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BURKINA FASO

La Patrie ou la Mort, nous Vaincrons

Order N° : ....

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Subject:

AI-powered prediction of the current and future distributions of *Mesosphaerum suaveolens* (L.) Kuntze, a major invasive plant species in Burkina Faso: implications for maize cultivation

Presented on July 17th 2025, by:

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DEDICATION

To my dear parents,

FALEROUN Bolarinwa Chédrack and OROBI Oluwasheoun Abiguel**,**

Your love, sacrifices, and unwavering support have made this work possible.

This is as much your achievement as it is mine.

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ABSTRACT

Invasive alien plant species are expanding globally due to climate change and human pressures, posing growing threats to biodiversity, ecosystem services and agricultural systems. One such species, *Mesosphaerum suaveolens*, is rapidly spreading across West Africa, where it disrupts rain-fed cropping systems including maize, a staple crop critical to food security in Burkina Faso. Despite its ecological and agronomic impacts, there's limited understanding of how climate change may affect its future distribution and potential interaction with maize cultivation zones. This study aimed to (i) determine the current distribution of *M. suaveolens* in Burkina Faso, (ii) forecast its future spread under different climate scenarios, and (iii) assess the spatial overlap between invasion risk and maize-growing areas. We compiled 3254 presence records of *M. suaveolens* and 51 environmental predictors. After reducing multicollinearity using a variance inflation factor threshold (VIF < 5), a subset of 9 uncorrelated predictors was retained. Three AI-based algorithms: Random Forest (RF), Support Vector Machine (SVM), and Convolutional Neural Network (CNN) were implemented in Python 3.10 to model current suitability. Models' performance were evaluated using AUC and TSS, and only RF and CNN, which outperformed SVM, were used for future projections under eight combinations of general circulation models (MIROC6 and HadGEM3-GC31-LL), scenarios (SSP245 and SSP585), and time horizons (2050 and 2080). Maize suitability was modeled using RF, based on 547 presence records and 11 predictors (VIF-filtered). Current and future maize maps were intersected with *M. suaveolens* risk maps to assess spatial overlaps and quantify exposure levels. CNN projected a 42 to 46% decline in suitable habitats for *M. suaveolens* by 2080, while RF predicted minor changes (-2.6% to +0.8%). Currently, high-suitability maize areas cover 107,336 km² (39.77%), increasing to 133,362 km² (HadGEM3-GC31-LL) and 136,881 km² (MIROC6) by 2090 under SSP5-8.5. Currently, 62% of maize zones overlap with high invasion risk (CNN), decreasing to 14-16% by 2090, while RF estimates remain stable at ca. 3-4%. These results highlight the CNN model's higher sensitivity to climate variability and the more conservative nature of RF projections. The combine use of SDMs and crop modeling in an AI framework offers a robust tool for anticipating invasive spread and informing climate-resilient agricultural planning. This study contributes to ecological forecasting and supports the achievement of SDGs 2**,** 13 and 15 through evidence-basedland-use strategies.
Keywords : AI; climate change; convolutional neural network; habitat suitability, invasive species; modeling; maize

RÉSUMÉ

Prévision assistée par intelligence artificielle de la distribution actuelle et future de *Mesosphaerum suaveolens* (L.) Kuntze, une espèce végétale envahissante majeure au Burkina Faso : implications pour la culture de maïs.

Les espèces végétales exotiques envahissantes, favorisées par le changement climatique et les pressions anthropiques, menacent la biodiversité, les services écosystémiques et l'agriculture. *Mesosphaerum suaveolens*, en forte expansion en Afrique de l'Ouest, perturbe les systèmes agricoles pluviaux, notamment les cultures de maïs au Burkina Faso. Pourtant, les effets futurs du climat sur sa distribution et son interaction avec les zones agricoles restent peu connus.

Cette étude visait à : (i) cartographier la distribution actuelle de *M. suaveolens* au Burkina Faso ; (ii) modéliser sa propagation future selon différents scénarios climatiques ; et (iii) évaluer le chevauchement spatial entre les zones à risque d'invasion et les zones de culture du maïs. Un total de 3 254 occurrences et 51 prédicteurs environnementaux ont été utilisés, avec réduction de la multicolinéarité (VIF < 5) pour sélectionner 9 prédicteurs. Trois algorithmes IA (RF, SVM, CNN) ont été testés sous Python 3.10. Les modèles RF et CNN, ayant montré de meilleures performances (AUC, TSS), ont été retenus pour les projections futures. Huit combinaisons composées de deux GCMs (MIROC6, HadGEM3-GC31-LL), deux scénarios (SSP245, SSP585) et deux horizons temporels (2050, 2080) ont été considérées. La distribution du maïs a été modélisée avec RF (547 occurrences, 11 variables après VIF). Les cartes d'aptitude du maïs et celles de risque d'invasion ont été croisées pour estimer l'exposition future.

Le modèle CNN projette une réduction de 42–46 % des habitats favorables à *M. suaveolens* d'ici 2080, tandis que RF prévoit peu de variation (–2,6 % à +0,8 %). Actuellement, 62 % des zones de culture du maïs chevauchent des zones à haut risque (CNN), mais cette proportion baisserait à 14–16 % en 2090. Les estimations RF restent stables autour de 3–4 %. Ces différences révèlent la sensibilité du CNN à la variabilité climatique, face aux projections plus conservatrices du RF.

L'intégration de la modélisation des espèces et des cultures par IA constitue un outil puissant pour anticiper les invasions biologiques et guider l'adaptation agricole. Cette recherche soutient les ODD 2, 13 et 15 grâce à des stratégies d'aménagement basées sur des données probantes.

Mots-clés : intelligence artificielle ; changement climatique ; CNN ; aptitude des habitats ; espèces envahissantes ; modélisation ; maïs.

ACRONYMS AND ABBREVIATIONS

Abbreviation/Acronym **:**	Full writing
AI **:**	**A**rtificial **I**ntelligence
AUC **:**	**A**rea **U**nder the **C**urve
BMFTR **:**	**B**undes**m**inisterium für **F**orschung, **T**echnologie und **R**aumfahrt (Federal Ministry of Research, Technology and Space)
CEC **:**	**C**ation **E**xchange **C**apacity
CMIP6 **:**	**C**oupled **M**odel **I**ntercomparison **P**roject **P**hase 6
CNN **:**	**C**onvolutional **N**eural **N**etwork
ED-ICC **:**	**É**cole **D**octorale – **I**nformatique pour le **C**hangement **C**limatique
FAO **:**	**F**ood and **A**griculture **O**rganization
GBIF **:**	**G**lobal **B**iodiversity Information Facility
GCM **:**	**G**eneral **C**irculation **M**odel
HFI **:**	**H**uman **F**ootprint **I**ndex
IAPS / IAS **:**	**I**nvasive **A**lien **P**lant **S**pecies / **I**nvasive **A**lien **S**pecies
ISRIC **:**	**I**nternational **S**oil **R**eference and **I**nformation **C**entre
ITCZ **:**	**I**nter**T**ropical **C**onvergence **Z**one
MAAHM **:**	**M**inistère de l'**A**griculture et des **A**ménagements **H**ydro-**A**gricoles (Burkina Faso)
MODIS **:**	**M**oderate **R**esolution **I**maging **S**pectroradiometer
NDVI **:**	**N**ormalized **D**ifference **V**egetation **I**ndex
ODD **:**	**O**bjectif de **D**éveloppement **D**urable
R **:**	**R** Statistical Software
RF **:**	**R**andom **F**orest

Abbreviation/Acronym	:	Full writing
ROC	:	**R**eceiver **O**perating **C**haracteristic
SDM	:	**S**pecies **D**istribution **M**odel / **M**odeling
SDG	:	**S**ustainable **D**evelopment **G**oals
SOC	:	**S**oil **O**rganic **C**arbon
SSP	:	**S**hared **S**ocioeconomic **P**athway
SVM	:	**S**upport **V**ector **M**achine
TSS	:	**T**rue **S**kill **S**tatistic
VIF	:	**V**ariance **I**nflation **F**actor
WASCAL	:	**W**est **A**frican **S**cience **S**ervice **C**entre on **C**limate **C**hange and **A**dapted **L**and **U**se

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INTRODUCTION

The introduction of non-native species presents a significant global environmental challenge due to their potential for invasion. They adversely affect native biodiversity, ecosystem integrity, and agricultural productivity, leading to substantial economic losses (Chen, 2023; Early et al., 2016; IPBES, 2023). Invasive alien plant species (IAPS) disrupt local trophic chains and reduces the resilience of native species (Weiskopf et al., 2020). Climate change is expected to further expand the range and virulence of these IAPS (Weiskopf et al., 2020) . Many IAPS exhibit traits that facilitate their adaptation to new environments and extreme climate events, such as heatwaves, droughts, and irregular precipitations. Such traits promote their establishment while undermining native species' resilience (Barros et al., 2014; Thakur et al., 2023; Yang et al., 2022). Although several studies have warned that climate change may accelerate the spread of IAPS (Adhikari et al., 2022), empirical evidence linking specific invasive species to climate-driven expansion remains limited, hampering the development of effective mitigation strategies (Hulme, 2017; Bonebrake et al., 2018)**.**

Among the IAPS, *Mesosphaerum suaveolens* (L.) Kuntze, formely known as *Hyptis suaveolens* (L.) Poit., is one of the most aggressive plant invaders in tropical and subtropical regions (Padalia et al., 2014). In Burkina Faso, the species spreads rapidly in cultivated lands and disturbed habitats, often associated with mechanized agriculture and overgrazing (Thiombiano et al., 2009). It thrives along roadsides, watercourses, degraded savannas and rangelands, where it forms dense thickets and releases allelochemicals that inhibit native plants germination and growth (Almeida-Bezerra et al., 2021). Modelling the distribution of *M. suaveolens* is therefore crucial for identifying current and future invasion zones in order to prevent the harmful effects of its invasion through guiding strategic interventions.

Maize (*Zea mays* L.) is a staple crop in Burkina Faso, cultivated on over 1 million hectares and accounting for about 37% of national cereal production in 2017–2018 (FAO et MAAHM, 2021). Despite its importance, maize production is increasingly threatened by numerous factors which include weed infestation (Imoloame & Omolaiye, 2017). Invasive alien plant species (IASPs), such as *Mesosphaerum suaveolens*, exacerbate this challenge by aggressively competing for essential resources, reducing crop yields, and increasing production costs due to labor-intensive management requirements (Eschen et al., 2021). Yet, little research has explored how climate change could affect the future spread of *M. suaveolens* and how its expansion might intersect with maize-producing zones.

Traditional modeling approaches like MaxEnt (Maximum Entropy) have been widely used to predict invasive species' distributions but suffer from limited spatial transferability (Liu et al., 2020), reliance on sparse datasets, and difficulties in predicting non-analogous environments (Chen, 2023). These constraints limit their effectiveness in capturing complex patterns and predicting future changes accurately (Hu et al., 2024). Emerging AI-based methods, including machine learning and deep learning, offer improved predictive power by processing large, multidimensional datasets, and better capturing spatial complexity (Dimobe et al., 2022; Rew et al., 2021). These tools enable the development of more reliable forecasts under changing climate scenarios, allowing proactive management of IAPS. This study integrates AI-powered species distribution models (SDMs) with future climate projections to predict the current and future distribution of *Mesosphaerum suaveolens* and evaluate its potential impact on maize cultivation in Burkina Faso. It fills critical knowledge gaps at the climate–invasion-agriculture nexus, supporting early detection and strategic intervention.

The thesis is organized into chapters covering background and rationale. It then formulates the problem statement, research questions, hypotheses, and objectives. Chapter 1 reviews relevant literature on invasive plant species and their effects on biodiversity and agriculture, and species distribution modelling. Chapter 2 describes the study area, the data used, and the methods applied for data collection, processing, and analysis. Chapter 3 presents the results of the modelling experiments, followed by an in-depth discussion of their implications for invasive species management and maize productivity under climate change in Burkina Faso. The thesis concludes with a synthesis of key findings and outlines potential perspectives for future research and action.

Problem statement

The geographic distribution of plant species is shaped by complex interactions among multiple biotic and abiotic factors, including climate conditions, soil properties, species interactions, and dispersal mechanisms (Flores-Tolentino et al., 2020). In Burkina Faso, *M. suaveolens has* emerged as a major invasive species, particularly in agricultural ecosystems and maize production zones. While some IAPS may offer marginal benefits, the aggressive expansion of *M. suaveolens* typically results in reduced native biodiversity, altered ecosystem functioning and lower agricultural yields.

