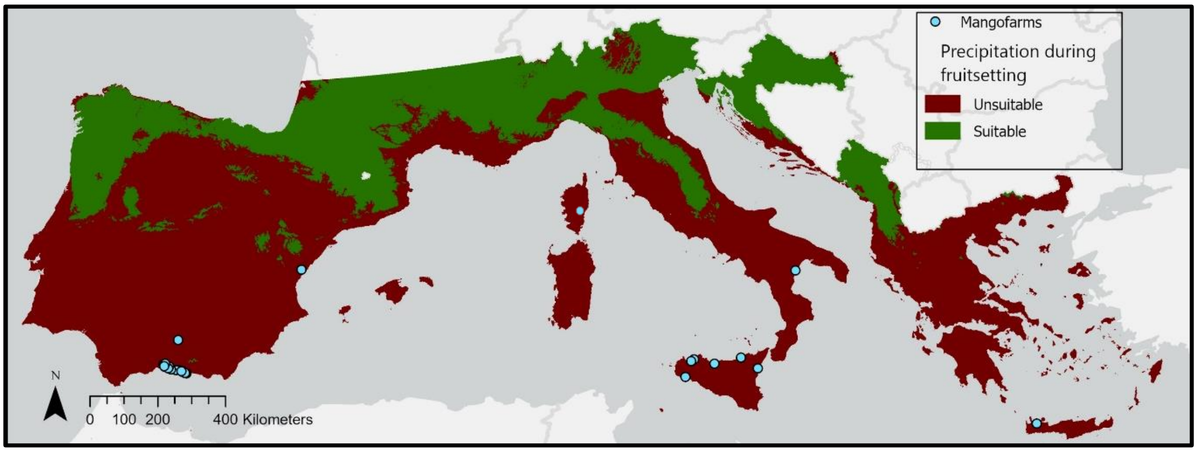

Figure 8 : (un)suitable mango cultivation area's based on precipitation during fruit setting stage

Multicollinearity

To avoid that multicollinearity, inter-correlations between predictor variables (Daoud, 2019), affects the accuracy of estimating variable contributions, pairwise correlations with the Pearsons coefficient area assessed (Table 4). Correlations exhibiting a Pearson coefficient of 0.75 or higher are classified as high to very high, leading to the exclusion of environmental variables exceeding this threshold, while prioritizing the retention of the most pivotal variables for model input. From an initial set of 14 variables, 5 were selected for incorporation into the algorithmic approach, based on their lack of significant intercorrelation. The decision to prefer "degree days" over other temperature variables was informed by its integrative measure of temperature variables, thereby indirectly encapsulating these individual temperature variables within the algorithmic approach. Air humidity and cloud cover were deemed more critical than minimum and maximum temperature readings, given that temperature is already represented within the model. Although soil erosion did not significantly correlate with other variables, the ratio of categorical variable with the quantity of presence points yielded unreliable results as not all categories could be included as a result of the low presence points. Consequently, this least important soil variable was omitted in the algorithm approach.

Table 4: Pearson correlation coefficients (>0,75 in red; green variables as input for algorithmic approach)

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Air humidity growing season	1	0,74345	0,25357	-0,13863	-0,19395	-0,06535	-0,63767	-0,53958	-0,53885	-0,51772	-0,62746	-0,68671	-0,787	-0,42451
2. Cloud cover growing season	0,74345	1	0,38702	-0,12913	-0,15771	-0,07926	-0,7451	-0,61004	-0,654	-0,66465	-0,75018	-0,78889	-0,77708	-0,57369
3. Elevation	0,25357	0,38702	1	-0,1601	-0,20559	0,0141	-0,81562	-0,77949	-0,86964	-0,8734	-0,79525	-0,75181	-0,57986	-0,83649
4. Soil depth	-0,13863	-0,12913	-0,1601	1	0,05174	0,06253	0,17564	0,09058	0,15945	0,18975	0,1928	0,16349	0,15464	0,10505
5. Soil erosion	-0,19395	-0,15771	-0,20559	0,05174	1	-0,23894	0,20878	0,16711	0,20533	0,21559	0,20689	0,1997	0,17926	0,17078
6. Soil texture	-0,06535	-0,07926	0,0141	0,06253	-0,23894	1	0,08024	0,05934	0,049	0,05065	0,07388	0,09909	0,14	0,00689
7. Degree days growing season	-0,63767	-0,7451	-0,81562	0,17564	0,20878	0,08024	1	0,87914	0,95338	0,96458	0,98115	0,99194	0,89989	0,87056
8. Av. Temp. Before growing season	-0,53958	-0,61004	-0,77949	0,09058	0,16711	0,05934	0,87914	1	0,94598	0,86259	0,84261	0,86831	0,75827	0,94803
9. Av. Temp. April	-0,53885	-0,654	-0,86964	0,15945	0,20533	0,049	0,95338	0,94598	1	0,97468	0,95032	0,92438	0,81765	0,92881
10. Av. Temp. Fruit growth stage	-0,51772	-0,66465	-0,8734	0,18975	0,21559	0,05065	0,96458	0,86259	0,97468	1	0,98087	0,93326	0,83035	0,87119
11. Av. Temp. June	-0,62746	-0,75018	-0,79525	0,1928	0,20689	0,07388	0,98115	0,84261	0,95032	0,98087	1	0,96942	0,90349	0,83617
12. Av. Temp. May	-0,68671	-0,78889	-0,75181	0,16349	0,1997	0,09909	0,99194	0,86831	0,92438	0,93326	0,96942	1	0,92778	0,84278
13. Annual Maximum Temp.	-0,787	-0,77708	-0,57986	0,15464	0,17926	0,14	0,89989	0,75827	0,81765	0,83035	0,90349	0,92778	1	0,66202
14. Annual Mininimum Temp.	-0,42451	-0,57369	-0,83649	0,10505	0,17078	0,00689	0,87056	0,94803	0,92881	0,87119	0,83617	0,84278	0,66202	1

The remaining five variables were evaluated for variance inflation factor (VIF). No VIF values of 5 or higher, which indicate high correlation (Senthilnathan, 2019), were observed, validating their inclusion as predictor variables in the model (Table 5).

Table 5: VIF coefficients of left over variables

Environmental predictor variables	VIF
Air humidity growing season	2.5
Cloud cover growing season	3.0
Soil depth	1.0
Soil texture	1.0
Degree days growing season	1.9

Aligning spatial resolution

Creating a consistent spatial resolution across different variable layers is a critical step to compare the suitability of area's and to serve as eligible input for the ENM. This process involves resampling to ensure that all layers have the same cell size, which is essential for accurate comparison and a combination of data layers (Long & Lawrence, 2016). The chosen spatial resolution of 1 km is taken as this aligns with the research objective where the difference of some environmental parameters is visible on a 1 km scale. All variables are available at this scale with the exception of air humidity (12,5 km) and cloud cover(12,5 km), thus air humidity and cloud cover were scaled to a spatial resolution of 1 km in ArcGIS Pro by overlaying them with temperature layers and resampling by bilinear interpolation technique.

Preparing for modelling software

To make sure that all input data can be used for modelling in Rstudio, the generated presence/absence layer and their subsets for evaluation are exported to CSV files and all environmental predictor variables are exported to ascii files. The biomod2 package is used as an ensemble platform for the environmental niche models, where algorithms such as GLM and BRT can be selected as options. The MaxEnt software of Phillips (2006) is used as a platform for MaxEnt as environmental niche model.

3.6 Suitability thresholds

After combining the algorithms and getting maps with probability and suitability scores, the threshold value for the suitable area of mango farms is determined. A distinction is made between four groups as is done in other relevant studies, such as Ramirez-Cabral et al. (2016) & Akhter et al. (2017) (Table 9).

3.6.1 Expert knowledge approach

For an area to be considered highly suitable, all variables must be suitable. For an area to be merely suitable, it may fail to meet the criteria for one of the following variables: temperature in April, temperature in May, temperature in June, Elevation, or Soil erosion, as these are deemed the least important (Table 10). Thus, even if these variables are not fully satisfactory, a mango farm may still be feasible.

3.6.2 Algorithmic approach

As output, the combination of models provide a average probability score ranging from 0 to 100, with higher values indicating a greater likelihood of species presence in the area. These values should be interpreted as a relative measure of suitability within the study area, rather than an absolute probability of presence. To identify suitable areas for mango farms, the 10th percentile training presence (TPTP) threshold method was utilized. The 10 Percentile Training Presence employs the suitability threshold associated with the presence record situated at the 10th percentile of presence records, meaning it uses the suitability score below which 10% of presence records' suitability's fall (Morrow, 2019).

Anticipating that mango farmers may have initiated mango farms in areas not yet fully suitable with a future perspective in mind, the threshold was adjusted to the 25th percentile training presences. This adjustment implies that among 17 farmers, 4 are situated in 'unsuitable' locations—a rise from 2 compared to 10% of presence records, due to the forward-looking vision of farmers and somewhat outdated data of between 2000 and 2017. Seventy-five percent of the mango farms fall within areas categorized as suitable, resulting in a sensitivity of 75% with this approach.

3.7 Evaluation of algorithms

ENMs are capable of delineating regions either as within or outside the species distribution range (Liu et al., 2009). Prior to interpreting the results produced by ENMs, it is imperative to rigorously evaluate the model's robustness. Pearce and Ferrier (2000) contend that the critical metric for assessing the efficacy of ENMs, particularly in binary outputs, is the model's capacity for discrimination. This involves gauging the model's proficiency in differentiating between locales with confirmed species presence and those with verified absence, utilizing an evaluation dataset.

To assess the efficacy of various models, two evaluation methods have been used: the Area Under the Receiver Operating Characteristic Curve (AUC) and the True Skill Statistic (TSS), both of which are extensively applied in Environmental Niche Modelling for assessing overall accuracy (ENM) (Liu et al., 2011; Jiménez-Valverde, 2012). The previously favoured kappa statistic over TSS was not adopted as a performance evaluation method due to its inherent dependency on prevalence, a characteristic which is argued to introduce statistical artifacts into estimates of predictive accuracy (Allouche et al., 2006). Additional evaluation metrics that ascertain the model's reliability and accuracy, such as specificity and sensitivity, are summarized in table 6.

The performance of the GLM and BRT models was tested in two ways, via the output of the Biomod2 package and the presenceabsence package. The biomod2 package did not provide complete metrics for model performance and these were supplemented with values from the presenceabsence package which also included a possibility to change the established thresholds for a ratio of sensitivity and specificity on which to base the (un)suitable area.

Beyond these indices, ENMs can also be evaluated through an analysis of how alterations in input variable values impact the model's output. This is achieved via Uncertainty Analysis (UA), a method for quantifying the uncertainty in ENM outputs as a function of input variability (Uusitalo et al., 2015). A sensitivity analysis is done by varying input parameters while observing the resulting changes in the model's output behaviour to assess the robustness and sensitivity of the model to different inputs (Convertino et al., 2014).

Table 6: Explanation of evaluation metrics (Allouche et al., 2006; Liu et al., 2009; Pearce and Ferrier, 2000)

Sensitivity	Percentage of records that was correctly predicted to be suitable from all records that were known to be suitable
Specificity	Percentage of records that was correctly predicted to be unsuitable from all records that were known to be unsuitable
TSS	The ability to accurately predict both presence and absence points is measured by the sum of sensitivity and specificity, which is then rescaled between -1 and 1.
ROC	Receiver Operating Characteristic (ROC) curves are constructed by using all possible thresholds to classify the scores into confusion matrices, obtaining sensitivity and specificity for each matrix, and then plotting sensitivity against the corresponding proportion of false positives (equal to 1 − specificity)
AUC	The area under the ROC curve. Measures the probability that the model will assign a higher score to a randomly chosen presence location over an absence location

The development of a model involves the utilization of both training data and test data by segmenting the available data into these two categories. Training data facilitates the model's learning of the relationship between species presence and environmental factors, whereas test data gauges the model's predictive accuracy (Fielding & Bell, 1997). Test data, being separate from what is presented during the model's training phase, aids in evaluating the model's capability to extrapolate its learned patterns to unfamiliar areas and/or environmental conditions. This validation ensures the model's reliability and its applicability to real-world scenarios. Conversely, fine-tuning the model based on training data, a process known as calibration, enhances its accuracy (Trucano et al., 2006).

By ensembling 10 runs for each algorithm, a reliable accuracy is achieved through averaging these results, thereby reducing uncertainty. This approach ensures that areas identified as highly probable in all models maintain this status in the consolidated outcome. Consequently, a decision was made to evenly combine the three models as spatial patterns vary within these models, including the strengths of all algorithms. Akpoti et al. (2022) assert that the integration of different algorithms can yield a dependable result, validating this methodological choice for achieving comprehensive and accurate predictions.

3.8 Variable importance of expert knowledge approach

Some variables are more important than others as a result of a bigger impact on the growing area of mango trees. The algorithmic approach determines the variable importance by calculations of significance and improvement of the model while in the expert knowledge approach variable importance is based on scientific literature and the outcome of the algorithmic approach. Since the variable importance for the algorithmic approach is derived from the algorithms' outputs, it is detailed in the results chapter.

The two mostly used variables in similar studies, and thus regarded as the most important variables, are temperature and water availability. Water is manually irrigated to mangoes and is thus not considered an environmental factor. Given the many variables related to temperature and its status as the most important explanatory variable, it contributes to 60% of the total. Degree-days, an aggregate of temperature variables, is considered the most reliable variable and thus carries the most weight.

The remaining variables consist of soil quality, elevation, cloud cover, and air humidity. Based on the variable importance ratio from the algorithmic approach, air humidity is slightly higher weighted than cloud cover. Among soil variables, the importance seems to be ranked as Soil depth = soil texture > soil erosion. Elevation is the least important because it is an indirect variable that also depends on temperature.

Despite some variables correlating, they can still indicate different suitable growth areas for mango trees. For instance, temperatures in April and May correlate, but it's possible for a location to be suitable for mango growth in April and not in May. Hence, all variables were included in the expert approach, unlike the algorithmic approach (Table 7).

To test the sensitivity of the model to different variable inputs, an equal weight distribution was established (Table 7). By comparing the effects of using equal weights versus weights based on expert knowledge, it can be assessed how sensitive the model is to variations in the weighting of different variables. Differences in results between these two approaches can reveal the impact of weighting choices on the model's outcomes. Using two different weighting schemes tests the model's robustness and highlights the influence of variable importance on the suitability analysis.

Table 7: Weight of variables for expert knowledge approach

Variable	***Equal weights***	***Own weights***
Min. temp.	7,14	6
Max. temp	7,14	6
Temp. Before growing season (Jan-March)	7,14	9
Temp. April	7,14	5
Temp. May	7,14	5
Temp. June	7,14	5
Temp. Fruit growth stage (July-Sep)	7,14	7
Degree days growing season (April - Sep)	7,14	15
Air humidity growing season (April - Sep)	7,14	12
Cloud cover growing season (April - Sep)	7,14	10
Elevation	7,14	2
Soil erosion	7,14	4
Soil texture	7,14	7
Soil depth	7,14	7
Total	100	100

4. Results

In this results chapter, the evaluation metrics of the algorithms are interpreted, followed by output of variable importance of the algorithmic approach and a depiction of variable response plots for each algorithm. Following this, the expansion of the mango growing area was quantified, and the current suitable mango growing areas in southern Europe were visualized on a map, addressing guiding question 3 "*Which areas in the southern Europe are currently suitable for growing mangoes?"*. This is supplemented with a spatial representation of change for both approaches and scenarios. Thus, guiding question 4 *"Under different climate scenarios, how would suitable areas for mango growth in southern Europe expand or contract in the future?"* was addressed. Following this, the water component was added to the analysis, thereby addressing guiding question 5: *" To what extent is water stress a factor in an environmentally suitable area for mangoes?"*. The Lambert Azimuthal Equal Area projection was chosen as the projected coordinate system because it accurately represents the size of areas in Europe.

4.1 Evaluation of algorithms

The various evaluation metrics are employed to calibrate and validate the model, ensuring optimal settings are established (Appendix D.1). This process included testing for differences between the number of pseudo-absences, percentage of data split and other algorithm settings (Appendix D.2, Table 16). A 50/50 split between training and test data resulted in failure due to an inadequate number of presence points; thus, calibrations were made using 70/30 and 90/10 ratios. The algorithms did not assign different weights to the response data (e.g., presence or absence of mango farms) based on their importance. The Generalized Linear Model (GLM) was set to perform 20 runs, while Boosted Regression Trees (BRT) and Maximum Entropy (MaxEnt) were limited to 10 runs, as these algorithms demand more computational power. The top 10 GLM runs, based on the True Skill Statistic (TSS) value, were selected to determine the predicted area for mango growth, in conjunction with the 10 runs from BRT and MaxEnt (Table 8).

According to Swets (1988), AUC values greater than 0.8 indicate high model accuracy. This criterion has been met by all algorithms, with AUC values minimally above 0.84 for test data. True Skill Statistic (TSS) values greater than 0.5 indicate good model performance, distinguishing between presence and absence locations (Sambou et al., 2024), while values above 0.65 signify very good performance. Consequently, all models demonstrate excellent calibration. The combination of algorithms on which the final result is based has a very good performance at the taken threshold of 0.75, based on the 25the percentile threshold rule.

Within the biomodpackage, no distinction can be made between the sensitivity and specifiticy of calibration and validation and so the total values for this were taken. Because the areas observed as unsuitable should mostly be classified as unsuitable, to test the performance a higher threshold than the optimal threshold is taken so that the specificity score is higher and no large areas in Europe are classified as suitable.

A lower validation TSS value for the GLM algorithm suggests diminished performance in new scenarios, such as those involving changing climates. This discrepancy can result from various factors, including an imbalance between Specificity and Sensitivity, leading to more false positives than false negatives, or generally low values for both metrics. This phenomenon is common in models with limited presence points and has been mitigated by reducing the number of (pseudo) absence points. While this difference is manageable, it should be considered when interpreting results. On the other hand, the high scores for specificity, combined with the less good scores off sensitivity the, suggest that the model may be overfitted as a result of low observationpoints.

Table 8: overview of evaluation metrics per algorithm

	GLM		Best of GLM		BRT		MaxEnt		Combi of all algorithms**
Number of runs	20		10		10		10		x
% of test data	10		10		30		20		x
number of PA	170		170		170		1700		x
	Calibration	Validation	Calibration	Validation	Calibration	Validation	Calibration	Validation	Totaldataset
Sensitivity	1	x	0,85*		0,76*		1***	0,75***	0,71*
Specificity	0,97	x	0,95*		0,93*		0,71***	1***	0,97*
TSS	0,95	0,58	0,93	0,76	0,92	0,69	0,75***	0,71***	0,68*
AUC	0,98	0,86	0,97	0,95	0,98	0,87	0,97***	0,94***	0,97*
Taken Threshold	0,58		0,50		0,50		0,6	0,6	0,75*

* Calculated with the presenceabsencepackage in R
** Except for the total of GLM runs
*** Calculated with caretpackage in R

4.2. Variable importance of algorithmic approach

The relative variable importance scores from various algorithms have been normalized to sum up to 100 for simpler interpretation (Grömping, 2009). In the context of algorithms variable importance refers to the measure of the relative contribution or influence of individual predictor variables on the model's predictive performance. The weighting of variables for the expert knowledge approach was determined in advance and is described in the methods chapter.

