

Simulated Effect of Agroforestry Shading on Robusta Coffee (*Coffea canephora*) Suitability Under Climate Change Scenarios in Uganda

Isaac T. Okurut

isaactomokurut@gmail.com

Makerere University

David Abigaba

Potsdam Institute of Climate Impact Research

Catherine Mulinde

National Forestry Resources Research Institute (NaFORRI)

Saul D. Dumba

National Forestry Resources Research Institute (NaFORRI)

David Williamson

Centre d'Études et de Recherches de Djibouti (CERD)

Daniel Waiswa

National Forestry Resources Research Institute (NaFORRI)

Bernard Fungo

National Forestry Resources Research Institute (NaFORRI)

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Abstract

Climate change is projected to affect coffee suitability in worldwide, yet the potential of Coffee Agroforestry Systems (CAFS) as a landscape-level adaptation strategy remains underexplored. This study assessed the effectiveness of CAFS in moderating climate impacts on coffee suitability. The objectives were: (1) to model current coffee suitability; (2) to project changes in suitability under future climate scenarios; and (3) to evaluate the influence of agroforestry on coffee suitability under projected conditions. Using a MaxEnt model, we applied agroforestry adjustments by reducing maximum temperature (T_{max}) 3°C and increasing minimum temperature (T_{min}) by 1°C. Two scenarios were modeled: (i) a *no-agroforestry* scenario using unadjusted climate variables, and (ii) an *agroforestry* scenario using temperature-adjusted variables. The models performed well (AUC = 0.75). Under SSP2–4.5, 14.7% of modeled areas were projected to lose suitability, 32.3% were stable, and 52.9% gained suitability—yielding a net gain of 38.2%. Under SSP5–8.5, 16.5% of areas lost suitability, 49.8% remained unchanged, and 33.7% gained, resulting in a net improvement of 17.2%. This study provides quantitative evidence of the adaptive potential of CAFS and highlights the need for integrated approaches to safeguard *C. canephora* under future climate change.

1. Introduction

Climate change is severely impacting coffee systems globally (Pham et al., 2019). Coffee producers have reported reduced yields linked to heat and acute water stress, increased production costs, price surges related to irregular seasons, the spread of pests and diseases, and decline in suitable area for cultivation (Kiyingi & Gwali, 2012; Mulinde et al., 2019; Ogundeji et al., 2019; Pham et al., 2019). These impacts threaten foreign exchange revenues and exacerbate poverty and food insecurity in countries which mostly depend on coffee. Uganda is one of the world's leading coffee producers, with export revenues exceeding US\$2 billion in 2024/25 alone (MAAIF, 2025). *Coffea canephora* accounts for about 80% of the total coffee produced in the country, and is indigenous to the forests of the Lake Victoria crescent (UCDA, 2019).

The *C. canephora* bioclimatic zone occurs mostly in areas with a temperature range of 22–26°C, with the species preferring mean annual rainfall in the range of 1200–1800 mm (Damatta et al., 2007; UCDA, 2019). A short dry spell lasting two to four months is crucial for phenological processes like flowering (Damatta et al., 2007; Kath et al., 2021; UCDA, 2019). Prolonged heat stress above these thresholds causes flower and fruit abortion, premature ripening, and reduced bean quality (Damatta et al., 2006; Kath et al., 2021). Over the past three decades, the primary *C. canephora* production zones in Uganda have experienced significant warming and drying trends (Mubiru et al., 2018; Mulinde et al., 2022; Najjuma et al., 2021). Climate projections point to further temperature increases of 1.5–2.5°C, more erratic rainfall patterns, and prolonged dry spells by 2050 (Bunn et al., 2019; IPCC, 2023; McSweeney et al., 2010). Such climatic conditions could cause extreme physiological stress, reduce yield, increase fruit and flower abortion, and lead to premature ripening of coffee berries (Damatta et al., 2006; Jassonge et al., 2013; Lwiza & Barkley, 2025; Sarmiento-Soler et al., 2020). Significant declines in suitability are also

projected, potentially varying between 9% – 64% by 2050 (Abigaba et al., 2024; Bunn et al., 2019; Mulinde et al., 2022).