Long-term monitoring by Thiombiano et al. (2009) revealed that the number of infestation sites by *M. suaveolens* in Burkina Faso rose from just two in 2000 to sixty by 2008, highlighting its rapid spread. The species' allelopathic properties cause the decline of native flora and crops, while also increasing pest and disease risks. These combined effects threaten maize production and food security. Climate change may exacerbate the risk by enabling the species to expand into new, climatically suitable areas (Chen, 2023; Fandohan et al., 2015). Yet, research linking climate scenarios to *M. suaveolens* expansion in Burkina Faso remains scarce. Similarly, none studies have quantified the spatial overlap between invasion hotspots and maize cultivation zones; information that is essential for prioritizing interventions.

To address the gaps of knowledge, this thesis applies advanced AI-based SDMs to predict the current and future distribution of *M. suaveolens* under different climate change scenario**s** in Burkina Faso. By overlaying these projections with maize suitability lands, the study identifies areas of potential conflict and estimates the invasion threat to this high value crop. The resulting high-resolution risk maps are intended to support early warning, targeted surveillance, and control strategies, contributing to more climate-resilient agricultural systems and informed invasive species management.

A. Research questions

Main: What is the current and future extent of *Mesosphaerum suaveolens* invasion in Burkina Faso, and its potential impact on maize cultivation?

Specific: There are three specific research questions related to this work. They are as follow:

- What is the current distribution of *Mesosphaerum suaveolens* in Burkina Faso?
- What is the future distribution range of *Mesosphaerum suaveolens* in Burkina Faso under climate change scenarios?
- What is the potential impact of *Mesosphaerum suaveolens* invasion on maize-growing areas in Burkina Faso?

B. Research hypothesis

Main: The invasive expansion of *Mesosphaerum suaveolens* in Burkina Faso will increase under future climate change scenarios, reducing maize production.

Specifics: This study is guided by three specific research hypotheses, which are as follow:

- *Mesosphaerum suaveolens* is currently widespread in Burkina Faso.
- The future distribution range of *M. suaveolens* will expand under climate change scenarios.
- The invasion of *M. suaveolens* in maize-growing areas significantly reduces the productivity.

C. Research objectives

Main: To assess the extent of *Mesosphaerum suaveolens* invasion in Burkina Faso and its impacts on maize cultivation.

Specific: This study aims to achieve the following specific objectives:

- To determine the current distribution of *Mesosphaerum suaveolens* in Burkina Faso.
- To predict the future distribution of *Mesosphaerum suaveolens* under different climate change scenarios using AI-based modeling.
- To evaluate the impact of the predicted spread of *M. suaveolens* on maize productivity in Burkina Faso.

CHAPTER1: LITTERATURE REVIEW

1.1. Invasive plant species in West Africa: impacts on biodiversity and agriculture

Invasive alien species (IAS) are widely regarded as one of the greatest threats to global biodiversity and ecosystem stability (Li et al., 2024). This problem is acute in Africa, where the introduction and spread of invasive plants have accelerated in recent decades. Sub-Saharan Africa has seen a surge of new invasive plant incursions, driven by factors such as increasing international trade, porous borders, and limited biosecurity measures (Kenis et al., 2022). The impacts of these invasions are profound: IAS disrupt native ecosystems, reduce agricultural productivity, and can incur enormous economic costs (IPBES, 2023). A recent continent-wide assessment estimated that Africa may incur on the order of tens of billions of dollars in annual losses (USD 65.58 billion per year) due to invasive species' impacts on crop yields, livestock production, and management expenses (Kenis et al., 2022). These losses reflect reduced harvests, poisoning or loss of grazing animals, and the labor and resources diverted to control invasive weed (Eschen et al., 2021; Kenis et al., 2022). In West Africa, where agriculture and pastoralism are key livelihoods, invasive plants pose a direct threat to food security and rural economies.

Numerous invasive plant species have established in West African countries, each with deleterious effects on biodiversity and agriculture. For example, *Parthenium hysterophorus* (Parthenium weed), native to tropical America like *M. suaveolens*, has invaded parts of West Africa and is known to aggressively colonize croplands, rangelands, and even protected areas(IUCN/PACO, 2013). *Parthenium* not only displaces native flora and crop species but is also toxic; it causes sickness in livestock and allergic reactions in humans, compounding its threat to agricultural productivity and public health (IUCN/PACO, 2013). Another notorious invader is *Chromolaena odorata* (Siam weed), which has spread throughout West and Central Africa. *C. odorata* forms dense thickets that suppress native plants and young trees, and it has become a serious weed in plantations (e.g. rubber, oil palm, cocoa) and fallows (Borokini & Babalola, 2012). In countries like Nigeria, *C. odorata* is reported as a major constraint to both subsistence and commercial agriculture, particularly in young crop plantations, and it negatively affects pastoral lands by overtopping forage species (Borokini & Babalola, 2012). The urgency of this issue has prompted regional studies to prioritize the most harmful species and to develop management strategies. In Ghana, for example, a 2022 horizon-scanning exercise identified nearly 200 alien plant species with the potential to harm agriculture, forestry, and the environment, underscoring the breadth of the invasive threat and the need for proactive measures (Kenis et al., 2022). Overall, invasive plants in West Africa represent a dual challenge for conservation and agriculture, necessitating integrated approaches that protect native biodiversity while safeguarding crop and pasture productivity.

1.2. Overview of *Mesosphaerum suaveolens*

Mesosphaerum suaveolens (Lamiaceae), also known by its synonym *Hyptis suaveolens* (common name "pignut" or "Bushmint"), is a branching aromatic herb native to tropical America (Almeida-Bezerra et al., 2022; Mishra et al., 2021). In West Africa (including Burkina Faso), it is recognized as a major invasive alien plant species, noted in national flora lists and invasive species surveys (POWO, 2025). *Mesosphaerum suaveolens* owes its invasiveness to a suite of weedy traits. It grows vigorously and produces allelochemical compounds that inhibit the germination and growth of neighboring indigenous plants (David et al., 2020; Mominul Islam & Kato-Noguchi, 2013). The species is a prolific seed producer with easy dispersal; dense infestations can shed up to 3000 seeds per square meter, facilitating rapid colonization of disturbed habitats (Afreen et al., 2018; State & Standards, 2020). Its seeds are small (with dimorphism in seed shape) and can germinate across a wide range of temperatures, indicating the species high phenotypic plasticity and adaptation to varied conditions (David et al., 2020). *Mesosphaerum suaveolens* can also regenerate from hardy rootstocks and forms persistent soil seed banks, making eradication difficult (David et al., 2020). Notably, the plant's pungent odor and chemical makeup render it unpalatable to livestock, which allows it to dominate overgrazed pastures where grazing pressure on other plants is high(State & Standards, 2020) . Its high photosynthetic efficiency, following the C3 pathway, supports rapid vegetative growth, while its deep taproot system enhances drought resistance (Mishra et al., 2021). These characteristics, allelopathy, prolific reproduction, broad environmental tolerance, and avoidance by herbivores, make *M. suaveolens* one of the world's most noxious invasive weeds, capable of displacing native vegetation and forming monocultures in invaded areas (David et al., 2020;Witt et al., 2018).

Native herbs, grasses, and seedlings are suppressed beneath its cover, leading to reduced species richness and diversity. Field studies provide quantitative evidence: in Nigeria, sites infested by

M. suaveolens showed more than 95% reduction in native seedling emergence from the soil seed bank compared to uninvaded sites (Akomolafe et al., 2024).

One of the most striking observations during our fieldwork was the remarkable fire resistance of *Mesosphaerum suaveolens*. In all the areas we surveyed, even when fire had devastated the surrounding vegetation, *M. suaveolens* persisted, often being the only species left standing. This suggests a high level of resilience and adaptive capacity, allowing it to survive and potentially dominate post-disturbance environments. Such fire tolerance may contribute significantly to its invasive success, especially in ecosystems frequently exposed to bushfires.

The ecological impacts include reduced plant biodiversity in invaded habitats and altered community structure, as native species are outcompeted or inhibited (Afreen et al., 2018). This trend was consistent with our broader field observations: in every location we surveyed, once *M. suaveolens* was established, it appeared to dominate the area entirely, occupying all available space and significantly reducing the presence of other vegetation.

In agricultural landscapes, dense stands of *M. suaveolens* can smother crops and reduce yields, and its dominance in rangelands diminishes available forage for livestock, thereby threatening both biodiversity and local livelihoods (State & Standards, 2020; Witt et al., 2018). Invasions of *M. suaveolens* carry socio-economic costs (Bukola, 2023; Rahaman et al., 2022). Farmers may need to invest more in weeding or herbicides. In Nigeria, some farming communities have abandoned fields that became overrun by *M. suaveolens* because reclaiming them was too labor-intensive. Similarly, during our fieldwork, in Bassignam (Burkina Faso), local populations reported that several farms had been abandoned due to the invasion of *Mesosphaerum suaveolens*. According to them, the spread of the species has rendered cultivation increasingly difficult, forcing many to leave their fields uncultivated. There are also indirect effects: increased fire risk (dry thickets of *M. suaveolens* can carry wildfires late in the dry season), and potential health issues as the plant's pollen is known to cause allergic reactions in some individuals (Oraon & Mondal, 2018). On the other hand, local people have found some uses for the plant (e.g., traditional medicinal applications and its insect-repellent properties) (Bienvenue et al., 2024). These uses, however, do not offset the broad negative impacts on agriculture and ecosystems.

Figure 1 illustrates both a close-up of *M. suaveolens* seeds and the general aspect of the plant in the field.

Figure 1: **(a)** Close-up of *Mesosphaerum suaveolens* seeds. **(b)** General view of *Mesosphaerum suaveolens* plant in the field.

1.3. Species Distribution Modelling (SDM) and AI-powered tools

Predicting the current and future distribution of invasive species relies on species distribution modelling (SDM), also known as ecological niche modelling. SDMs use occurrence data (records of where a species is present, and sometimes absent) together with environmental variables (climate, soil, land use, etc.) to statistically or mechanistically infer the suitable habitat for a species. By correlating species occurrences with environmental conditions, SDMs can identify the environmental niche requirements of a species and map areas of potential habitat suitability (Padalia et al., 2015; David et al., 2020). In the context of invasive species, SDMs are invaluable for revealing areas at risk of invasion (including regions the species has not yet reached) and for forecasting how distributions might shift under scenarios like climate change (David et al., 2020). The importance of these models is widely recognized for effectively predicting an invasive species' potential range is crucial for developing prevention, early detection, and control strategies (Zhang et al., 2024). By pinpointing hotspots of suitability, SDMs guide managers on where to focus surveillance and management efforts before the invader becomes irreversibly established.

Traditional SDM techniques range from statistical models (generalized linear models and generalized additive models) to more specialized approaches like MaxEnt (Maximum Entropy), which is a machine-learning-based algorithm popular for presence-only data(Padalia et al., 2015). In recent years, there has been a shift toward incorporating more robust machine learning (ML) and deep learning (DL) methods into SDM to improve predictive accuracy. Algorithms such as Random Forests (RF)**,** boosted regression trees (e.g. XGBoost, MaxEnt's principles), support vector machines (SVM)**,** and neural networks have all been applied to species distribution predictions (Zhang et al., 2024). These AI-driven models often handle complex, non-linear relationships better than simple statistical models, and they can integrate large numbers of predictor variables with reduced overfitting through techniques like bagging and regularization.

In addition to conventional ML methods, deep learning has recently entered the field of species distribution modeling. Deep learning models (such as deep neural networks, DNNs) can automatically learn complex feature representations and interactions in the data, potentially capturing ecological relationships that are hard to specify a priori. One advantage of deep learning is its ability to incorporate "big data" sources, for instance, time-series remote sensing data or massive citizen-science occurrence datasets to generate fine-grained distribution maps. A 2024 study by (Brun et al., 2024) modeled the distributions of over 2,400 plant species using an ensemble of deep neural networks trained on millions of crowd-sourced observations, achieving higher accuracy in predicting species occurrence (and even community composition) compared to traditional SDM approaches.

However, deep models typically require large datasets and careful tuning to avoid overfitting, and their interpretability can be limited compared to simpler models. Despite these challenges, AI-powered tools, from tree-based ensemble classifiers to neural networks, are increasingly being adopted to improve the precision and scope of species distribution models. This is particularly relevant for invasive species, where small improvements in predictive performance can translate to large gains in management efficiency (by accurately targeting high-risk invasion fronts).