Degree days is the variable which contributes most significantly by determining the distribution of mangoes, rendering temperature, according to the models, the most crucial variable (Table 9). Notably, within both BRT and MaxEnt algorithms, the importance of degree days is almost entirely explanatory for the location of mango farms, especially in BRT where it accounts for 94% of the total. In the GLM algorithm, while degree days remain the most significant variable, its relative importance is less dominant compared to the other algorithms. Air humidity, the second most important variable, is considerably less determinative for the distribution of mangoes and, similar to other variables, will have a lesser impact on predicting suitable mango areas in the future compared to degree days. It is observed that topographical variables such as soil texture and soil depth possess a very low explanatory power.

Table 9: Relative importance of environmental variables in algorithmic approach (normalized to sum 100%)

	GLM	BRT	MaxEnt	Average
Degree days	40,9	94,0	75,7	69,6
Air humidity	24,7	2,0	18,7	14,5
Cloud cover	20,9	1,0	0,9	7,4
Soil texture	11,1	3,0	3,6	6,9
Soil depth	2,4	0,0	1,0	1,6

4.3 Response curves

The environmental predictor response curves of the probability occurrence of mangofarms are different per algorithm (Figure 9). In each box the curves of the ten model runs for BRT and MaxEnt, and twenty model runs for GLM, are shown for each variable. The visuals of the response plots look different for MaxEnt as this is done in the MaxEnt software (Phillips, 2006) and GLM and BRT response plots are created in biomod2 using ‘bm_PlotResponseCurves’ function.

For GLM and BRT, the response curves illustrate the variation in the predicted probability of presence as each environmental variable changes, while all other variables are held constant at their average values. This analysis reveals the model's sensitivity to specific variables without considering the interactions between them. Conversely, the response plots from MaxEnt models account for the dependency of predicted suitability not only on the selected variable but also on the correlations between the selected variable and others. The y-axis denotes the probability of occurrence (0 being not suitable, 1 being highly suitable), and the x-axis displays the range of environmental variable values, for example, cloud cover ranging from 0 to 70.

The response plots indicate considerable variability in variable values and predicted probabilities across different algorithms. A commonality among the three algorithms is a significant increase in the predicted probability for degree days, starting at approximately 1500, followed by a slight unexpected decrease observed in the MaxEnt plots which is uncertain as shown by the blue area. This consistent pattern of degree-days reinforces the result, as this variable also has the highest relative importance.

Overall, MaxEnt aligns most closely with the anticipated pattern between environmental variables and suitable areas for mango farms based on expert knowledge. Furthermore, low cloud cover, relative air humidity around 70%, and soil depth greater than 70 cm are associated with higher predicted probabilities for mango farms. Notably, soil with a medium/fine texture (3) is more suitable for mango farms than fine texture (5). Categories 0 and 9, representing cells without information, were included to avoid excluding a large area within southern Europe.

In the BRT algorithm, variables other than degree days show little differentiation in predicted probabilities for mango farms across high and low values, aligning with expectations derived from the variable importance ratios. A slight increase in predicted probability is observed with low cloud cover and high air humidity, as well as with fine soil texture.

The GLM algorithm exhibits greater variability in predicted probabilities across variables. The patterns of response curves of degree days and cloud cover match the expected pattern of the expert knowledge and patterns of other algorithms, however, the air humidity response curves are opposite to the MaxEnt output, namely high air humidity is suitable for mango growth. Response curves with a difference within the algorithm indicate a less robust estimation of their true contribution, and these variables therefore provide less insight. In GLM and BRT, categories are assigned values ranging from 1 to 7, and it may appear as though these values continuously transition between categories. However, this is not the case as the specific value associated with each category number must be considered.

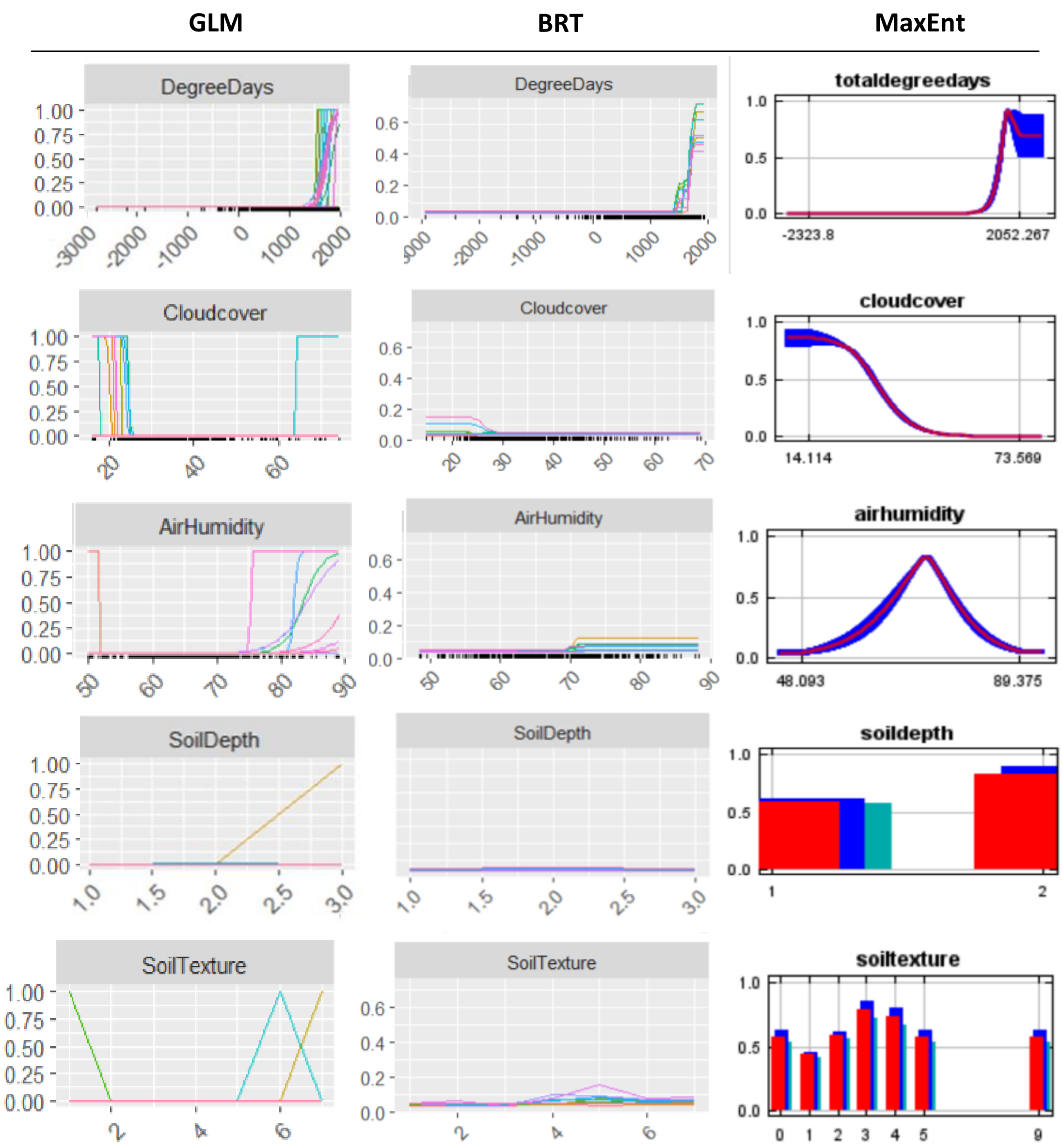

Figure 9: Response curves of algorithms

4.4 Suitability thresholds

In the expert knowledge approach for an area to be considered highly suitable, all variables must be suitable. An area is designated in the algorithmic approach as suitable if its predicted probability exceeds 75, as per the threshold method utilized (Table 10).

Table 10: Suitability scales based on probability of occurrences

Suitability category	Exp. Knowledge approach (value of suitability)	Algorithmic approach (value of occurrence probability)
Highly unsuitable	0-79	0-37
Unsuitable	80-94	38-74
Suitable	95-99	75-84
Highly suitable	100	85-100

4.5 Trend comparison of suitable areas & approaches

Figure 10 illustrates the total suitability across different years and scenarios within the two approaches based on a suitability threshold above 0.95 for the expert knowledge approach and a probability exceeding 755 out of 1000 for the algorithmic approach. A breakdown of various suitability levels is provided in Table 9.

In the current situation of the expert knowledge approach 3.74% (75,613 km² out of 2,016,812 km²) of southern Europe is deemed suitable for mango farms, while only 0.8% (15,278 km² out of 2,018,320 km²) of southern Europe is deemed suitable for mango farms in the algorithmic approach. There is a significant increase of future suitable area for mango farms in southern Europe (Figure 10). Notably, the total suitable area in the SSP1 scenario for the expert knowledge approach increases more sharply than in the SSP5 scenario. This difference is largely attributable to the substantial drop in suitable air humidity in the inland of Spain and Italy in SSP5, rendering these areas unsuitable for mango cultivation, a trend less pronounced in SSP1 (Figures 19 & 20). An interesting observation is a higher percentage of highly suitable areas in the SSP5 scenario, which contrasts with the ratio of total suitability (Appendix D.1). In the SSP5 scenario, there are more highly suitable areas but fewer moderately suitable areas compared to the SSP1 scenario.

The algorithm approach identifies fewer suitable areas in the current scenario, and although it shows a relatively larger increase compared to the expert knowledge approach, it predicts fewer suitable areas for mango growth in future scenarios (Figure 10). Notably, the SSP1 scenario in 2070 has more suitable areas than the SSP5 scenario for both the expert knowledge approach and the algorithm approach. The ratio between the approaches in 2030 for both the SSP1 and SSP5 scenarios appears similar. The trend, however, differs between the approaches. While the area of both scenarios in the expert knowledge approach increases significantly, it does not in the algorithm approach and even decreases from 2050 to 2070.

A significant increase in the algorithmic approach SSP5 scenario in 2050 seems attributable to Northern Greece being suitable in terms of air humidity, which is not the case in 2070 SSP5 and SSP1 and 2050 SSP1 scenarios (Figures 19 & 20). This pattern can largely be explained by the GLM algorithm identifying this area as highly suitable.

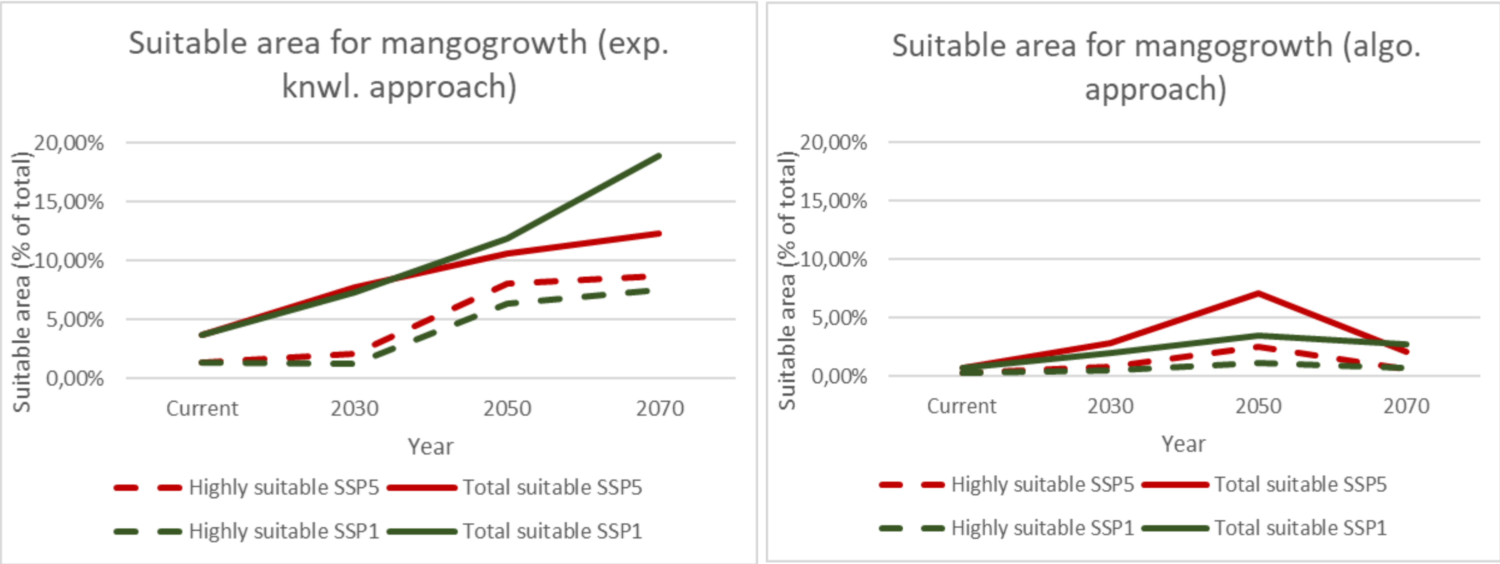

Figure 10: Change of suitability per scenario over different years

An unexpected pattern at the algorithmic approach is the decrease in suitable area in both scenario's in 2070 compared to 2050, with the SSP5 scenario even having fewer suitable areas in 2070 than the SSP1 scenario (Figure 10). The stronger rise can be attributed to the high importance of temperature, which on average increases more in the SSP5 scenario. The decline in 2070 seems to be due to a drop in air humidity in inland areas of Spain and Italy, causing these values to fall below the suitability threshold determined by the algorithms (Figure 19 & 20). This also explains why the SSP1 scenario has more suitable areas in 2070, as air humidity in inland areas decreases less in this scenario.

4.6 Spatial comparison of suitable area

4.6.1 Current situation

Due to the different methodologies used by both approaches regarding probability scores and suitability scores, the maps may display different colour patterns and categories. However, they can still be compared by stating that a probability of >75% and a suitability score of >0.95 are considered suitable. It is observed that in the current situation for both approaches, suitable land for mango cultivation is already available, particularly in the south of Spain, along the coastal areas of Sicily, and the toe regions of Italy (Figures 11 & 12). Additionally, many Greek islands are highly suitable for mango growth. The expert knowledge approach classifies the southern inland of Spain as suitable, while the algorithmic approach does not and generally classifies fewer areas as suitable. For detailed maps per scenario and future years, refer to Appendix E.2 & E.3.

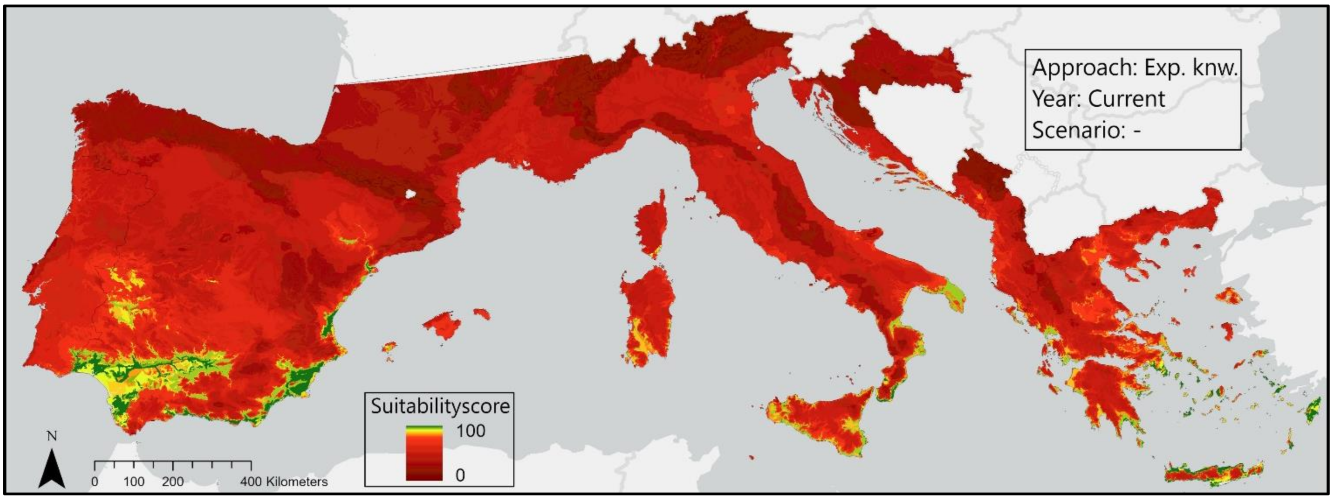

Figure 11: Current suitability for mango cultivation (based on expert knowledge approach)

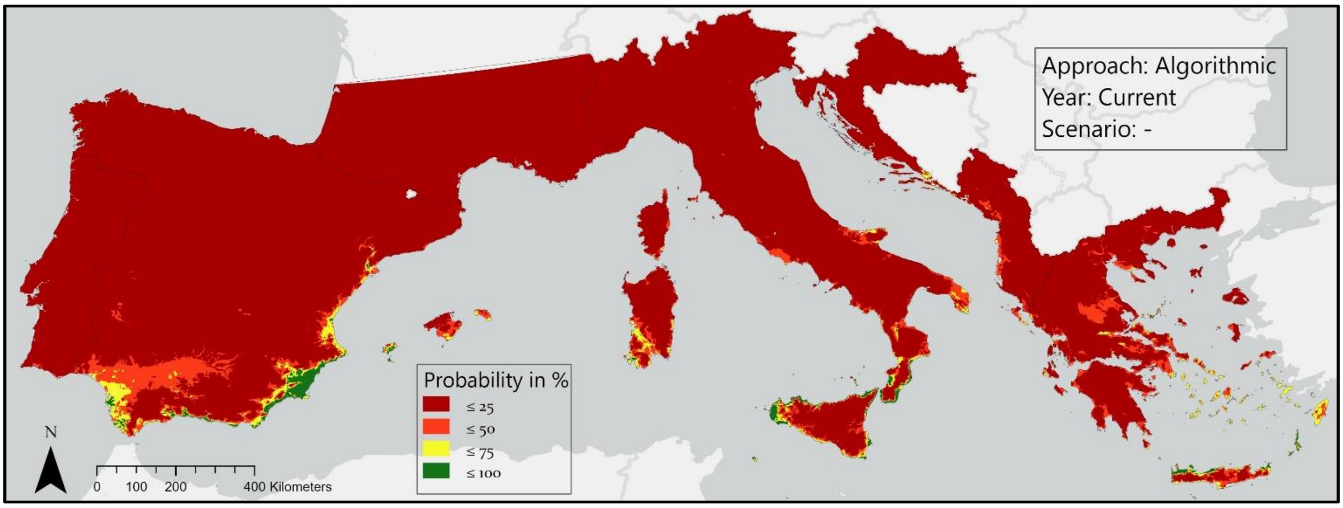

Figure 12: Current suitability for mango cultivation (based on algorithmic approach)

4.6.2 Current vs 2050

Expert knowledge approach

The current suitable areas expand by 2030 into central Spain, and more Greek islands become suitable for mango cultivation. There is little distinction between the SSP1 and SSP5 scenarios in 2030 (Table 11). Generally, a spatial pattern of higher suitability in coastal regions is evident. This trend continues in both scenarios by 2050, with mostly an expansion of current suitable areas along the coastlines (Figure 13). By examining the green areas, one can observe which areas remain suitable, with many of the same areas remaining suitable in both scenarios, with a few exceptions. The blue colour indicates the expansion of suitable areas, and here a significant difference is visible. Although many areas in both scenarios are suitable (dark blue), the SSP1 scenario indicates many new suitable areas in the southeastern inland of Spain, while the SSP5 scenario deems a valley area below the Pyrenees and scattered areas in Greece as suitable.