Reversing such trends requires implementation of climate smart interventions like coffee agroforestry. Coffee Agroforestry Systems (CAFS)(see Fig. 1) are a climate smart approach that integrate trees and crops within coffee farms. CAFS offer key ecological services like carbon sequestration (Tumwebaze & Byakagaba, 2016), biodiversity conservation (Pantera et al., 2021), and socio-economic advantages like diversifying farmer income through marketable products (van Asten et al., 2011). They also improve soil health via organic matter replenishment (Fahad et al., 2022). Crucially, CAFS have the potential to buffer microclimatic extremes more effectively compared to coffee monocrops (Araújo et al., 2016; de Carvalho et al., 2021; Sarmiento-Soler et al., 2020). Empirical studies have shown that CAFS can buffer microclimatic extremes by lowering maximum canopy temperatures by about 3°C, while also increasing minimum temperatures by about 1°C (Araújo et al., 2016; Merle et al., 2021; Sarmiento-Soler et al., 2019; Vaast & Somarriba, 2014).

Such microclimatic modification can significantly influence coffee suitability by shifting the species' realized niche, the area where the species occurs, even under future climate conditions. Species Distribution Models (SDMs) are powerful ecological modelling tools that can enable us understand the changes in species' environmental and geographical space (Austin, 2002; Franklin, 2009; Guisan & Thuiller, 2005). These models use species occurrence data, together with climatic, topographic, and soil-related environmental variables, to predict how a species' optimal environment will change over time and how the species is likely to respond to these changes. Recent advances in species distribution modelling have incorporated microclimatic correction factors, enabling more accurate prediction and inference of changes in coffee suitability (Abigaba et al., 2024; Gomes et al., 2020). Such predictions are crucial in establishing mapping priority areas for adaptation interventions in coffee growing landscapes.

However, while several studies have focused primarily on the effect of climate change on coffee suitability (Jassonge et al., 2013; Lwiza & Barkley, 2025; Mulinde et al., 2022), few have quantified the microclimatic effects of agroforestry shading on coffee suitability (Abigaba et al., 2024). Consequently, the capacity of agroforestry to offset or increase coffee suitability under future climate scenarios remains largely unknown. This study evaluated the effect of CAFS on coffee suitability under projected climate change scenarios. Specifically, the study: (1) modelled the current potential suitability of *C. canephora*; and (2) projected changes in suitability under future climate change scenarios; and (3) evaluated the influence of agroforestry on maintaining or enhancing coffee suitability under these projected conditions.

2. Materials and Methods

2.1. Study Area

Uganda lies between 4° N–1° S and 29.5°–35.5° E, with elevations ranging from 614 m to 4,682 m.a.s.l. (Fig. 2). Agriculture is the main land use, occupying approximately 75% of the land (Uganda Bureau of

Statistics, 2022). Rainfall varies from 500–2,800 mm yr⁻¹, averaging about 1,600 mm. The northern region experiences a unimodal rainfall pattern (March–May), while the central, southern, western, and eastern regions exhibit a bimodal regime with rainy seasons from March–May (MAM) and September–October (SON) (Nsubuga et al., 2014). A dry season with minimal precipitation and high temperatures separates the two wet periods.

2.2. Environmental Data

Baseline climatic data were obtained from the WorldClim v2.1 database (<https://www.worldclim.org>) at 30 arc-second (~ 1 km) resolution (Fick & Hijmans, 2017). WorldClim provides high-resolution global climatic and derived bioclimatic datasets. From the bioclimatic dataset, eight variables were selected based on their ecological relevance to coffee suitability (Table 1). Future climate projections were sourced from the CMIP6 (Coupled Model Intercomparison Project Phase 6) dataset under the Shared Socioeconomic Pathways (SSP) frameworks SSP2–4.5 and SSP5–8.5, representing moderate and high-emission trajectories. The Digital Elevation Model (DEM) was obtained from WorldClim. Soil pH, clay content, and soil type were obtained from SoilGrids 2.0 (<https://soilgrids.org>) and the FAO soil database. Soil variables from SoilGrids were validated against field measured samples, and underwent bias-correction.