CHAPTER 2: MATERIAL AND METHODS

2.1. Study area

2.1.1. General characteristics

The study was carried out at the country scale, Burkina Faso a landlocked Sahelian country located in West Africa, between latitudes 9° and 15°N and longitudes 5°30′W and 2°E. The figure 2 shows the location of the country. It covers a surface area of approximately 274,120 km² (DGE, 2005) and shares borders with Mali, Niger, Benin, Togo, Ghana, and Côte d'Ivoire. In 2022, the population of Burkina Faso is estimated at 22,100,874 inhabitants, including 11,412,644 women (INSD, 2022), with 70% living in rural areas. The country faces a rapid population growth rate (3% annually), a youthful demographic profile (median age: 16.8 years), and a high incidence of poverty (Direction Générale de l'Environnement, 2005), all contributing to growing pressure on land, water, and biodiversity (World Bank, 2017).

2.1.2. Climate context

The country is characterized by a tropical climate with two very distinct seasons: a rainy season, generally from June to October, and a dry season from November to May (Ibrahim et al., 2014). The exact timing and duration of these seasons vary depending on the climatic zone. The rainy season can last from about 3 to 7 months, decreasing in length from the south (Sudanian zone) to the north (Sahelian zone), and has been shrinking over time due to climate change (Barros et al., 2014; Pieyns et al., 2017). Burkina Faso predominantly experiences a dry tropical climate. In general, this is characterized by a relatively short rainy season and a long dry season, though these patterns vary by region (DGE, 2005). These seasonal patterns are largely governed by the movement of the Intertropical Convergence Zone (ITCZ) (Crawford, 2016). Rainfall is highly variable and often unpredictable, leading to challenges for communities and livelihoods (Crawford, 2016). Average annual temperatures range from 27°C to 30°C, with monthly temperatures fluctuating between 15°C and 45°C (USAID, 2017).

According to Pieyns et al. (2017), the country is divided between three climatic zones (Figure 2) including: the Sahelian zone, the Sudano-Sahelian zone and the Sudanian zone. Each of the zones is characterized by distinct rainfall patterns, evapotranspiration levels, evaporation potential

(PET), and average annual temperatures. The characteristics of each of the three zones are summarized in the table 1.

Table 1: Main climatic indicators by zone in Burkina Faso

Climate type	Mean rainfall (mm)	Rainy days	Potential evapotranspiration (mm)	Evaporation (mm)	Mean annual temperature (°C)
Sahelian	< 600	< 45/110	2200 to 2500	3200 to 3500	29
Sudano-Sahelian	600-900	50 to 70/150	1900 to 2100	2600 to 2900	28
Sudanian	> 900	85 to 100/180 to 200	1500 to 1700	1800 to 2000	27

Source: (Pieyns et al., 2017)

2.1.3. Environmental dynamics

Since the early 1970s, Burkina Faso has undergone significant environmental degradation. Notably, natural vegetation cover has diminished by over 35%, while areas of bare soil have expanded by more than 10% (Pieyns et al., 2017). These changes are attributed to factors such as drought-induced wildfires and agricultural burning. Consequently, the country has experienced intensified soil erosion, sedimentation of reservoirs, and localized flooding. These environmental challenges have led to substantial economic and human losses (Pieyns et al., 2017). These transformations have fostered ideal conditions for the invasion and spread of species like *Mesosphaerum suaveolens*, which thrives in disturbed landscapes and degraded soils (Padalia et al., 2015).

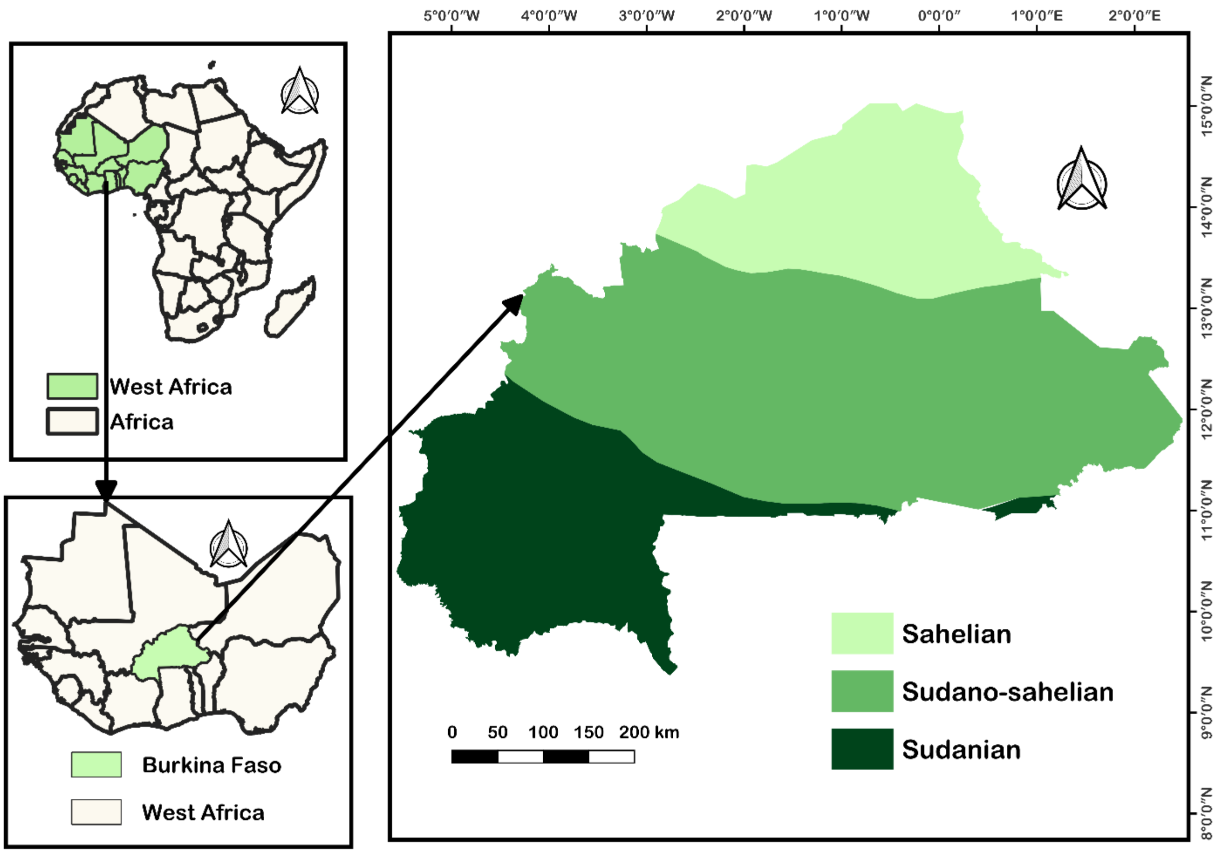


Figure 2: Study area

2.2. Data collection

2.2.1. Occurrence data

Occurrence data for *Mesosphaerum suaveolens* were compiled from two complementary sources: the Global Biodiversity Information Facility (GBIF; downloaded on January 10th 2025) and field surveys, comprising my own data as well as records collected by PhD students and researchers of the Laboratoire de Biologie et Écologie Végétales (LaBEV) at Université Joseph Ki-Zerbo. GBIF provided historical presence records across Africa, which were filtered to retain only georeferenced and spatially accurate observations within Burkina Faso. Duplicate, erroneous, and spatially clustered points were removed to reduce sampling bias. This hybrid dataset served as the foundation for pseudo-absence generation and environmental variable extraction, a critical input for robust species distribution modeling (Phillips et al., 2006, Elith & Leathwick, 2009). Table 2 presents the number of presence points contributed by each source and their respective percentages of the total dataset.

<u>Table 2</u>: Number and percentage of occurrence points of *Mesosphaerum suaveolen*s obtained from GBIF and field surveys

Sources	Number of points	Percentage
GBIF	36	1.1
Field surveys	3,218	98.9
Total	3,254	100.00

As shown in Table 2, the dataset was dominated by presence points collected from field surveys (98.9%), with only a small proportion (1.1%) obtained from historical GBIF records. This highlights the importance of recent field data for accurately characterizing the current distribution of *Mesosphaerum suaveolens* in Burkina Faso.

The occurrence data for *Zea mays* correspond to areas where maize is currently cultivated in Burkina Faso. These data were derived from national agricultural surveys and projects focused on cereal production, including maize. A total of 547 presence-only occurrence points were compiled from field observations and imported as a georeferenced shapefile. After filtering for valid coordinates and removing duplicates, points were assigned a binary response value (1) and projected in the WGS84 coordinate reference system.

2.2.2. Environmental data

The environmental variables used (summarised in table 3) in this study were carefully selected to represent a wide range of ecological, edaphic, topographic, and anthropogenic conditions that may influence the distribution of *Mesosphaerum suaveolens*. These predictors were derived from globally recognized datasets and preprocessed to ensure spatial consistency. All environmental datasets were spatially harmonized to ensure consistency across layers. This involved reprojecting

all raster files to a common coordinate reference system (WGS84), aligning them to the same geographic extent (the national boundaries of Burkina Faso), and resampling them to a uniform spatial resolution of approximately 1 km (30 arc-seconds). This preprocessing step ensured that all variables were directly comparable and could be accurately used in species distribution modeling.
We used the 19 bioclimatic variables (bio1 to bio19) from the WorldClim v2.1 dataset (available here). These variables, derived from monthly temperature and precipitation data, are commonly used in species distribution modeling due to their ecological relevance. For the current period**,** we used baseline climate data corresponding to the 1970-2000 average, at a spatial resolution of 30 arc-seconds (1 km) (Fick & Hijmans, 2017).
Soil-related predictors were extracted from the SoilGrids dataset developed by ISRIC. The dataset includes global predictions of key soil properties: sand (%), silt (%), clay (%), pH (H2O), soil organic carbon (SOC in g/kg), and cation exchange capacity (CEC), all provided for five standard depth intervals (0-5 cm, 5-15 cm, 15-30 cm, 30-60 cm, 60-100 cm). Originally at 250 m resolution, these rasters were aggregated to ~1 km resolution to match other layers
Vegetation productivity was represented using the Normalized Difference Vegetation Index (NDVI) from the MODIS MOD13C2 product, which provides 16-day composites at 250 m spatial resolution (Didan et al., 2015).
The 2009 version of the HFI (Human Footprint Index) was used, with a spatial resolution of 1 km.
To project the future distribution of *Mesosphaerum suaveolens* under climate change, this study used climate projections for two horizons, 2050 and 2080 under two Shared Socioeconomic Pathways: SSP245, representing an intermediate emissions trajectory, and SSP585, a high emissions "worst-case" scenario. These scenarios were chosen to capture a wide range of plausible socio-economic and climate futures relevant for ecological forecasting (O'Neill et al., 2017). To incorporate model uncertainty and improve the robustness of projections, two Global Climate Models (GCMs) from the CMIP6 ensemble were selected: HadGEM3-GC31-LL, and MIROC6. These models were chosen based on their proven ability to reproduce historical and regional climate features over West Africa, including precipitation variability and temperature patterns. HadGEM3-GC31-LL, a high-resolution model from the UK Met Office, excels in simulating interannual rainfall variability and climate extremes, making it valuable for assessing potential range shifts of invasive species under stress scenarios (Roberts et al., 2019). MIROC6, developed by the Japan Agency for Marine-Earth Science and Technology, offers a balanced representation

of climate sensitivity and strong land–atmosphere coupling, with reliable simulation of West African climate trends (Tatebe et al., 2019). The inclusion of these two models, spanning low to high climate sensitivities, aligns with best practices in species distribution modeling, where ensemble approaches are recommended to reduce projection uncertainty and improve the ecological relevance of future scenarios (Araújo & New, 2007; Buisson et al., 2010). Both models have been extensively used in recent peer-reviewed species distribution modeling (SDM) studies across West Africa and globally, particularly under SSP245 and SSP585 scenarios. For instance, HadGEM3-GC31-LL has been applied to model the future distribution of *Combretum glutinosum* in Burkina Faso (Dembélé et al., 2025), , in Togo for *Prosopis africana* (Gbadamassi et al., 2025) and in Ethiopia for *Balanites* species (Sambou et al., 2024). Similarly, MIROC6 has been widely adopted in SDMs across West Africa, including for (Tietiambou et al., 2024) in Benin and Burkina Faso and *Detarium senegalense* across West Africa (Dassou et al., 2024). The broad and growing adoption of HadGEM3-GC31-LL and MIROC6 in recent ecological research highlights their reliability and relevance for modeling species distributions under climate change conditions, especially in the West African context.