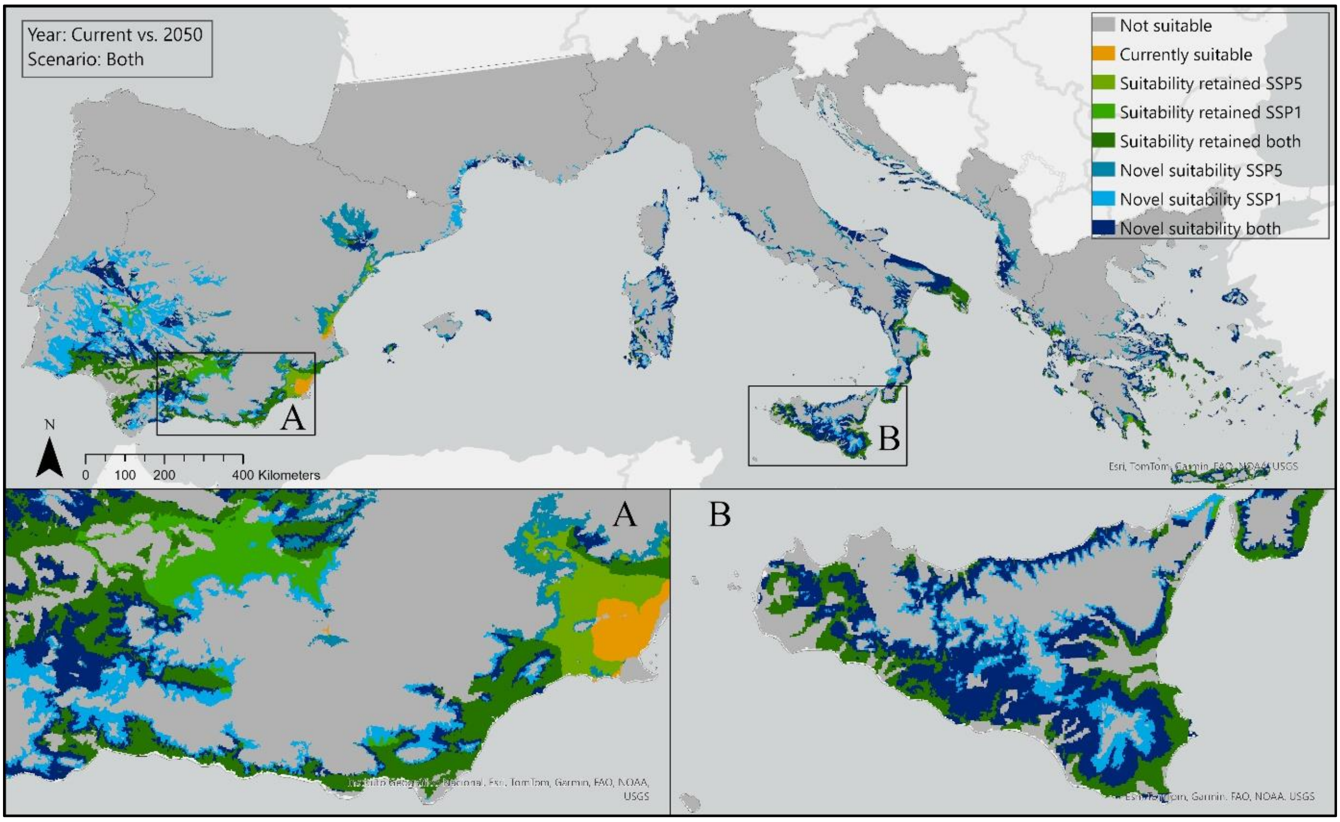

Figure 13: Change of suitability between current situation & 2050 (based on exp. knowledge approach)

Table 11: Change of suitability between current situation & 2050 in numbers (based on exp. knowledge approach)

Suitability category	km²	% of total
Not suitable	1.716.785	85,12
Currently suitable	2.705	0,13
Suitability retained SSP5	7.852	0,39
Suitability retained SSP1	8.062	0,40
Suitability retained both	56.275	2,79
Novel suitability SSP5	49.696	2,46
Novel suitability SSP1	76.100	3,77
Novel suitability both	99.341	4,93
Total	2.016.816	100

Algorithmic approach

Similar to the expert knowledge approach, the algorithmic approach also indicates a gradual expansion of suitable mango areas in 2050, continuing the steady trend observed in 2030 (Appendix E.3). In the current situation, only a few areas are suitable, and most of these areas remain suitable, with exceptions including the area around Malaga, the coastline of the toe of Italy, and the southernmost islands of Greece (Figure 14). Although there is little difference in suitable areas between the scenarios in 2030, this difference becomes apparent in 2050 (Table 12). The SSP5 scenario classifies the coastline in the middle of Italy, Northern Greece, and further inland areas of Spain as suitable compared to the SSP1 scenario. This is largely due to the higher rise of temperature in the SSP5 scenario.

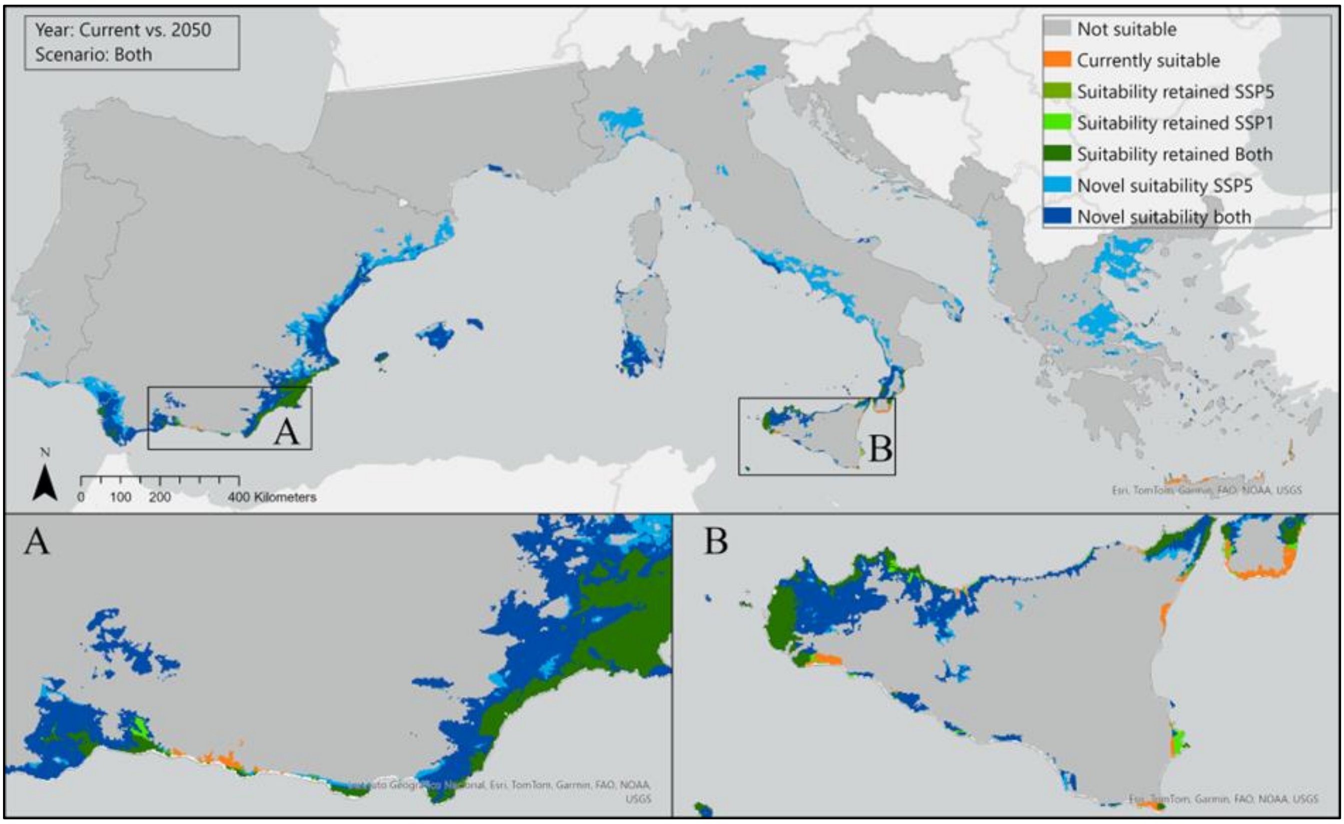

Figure 14: Change of suitability between current situation & 2050 (based on algorithmic approach)

Table 12: Change of suitability between current situation & 2050 in numbers (based on algorithmic approach)

Suitability category	km²	% of total
Not suitable	1.860.865	92,23
Currently suitable	2.285	0,11
Suitability retained SSP5	694	0,03
Suitability retained SSP1	233	0,01
Suitability retained both	11.625	0,58
Novel suitability SSP5	83.698	4,15
Novel suitability SSP1	0	0,00
Novel suitability both	58.248	2,89
Total	2.017.648	100

4.6.3 2050 vs 2070

Expert knowledge approach

From 2050 onwards, a different trend emerges compared to the steady trend observed from the current situation to 2030 and 2050. In the predicted scenarios of 2070, the suitable area for mango cultivation generally expands, but the suitable regions change significantly in both scenarios (Figures 15, 16 & Table 13). Central Spain becomes less suitable due to low air humidity in both scenarios, more pronounced in the SSP5 scenario. As a result, inland areas are more suitable in the SSP1 scenario.

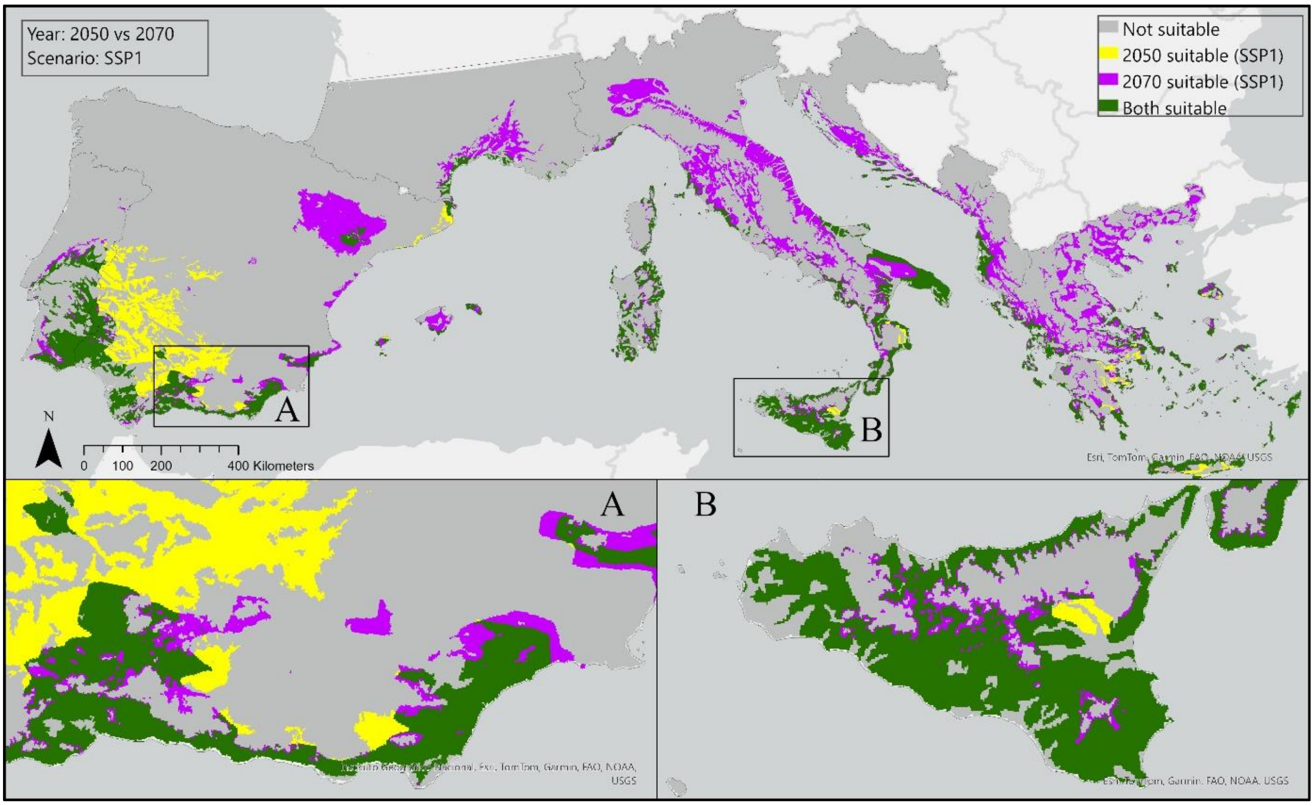

Figure 15: Change of suitability for mango cultivation between 2050 & 2070 SSP1 scenario (based on exp. knowledge approach)

Table 13: Change of suitability for mango cultivation between 2050 & 2070 in numbers scenario (based on exp. knowledge approach)

Suitability category (Exp. knowledge approach)	SSP1 (%)	SSP5 (%)
Not suitable	77,7	82,7
2050 suitable	10,4	6,7
2070 suitable	3,4	4,9
Both suitable	8,5	5,6
Total	100,0	100,0

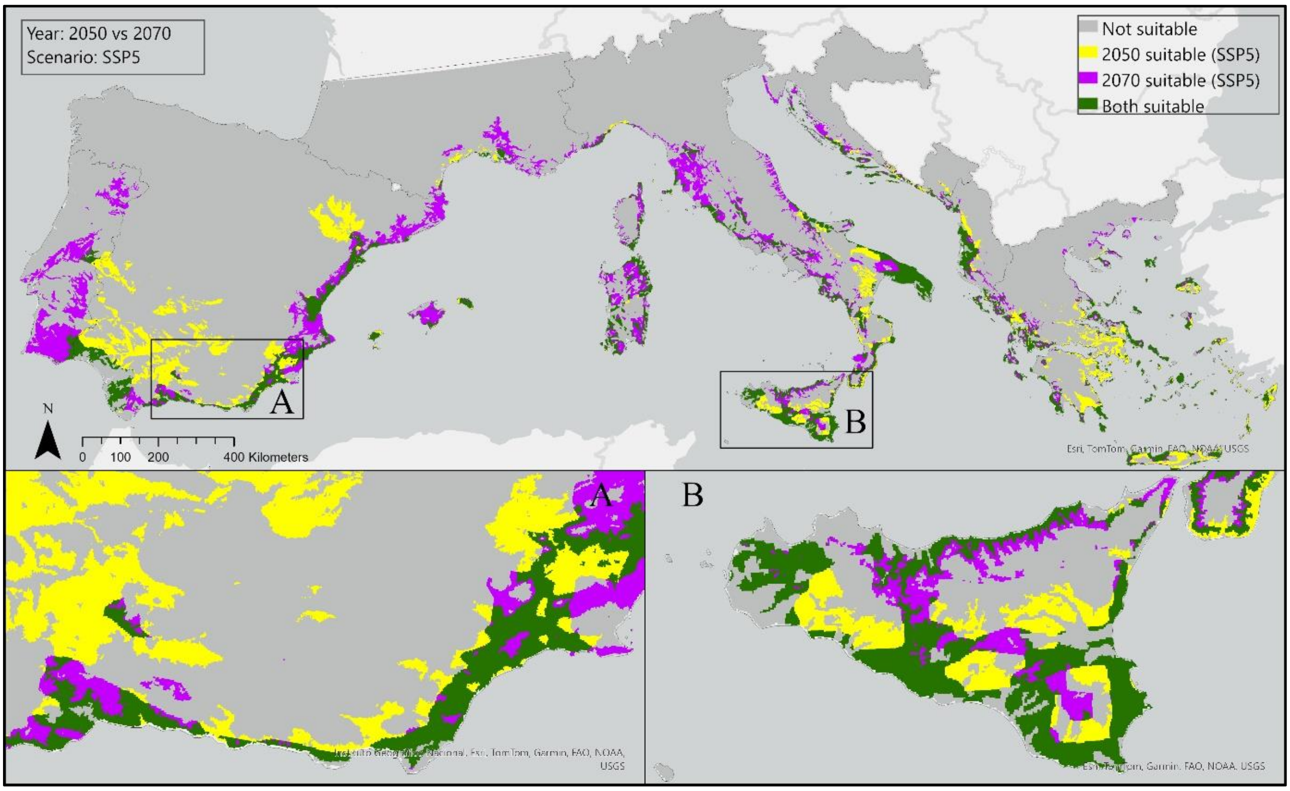

Figure 16: Change of suitability for mango cultivation between 2050 & 2070 SSP5 scenario (based on exp. knowledge approach)

Algorithmic approach

In 2070, the number of areas with suitability drastically decreases in the SSP5 scenario compared to 2050 (Table 14), leaving only a narrow coastal strip in the south and west of Spain, the west of Portugal, the south of France, and the southern coastal areas of Italy and the western coastal regions of Greece as suitable (Figure 18). There are a few areas that remain suitable, mostly along the coast, and the islands of Ibiza, Mallorca, and Menorca are highly suitable for mango cultivation in the SSP5 scenario. In the SSP1 scenario, these suitable areas extend more inland, likely due to more suitable air humidity in this scenario (Figure 17). The difference between the SSP5 and SSP1 scenarios widens as time continues, suggesting that the future suitable area for mango cultivation will likely fall somewhere between these two projections.