Table 1
Environmental and occurrence datasets used for modeling *C. canephora* suitability.

Data	Data Type	Source	Resolution / Description
Coffee occurrence points	Vector (points)	Field survey, UCFA, GBIF, Published literature	~ 1 km
Bioclimatic variables (BIO2, BIO3, BIO8, BIO13, BIO14, BIO15, BIO18, BIO19)	Raster	WorldClim v2.1	30 arc-seconds (~ 1 km)
Future climate projections (BIO2, BIO3, BIO8, BIO13, BIO14, BIO15, BIO18, BIO19)	Raster	WorldClim v2.1 SSP2-4.5 & SSP5-8.5	30 arc-seconds (~ 1 km)
DEM	Raster	SRTM – Shuttle Radar Topography Mission	30 arc-seconds (~ 1 km)
Soil pH, clay	Raster	SoilGrids 2.0	250 m (~ 0.25 km)
Soil type	Vector / Raster	FAO Soil Database	250m

*BIO2: Mean diurnal range; BIO3: Isothermality; BIO8: Mean temp of wettest quarter; BIO13: Precip. wettest month; BIO14: Precip. driest month; BIO15: Precip. seasonality; BIO18: Precip. warmest quarter; BIO19: Precip. coldest quarter.

2.3. Species Occurrence Data

Occurrence records for *C. canephora* were compiled from multiple sources, including a primary field survey conducted in 2024, the Global Biodiversity Information Facility (GBIF) repository (<https://www.gbif.org/>), the Uganda Coffee Farmers' Alliance (UCFA), and published literature (Abigaba et al., 2024). GBIF is a global network of institutions that provides open-access species occurrence data and has been widely used in ecological and distribution modelling studies. The consolidated dataset was filtered to remove points with incorrect geographic coordinates, duplicates, and spatially clustered points. Spatial thinning was applied to reduce sampling bias, ensuring that presence points were reasonably distributed across the landscape. The final dataset included records from over 900 farmers.

2.4. Species Distribution Modeling Framework

SDMs were developed in R software using the 'dismo' package, which implements the Maximum Entropy (MaxEnt) algorithm (Phillips et al., 2004). MaxEnt was selected for its robustness with presence-only data and capacity to model complex nonlinear relationships (Tsoar et al., 2007). To minimize multicollinearity, environmental predictors were screened using Pearson's correlation analysis ($r < 0.7$) and Variance Inflation Factor (VIF) diagnostics. The models were calibrated with baseline climatic data and twelve environmental predictors. A beta multiplier of 3 was applied to prevent overfitting, and 10-fold cross-validation was used to evaluate robustness. Model performance was assessed using the Area Under the Receiver Operating Characteristic Curve (AUC). AUC values range from 0.5 to 1, where 0.5 indicates performance no better than random, 0.6–0.7 indicates fair discrimination, 0.7–0.8 indicates good performance, 0.8–0.9 indicates very good performance, and values above 0.9 indicate excellent predictive ability (Fielding & Bell, 1997). Response curves and jackknife tests were used to determine variable importance and ecological response patterns of *C. canephora* suitability. Model outputs were generated in logistic format to represent suitability probabilities.

2.5. Climate Change Projections and Ensemble Modeling

Future suitability was projected to mid-century (2050; mean 2041–2060) using five General Circulation Models (GCMs)—BCC-CSM2-MR, MIROC6, IPSL-CM6A-LR, UKESM1-0-LL, and MRI-ESM2-0 (Table 2). These GCMs were selected for their reliability in simulating East African climate (Najjuma et al., 2021). Each GCM–SSP combination was modeled independently at 30 arc-second resolution. Ensemble products were derived to represent the multi-model mean and standard deviation.

Table 2
Summary of Selected Global Climate Models (GCMs) Used for Coffee Suitability Projections.