Table 3: Summary of environmental variables used

Codes	Variables	Units
bio1	Annual Mean Temperature	Degrees Celsius
bio2	Mean Diurnal Range (Mean of monthly (max temp – min temp))	Degrees Celsius
bio3	Isothermality (bio2/bio7) (×100)	Degrees Celsius
bio4	Temperature Seasonality (standard deviation ×100)	Degrees Celsius
bio5	Max Temperature of Warmest Month	Degrees Celsius
bio6	Min Temperature of Coldest Month	Degrees Celsius
bio7	Temperature Annual Range (bio5-bio6)	Degrees Celsius
bio8	Mean Temperature of Wettest Quarter	Degrees Celsius
bio9	Mean Temperature of Driest Quarter	Degrees Celsius
bio10	Mean Temperature of Warmest Quarter	Degrees Celsius
bio11	Mean Temperature of Coldest Quarter	Degrees Celsius
bio12	Annual Precipitation	Millimeters
bio13	Precipitation of Wettest Month	Millimeters
bio14	Precipitation of Driest Month	Millimeters
bio15	Precipitation Seasonality (Coefficient of Variation)	Millimeters
bio16	Precipitation of Wettest Quarter	Millimeters
bio17	Precipitation of Driest Quarter	Millimeters
bio18	Precipitation of Warmest Quarter	Millimeters
bio19	Precipitation of Coldest Quarter	Millimeters
sand_1	Percentage of sand in the soil (0–5 cm depth)	Percent (%)
sand_2	Percentage of sand in the soil (5–15 cm depth)	Percent (%)
sand_3	Percentage of sand in the soil (15–30 cm depth)	Percent (%)
sand_4	Percentage of sand in the soil (30–60 cm depth)	Percent (%)
sand_5	Percentage of sand in the soil (60–100 cm depth)	Percent (%)
silt_1	Percentage of silt in the soil (0–5 cm depth)	Percent (%)
slit_2	Percentage of silt in the soil (5–15 cm depth)	Percent (%)

slit_3	Percentage of silt in the soil (15–30 cm depth)	Percent (%)
slit_4	Percentage of silt in the soil (30–60 cm depth)	Percent (%)
slit_5	Percentage of silt in the soil (60–100 cm depth)	Percent (%)
clay_1	Percentage of clay in the soil (0–5 cm depth)	Percent (%)
clay_2	Percentage of clay in the soil (5–15 cm depth)	Percent (%)
clay_3	Percentage of clay in the soil (15–30 cm depth)	Percent (%)
clay_4	Percentage of clay in the soil (30–60 cm depth)	Percent (%)
clay_5	Percentage of clay in the soil (60–100 cm depth)	Percent (%)
orgcarbon_1	Soil Organic Carbone (0–5 cm depth)	g/kg
orgcarbon_2	Soil Organic Carbone (5–15 cm depth)	g/kg
orgcarbon _3	Soil Organic Carbone (15–30 cm depth)	g/kg
orgcarbon _4	Soil Organic Carbone (30–60 cm depth)	g/kg
orgcarbon _5	Soil Organic Carbone (60–100 cm depth)	g/kg
cec_1	Cation Exchange Capacity (0–5 cm depth)	Percent (%)
cec_2	Cation Exchange Capacity (5–15 cm depth)	Percent (%)
cec_3	Cation Exchange Capacity (15–30 cm depth)	Percent (%)
cec_4	Cation Exchange Capacity (30–60 cm depth)	Percent (%)
cec_5	Cation Exchange Capacity (60–100 cm depth)	Percent (%)
pH_1	pH of the soil (0–5 cm depth)	pH units
pH_2	pH of the soil 5–15 cm depth)	pH units
pH_3	pH of the soil (15–30 cm depth)	pH units
pH_4	pH of the soil (30–60 cm depth)	pH units
pH_5	pH of the soil (60–100 cm depth)	pH units
MODIS_NDVI	Normalized Difference Vegetation Index	
HFP	Human Footprint Index	

2.3. Statistical analysis

2.3.1. Distribution modeling of *Mesosphaerum suaveolens*

All modelling and spatial analyses were conducted in Python 3.10, using machine learning libraries (Scikit-learn, TensorFlow) and geospatial packages (Rasterio, Geopandas). We used 51 environmental predictors encompassing climate, soil, vegetation, and anthropogenic pressure. These included 19 bioclimatic variables from WorldClim, 30 soil variables, comprising cation exchange capacity (Cec), clay (%), sand (%), silt (%), soil organic carbon (g/kg), and pH at five depth intervals (0–5 cm to 60–100 cm), the Normalized Difference Vegetation Index (NDVI) from MODIS (MOD13C2; Didan et al., 2015) and the Human Footprint Index (HFI; (Venter et al., 2016;HU, 2021) which aggregates human pressure indicators such as population density, roads, croplands, and nightlights.

To reduce multicollinearity, we computed pairwise Pearson correlation coefficients among all predictors and retained only the 9 variables with $|r| < 0.7$ (Dimobe et al., 2022), prioritizing those with known biological relevance.

To model the current potential distribution of *Mesosphaerum suaveolens* in Burkina Faso, we applied three algorithms: Random Forest (RF), Support Vector Machine (SVM) and Convolutional Neural Networks (CNN). The modelling dataset consisted of environmental predictors extracted at 1000 spatially balanced points (presence and pseudo-absence), and was split into training and validation sets using an 80/20 stratified split to preserve class balance.

RF was trained using 100 decision trees with default parameters. SVM was implemented with 100 boosting iterations. Both were evaluated using two metrics: the Area Under the Receiver Operating Characteristic Curve (AUC), which measures model discrimination, and the True Skill Statistic (TSS), which incorporates both sensitivity and specificity.

In parallel, we implemented a CNN approach inspired by Deneu et al. (2021), which uses spatial patches to capture context not represented in tabular models. We extracted 64×64 pixel patches from the environmental raster stack centered on each presence or absence location. The CNN architecture consisted of convolutional layers, max-pooling layers, and fully connected dense layers, ending with a sigmoid activation. The model was trained using binary cross-entropy loss and validated with AUC and TSS to ensure comparability with RF and SVM.

All models were projected over the full extent of Burkina Faso to generate continuous suitability maps. RF and SVMSA produced per-pixel predictions from the environmental stack, while CNN predictions were generated through a sliding window approach. Predicted suitability scores were thresholded at 0.5 for CNN and 0.2 for RF and SVM to produce binary presence/absence maps. Final outputs were clipped to the Burkina Faso boundary and exported in GeoTIFF format for post-processing and visualization. ROC curves were also generated to visualize model performance.

To assess future distribution shifts of *M. suaveolens*, we projected model outputs under two Shared Socioeconomic Pathways (SSP245 and SSP585), two general circulation models (MIROC6 and HadGEM3-GC31-LL), and two time horizons (2050 and 2080), yielding eight scenario combinations. Future bioclimatic layers were sourced from downscaled CMIP6 data and harmonized to the current layer resolution and extent.

Due to consistently superior performance, only RF and CNN were retained for future projections. SMV was excluded from this step due to lower AUC and TSS values, ensuring model parsimony and analytical robustness. CNN projections were made using sliding windows, while RF predictions were generated per-pixel.

2.3.2. Distribution Modeling of *Zea mays*

To model the current and future distribution of *Zea mays* in Burkina Faso, we implemented a species distribution modeling framework in R version 4.2.1. Multicollinearity among the predictors was assessed using the Variance Inflation Factor (VIF) method implemented in the usdm package. Predictors with VIF > 5 were iteratively removed, resulting in a final selection of 11 variables.

We used the sdm package to train a RF model. A total of 1000 pseudo-absence points were generated randomly within the study area using the gRandom method. The model was replicated using bootstrap resampling (n = 3) with 30% of data withheld for testing. Variable importance was calculated based on permutation-based metrics.

Model predictions under current conditions were generated using the reduced predictor set. Future projections were made using downscaled and bias-corrected climate data for the period 2081–2100 under the SSP585 scenario from two general circulation models (HadGEM3-GC31-LL and MIROC6). All future rasters were resampled and aligned to the reference grid using bilinear interpolation. The final suitability maps were exported in GeoTIFF format, with values ranging from 0 (unsuitable) to 1 (highly suitable).

2.3.3. Assessing invasion risk on maize production areas

To evaluate the potential spatial overlap between *Zea mays* cultivation zones and suitable habitats for the invasive species, we compared species distribution predictions from RF and CNN models under both current and future climatic conditions. All analyses were performed in R 4.2.1.

We first clipped predicted habitat suitability maps of *M. suaveolens* (RF and CNN outputs) and *Zea mays* cultivation suitability maps to Burkina Faso's national boundaries using the sf and raster packages. A suitability threshold of 0.3 was applied to RF and CNN predictions to produce binary invasion risk maps (presence = 1, absence = 0). These were overlaid with current and future maize suitability maps to calculate spatial overlaps.

To quantify the potential impact, we calculated the proportion of maize production areas exposed to invasion risk by computing the percentage of overlapping cells. In addition, RF and CNN suitability predictions were reclassified into three severity categories (Low: <0.3; Medium: 0.3–0.6; High: >0.6), and these were masked to maize-suitable areas to map potential invasion risk intensity. Future projections were assessed under the SSP585 scenario using two global circulation models: MIROC6 and HadGEM3-GC31-LL, for the period 2081- 2100. All future rasters were resampled and aligned to a 1-km resolution grid using bilinear interpolation. The invasion risk under future conditions was estimated using the same spatial overlay, thresholding, and classification procedures as for the current scenario. Suitability maps and risk zones were exported as GeoTIFF files and visualized using categorical color schemes to support interpretation.

CHAPTER 3: RESULTS

3.1. Distribution modeling of *Mesosphaerum suaveolens* in Burkina Faso

3.1.1. Model performance

The performance of the three algorithms evaluated using AUC and TSS is summarized in Table 4. All models showed good predictive ability (AUC = 0.92–0.99; TSS = 0.85–0.96). However, the Random Forest (RF) model performed best (AUC = 0.99; TSS = 0.96), followed by Support Vector Machine (SVM) (AUC = 0.96; TSS = 0.87) and Convolutional Neural Network (CNN) (AUC = 0.92; TSS = 0.85). These results highlight the strong predictive power of RF and the utility of combining machine learning and deep learning approaches for robust invasive species modeling.

Table 4: Comparison of the three modeling algorithms performance by the area under the ROC curve (AUC) and the true skill statistic (TSS) values

Algorithms	**AUC**	**TSS**
CNN	0.92	0.85
RF	0.99	0.96
SVM	0.96	0.87

3.1.2. The relative importance of predictors

Among the 51 environmental variables, nine were retained after VIF filtering (VIF < 5). They are pH1, orgcarbon5, MODIS_NDVI, HFI2, clay5, cec3, bio9, bio19 and bio11. Precipitation of the coldest quarter (bio_19), NDVI, and mean temperature of the coldest quarter (bio_11) were the most influential, together accounting for the largest contribution to the model (Figure 3). Notably, bio_19 alone explained nearly 30% of the variance in model predictions. Soil-related variables, such as pH at 0–5 cm, organic carbon at 60–100 cm, and clay content at 60–100 cm, contributed moderately, underscoring the importance of both climatic and edaphic factors in shaping the distribution of *M. suaveolens*.