Table 14: Change of suitability for mango cultivation between 2050 & 2070 in numbers (based on algorithmic approach)

Suitability category (Algorithmic approach)	SSP1 (%)	SSP5 (%)
Not suitable	95,5	92,2
2050 suitable	1,7	5,7
2070 suitable	1,0	0,8
Both suitable	1,8	1,4
Total	100,0	100,0

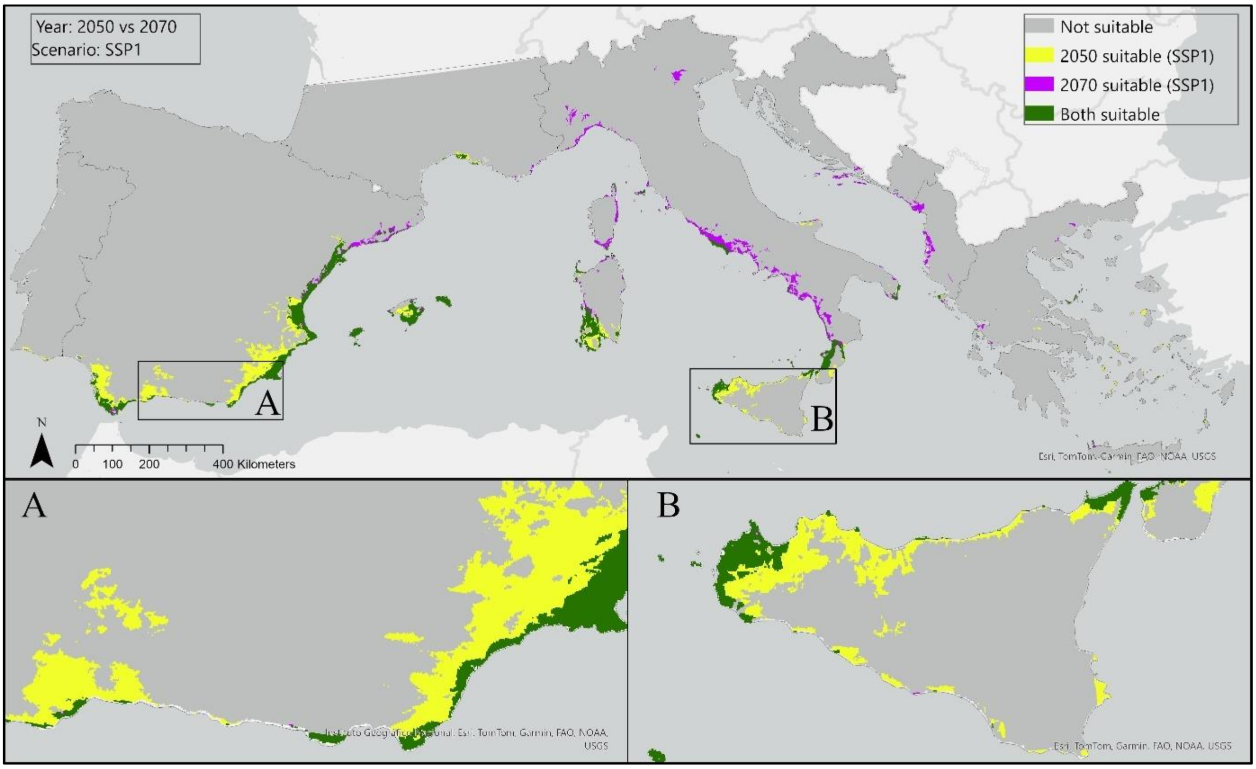

Figure 17: Change of suitability for mango cultivation between 2050 & 2070 SSP1 scenario (based on algorithmic approach)

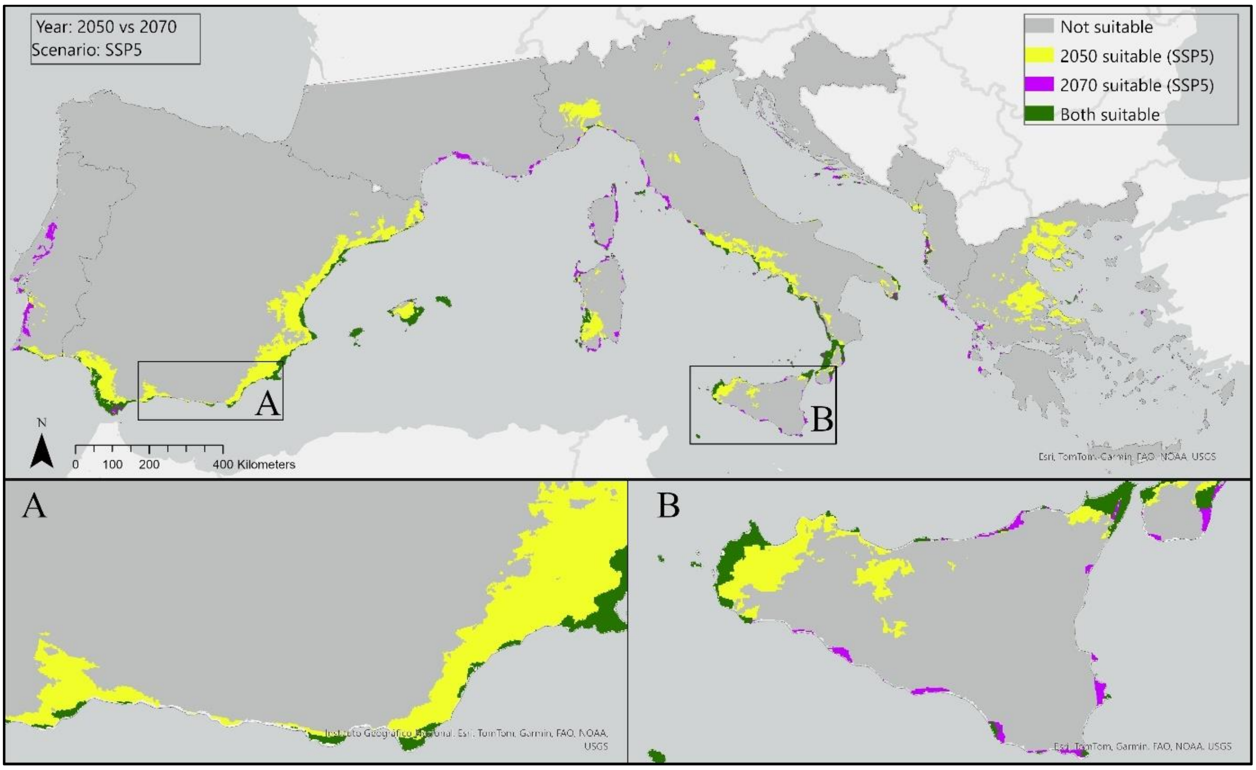

Figure 18: Change of suitability for mango cultivation between 2050 & 2070 SSP1 scenario (based on algorithmic approach)

4.7 Impact of Air humidity

As previously highlighted, the change in air humidity results in an unexpected future trend regarding suitable areas for mango cultivation. In 2070, many inland areas classify themselves as unsuitable because the air humidity becomes too low, particularly in the SSP5 scenario and a little in the SSP1 scenario (Figure 20). This trend is already visible in the expert knowledge approach SSP5 as of 2050, where the suitability of air humidity decreases in inland areas (Figure 19). While in the algorithmic approach, the air humidity in many inland areas becomes unsuitable as of 2070. This difference may be attributed by giving less weight to air humidity variables and using less strict thresholds.

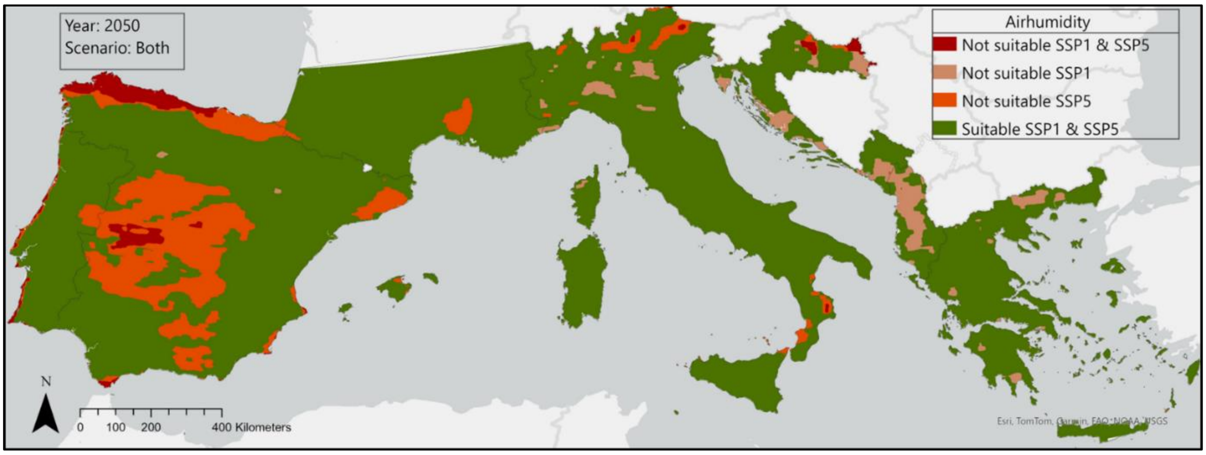

Figure 19: Suitability of variable air humidity in 2050 (based on expert knowledge approach)

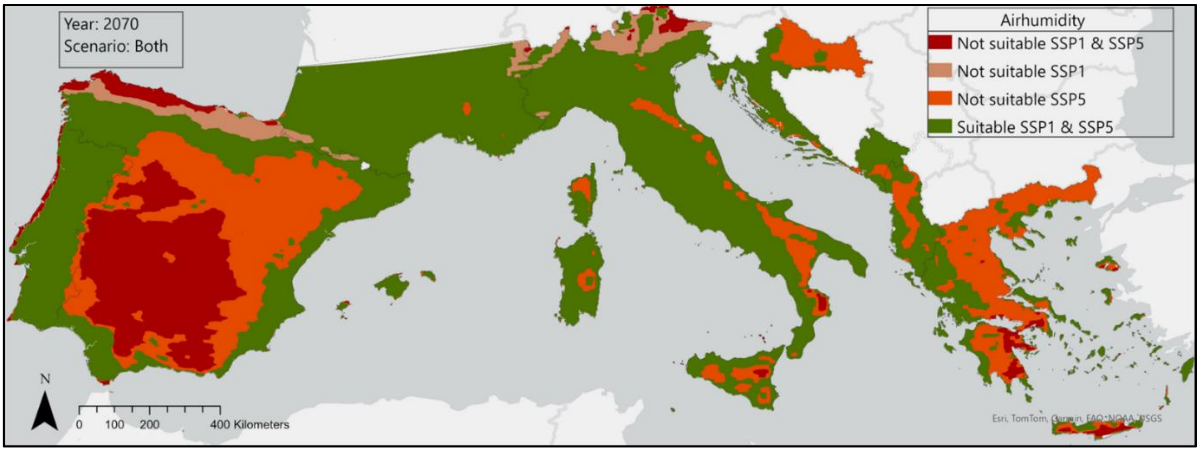

Figure 20: Suitability of variable air humidity in 2070 (based on expert knowledge approach)

4.8 Uncertainty analysis

The uncertainty of the output from the expert knowledge approach is challenging to assess, but efforts have been made to mitigate this uncertainty by incorporating a wide array of variables into the model. Especially regarding the key variable of temperature, various growth phases and averages of multiple years were considered to ensure the most reliable outcome. In the algorithm approach, many variables were found to be highly correlated, leading to their exclusion from the model calculation. To reduce the high uncertainty associated with this, three different algorithms were run ten times each and their results were aggregated. This approach also helps to minimize the impact of outliers on the final result.

The spatial uncertainty of the final results is illustrated by the standard deviation for each algorithm separately in the current scenario (Figures 21, 22 & Appendix E.4). A general pattern emerges showing that the variability of probabilities increases as the probability increases. Thus areas deemed more suitable are also less certain of this suitability compared to the unsuitability of unsuitable areas. The variability of the probability of occurrences is by far the highest in the GLM model, indicating that this model has the most significant internal differences across the 10 runs (Figure 21). A standard deviation above 300, with a maximum of 1000, is considered high, which is often observed in GLM. MaxEnt and BRT exhibit less variability in the probability of occurrences and therefore have a more stable, less uncertain result (Appendix E.4). When combining the algorithms, the valley region in the south of Spain and the islands of Greece, there is not only a high probability of occurrences but also high variability (Figure 22). This is also true, albeit to a lesser extent, for the eastern coastal area of Spain and the coastal areas of Sicily.

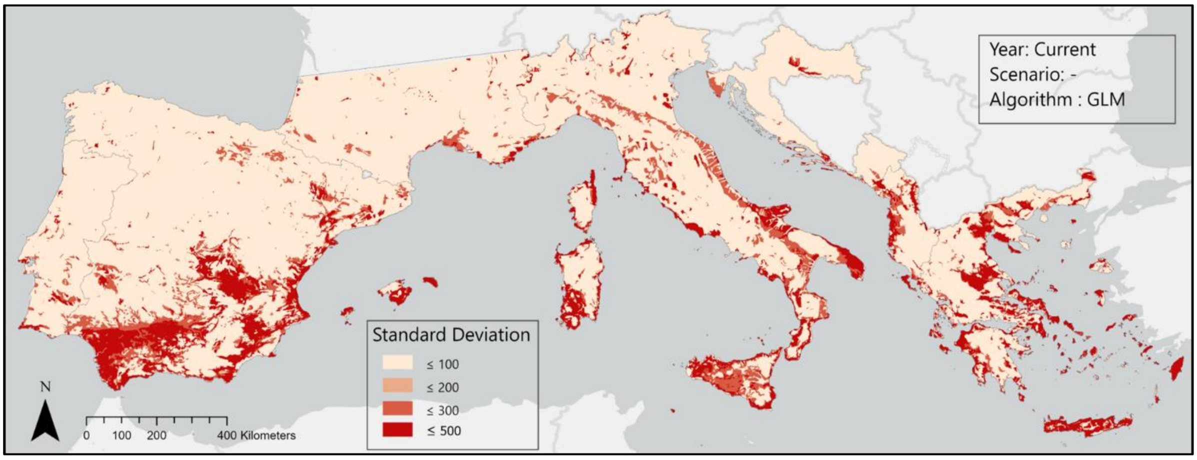

Figure 21: Variability of suitability score for mango cultivation area's (algorithm approach GLM)

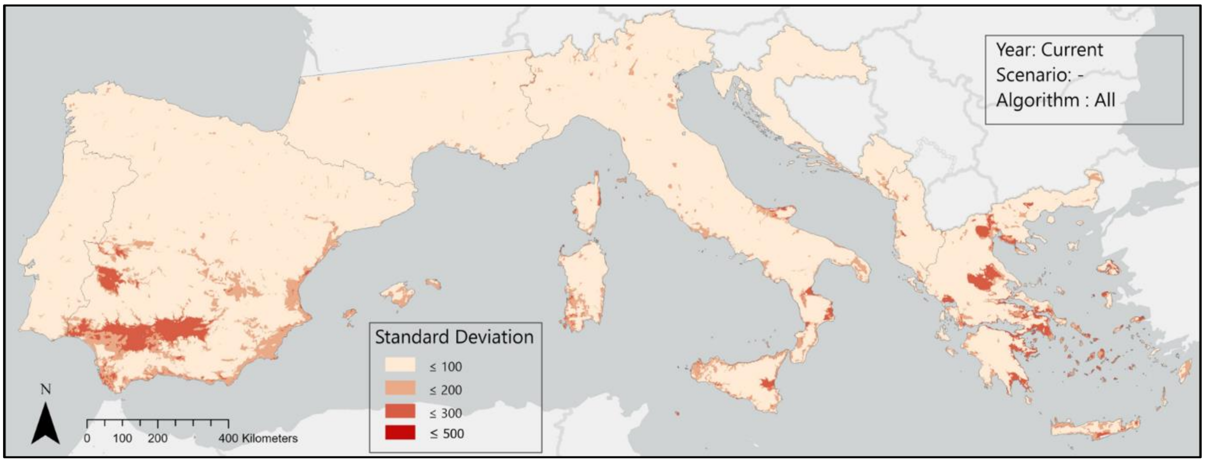

Figure 22: Variability of suitability score for mango cultivation area's (Average of algorithms)

4.9 Sensitivity analysis

The effects of using equal weights for all variables versus using the weights based on expert knowledge is tested to see if changing the weights led to big differences in the results, showing how sensitive the model is to different variables (Figure 23). Some differences were found, especially in areas where mango cultivation was highly suitable. In these areas, the equal weights method tended to show lower suitability compared to self-set weights, while areas deemed unsuitable in self-set weights showed higher suitability with equal weights. But overall the differences were small and in most places insignificant.

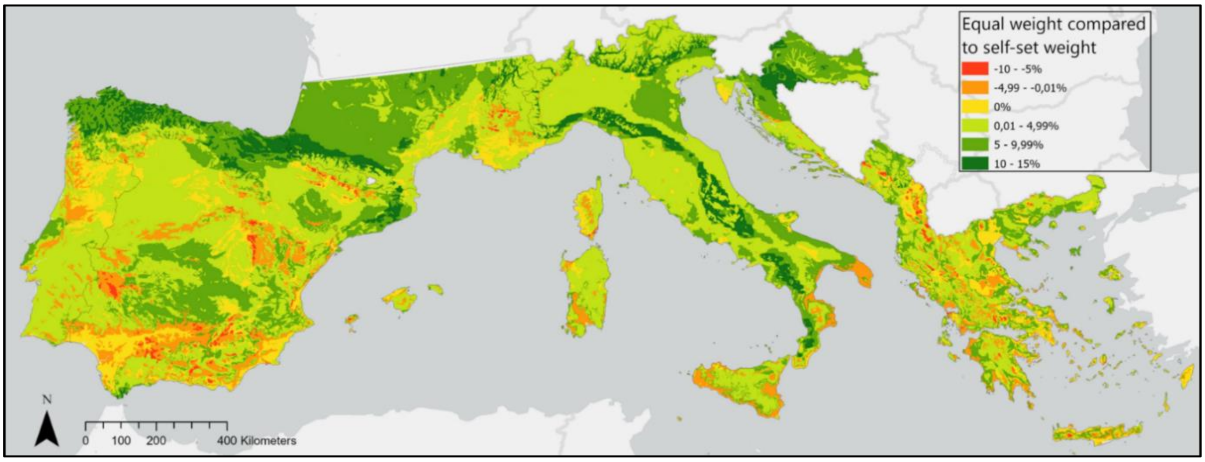

Figure 23: Suitability score difference as a result of different weights (based on exp. knowledge approach)

In the algorithm approach, the model itself determines the weights for variables, so we can't directly test sensitivity by changing the weights. Figure 24 shows the importance of each environmental variable by running models with only one variable at a time and excluding each variable once, to see how the model performance changes (Figure 24). It is evident that without the degree days, the performance of the model is significantly weakened, indicating that it is highly dependent on and sensitive to changes in this variable.

Additionally, in Appendix D.2, show changes in input parameters and environmental variables affect the model's predictions, based on evaluation metrics. There were differences in how well the model performed with different settings & input parameters, indicating that the model is sensitive to changes in parameters. However, we chose the models with the best evaluation metrics and combined them, which helps to mitigate concerns about differences between models.

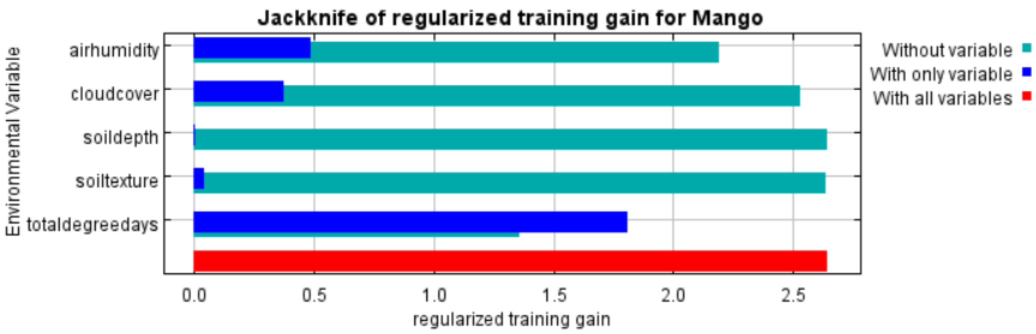

Figure 24: Performance change by excluding variables

4.10 Adding the water component

The combined result of the expert knowledge and algorithm approach is overlaid on the water stress per region. In the current scenario, nearly all areas directly along the Mediterranean Sea are experiencing extreme water stress (Figure 25). The suitable areas*, in both approaches, are almost entirely in these regions, meaning mango farms in these areas will demand water from an already scarce environment, as is already happening (McGeer, 2023). The only area where water stress is low and the environmental factors are conducive to mango farming is near Barcelona (Figure 25).