Model	Full Name
MIROC6	Model for Interdisciplinary Research on Climate version 6
IPSL-CM6A-LR	Institut Pierre-Simon Laplace Climate Model 6A – Low Resolution
UKESM1-0-LL	UK Earth System Model 1.0 – Low Land resolution
MRI-ESM2-0	Meteorological Research Institute Earth System Model version 2.0

2.6. Modelling the Agroforestry Shade Effect on Coffee Suitability

The shade effect of CAFS was simulated using the ‘biovars’ function in R. Maximum temperature (T_{max}) was reduced by 3°C and minimum temperature (T_{min}) was increased by 1°C (Abigaba et al., 2024; Gomes et al., 2020). Adjustments were applied to temperature related bioclimatic variables BIO3 (isothermality), BIO4 (temperature seasonality), and BIO10 (mean temperature of the warmest quarter), while soil and topographic predictors remained unchanged. Two management scenarios were simulated: (i) a ‘no agroforestry’ scenario using unadjusted climate variables, and (ii) an ‘agroforestry’ scenario using temperature-adjusted variables. Net changes between scenarios represented the microclimatic regulation potential of shade agroforestry on *C. canephora*.

2.7. Spatial Analysis and Map Generation

All spatial analyses were conducted in ArcMap 10.4. Three change categories were defined for suitability changes: (i) high impact—currently suitable but projected unsuitable; (ii) low impact—suitable under both time periods; and (iii) newly suitable—areas gaining suitability in the future. Differences between ‘no agroforestry’ and ‘agroforestry’ scenario were mapped to highlight micro-climatically buffered zones, where shade increased suitability or offset suitability loss. All outputs were standardized to a common spatial reference system for overlay and area computation.

3. Results

3.1. Current Suitability and key environmental predictors of *C. canephora* suitability

The MaxEnt models demonstrated good predictive performance (AUC = 0.75), indicating good model discrimination (see Figure S1). The current suitability is shown in Fig. 3. Optimally productive areas (High and Very High) accounted for 22% of the modelled area while sub-optimal areas accounted for 78% of the predicted suitability. Specifically, suitability varied as High (16.1%), Very High (5.9%), Moderate Suitability (22.5%), Low (35.0%), and Very Low (20.3%).

Precipitation of the warmest quarter (BIO18) contributed the most to model performance (32.2%), followed by soil type (20.3%), precipitation of the wettest month (BIO13, 16.2%), and precipitation of the

coldest quarter (BIO19, 14.6%) (Table 3). Together, these four variables accounted for over 80% of total model contribution, suggesting they are the primary environmental predictors for *C. canephora* suitability. Permutation importance ranked precipitation of the coldest quarter (BIO19, 37.1%) and precipitation of the wettest month (BIO13, 30.4%) as the most influential factors in determining model accuracy. Soil pH and clay content each contributed less than 2%.

Table 3
Relative contribution and permutation importance of environmental predictors in the *C. canephora* suitability model.

Environmental Variable	Percent Contribution (%)	Permutation Importance (%)
BIO18 – Precipitation of the Warmest Quarter	32.2	2.1
Soils (FAO classification)	20.3	9.9
BIO13 – Precipitation of the Wettest Month	16.2	30.4
BIO19 – Precipitation of the Coldest Quarter	14.6	37.1
BIO3 – Isothermality	5.6	1.6
BIO8 – Mean Temperature of the Wettest Quarter	5.6	4.1
BIO14 – Precipitation of the Driest Month	1.6	2.8
Soil pH	1.2	2.5
BIO15 – Precipitation Seasonality	0.8	1.2
BIO2 – Mean Diurnal Range	0.8	1.2
Digital Elevation Model (DEM)	0.1	5.9
Clay Content (%)	0.1	0.5

The Jackknife analysis revealed that soil type, precipitation of the coldest quarter (BIO19), precipitation of the wettest month (BIO13), and precipitation of the warmest quarter (BIO18) were the most informative variables (see Figure S2). When used in isolation, soil type produced the highest training gain. Conversely, model performance dropped most markedly when precipitation of the coldest quarter (BIO19) was omitted. Soil pH and clay content contributed minimally.