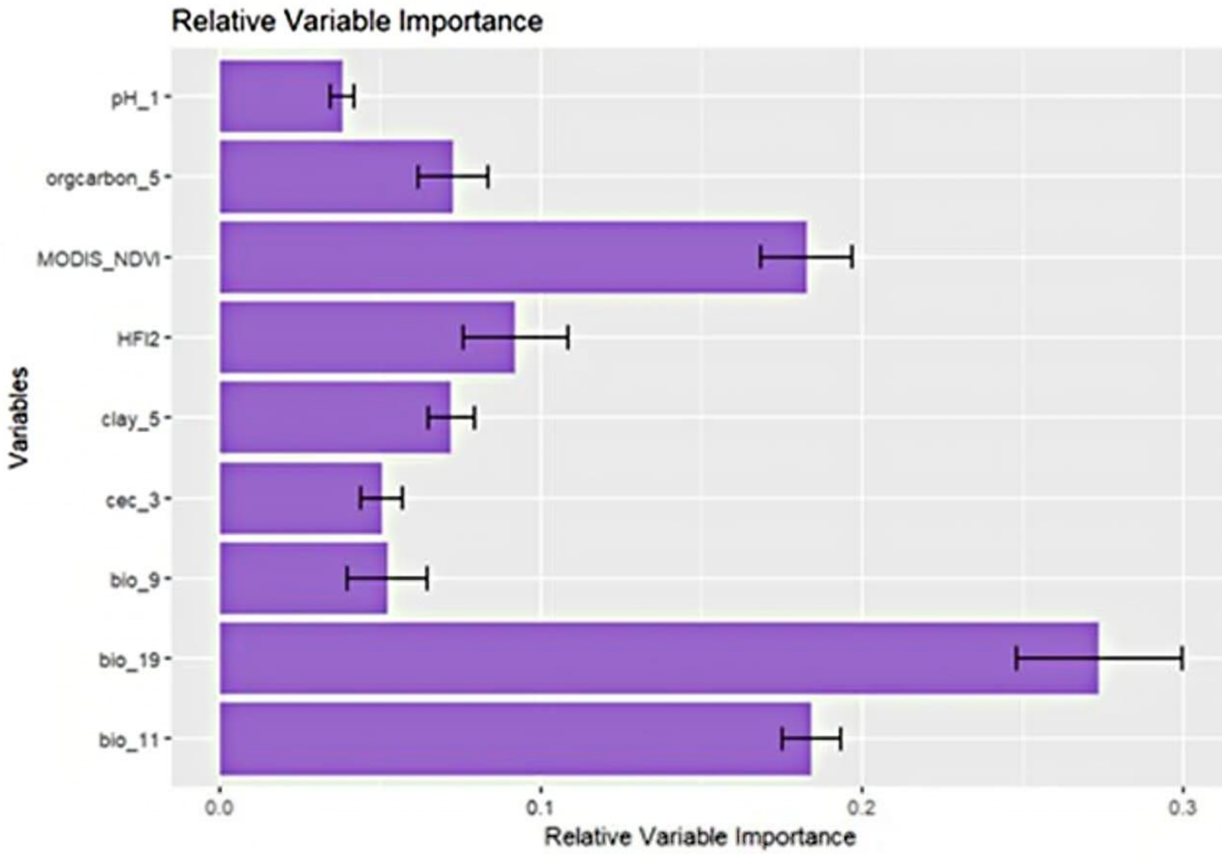


Figure 3: Relative importance of environmental variables used in modeling the distribution of *Mesosphaerum suaveolens*.

3.1.3. Dynamics of the current distribution habitats of *Mesosphaerum suaveolens*

The dynamics of the current distribution areas of *M. suaveolens* are presented in Figure 5. The estimated current suitable habitat for *M. suaveolens* varied markedly according to the algorithm performed (Figure 4). The CNN model predicted the species to occupy 76.93% of the national territory, suggesting widespread suitable habitat. In contrast, the RF model projected a much more restricted range, with only 14.69% of the area being suitable for *M. suaveolens*. SVM showed intermediate situation, identifying 24.82% as suitable habitat. These discrepancies highlight the influence of algorithmic architecture on habitat suitability estimates, with deep learning models such as CNN tending to generalize suitability more broadly than ensemble or kernel-based methods.

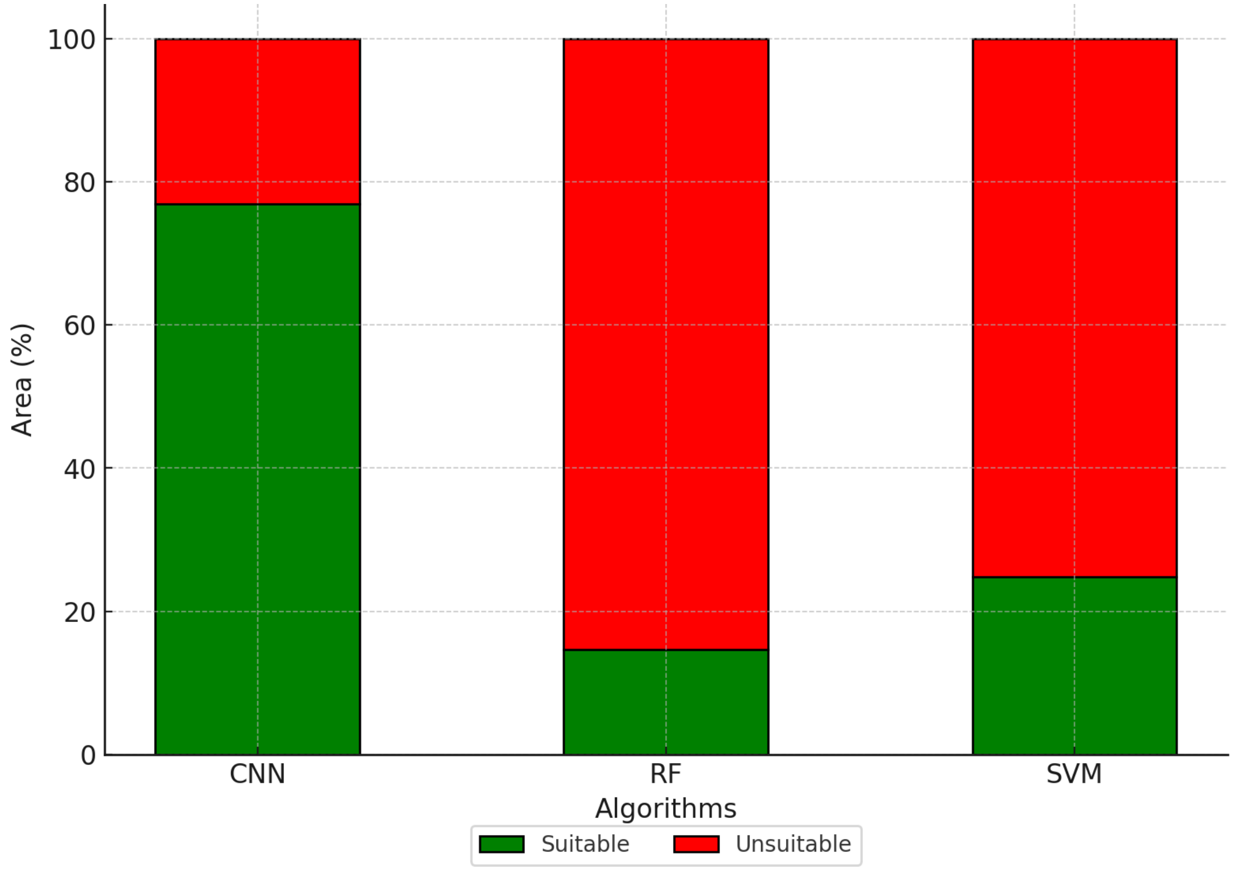
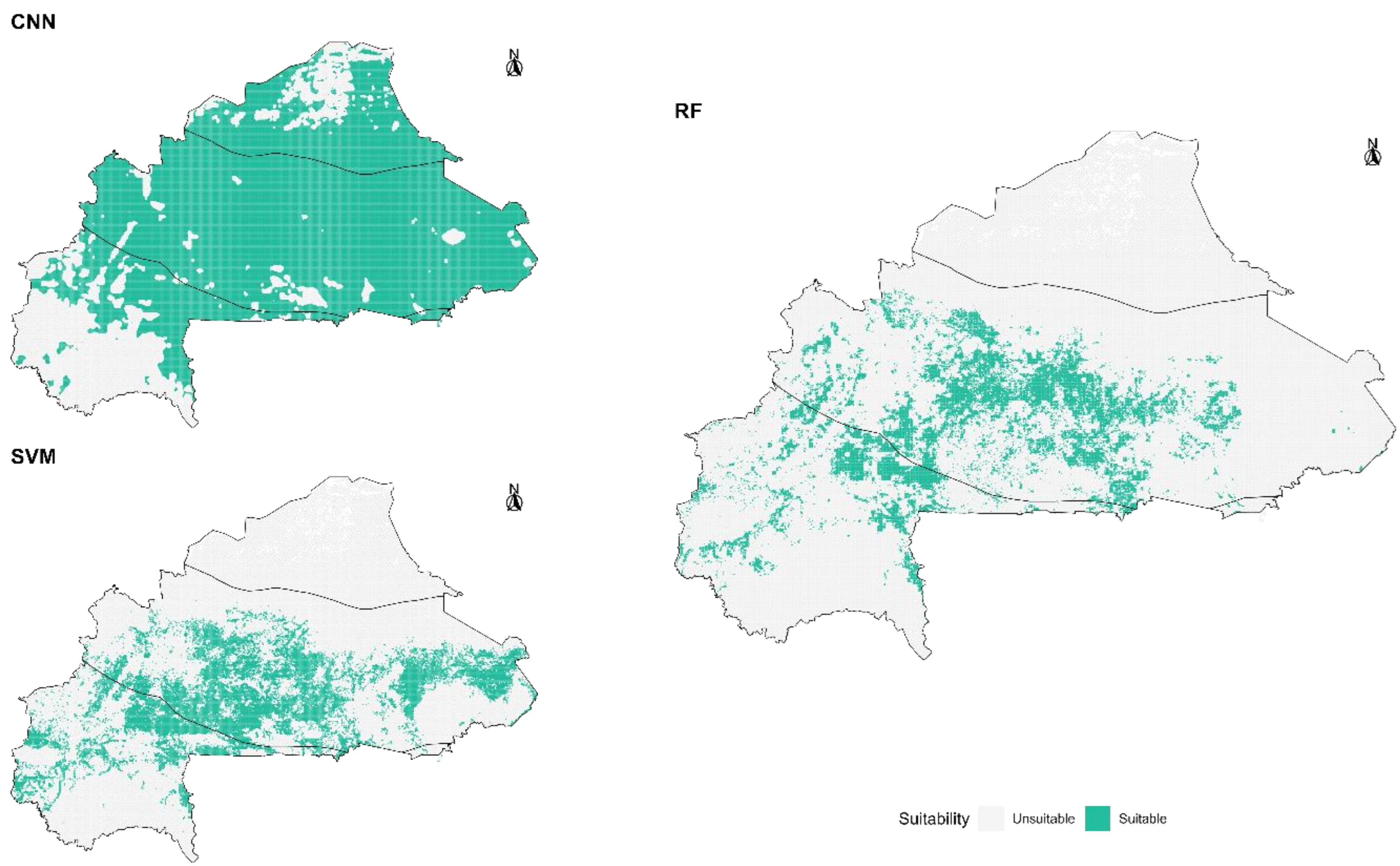


Figure 4: Predicted suitable and unsuitable habitats for *Mesosphaerum suaveolens* under current conditions in Burkina Faso using Random Forest (RF), Support Vector Machine (SVM), and Convolutional Neural Network (CNN) models

Figure 5: Current distribution of *Mesosphaerum suaveolens* in Burkina Faso using Random Forest (RF), Support Vector Machine (SVM), and Convolutional Neural Network (CNN) models



3.1.4. Future distribution of *Mesosphaerum suaveolens* in Burkina Faso

The future distribution areas of *M. suaveolens* are presented in Figures 6 and 7. Projections using the CNN model under the HadGEM3-GC31-LL scenario indicate a marked reduction in suitable habitats for *M. suaveolens*, with losses ranging from 44.5% to 46.3% across both SSP245 and SSP585 by 2050 and 2080 (Figure 8a). This trend is mirrored by proportional increases in unsuitable areas, pointing to a consistent shift toward climatically unfavorable conditions. Similarly, the MIROC6-driven CNN outputs reveal comparable contractions, with suitable habitat losses of 42.7–44.1% under SSP245 and 43.3–43.5% under SSP585 (Figure 8b). These results underscore a robust pattern of habitat contraction regardless of emission scenario or GCM. In contrast, the RF algorithm shows limited sensitivity to future climate change. Under HadGEM3-GC31-LL, projected changes in suitable areas are minimal, ranging from +0.3% in 2050 to -2.6% in 2080 for SSP245, and from -0.7% to -0.2% for SSP585 (Figure 8c). The MIROC6-based RF outputs echo this stability, with negligible variation (+0.1% to +0.8% under SSP245 and -2.6% to -1.2% under SSP585; Figure 8d). This consistency reflects the RF model's conservative response, contrasting sharply with the dynamic shifts captured by CNN.