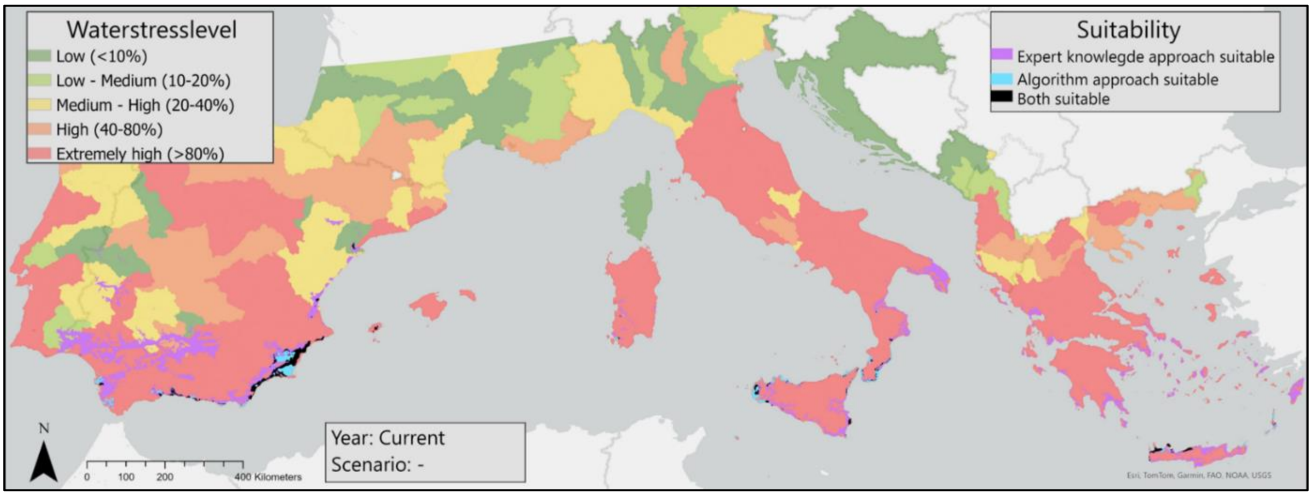

Figure 25: Suitability area's for mango cultivation & waterstresslevel (Current)

Looking ahead, water scarcity is expected to become a bigger issue in both future scenarios (Figure 26 & 27). Regions like southern Spain, Italy, and Greece will face increasing water scarcity levels while places like southern France, northern Italy, and Croatia will see less water scarcity. Some of these regions could be good for growing mangoes, both because of the environment and the potential for irrigation.

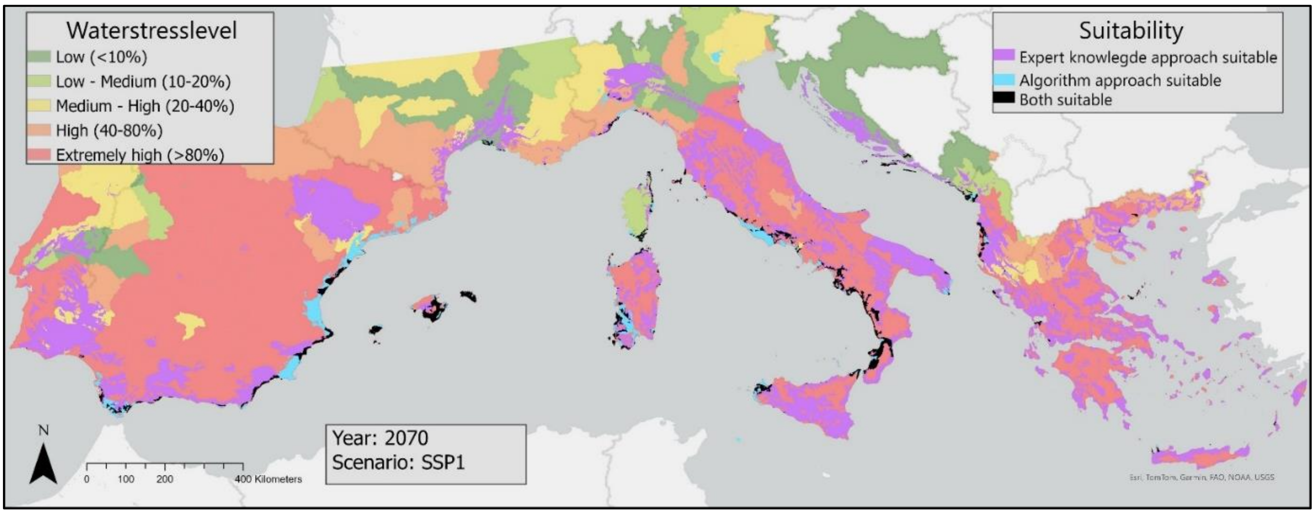

Figure 26: Suitability area's for mango cultivation & waterstresslevel (2070 SSP1)

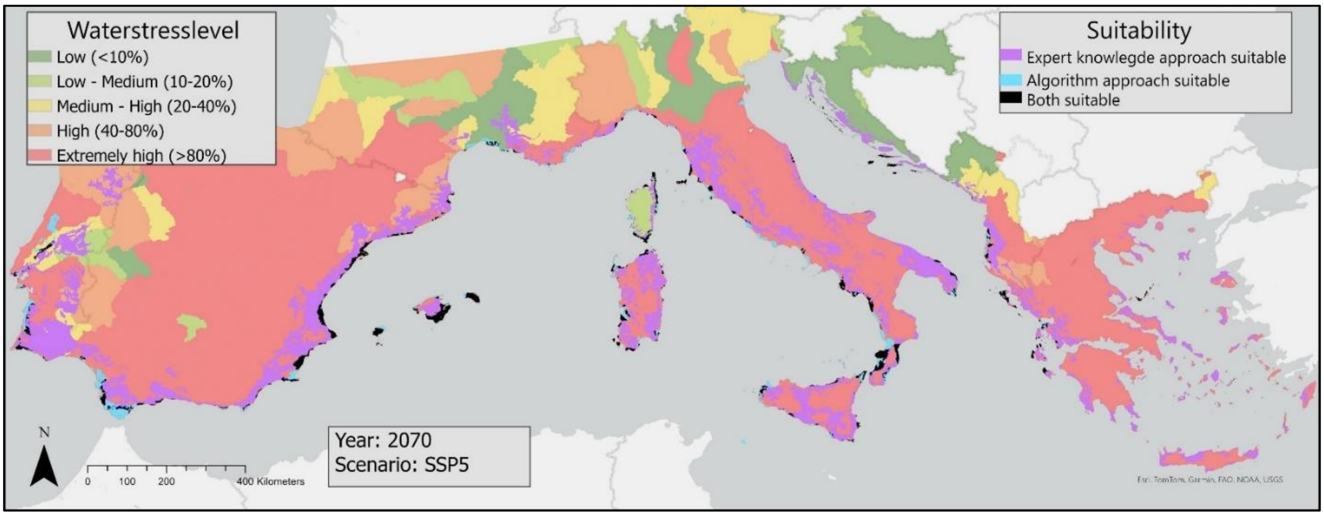

Figure 27: Suitability area’s for mango cultivation & waterstresslevel (2070 SSP5)

A comparison between the relationship of water stress levels and suitable area’s for mango farms in both current and 2070 scenario’s is given in figure 28. Despite the expected increase in water stress, we see more suitable mango areas with acceptable water stress levels as a result of expanding mango cultivation into regions with lower water stress levels. However, still many areas with good environmental conditions for growing mangoes have limitations on irrigation due to high water stress levels.

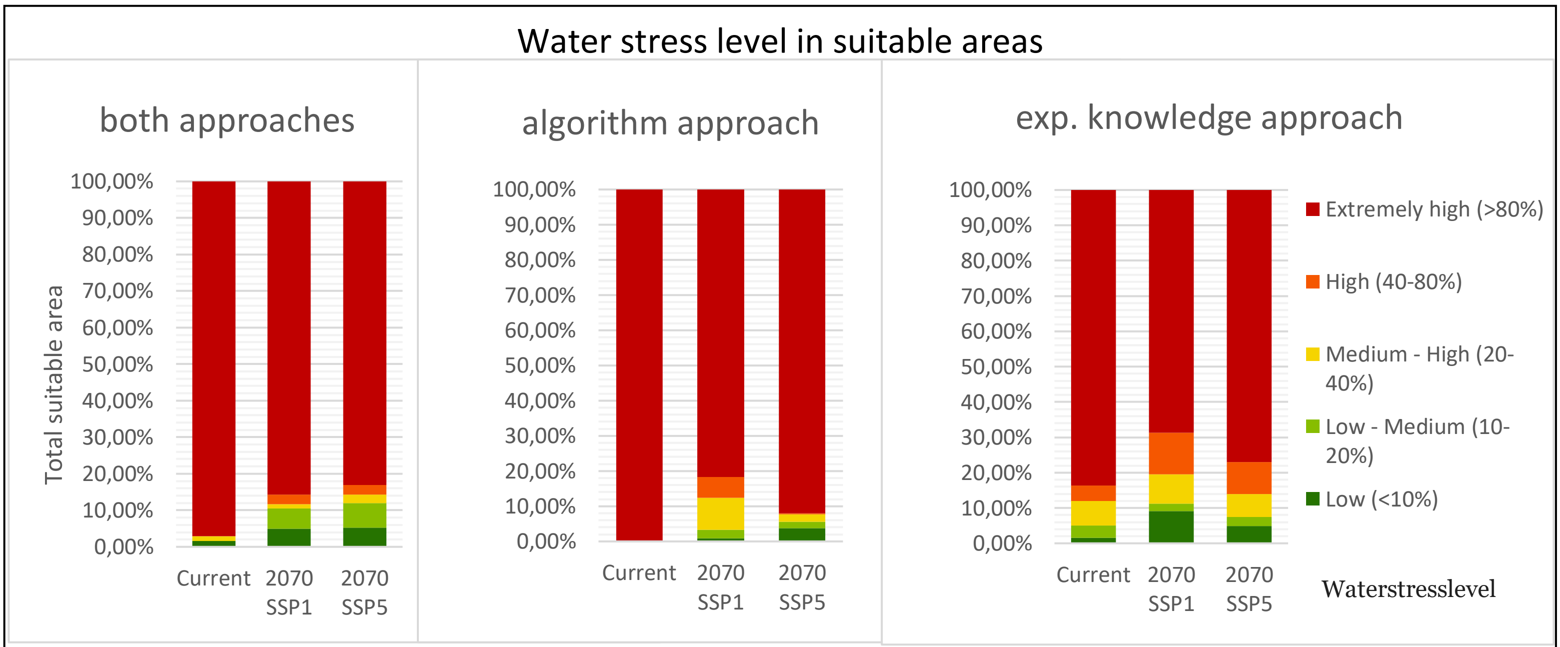

Figure 28: Waterstresslevel of suitable areas

5. Discussion

In this discussion chapter, we begin by interpreting the findings, drawing comparisons to existing scientific literature where applicable and highlighting any unexpected outcomes. Following this, the research limitations are examined, leading to recommendations for further investigation.

5.1 Interpretation of Results

5.1.1 Future expansion of mango cultivation in southern Europe

This study conclusively predicts an expansion of suitable regions for mango cultivation in southern Europe across all future scenarios, corroborating findings from research such as that by Santos et al. (2017), Osorio-Marín et al. (2024), and Paź-Dyderska et al. (2021) concerning the influence of climate change on the optimal conditions for fruit and nut cultivation in Europe. Santos et al. (2017) report that fruit-bearing trees in Portugal are anticipated to benefit from enlarged growth regions due to elevated temperatures predicted in future scenarios. Likewise, Osorio-Marín et al. (2024) and Paź-Dyderska et al. (2021) conclude an anticipated northward expansion of the growth zones for various fruits and nuts. In contrast, Arenas-Castro et al. (2020) observe a decline in the suitability of olive production in southern Spain, which is projected to be highly suitable for mango cultivation in the future. Thus, there may be a strategic advantage in pivoting to mango cultivation in regions traditionally known for olive production.

There is an inconsistency observed in the suitability percentages of area's between the SSP1 and SSP5 scenarios. In both approaches, in no one scenario does there seem to be a pattern between the different timeframes. This is in contrast with findings by Osorio-Marín et al. (2024), who report a general increase in fruit production in Europe under the SSP5 scenario compared to SSP1. The deviation noted in this research could stem from factors such as the inclusion of air humidity, enhanced spatial resolution, or alternate thresholds for determining suitable areas.

Despite the overall rising suitability of most environmental variables for mango cultivation, precipitation does not follow this trend. This combined with high water stress levels due to low water availability in environmentally suitable mango cultivation areas, skews the view that southern Europe is suitable for mango cultivation. This research echoes the concerns raised by Osorio-Marín et al. (2024) regarding water stress, noting that even as the land areas deemed suitable for cultivation— also accounting for water stress levels—increases, areas that do not already experience water stress may eventually experience it due to the increased intensity of mango farming.

5.1.2 Two Different Approaches

Uncertainty inherent in all types of Ecological Niche Models (ENMs) has led agricultural impact modelers to advocate for comparisons between modelling approaches (Estes et al., 2013). Due to the occasional absence of reliable, necessary physiological information in the expert knowledge approach, and the lack of occurrence data in the algorithmic approach, it was decided to include both approaches and derive a general conclusion from them as neither is inherently superior to the other. Consequently, the two approaches yield different results, potentially due to the reason of a broader range of environmental variables in the expert knowledge approach, incorporating a more comprehensive spectrum of environmental factors compared to the algorithmic approach. Two other reasons are of a variance of weighting & different thresholds for determining suitable area's between the two approaches.

5.2 Limitations & future recommendations

The limitations inherent in this research recognize that each constraint presents a unique opportunity for future investigation. By openly discussing these limitations, a balanced view of the findings is provided, suggesting practical avenues for subsequent studies to build upon. Additionally, recommendations are offered that are designed to address these limitations and advance the field.

There are several issues related to the use of ENM models that also pertain to this research (Elith & Leathwick, 2009). This research has focused its scope on environmental factors; however, non-environmental factors that may impact occurrence data, such as agricultural techniques, economic activities, and legislation, have not been considered, though these factors do play a role in the real-world suitability for mango cultivation. Another non-environmental factor influencing mango cultivation is water addition, as irrigation can pose challenges in areas with high water stress levels. A suggestion for future research is to explore how water management can be specifically addressed in these areas and to what extent the introduction of mango cultivation impacts water stress levels. Additionally, a recommendation for future research is to include the aforementioned non-environmental factors as variables that explain mango occurrence.

Elith & Leathwick (2009) also propose that species may adapt to conditions in the future, either through natural mutations or those induced by humans, which impacts the reliability this ENM approach. Besides, several mango varieties can differ from each other in terms of optimal growing conditions. So the choice of variety can also have an impact on the growing area and harvesting period. In a differentiation of environmental variable parameters, the choice is made to include the parameters corresponding to those of the Osteen mango, where possible, as 'Osteen' are more suited for high summer Mediterranean climates (Liguori et al, 2020). But environmental variables may change in the future such that a different variety might be more suitable. Future research could thus consider the possibility of these mutations and include a variety of mango breeds to test each area for its optimal future growth area.

A major limitation of this research was the small sample size due to the limited number of mango farms currently in Europe. Since other regions with more mango farms have very different environmental parameters, these areas cannot be mapped onto southern Europe, as no area would be classified as suitable. This small sample size increases the risk of overfitting and may not adequately capture the full range of variability in environmental conditions. The negative impacts of this small sample size have been mitigated by the cross-validation technique of bootstrapping and incorporating ensemble modelling. In future research, a smaller area could be selected, or it may be necessary to wait until more mango farms are established in Europe. The reliability of occurrence data points is also questionable since mango farms have been located via various online sources. Future research might utilize less biased datasets from the FAO, which do not yet exist, containing locations of mango farms in southern Europe.

The tuning of model parameters is complex, and the results of this research are not beyond criticism. Although many different settings have been tested for performance, these have a significant impact (Čengić et al., 2020), and future research could involve more varied settings and perhaps different algorithms to achieve an ensemble result. In addition, despite logical reasoning, applying the 25the percentile rule for threshold is fairly subjective which makes the total classified areas more unreliable This doesn’t detract from the trends found. Subsequent studies can examine the ideal threshold for improved model performance. Additionally, comparing different approaches was not within the scope of this research, but this could be more prominently addressed in future research.

6. Conclusion

This study aimed to assess the impact of climate change on the expansion or contraction of suitable area's for the mango (Mangifera indica L.) cultivation in the southern Europe, a fruit which is gaining global popularity. The Environmental Niche Model (ENM) applied in this research has elucidated the complex interplay between various environmental variables and mango cultivation, offering a nuanced understanding of future cultivation prospects in southern Europe. This has been addressed using two approaches, the correlative approach carried out through the use of three algorithms, and a more mechanistic approach conducted with expert-based knowledge. Since the outcomes of the methods can greatly vary and the research objective does not specifically lend itself to one method, it is decided to apply and compare both approaches. The results of these approaches not only identify current suitable areas for mango cultivation but also projects changes in these areas under future climate scenarios. This indicates a potential expansion of suitable cultivation areas suggesting that climate change could offer new opportunities for mango cultivation in southern Europe.

However, the study also cautions against overly optimistic interpretations of these findings. Although temperatures will become more suitable in the future as a result of climate change, changes in air humidity and precipitation pose future challenges, with increasing variability and potential decreases in some areas affecting the sustainability of mango cultivation. Water stress, particularly in regions that are becoming warmer and potentially drier, poses a significant challenge to expanding mango cultivation. The sustainability of mango farming in new areas will depend critically on irrigation practices and the efficient use of water resources. This includes the development of water-efficient cultivation techniques, the selection of climate-resilient mango varieties, and the consideration of new agricultural practices suited to the changing climatic conditions in southern Europe.

Apart from the pressure that mango farming has on water supplies in southern Europe under current and future climatic conditions, other environmental variables are generally becoming more suitable for mango cultivation. The increase in degree days, which emerged as the most significant variable, and the reduction in cloud cover foster an expansion in suitable regions for mango cultivation, especially in coastal areas as the rise in air humidity will classify inland areas as unsuitable in future scenario's. It should be noted that while other topographical factors such as soil characteristics remain constant, they delineate specific limited areas as unsuitable for mango farming.

There is no equivalent change of suitable area's observed between the two scenarios, encompassing both the expert knowledge approach and the algorithms approach. The expert knowledge approach concludes that under the optimistic SSP1 scenario, more areas will become suitable for mango cultivation in the future compared to the pessimistic SSP5 scenario. Conversely, the algorithm approach identifies more areas as suitable under the SSP5 scenario, except in the distant future of 2070, due to an increase in air humidity.

The varying impacts of different climate change scenarios per approach highlights the complexity of predicting agricultural suitability in the context of climate change, underscoring the importance of integrating diverse methodologies to capture the multifaceted impacts on regional agriculture and limit the uncertainty. This is mitigated by running various algorithms multiple times and comparing these results with the expert knowledge approach.

In conclusion, while climate change may expand the horizons for mango cultivation in southern Europe, realizing this potential will require careful planning, innovative water-efficient cultivation practices, and a nuanced understanding of the interplay between local climate change and agricultural suitability. This study underscores the need for adaptive strategies to harness the opportunities presented by climate change while mitigating its potential adverse effects. The findings of this study contribute valuable insights to this endeavour, offering a foundation for future research and policy-making aimed at ensuring the sustainable expansion of mango cultivation in the southern Europe.