3.2. Response of *C. canephora* to Environmental Conditions

3.2.1. Climatic Drivers

C. canephora exhibited broad tolerance to mean diurnal range (BIO2). Temperature response curves indicated optimal suitability at mean temperatures of the wettest quarter (BIO8) between 10–20°C, with

marked declines below 5°C or above 25°C (see Figure S3). Suitability increased sharply with precipitation of the wettest month (BIO13) up to ~ 100–150 mm, stabilizing beyond this range. Suitability peaked under moderate precipitation seasonality (BIO15: 40–70% coefficient of variation), reflecting the species' dependence on distinct wet and dry phases for flowering and fruit set. Conversely, precipitation of the coldest quarter (BIO19) showed a negative relationship, with highest suitability below 100 mm, indicating preference for relatively dry cool periods.

3.2.2. Topographic and Soil Variables

Optimal suitability occurred between 600–1,500 m.a.s.l (Figure S3). Areas with slightly acidic soils (pH 4.5–5.5) and moderate clay content (~ 20%) were similarly optimal, emphasizing the species' need for optimal drainage and root aeration. Suitability declined at both highly acidic/alkaline pH and extreme clay or sandy textures. Among soil types, Acric Ferralsols, Nitisols, and Lixic Ferralsols/Luvisols exhibited the highest suitability, reflecting their deep profiles and good moisture retention. In contrast, Vertisols (poor drainage) and Arenosols (low fertility and water-holding capacity) showed the lowest suitability (see Figure S3).

3.3. Projected Coffee Suitability under Future Climate Scenarios

As shown in Supplementary Figure S4, under SSP2–4.5, Highly suitable (9.3%) and moderately suitable (18.7%) areas are concentrated northwest of Lake Victoria and parts of central Uganda. Unsuitable and marginally suitable zones (72%) dominated the northeast and southwest. Model uncertainty maps showed higher variability in predictions under SSP5-8.5 than under SSP2-4.5 (see Figure S5). Areas of high suitability often coincide with areas of higher uncertainty, indicating that while the potential is great, the robustness of this prediction is lower.

3.4. Coffee Suitability Transitions under Climate Change

Under SSP2-4.5, suitability losses were predicted in central, eastern, and southwestern regions, while gains emerge in the northern region (see Figure S6). Under SSP5-8.5, these suitability losses increase, with only limited stable areas remaining. Notable declines in the extent of loss and gain in stability are projected under the agroforestry scenario. However, even under agroforestry, notable losses are still expected under SSP5-8.5. This suggests that while agroforestry is an effective adaptation strategy, its capacity to offset extreme climate impacts is limited.

3.5. Net Effect of Agroforestry on Coffee Suitability under Climate Change

Simulations under agroforestry showed a marked improvement in coffee suitability under both emission scenarios (Fig. 4). Under SSP2–4.5, 14.7% of modeled areas were projected to lose suitability, 32.3% remained stable, and 52.9% gained suitability—yielding a net gain of 38.2% (. Under SSP5–8.5, 16.5% of areas lost suitability, 49.8% remained unchanged, and 33.7% gained, corresponding to a net improvement of 17.2%. Spatially, suitability gains under agroforestry were most pronounced around Lake

Victoria, central Uganda, and portions of the western highlands, suggesting that shade trees can buffer adverse temperature extremes and sustain production potential under climate stress.

4. Discussion

4.1. Model Performance and Interpretation of Current Suitability Patterns

The modeled current suitability of *C. canephora* corroborates previous studies in the country (Abigaba et al., 2024; Bunn et al., 2019; Mulinde et al., 2022). These zones coincide with the established niche of *C. canephora* around the L. Victoria crescent (Damatta et al., 2007; UCDA, 2019). Areas in the northern and northeastern part of the country are of relatively low suitability compared to the central due to the hotter and drier climate. Such areas would require substantial irrigation and management to offset current climatic limitations (Mubiru et al., 2012).