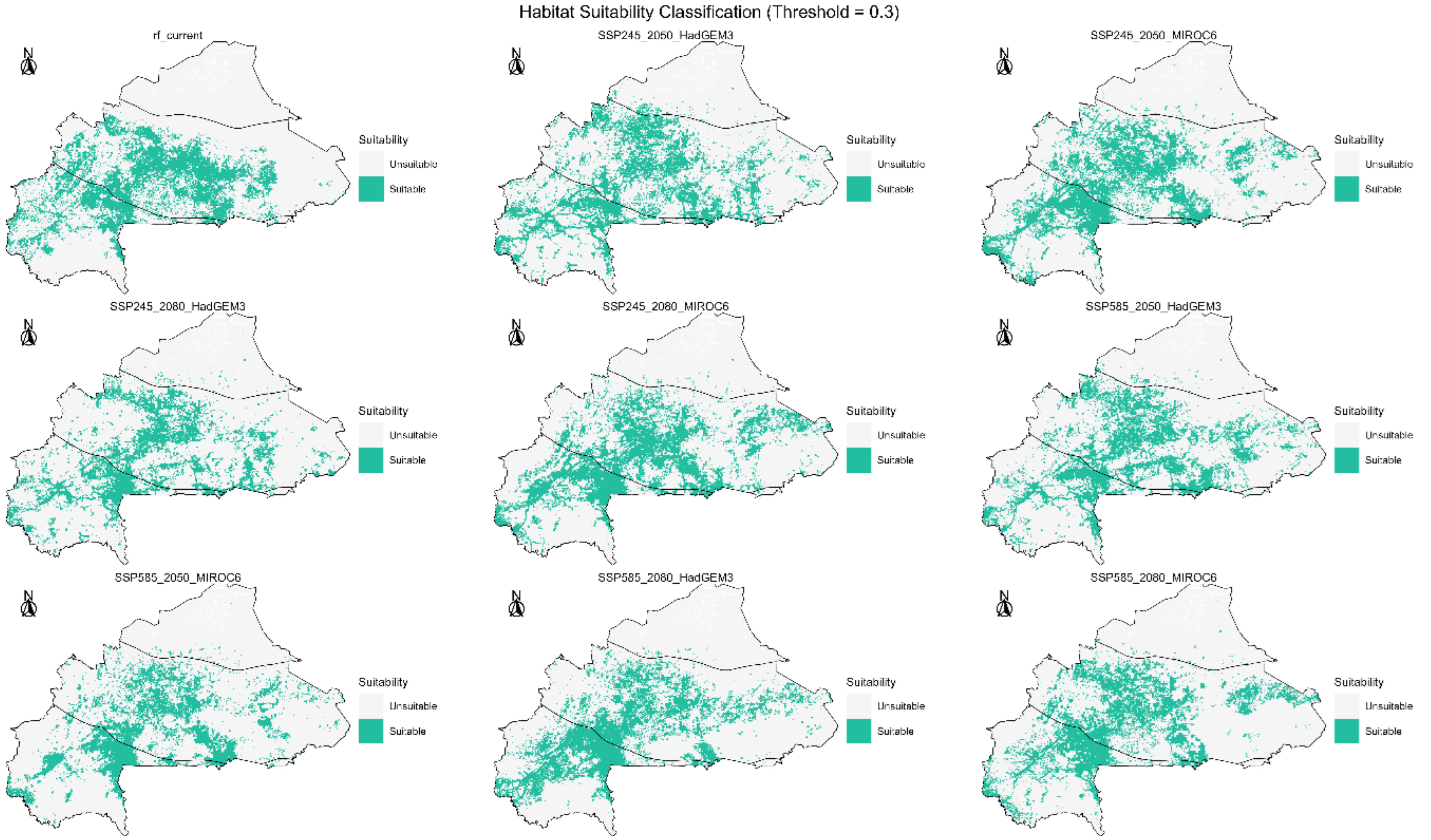


Figure 6: Future suitable areas for *Mesosphaerum suaveolens* in Burkina Faso under climate scenarios SSP245 and SSP585, using the RF algorithm with HadGEM3-GC31-LL and MIROC6 models for the years 2050 and 2090

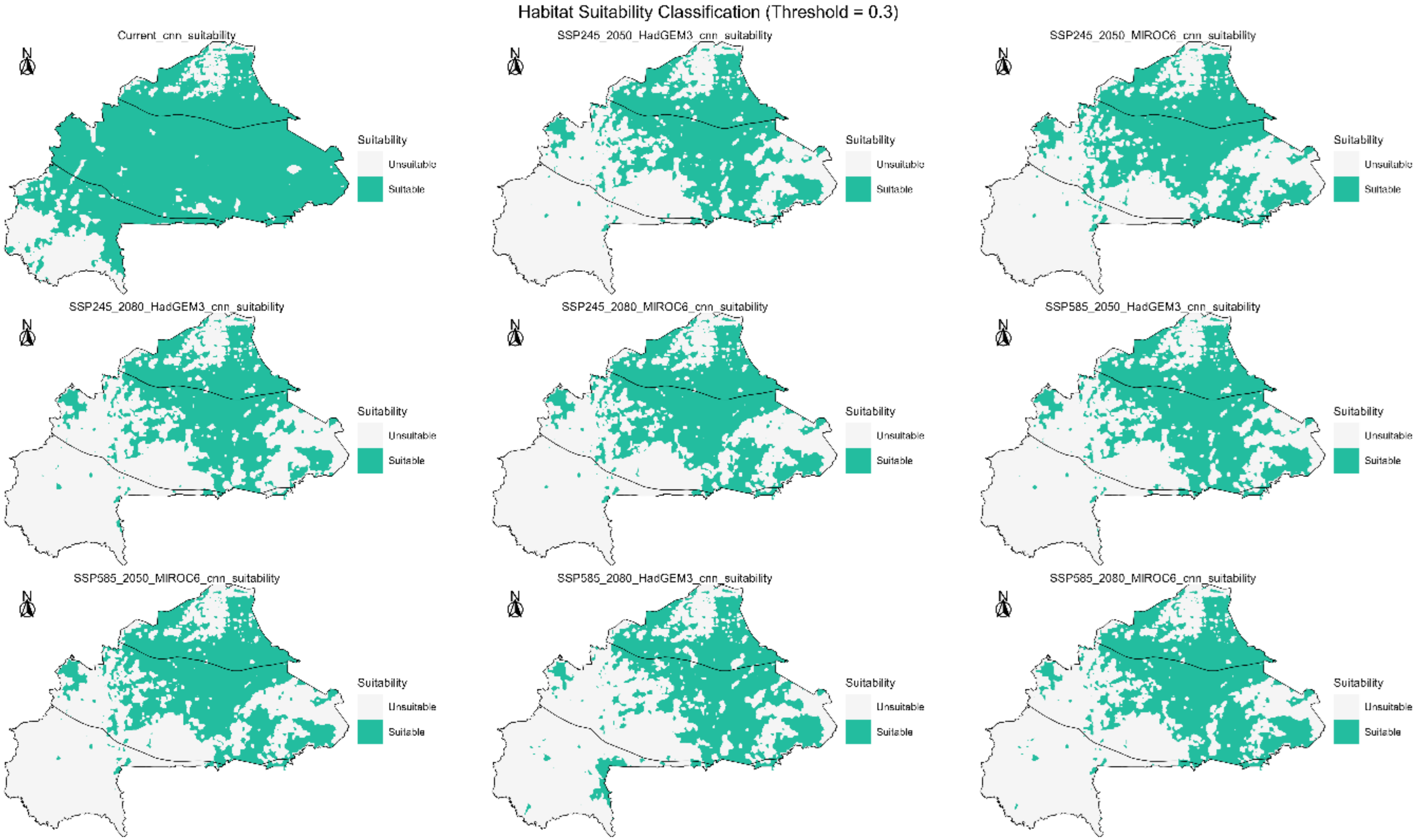
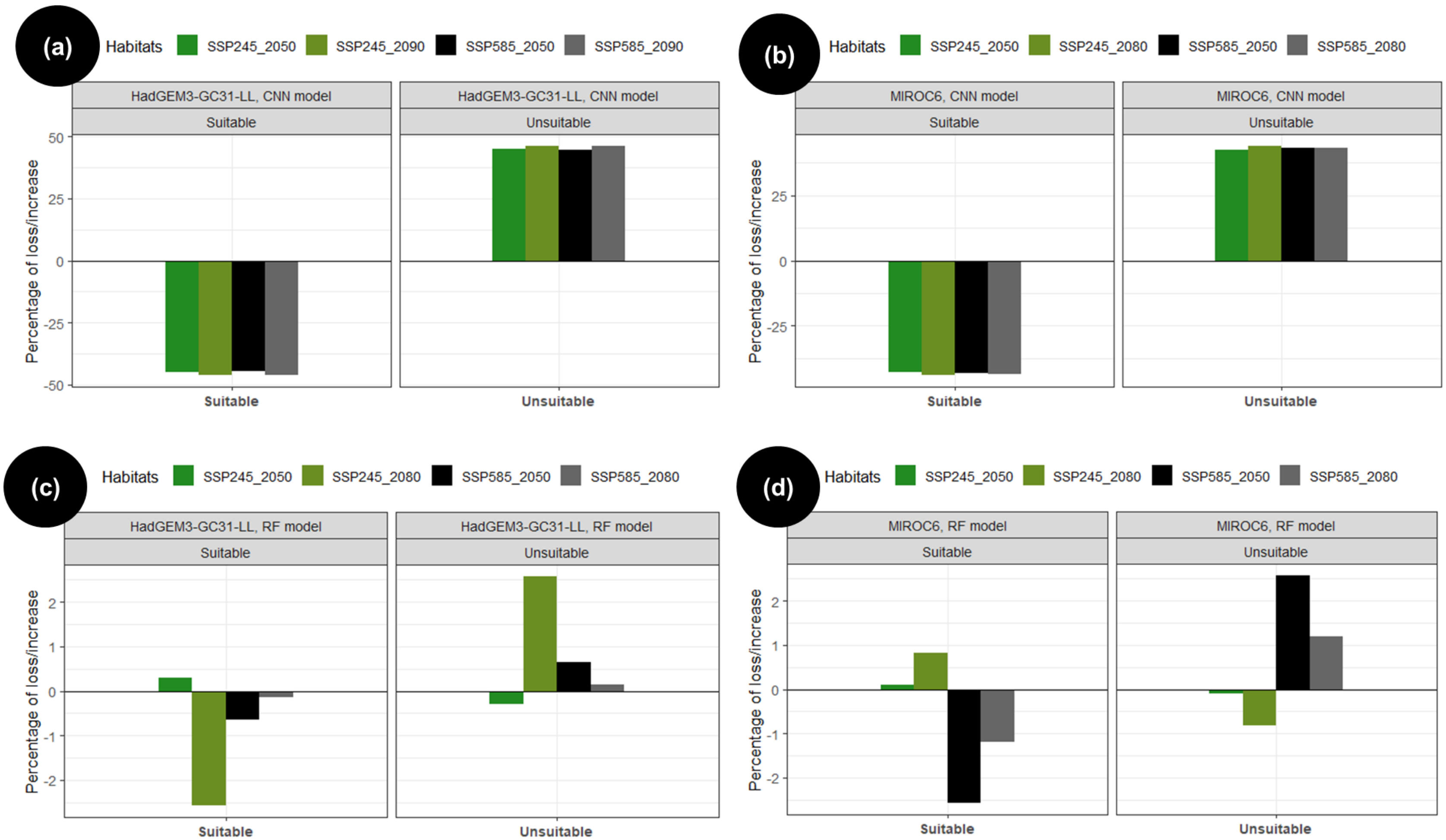


Figure 7: Future suitable areas for *Mesosphaerum suaveolens* in Burkina Faso under climate scenarios SSP245 and SSP585, using the CNN algorithm with HadGEM3-GC31-LL and MIROC6 models for the years 2050 and 2080



<u>Figure 8</u>: Projected distribution changes of *Mesosphaerum suaveolens* under future climate conditions using RF and CNN algorithms. Projections are based on HadGEM3-GC31-LL and MIROC6 models, under SSP245 and SSP585 scenarios for the years 2050 and 2080.