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8. Appendix

A. Contents supplementary ZIP file

1. R-Code for GLM & BRT algorithmic approach + testing performance
2. Documentation BIOMOD2-package
3. ArcGisprojects, including:
    a. Correlationvariables + current suitability maps
    b. Mangofarmlocations
    c. Calculations examples of expert knowledge approach
    d. Endresultmaps of Expert knowledge approach
    e. Endresultmaps of Algorithms approach
    f. Visualisation of airhumidy & cloudcover + study area
    g. Waterstress + merging of the two approaches
4. Pseudoabsencepoints + predicted probabilities
5. MaxEnt_results
6. GLM/BRT results
7. Modelruns of GLM/BRT
8. Inputdata of environmental variables + occurencepoints

B. Data collection

Table 15: presence-points of mango cultivation farms

Name	Adres	Province/region/country	Source
Finca los Pepones	29718 Los Pepones, Málaga, Spanje	Malaga/Andalucia/Spain	Link
Cortijo Robledo	23680 Alcalá la Real, Jaén, Spanje	Granada/Andalucia/Spain	Link
Cortijo Rando	36°47'17.9"N 4°08'07.7"W	Malaga/Andalucia/Spain	Link
La Mayora	29750 Algarrobo, Málaga, Spanje	Malaga/Andalucia/Spain	Link
La Finca Experimental El Zahorí	Diseminado Bco Itrabo Pol 26, 235B,18690, Granada, Spanje	Granada/Andalucia/Spain	Link
PaPaMango	Contrada Giancola, 98076 Sant'Agata di Militello ME, Italië	Sicilia/Italy	Link
Mangolime	Via Savochelli, 13, 95016 Mascali CT, Italië	Sicilia/Italy	Link
Zuccarella Giovanni	Via Parisi, 16, 75020 Scanzano Jonico MT, Italië	Metapontino/Italy	Link
Canalotto Farm	Via Errante, Contrada Canalotto, 58, 91022 Castelvetrano TP, Italië	Palermo/Italy	Link
Finca Refijo	Calle Valle del Tera, 70 (Polígono Los Zamoranos) 29700 Vélez-Málaga, (Málaga)	Malaga/Andalucia/ Spain	Link
Rancho Oriental	Leon Guallart, 57 31500 Tudel a (Navarra)	Algarrobo/Andalucia/Spai n	Link
Dehesa de Cútar	S.L. Calle Juan Gris, 20. 29700 Vélez-Málaga (Málaga)	Malaga/Andalucia/ Spain	Link
El Peñoncillo, Torrox, ES	S.L Explanada de la Estación, 29. Vélez-Málaga (Málaga)	Malaga/Andalucia/ Spain	Link
Loma del Gato, Almuñecar, ES	S.L.U. C/ Alcalde Caridad, 17 18698 Otívar (Granada)	Granada/Andalucia/Spain	Link
Hacienda Altos de Cantarriján, Almuñecar, ES	SL Ctra. Suspiro (del), km. 47 18699 Lentegí (Granada)	Almunecasr/Andalucia/Sp ain	Link
Huertas Salobreña, Salobreña, ES	Huertas Salobreña · Salobreña, Spain	Huertas Salobreña · Salobreña, Spain	Link
Finca Montealegre, Competa, ES	SL C/ Huelva, 11 29793 Torrox Costa (Málaga)	Torrox/Andalucia/Spain	Link
Finca Aguasvivas, Artana, ES	Arcadi García Sanz 19 Planta 1ºA 12540 Vila-real (Castellón)	Artana/Valencia/Spain	Link
Rancho del Tio Esteban, Vélez-Málaga, ES	S.L. Ctra. Algarrobo, km 2,5. 29750 Algarrobo (Málaga)	Malaga/Andalucia/ Spain	Link
Alhambra Tropical, Motril, ES	Luja s/n Gualchos-Puntalón 18600 Motril (Granada)	Motril/ Andalucia/ Spain	Link
La Reala, Motril, ES	SCA Ctra. Almería km 16. 18600 Motril (Granada)	Motril/ Andalucia/ Spain	Link
Mango Hellas	Theriso 731 00, Griekenland	Crete/Greece	Link
Palazzolo produzio biologica	Terrasini in Via Mimose en Azalea n. 7	Palazzolo/Italy	Link
Talia	90041 Balestrate, Palermo, Italie	Palermo/Italy	Link
PapaMango		Palermo/Italie	Link
Domaines De La Taste	Pianiccia, 20270 Tallone, France	Tallone/France	Link
MangoLime	See google maps link	Palermo/Italy	Link
Mennuli&Alivifarm	See google maps link	Palermo/Italy	Link

C. Data preprocessing

C.1 Spatial autocorrelation output

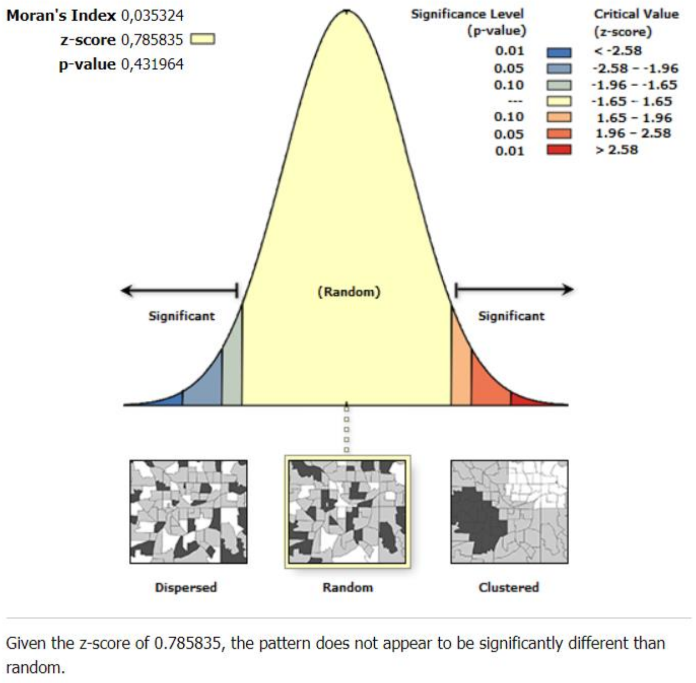


Figure 29: Spatial autocorrelation function Arcgis Pro output (all occurrence points with feature degree days)

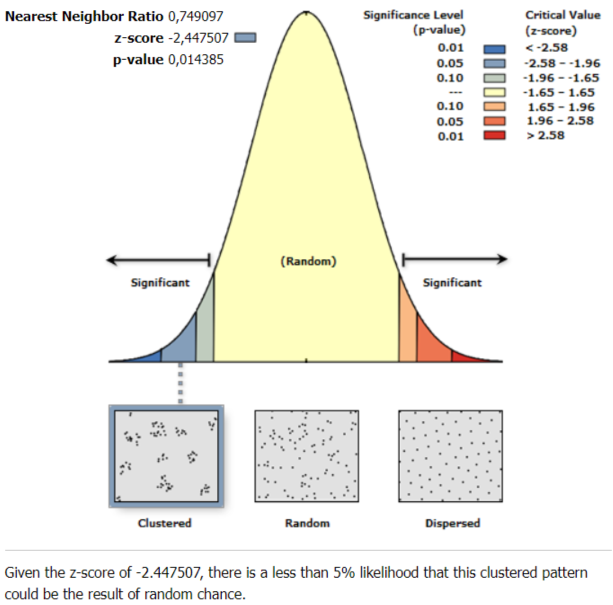


Figure 30: Output ‘Average Nearest Neighbor function’ Acrgis Pro study area without preprocessing

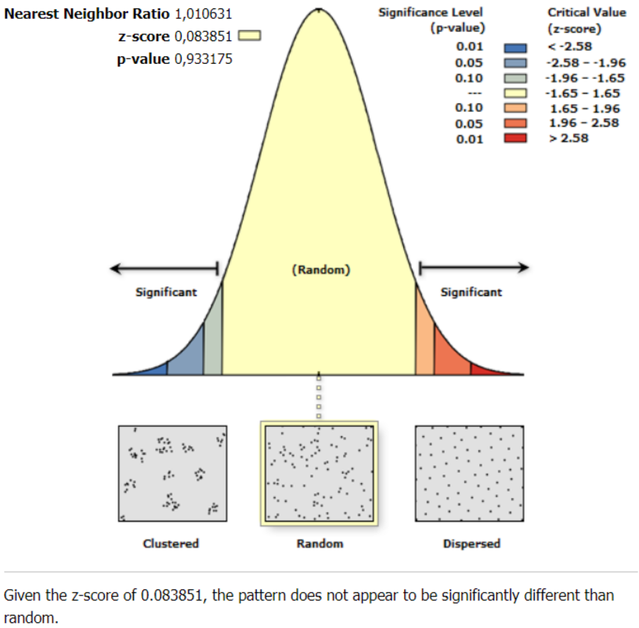


Figure 31: Output 'Average Nearest Neighbor function' after excluding of points within 10 kilometers

D. Evaluation metrics of different algorithm settings

D.1 Algorithm settings

GLM: 2 Pseudo-absence random distribution layers, variable importance = 4, type = simple, test = AIC, interaction level = 1

The 'simple' type was chosen due to basic relationships, while more complex types such as quadratic and polynomial would introduce unnecessary complexity. AIC, as a test, seeks a balance between complexity and fit. The interaction level is set to 1 to capture average interactions between variables.

GBM (BRT): 2 Pseudo-absence random distribution layers, Bernoulli distribution, variable importance = 4, number of trees = 2000, shrinkage = 0.001, bag.fraction = 0.5, interaction.depth = 1, n.minobsinnode = 5

The Bernoulli distribution was selected because the response variable is binary, and the model outcomes range between 0 and 1 (suitable or unsuitable). No weights were assigned to observations as there are no observations of greater importance. The number of trees, in combination with interaction depth, was set to prevent overfitting by using a reasonable number of trees but a low value for interaction complexity. The shrinkage was kept at default in proportion to the number of trees.

MaxEnt: 1 Pseudo-absence random distribution layer, Cloglog, Test percentage 20%, bootstrap, regularization multiplier = 1, maximum number of iterations = 2000, convergence threshold = 0,00001

Cloglog output is used because we want a probability scale. For studies based on presence-only data where minimizing overprediction is crucial, cloglog output is the most suitable. A test percentage of 20% was chosen to ensure good model calibration fit. Bootstrapping is optimal for datasets with few occurrence points, as Maxent will be allowed to test the model with occurrences that may have been used to train it. The regularization multiplier was left at default. The number of trees was set higher than the default value as this improves the accuracy of the model with low occurrences, while the convergence threshold was lowered, requiring more computational power but improving the model.

D.2 Evaluation metric values

The values below are based on thresholds determined by the model itself and so the 25th percentile threshold has not yet been included in the determination of these performance factors. These numbers came from the output of the biomod2 package itself.

Table 16: Evaluation metrics of different parameters of runs

Pseudo-absences	Algoritm	Regularization multiplier	Nmbr of PA layers	Perc. of trainig data	Run	TSS calibration	TSS validation	AUC calibration	AUC validation	Accuracy validation	Accuracy sensitivity	Accuracy specificity
x10 (1700)	MaxEnt	1	1	0,8	Yes	0,56	1,00	0,97	0,94	x	84.4	71.4
Big number (10000)	MaxEnt	0,5	1	0,8	No							
x10 (1700)	MaxEnt	0,5	1	0,8	Yes			0,99	0,96			
Big number (10000)	MaxEnt	1	1	0,8	Yes			0,99	0,96			
100 PA	GLM	x	2	0,5	No							
1700 PA	GLM	x	2	0,5	Yes	0,94	0,37	0,99	0,75	0,98	78	100
10000 PA	GLM	x	2	0,5	No							
100 PA	GLM	x	2	0,7	Yes	0,99	0,52	0,99	0,75	0,87	100	99
1700 PA	GLM	x	2	0,7	Yes	0,97	0,47	0,98	0,78	0,99	100	97
10000 PA	GLM	x	2	0,7	Yes	0,99	0,52	0,99	0,75	0,89	100	99
100 PA	GLM	x	2	0,9	No							
1700 PA	GLM	x	2	0,9	Yes	0,99	0,6	0,99	0,85	0,98	55	100
10000 PA	GLM	x	2	0,9	No							
100 PA	BRT	x	2	0,5	No							
1700 PA	BRT	x	2	0,5	Yes	0,88	0,75	0,95	0,93	0,99	3,1	100
10000 PA	BRT	x	2	0,5	No							
100 PA	BRT	x	2	0,7	Yes	0,87	0,67	0,98	0,93	0,96	80	100
1700 PA	BRT	x	2	0,7	Yes	0,85	0,75	0,97	0,92	0,99	17	98
1700 PA	BRT	x	2	0,7	Yes	0,85	0,65	0,97	0,88	0,99	33	100
10000 PA	BRT	x	2	0,7	No							
100 PA	BRT	x	2	0,9	No							
1700 PA	BRT	x	2	0,9	Yes	0,84	0,5	0,97	0,9	0,98	17	100
10000 PA	BRT	x	2	0,9	Yes	0,86	0,68	0,96	0,94	0,99	0,33	100

E. Comparison of suitable area's

E.1 Statistical comparison

Table 17: Suitable area for mango cultivation in SSP5 scenario (based on expert knowledge approach)

SSP5 scenario	**Current**	**2030**	**2050**	**2070**
Highly unsuitable	92,3%	78,2%	74,6%	57,3%
Unsuitable	4,0%	14,0%	14,8%	30,3%
Suitable	2,4%	5,7%	2,5%	3,7%
Highly suitable	1,3%	2,1%	8,0%	8,7%
Sum Suitable	***3,7%***	***7,8%***	***10,6%***	***12,3%***

Table 18: Suitable area for mango cultivation in SSP1 scenario (based on expert knowledge approach)

SSP1 scenario	**Current**	**2030**	**2050**	**2070**
Highly unsuitable	92,3%	80,5%	69,4%	59,0%
Unsuitable	4,0%	12,2%	18,7%	22,1%
Suitable	2,4%	6,1%	5,5%	11,4%
Highly suitable	1,3%	1,3%	6,4%	7,5%
Sum Suitable	***3,7%***	***7,3%***	***11,9%***	***18,9%***

Table 19: Change of suitable area for mango cultivation per scenario (based on expert knowledge approach)

	SSP1		SSP5	
	Total suitable area for mango cultivation (km²)	Difference compared to current* (%)	Total suitable area for mango cultivation (km²)	Difference compared to current* (%)
Current	75.600	x	75.600	x
2030	149.000	197%	157.000	208%
2050	240.300	318%	213.700	283%
2070	382.100	505%	249.000	329%

Table 20: Suitable area for mango cultivation in SSP5 scenario (based on algorithmic approach)

SSP5 scenario	**Current**	**2030**	**2050**	**2070**
Highly unsuitable	95,8%	76,7%	56,3%	44,2%
Unsuitable	3,4%	20,5%	36,7%	53,7%
Suitable	0,5%	2,0%	4,5%	1,6%
Highly suitable	0,3%	0,8%	2,6%	0,6%
Sum Suitable	***0,8%***	***2,8%***	***7,1%***	***2,1%***

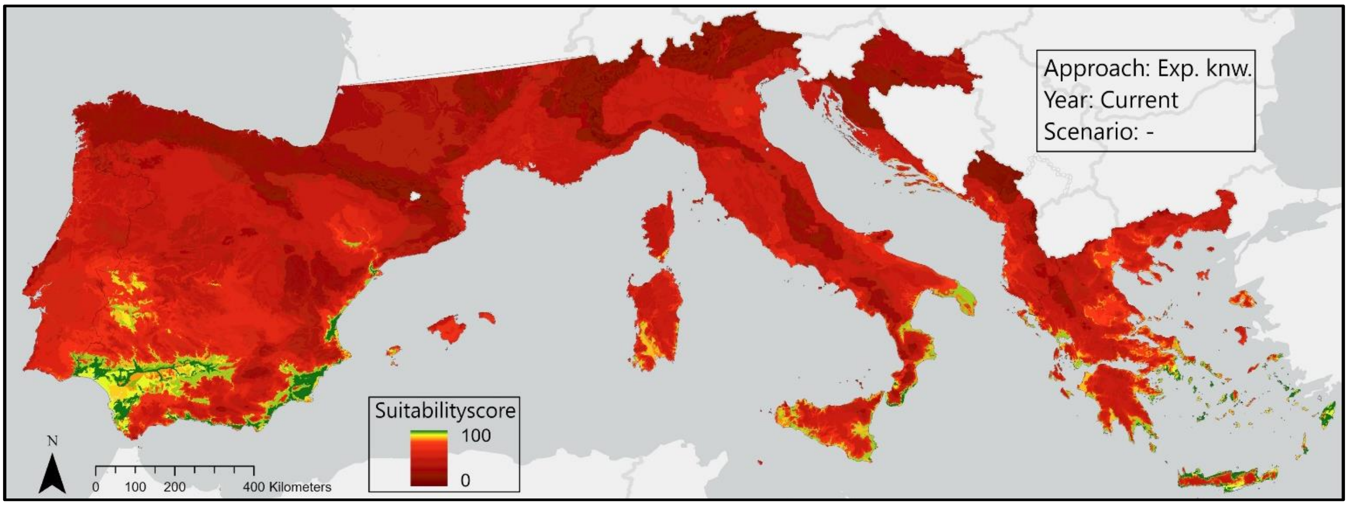
Table 21: Suitable area for mango cultivation for SSP1 scenario (based on algorithmic approach)

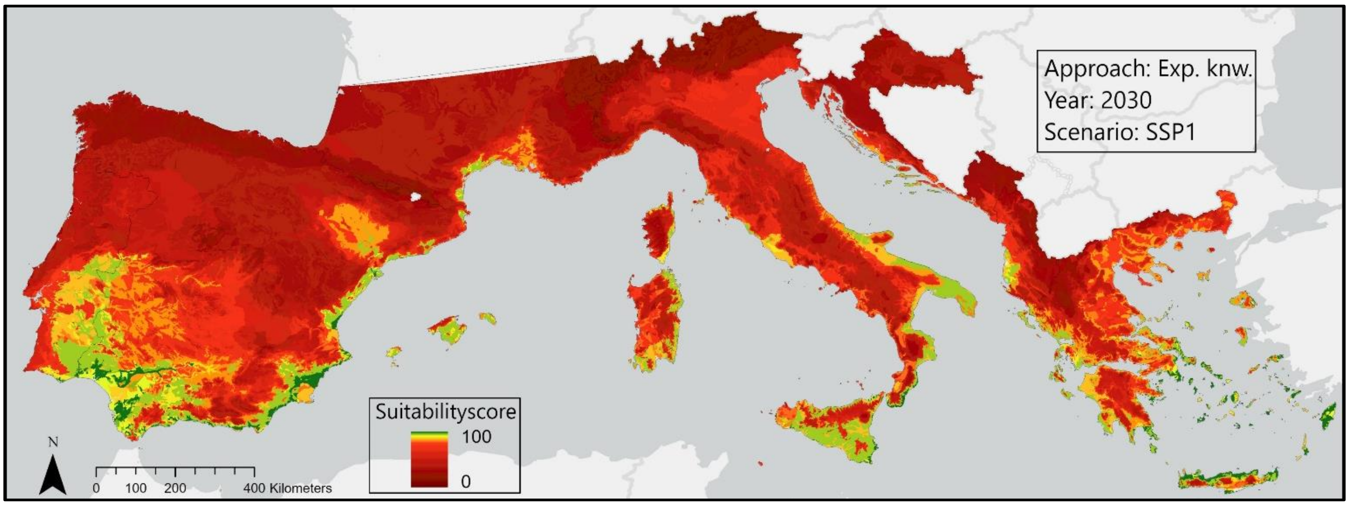
SSP1 scenario	**Current**	**2030**	**2050**	**2070**
Highly unsuitable	95,8%	80,9%	67,2%	64,6%
Unsuitable	3,4%	17,1%	29,2%	32,6%
Suitable	0,5%	1,5%	2,4%	2,1%
Highly suitable	0,3%	0,5%	1,1%	0,7%
Sum Suitable	***0,8%***	***2,0%***	***3,5%***	***2,8%***