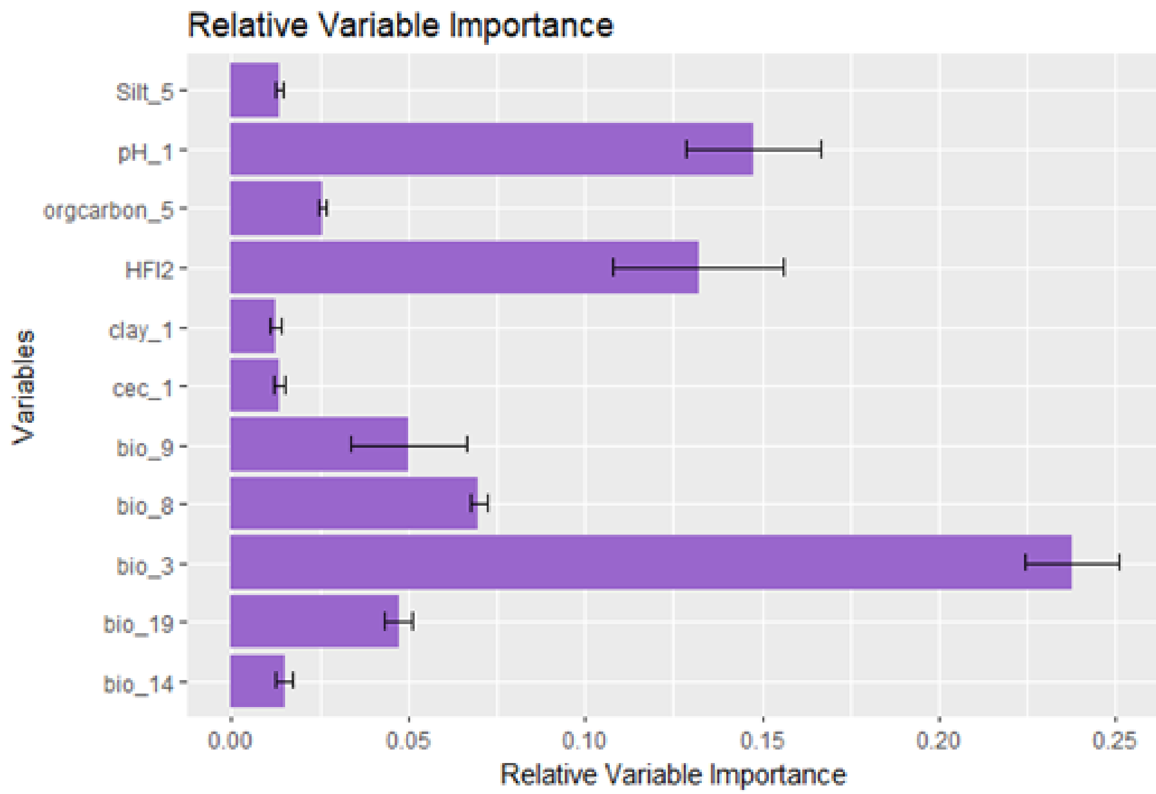
3.2. Distribution of maize cultivation areas in Burkina Faso

3.2.1. Model performance

The RF model for maize cultivation areas distribution in Burkina Faso showed high and consistent performance across three iterations, with AUC of 0.97 and TSS of 0.82 to 0.836. These metrics indicate strong predictive ability and reliable discrimination between suitable and unsuitable maize-growing areas.

3.2.2. The relative importance of predictors

Four main variables influenced most to the maize distribution model in Burkina Faso : isothermality (bio_3), soil pH at 0-5 cm depth (pH_1), Human Footprint Index (HFI2), and mean temperature of the wettest quarter (bio_8) (Figure 9). In particular, bio_3 and pH_1 together accounted for the largest share of predictive power, highlighting the influence of thermal stability and topsoil conditions on maize suitability in Burkina Faso.



<u>Figure 9</u>: Relative importance of environmental predictors in the Random Forest model predicting maize distribution in Burkina Faso

3.2.3. Current and future distribution of maize cultivation of areas in Burkina Faso

The dynamics of the current and future distribution of maize cultivation areas under current and future climatic conditions (HadGEM3-GC31-LL and MIROC6 models under SSP585 scenario for the year 2090) are presented in Table 4. Results showed that under current conditions, highly suitable areas cover 107335.95 km² representing 39.77% of the total studied area, while medium and low suitability areas occupy 139481.40 km² (51.68%) and 23100.59 km² (8.56%), respectively. Under future climate scenarios, a spatial shift in suitability levels is observed. In particular, highly suitable areas are projected to expand under both HadGEM (133,362 km² (49.09%)) and MIROC6 (136,881 km² (50.39%)) models. Conversely, medium suitability areas are expected to decrease by 23-27%, dropping to 102547.19 km² (37.75%) and 106825.81 km² (39.33%) under HadGEM and MIROC6, respectively. The proportion of low suitability areas remains limited across all scenarios, not exceeding 13.2%. These projections suggest a relative stability and even expansion of high-potential zones for maize cultivation by 2090, particularly under high-emission trajectories. Such trends may indicate a resilience of maize to future climatic conditions and highlight regions that could be prioritized for maize-based agriculture in climate adaptation planning.

Table 5: Current and projected distribution of maize cultivation suitability zones (km² and %) under present and future climate scenarios (HadGEM3-GC31-LL and MIROC6, SSP585, year 2090), including changes from current conditions

Scenario	Suitability	Area (km²)	Proportion (%)	Change from current (km²)	Change (%)
Current	Low	23100.59	8.56	–	–
	Medium	139481.40	51.68	–	–
	High	107335.90	39.77	–	–
HadGEM_2090	Low	35720.11	13.15	+4.59	+54.63%
	Medium	102547.20	37.75	-13.93	-26.45%
	High	133362.10	49.10	+9.33	+24.25%
MIROC6_2090	Low	27922.56	10.28	+1.72	+20.87%
	Medium	106825.80	39.33	-12.35	-23.41%
	High	136881.00	50.39	+10.63	+27.53%

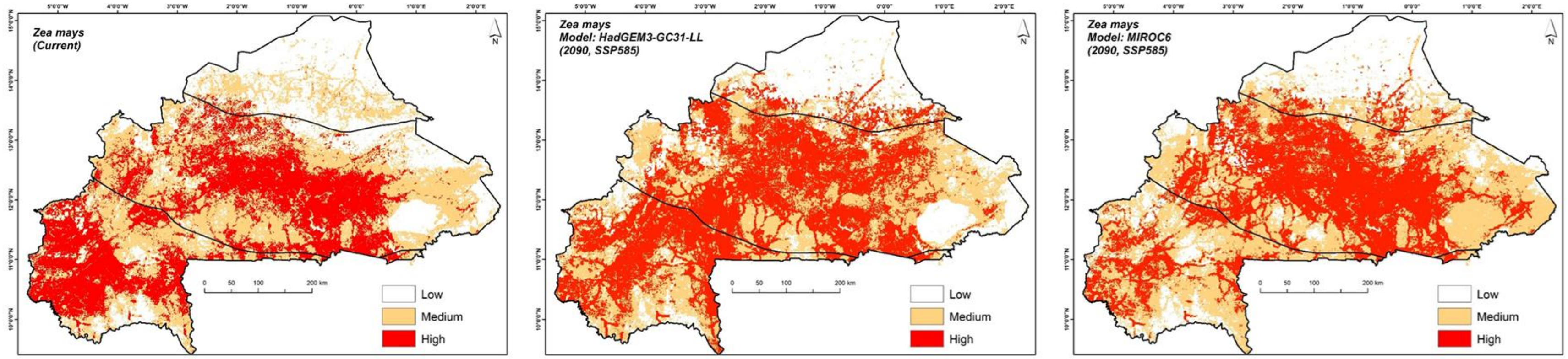


Figure 10: Potential current and future suitable areas for the distribution of *Zea mays* in Burkina Faso under HadGEM3-GC31-LL and MIROC6 climate scenarios.

3.2.4. Current and future invasion risk of *Mesosphaerum suaveolens* on maize (*Zea mays*) cultivation areas in Burkina Faso

The assessment of current and future invasion risk of *M. suaveolens* on *Z. mays* cultivation areas in Burkina Faso reveals substantial variation between modeling algorithms (Figure 11). Under present climatic conditions, the CNN model classified more than 62% of maize-growing areas as high risk of invasion by *M. suaveolens,* and only 21.6% as low risk. The RF model showed a more conservative perspective, identifying approximately 85% of areas as low risk and fewer than 4% as high risk. This contrast highlights the influence of the underlying modeling approach and algorithmic sensitivity on invasion risk predictions, and underscores the need for critical model selection. Under future climate projections (2081–2100) from HadGEM3-GC31-LL, the CNN model indicated a notable reduction in high-risk areas to 14% and a concurrent increase in low-risk zones to 66.9%, while the RF model projections remained stable with only 4% high-risk and 85% low-risk areas. Similarly, under the MIROC6 scenario, the CNN model projected 16.3% of maize areas at high risk of invasion and 65.8% at low risk, whereas the RF model again projected minimal change, with just 3.4% of areas at high risk and nearly 86% at low risk. Together, these results demonstrate the CNN model's higher sensitivity to climatic variability and potential shifts in invasion dynamics, while RF maintains a more stable and conservative outlook across time and scenarios.

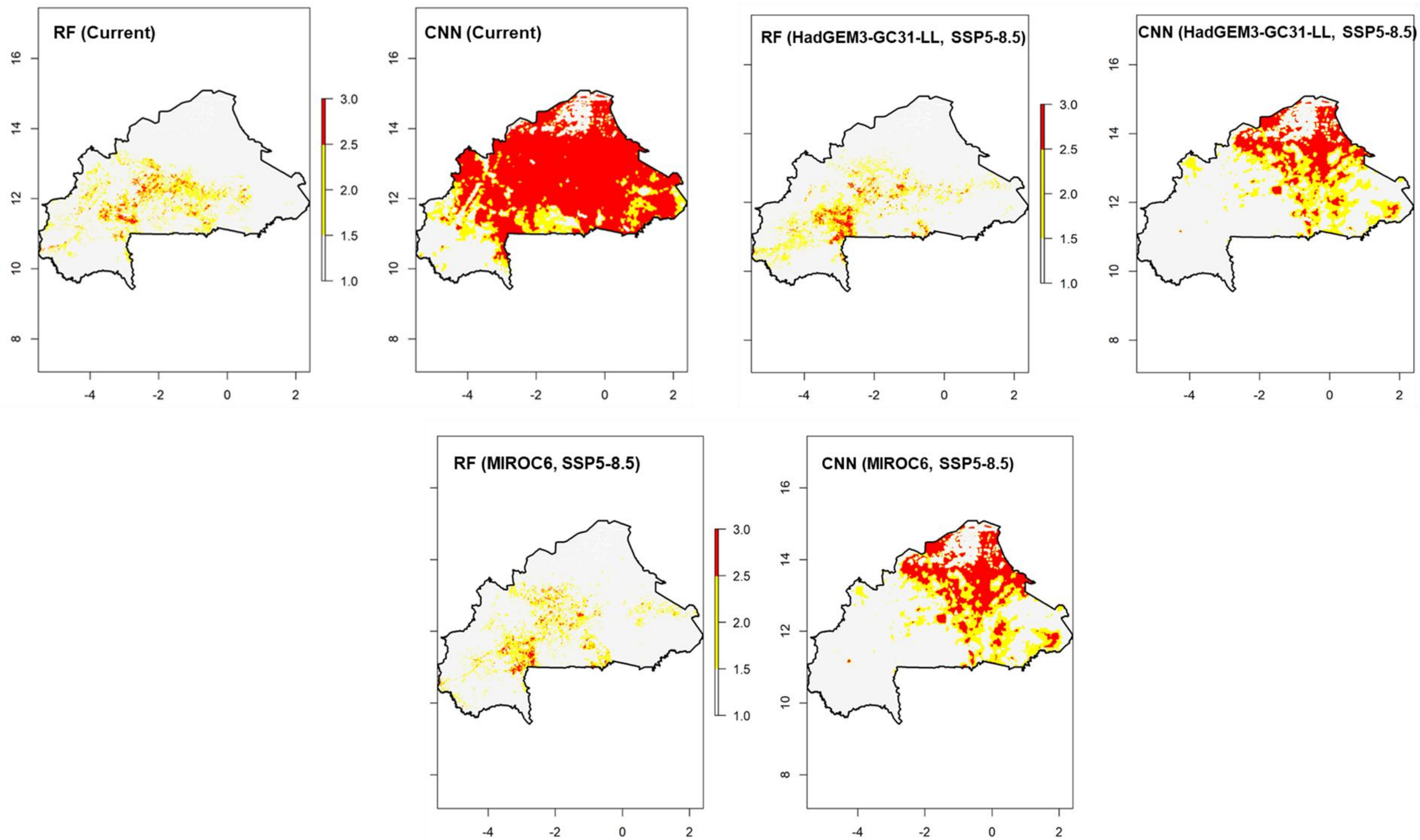


Figure 11: Current and future (2081–2100) invasion risk of *Mesosphaerum suaveolens* on maize (*Zea mays*) cultivation areas in Burkina Faso under SSP585 scenarios using RF and CNN combined with HadGEM3-GC31-LL and MIROC6 climate models.

CHAPTER 4: DISCUSSION

4.1. Spatial overlap and ecological validity of AI-based predictions of *M. suaveolens* and Maize areas in Burkina Faso

The AI-based species distribution models (SDMs) demonstrated strong predictive capability, as reflected by high validation scores. In line with other studies, the Random Forest (RF) algorithm in particular showed excellent performance in identifying suitable habitat patterns. It performs well in ecological prediction (Soumaïla et al., 2024). Cross-validation and ensembling helped mitigate overfitting, but model reliability still depends on input data quality and the assumptions of SDMs. For instance, presence-only models (such as MaxEnt and RF with pseudo-absence) can be sensitive to sampling bias and pseudo-absence selection. We therefore interpret the AI predictions cautiously, acknowledging that factors like spatial autocorrelation or incomplete occurrence records can influence results. Nonetheless, the high accuracy metrics suggest that the models captured key environmental constraints on *M. suaveolens* and maize.

Our predicted distribution of *M. suaveolens*, concentrated in the Sudano-sahelian zone of Burkina Faso is broadly consistent with the known ecology of the species in West Africa (Padalia et al., 2015; David et al., 2020; Aïkpon et al., 2021). The models showed high suitability in southern and central regions (with annual rainfall >600 mm), and low suitability in arid northern zones. This agrees with findings from Nigeria, where MaxEnt modeling indicated that *M. suaveolens* thrives in areas with moderate rainfall (200–800 mm) and is poised to invade even more humid zones (David et al., 2020). According to those authors, the species could potentially occupy large portions of north-central Nigeria. Similarly, our model suggests expansion into Burkina's moister south-west and south-central agro-ecological zones. These results align with regional surveys. For instance, in Benin (a neighboring country) *M. suaveolens* was observed almost ubiquitously in cultivated and fallow lands, and are present throughout the territory, regardless of climatic zone (Aïkpon & Ganglo, 2024). Notably, the study from Benin found *M. suaveolens* most abundant in crop–fallow mosaics and near settlements, which mirrors our finding that cultivated areas in Burkina Faso offer prime habitat. Altogether, the predicted range in Burkina Faso matches the general pattern of *M. suaveolens* being a major invader in disturbed croplands across West Africa.

The modeled maize cultivation areas likewise agrees with agricultural data for Burkina Faso. Only about 20% of the country is highly suitable for maize, mainly in the southwestern and central-southern regions (Röhrig et al., 2021). These zones coincide with the humid Sudanian savannah, where annual rainfall is sufficient for maize (600-1200 mm). National agricultural statistics confirm that maize cultivation is concentrated in the wetter Sudanian zones where its yields and areas peak. In fact, maize (together with sorghum and millet) covers roughly 80% of Burkina Faso's arable lands (Röhrig et al., 2021). Our model's maize suitability map reflects that optimal maize habitat overlaps with the same regions where subsistence farmers traditionally grow maize (e.g. Hauts-Bassins, Boucle du Mouhoun, Centre-Ouest regions). These modeled patterns are in line with previous agroecological zoning, which shows maize favored in the southern half of Burkina Faso and largely unsuitable in the arid Sahelian north. However the relative stability and even expansion of high-potential zones for maize cultivation by 2090, particularly under high-emission trajectories may indicate a resilience of maize to future climatic conditions and highlight regions that could be prioritized for maize-based agriculture in climate adaptation planning.

Spatially, there is a significant overlap between *M. suaveolens* habitat and maize cultivation areas. The weed's affinity for anthropogenic habitats (crop fields, fallows, village edges) (Aïkpon & Ganglo, 2024) means that much of its suitable area coincides with maize cropland. For example, the Benin analysis reported that nearly half of *M. suaveolens* occurrences range were in crop–fallow mosaics and agglomerations (Aïkpon & Ganglo, 2024), indicating a strong co-location with agricultural fields. This overlap implies that co-occurrence between *M. suaveolens* habitat and maize cultivation is most pronounced in the Sudano-Sahelian zone, even though maize is predominantly produced in the Sudanian zone. This pattern indicates that maize fields in the Sudano-Sahelian zone are particularly exposed to invasion risk. Competition for lands between weeds and crops is a common pattern. Invasive herbaceous weeds often flourish in disturbed farmland and can establish in mixed cropping systems (as noted for *H. suaveolens* in Nigeria and Malawi) (Eschen et al., 2021). Our overlap analysis thus highlights key hotspots (central Burkina) where *M. suaveolens* infestation is most likely to impact negatively maize.

4.2. Effect of climate change on *M. suaveolens and Z. mays* distribution patterns

Climate change is a key driver of species distributions shift. Plant distribution ranges are principally governed by temperature and precipitation regimes, so warming and altered rainfall inevitably reshape suitable habitats. Aïkpon et al. (2021) emphasize that *M. suaveolens*' distribution is strongly influenced by climatic factors (especially precipitation and temperature variability)(AÏKPON et al., 2021). Consequently, their model projects a "considerable increase in the current ranges" of *M. suaveolens* by 2055 under RCP4.5/8.5 (Aïkpon et al., 2021). We similarly find that future climate scenarios enlarge the weed's potential range northward, likely because higher CO_2 and warmer, wetter conditions in previously marginal areas create new suitable niches. By contrast, Padalia et al.(2015) found that under high-emissions scenarios (*HadCM3* A2), bushmint's global niche might shrink, highlighting that outcomes depend on scenario details (Padalia et al., 2015). Nonetheless, there is broad scientific agreement that climate change will drive plant species range shifts.

Maize is no exception. Burkina Faso's rainfed maize production is highly sensitive to warming and rainfall declines. Our modeling assumes modest warming (0.5–3°C) and increasing dry-season length, consistent with CMIP6 projections for West Africa (Barros et al., 2014). Waongo *et al.* (2024) used CMIP6 and found that nationwide, maize yields will "predominantly decrease" under both moderate and high emission scenarios; losses of 20% are expected in most regions, with up to 40% declines in the crucial southwestern zone under RCP8.5 (Waongo et al., 2024). Likewise, Zelaya *et al.* (2022) project an 18% drop in cereal (incl. maize) yields in northern BF due to higher temperatures and evapotranspiration (Laudien et al., 2022). Together, these findings indicate that climate warming will shrink the climatically optimal areas for maize (especially in the north) even as it makes some new areas marginally drier. In summary, climate change is likely to expand *M. suaveolens* into new areas while simultaneously reducing maize suitability in parts of Burkina Faso, compounding the risks identified.

4.3. Risk implications for maize production and food security in Burkina Faso

The intersection of a broad *M. suaveolens* invasion front with Burkina Faso's maize belt has serious consequences for food security. Maize is a staple crop in Burkina Faso, the second-largest cereal after sorghum (Waongo et al., 2024) and supports the diets and incomes of millions of smallholders. Even modest yield losses could exacerbate hunger. Currently, about 30% of Burkina's Gross Domestic Product and the livelihoods of roughly 80% of the population depend on rainfed agriculture(Waongo et al., 2024). Notably, from 2017–2019 nearly half the population faced moderate or severe food insecurity (Laudien et al., 2022), a situation only worsened by recent conflicts and economic shocks (Laudien et al., 2022). In this fragile context, additional crop loss from invasive weeds would be particularly damaging.

Evidence from other invasive species underscores these high stakes. *Parthenium hysterophorus*, for instance, has been shown to reduce maize yield by roughly 14-46% at different infestation levels (Naderi et al., 2024). Furthermore, *M. suaveolens* may harbor pests or pathogens and produce allelochemicals (its essential oils are known to have bioactivity) that could indirectly harm crops or soil health. Thus, the presence of dense *M. suaveolens* stands not only lowers maize yield potential but also increases management costs and labor requirements for farmers, exacerbating rural poverty cycles. The spatial risk maps indicate that where *M. suaveolens* suitability overlaps maize fields, especially in the agro-climatic south, farmers will face reduced production unless control measures are taken. In short, the predicted invasion represents a significant threat to Burkina's maize productivity, which in turn endangers the food security of maize-dependent households. These findings underscore the urgency of including invasive weed management in food security planning.

4.4. Implications for invasion management to save maize production

To protect maize production, an integrated management approach is needed. First, early detection and surveillance must be strengthened. International frameworks emphasize a three-stage strategy of prevention, early detection, and rapid control (International Plant Protection Convention (IPPC) Secretariat, 2022). In practice, this means training local extension agents and farmers to recognize *M. suaveolens* and report outbreaks quickly (via community-based monitoring or "citizen science" networks). Timely detection allows manual removal before the plant produces seed, which is critical given its prolific seeding. Second, agroecological control methods should be employed. No single tactic will suffice. In Ethiopian maize fields, for instance, farmers routinely use a combination of hoeing, hand-weeding and pre-emergent herbicides (Negewo et al., 2024), yet each alone is only partially effective. Experts therefore advocate Integrated Weed Management (IWM), combining cultural, mechanical and, if feasible, biological measures. In practical terms, this might involve crop rotation or intercropping (planting *Mucuna*, cowpea or sorghum before maize) to suppress *M. suaveolens* germination; mulching or cover crops to outcompete seedlings; and timely hand-weeding or shallow tillage to remove young weeds. For example, experimental rotations of maize with cover crops (e.g. velvet bean, lablab) have been shown to reduce weed pressure in similar environments (Negewo et al., 2024). Maintaining a weed-free period of 4-6 weeks after planting (through repeated weeding) is known to preserve >90% of maize yield (Negewo et al., 2024), and would be critical for *M. suaveolens*. Finally, community-led actions and capacity building are key. Management will be most effective if smallholders organize collective efforts (e.g. coordinated weeding days in villages) and share best practices. Farmer field schools or local cooperatives can disseminate identification guides and control techniques. Extension services might encourage the use of *M. suaveolens* biomass for organic compost or bio-fuel (turning a pest into a resource), as has been tried with other weeds. Importantly, all strategies should be adapted to local conditions; for instance, high-risk zones identified by the SDM maps should be prioritized for surveillance and intervention. By combining early-warning systems with diversified, ecological control methods, Burkina Faso can mitigate the dual threat of the invasion of *M. suaveolens* and protect maize yields and food security.

RECOMMANDATIONS

The following measures are proposed to reduce invasion risk and safeguard maize productivity, particularly in the high-risk zones identified through our predictive models:

- ❖ **Early Planting & Land Preparation:** It is suggested that maize be sown immediately after the first rains, with weeds cleared well in advance of planting, to give crops a competitive edge over *M. suaveolens*.
- ❖ **Weeding & Mulching:** Regular manual weeding combined with mulching (such as crop residues or cowpea) could help suppress *M. suaveolens* growth and conserve soil moisture.
- ❖ **Crop Rotation & Intercropping:** Rotating maize with less weed-susceptible crops or introducing legumes/cereals in rotation may break the life cycle of *M. suaveolens*.
- ❖ **Improved Soil Fertility:** Enhancing soil fertility through organic manures or controlled fertilizer use might improve maize's ability to compete with weeds.
- ❖ **Community Monitoring & Early Warning:** It is proposed to use risk maps for prioritizing surveillance in high-suitability areas, alongside awareness campaigns and participatory mapping for targeted control efforts.

- ❖ **Biological Control & Local Use:** Research into potential biological control agents (e.g. insects or pathogens) could be explored, as well Microsoft.QuickAction.MobileHotspotas the local use of *M. suaveolens* for traditional medicine, incentivizing its removal.
- ❖ **Policy & Institutional Support:** Policies supporting smallholders with integrated weed management, including subsidies for tools or herbicides, and investment in climate-smart agriculture, could be recommended.

CONCLUSION AND PERSPECTIVES

This study applied advanced artificial intelligence approaches to model the current and future distribution of *Mesosphaerum suaveolens* and evaluate its potential impact on maize production under climate change. The integration of machine learning and deep learning techniques enabled the generation of high-resolution, future-facing invasion risk maps that can support targeted decision-making. The findings confirm that *M. suaveolens* currently occupies wide areas across Burkina Faso, and that future suitable habitats will either expand or contract depending on the climate scenario and the algorithm used. The study fills a critical knowledge gap by systematically mapping the spatial interaction between an invasive plant and a key staple crop. It offers a valuable reference for identifying priority zones for invasive species management in order to protect maize production and strengthen food security. It can be conclusively noted that questions from the hypotheses have been answered as stated below:

- ❖ First hypothesis: verified; the current distribution of *M. suaveolens* is wide across Burkina Faso.
- ❖ Second hypothesis: partially verified; suitable areas are projected to expand in some scenarios and contract in others
- ❖ Third hypothesis: verified; high-risk zones were identified where maize production could be affected by the presence of *M. suaveolens*

Although this study provides valuable insights, future research could address its limitations to improve predictions. The use of ensemble modeling techniques would help reduce overfitting and increase model robustness. Combining multiple climate models through ensemble means could better capture climate variability and uncertainty. Long-term monitoring and the collection of more precise occurrence data across the country would enhance the quality of species distribution models. Future studies could also explore additional machine learning approaches and integrate management scenarios to guide practical interventions against *M. suaveolens* invasion.

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