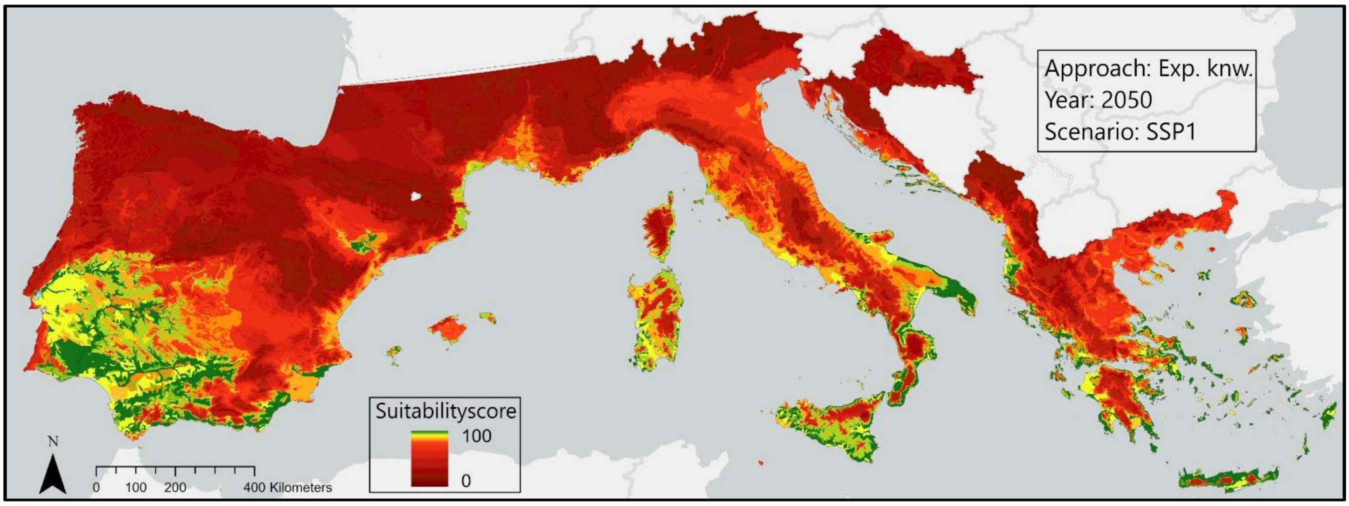
Table 22: Change of suitable area for mango cultivation per scenario (based on algorithmic approach)

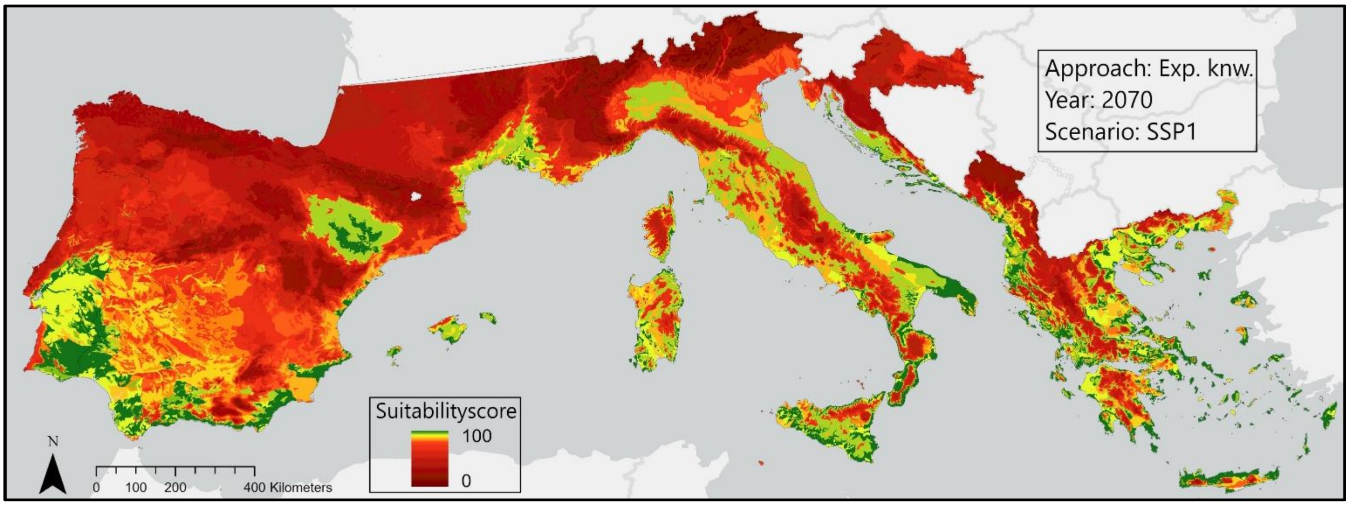
	SSP1		SSP5	
	Total suitable area for mango cultivation (km²)	Compared to current (%)	Total suitable area for mango cultivation (km²)	Compared to current (%)
Current	15.278	x	15.278	x
2030	40.384	264%	57.289	375%
2050	70.785	463%	142.664	934%
2070	55.766	365%	42.719	280%

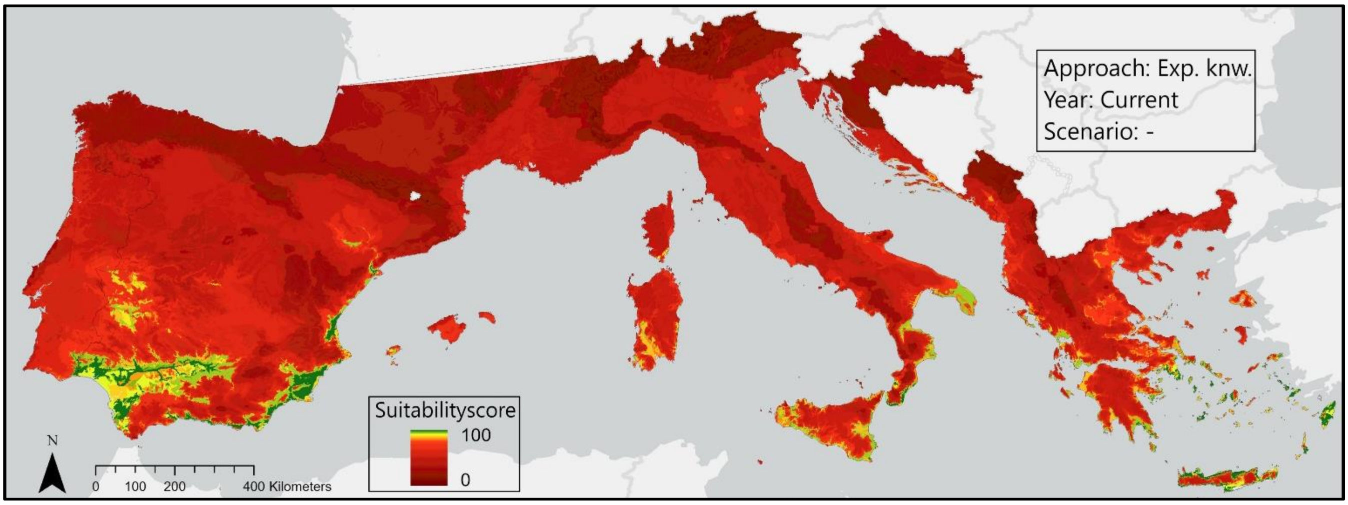
E.2 Spatial comparison of suitability maps (expert knowledge approach)

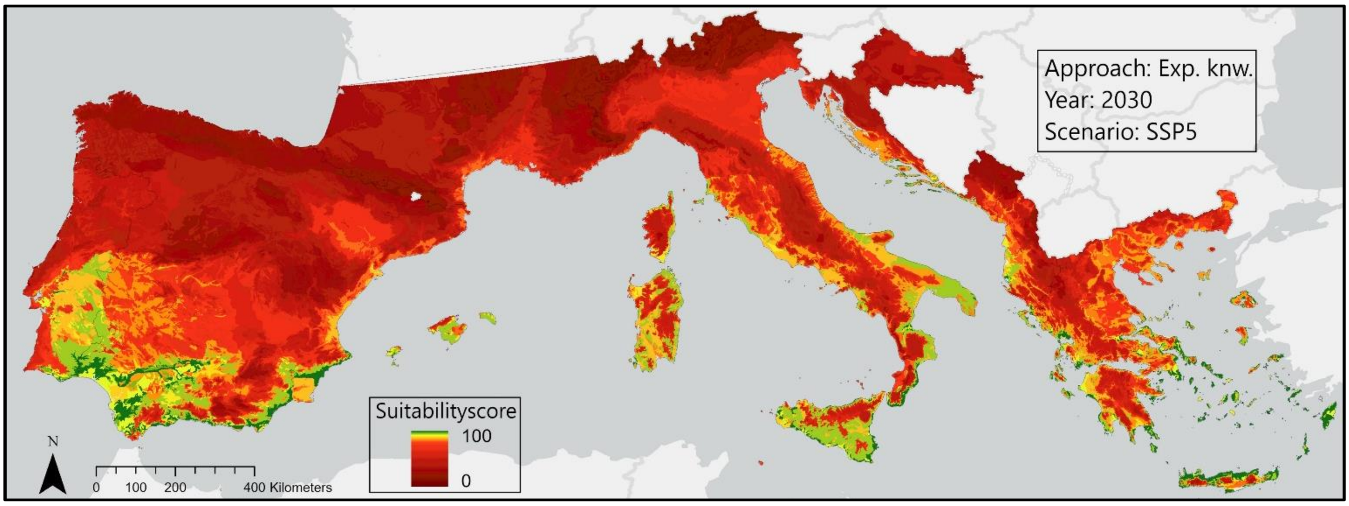









Approach: Exp. knw.
Year: Current
Scenario: -
Suitabilityscore
100
0
N
0 100 200 400 Kilometers


Approach: Exp. knw.
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Scenario: SSP5
Suitabilityscore
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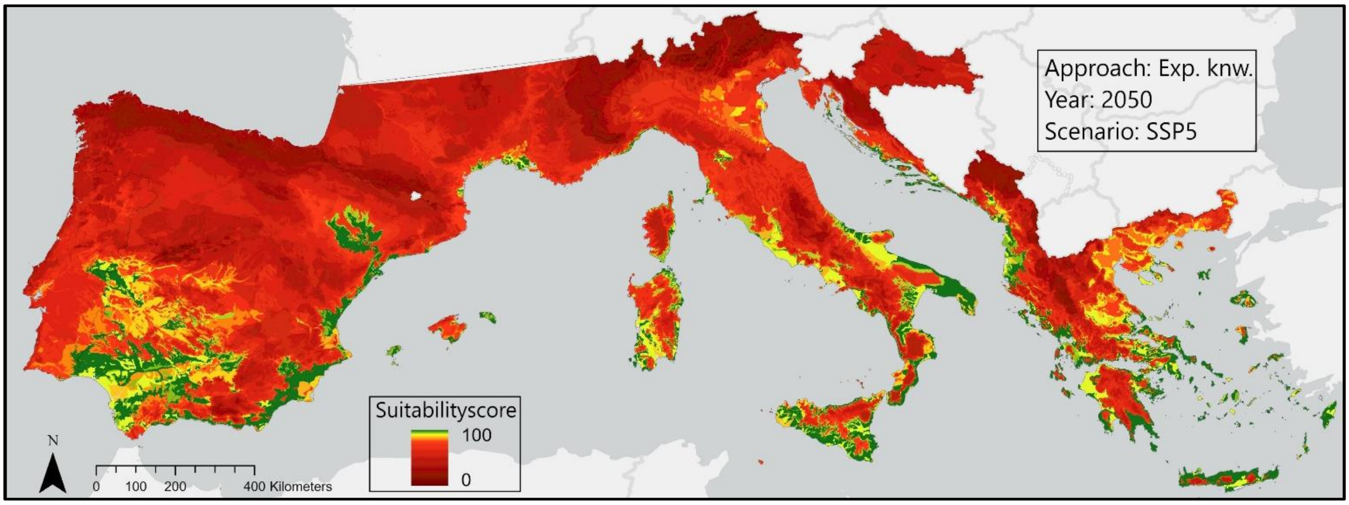
0
N
0 100 200 400 Kilometers


Approach: Exp. knw.
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Scenario: SSP5
Suitabilityscore
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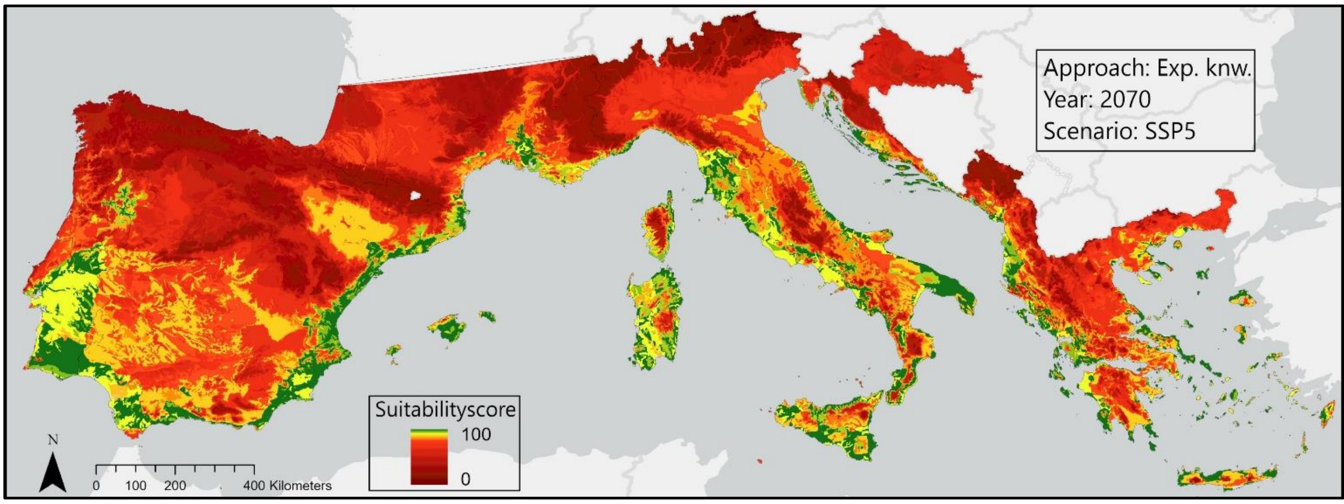
0
N
0 100 200 400 Kilometers


Approach: Exp. knw.
Year: 2070
Scenario: SSP5
Suitabilityscore
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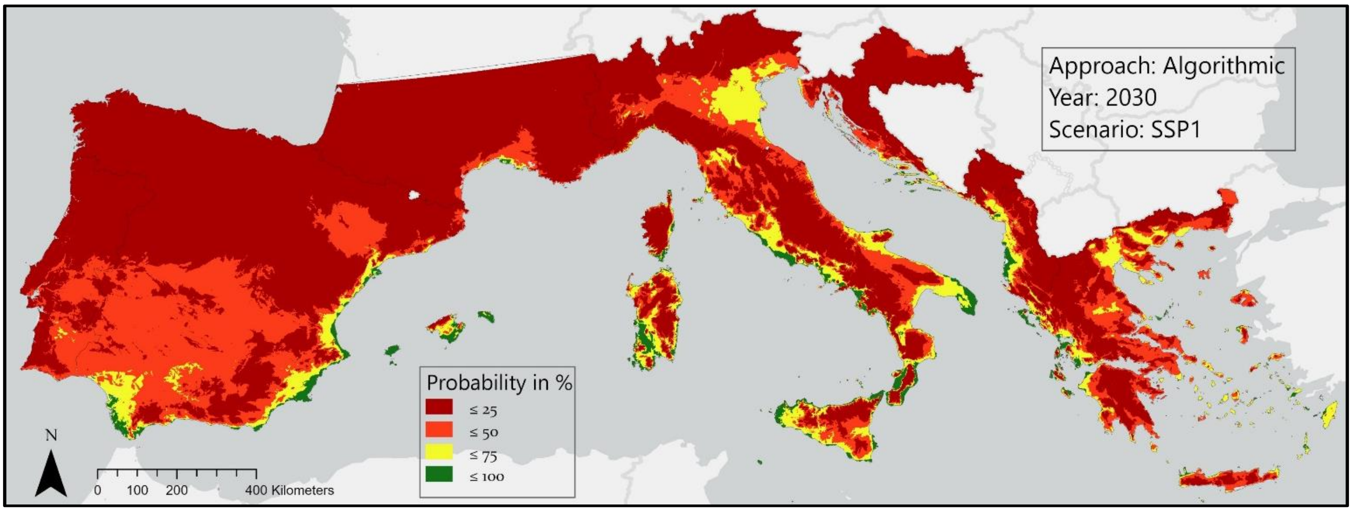
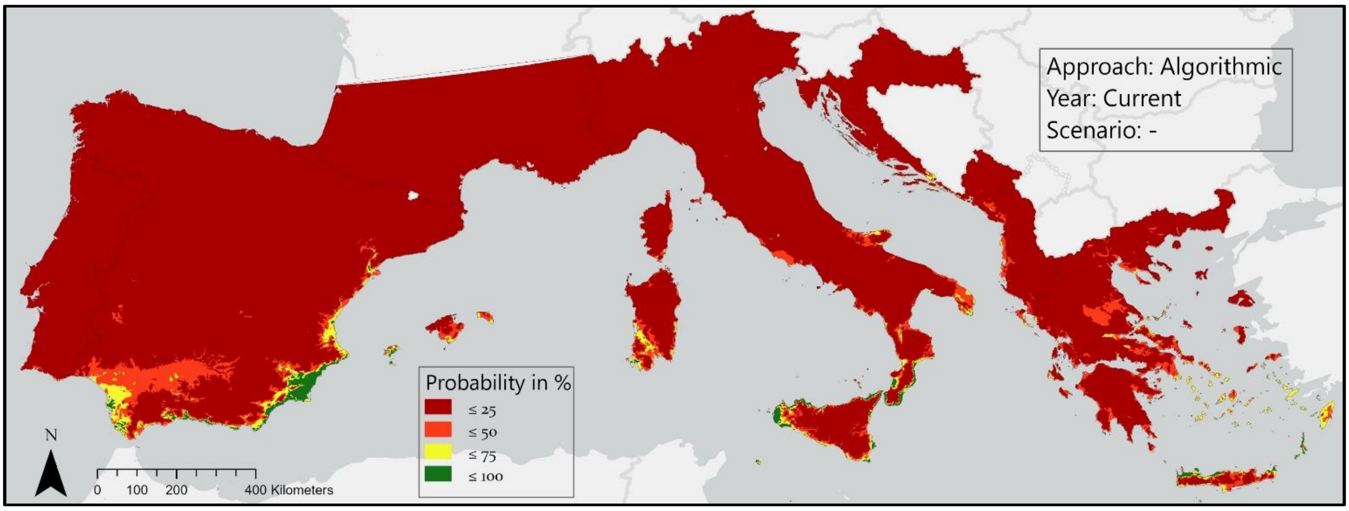
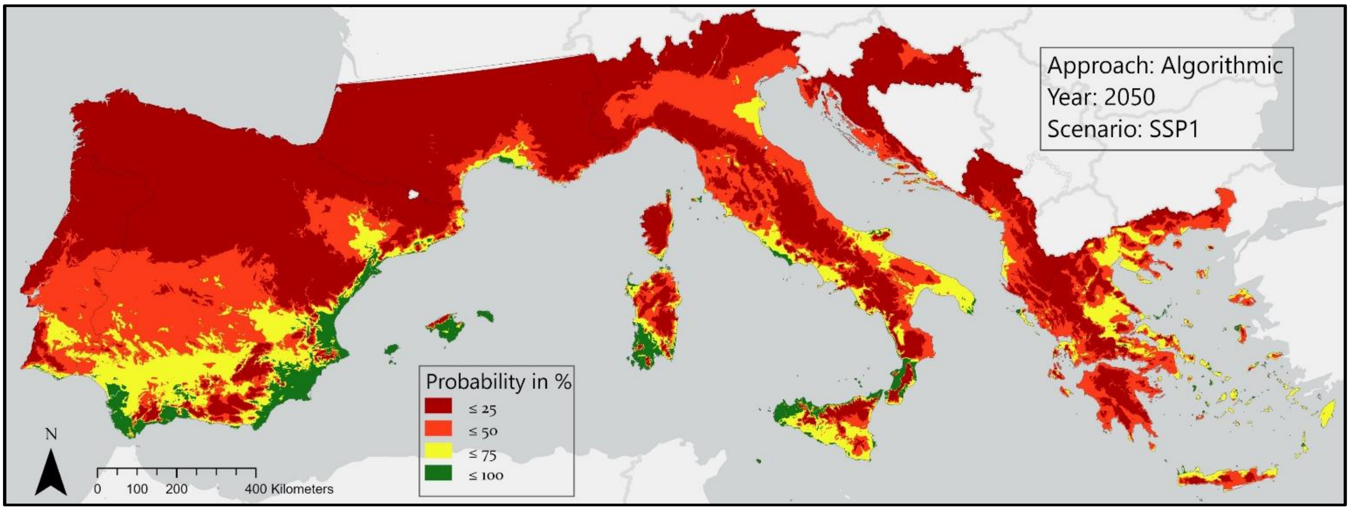
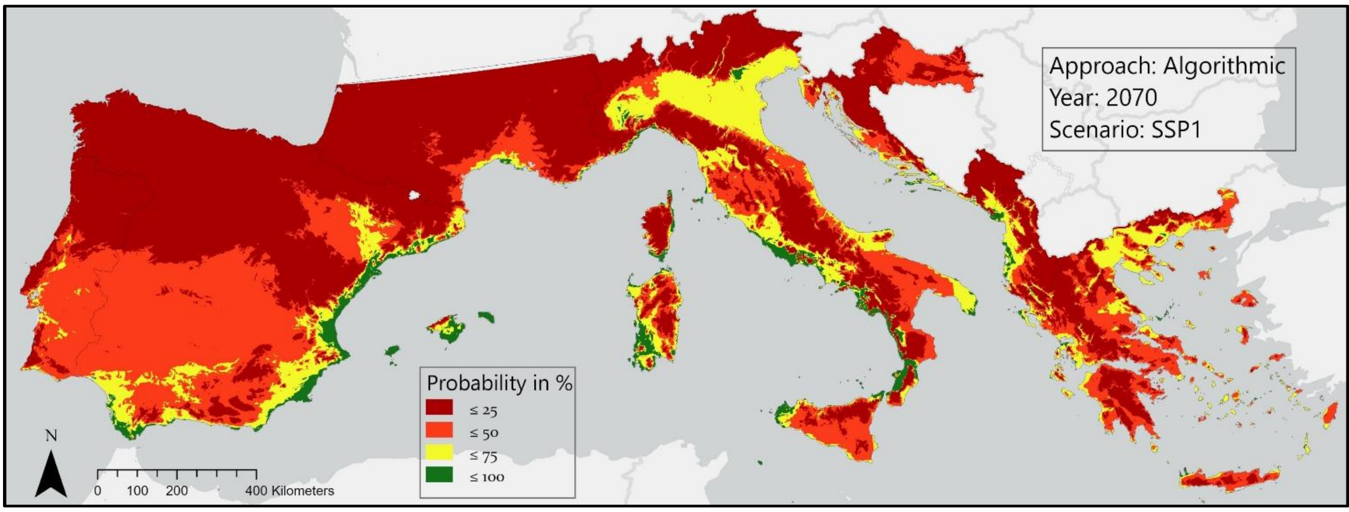
0
N
0 100 200 400 Kilometers

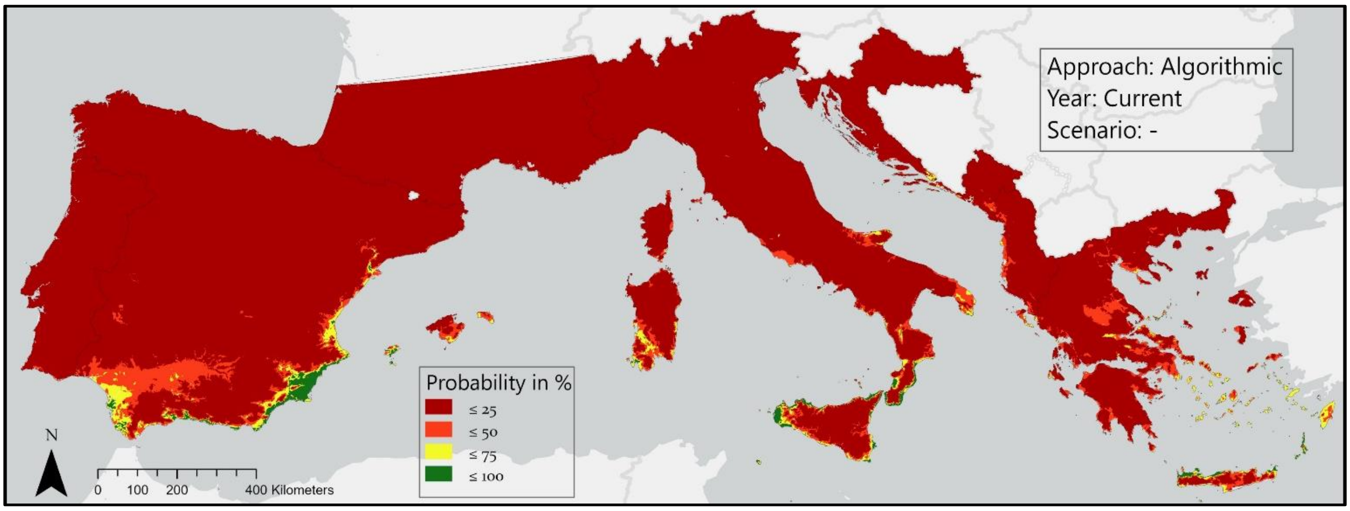
E.3 Spatial comparison of suitability maps (Algorithmic approach)

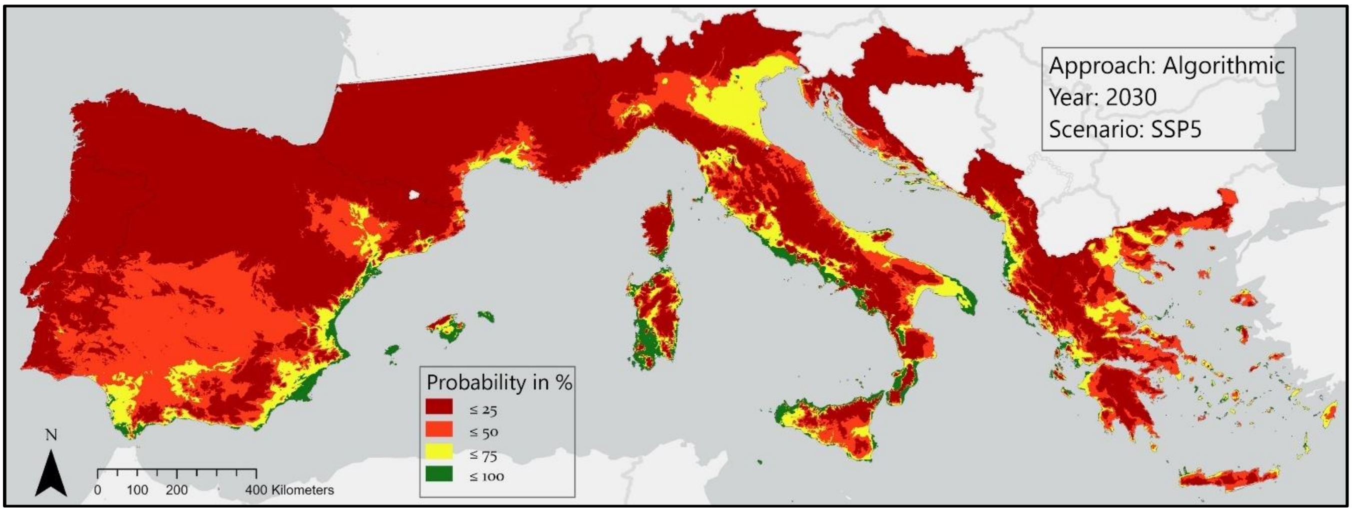


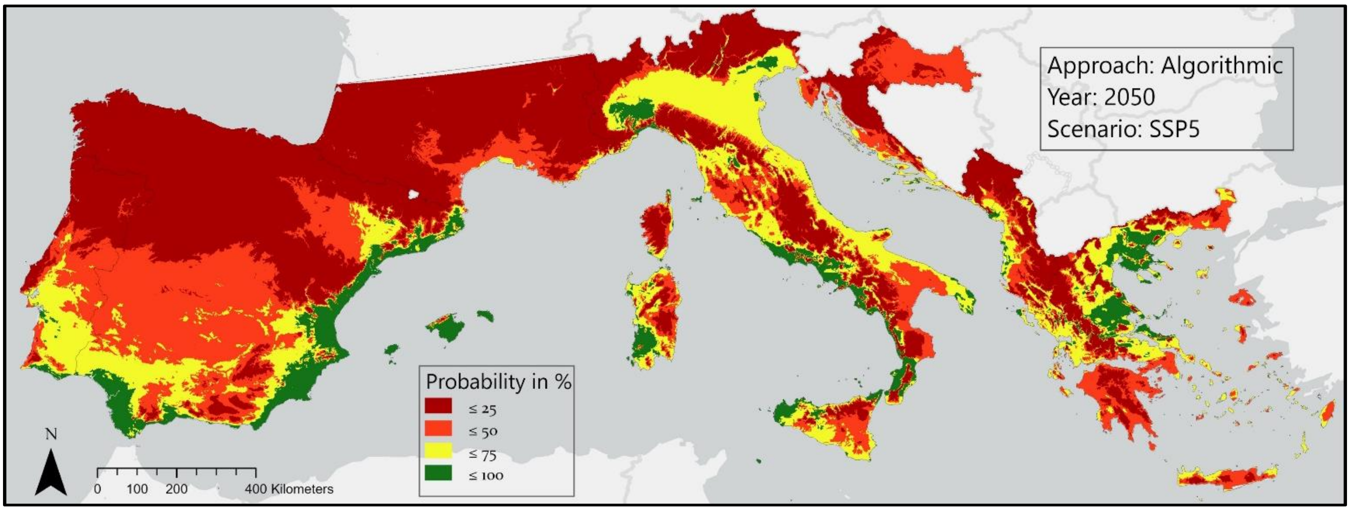


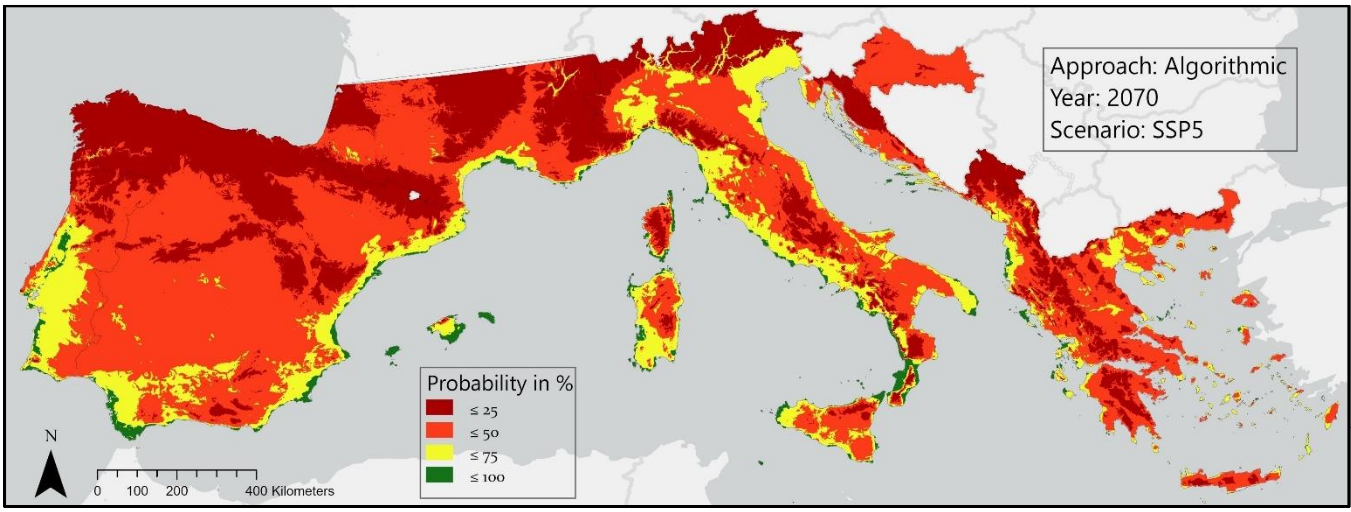





Approach: Algorithmic
Year: Current
Scenario: -
Probability in %
≤ 25
≤ 50
≤ 75
≤ 100
N
0 100 200 400 Kilometers


Approach: Algorithmic
Year: 2030
Scenario: SSP5
Probability in %
≤ 25
≤ 50
≤ 75
≤ 100
N
0 100 200 400 Kilometers


Approach: Algorithmic
Year: 2050
Scenario: SSP5
Probability in %
≤ 25
≤ 50
≤ 75
≤ 100
N
0 100 200 400 Kilometers


Approach: Algorithmic
Year: 2070
Scenario: SSP5
Probability in %
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≤ 50
≤ 75
≤ 100
N
0 100 200 400 Kilometers

E.4 Variability of suitability score (Algorithmic approach)

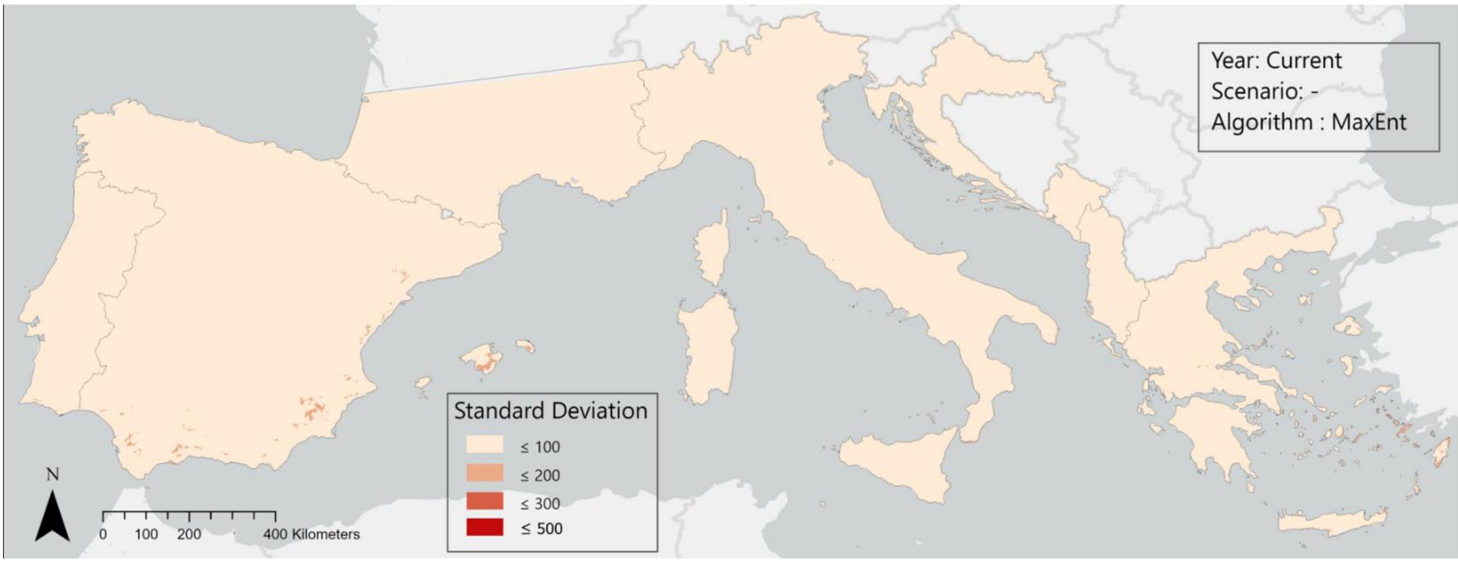

Figure 32: Variability of suitability score for mango cultivation area's (algorithm approach MaxEnt)

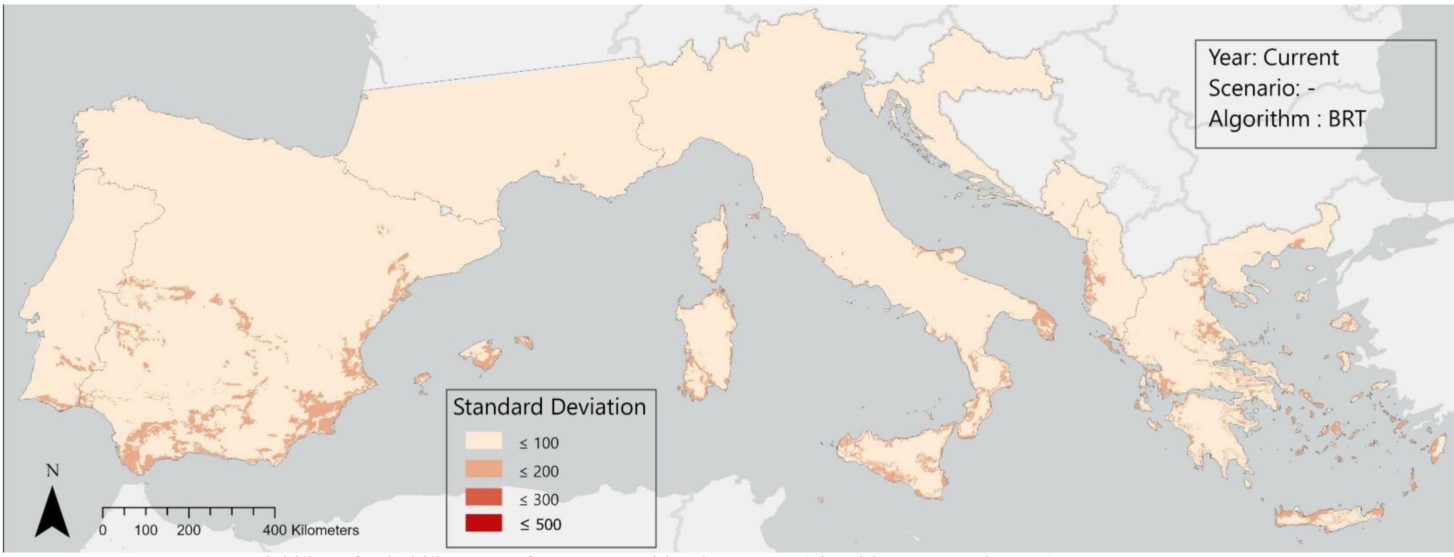

Figure 33: Variability of suitability score for mango cultivation area's (algorithm approach BRT)