4.2. Environmental Drivers of *C. canephora* Suitability

Precipitation variables are a primary driver of *C. canephora* distribution. In particular, precipitation of the warmest quarter (BIO18), the wettest month (BIO13), and the coldest quarter (BIO19) contribute significantly to the model's predictive power. These variables correspond to critical phenological stages of *C. canephora*, including flowering, bean filling, and the onset of drought stress (Damatta et al., 2007; Kath et al., 2021). Suitability peaks where rainfall is moderately seasonal and just sufficient to maintain moisture during flowering, but with a distinct short dry period. Excessive or erratic precipitation disrupts these stages, while prolonged dry spells reduce yields, highlighting the crop's physiological sensitivity to water availability (Damatta et al., 2006; Kath et al., 2021; UCDA, 2019).

Response curves showed that *C. canephora* is mostly suitable under moderate thermal conditions, consistent with its ecological niche (Damatta et al., 2007; UCDA, 2019). High temperatures beyond physiological thresholds reduce pollen viability and bean filling efficiency, while cooler conditions at higher elevations slow metabolic processes (Damatta et al., 2006; Kath et al., 2021; UCDA, 2019). Optimal elevation for *C. canephora* suitability was shown to be between 600–1,500 m above sea level, where temperatures are moderate and soils are well-drained with slightly acidic pH (Damatta et al., 2007; UCDA, 2019). Soils such as Acric Ferralsols, Nitisols, and Lixic Ferralsols or Luvisols provide deep profiles with good water-holding capacity, supporting root growth and stable yields for coffee (Fungo et al., 2020; Kyalo et al., 2023). In contrast, Vertisols and Arenosols, which have poor drainage or low fertility, constrain suitability.

4.3. Projected Coffee Suitability under Future Climate Change

Projected changes in suitability under both moderate and extreme climate warming pathways around L. Victoria are attributed to temperature increases and erratic rainfall patterns (Abigaba et al., 2024; Mubiru et al., 2018; Mulinde et al., 2022). Conversely, higher-elevation environments in northern and northwestern Uganda may become increasingly suitable, suggesting a gradual northward and altitudinal

shift (Abigaba et al., 2024; Mulinde et al., 2022). The spatial patterns of projected suitability reflect the species' sensitivity to temperature and precipitation. The core suitable areas for *C. canephora* is in the northwest of Lake Victoria, consistent with the species' established ecological niche (Damatta et al., 2007; Kath et al., 2020; UCDA, 2019). The marginal and unsuitable zones in much of the north and northeast under moderate warming mirror the hotter, more variable, and often moisture-limited climatic conditions in these areas (Mubiru et al., 2012, 2018). The intensification of these patterns under the extreme warming scenario has also been widely reported by other researchers (Bunn et al., 2019; Mulinde et al., 2022).

4.4 Effectiveness of Agroforestry as a Climate Adaptation Strategy

The modelling results confirm that simulated shading conditions under agroforestry substantially enhance *C. canephora* suitability, reinforcing its adaptation potential under climate change. Regions where gains are highest under moderate warming should be treated as priority areas for scaling up agroforestry intervention, as these landscapes can maximize the benefit of shade tree-mediated climate buffering. The doubling of net gains in suitability in the moderate warming scenario compared to the extreme scenario implies that the effectiveness of agroforestry diminishes under extreme warming.

These findings align with established evidence that agroforestry buffers climatic stresses (Araújo et al., 2016; de Carvalho et al., 2021; Lin, 2007; Pezzopane et al., 2015). CAFS are a proven adaptation strategy for mitigating climate change in *C. canephora* production systems, with shade trees buffering extreme temperatures, reducing evapotranspiration, and maintaining soil moisture during dry spells (de Carvalho et al., 2021; Kobusinge et al., 2023). These systems also enhance soil fertility by increasing organic carbon and reducing erosion, thereby supporting long-term productivity (Eddy & Yang, 2022; Misgana et al., 2024; Pinho et al., 2012).

4.5. Model Uncertainty and Inter-Model Consensus

Higher model uncertainty under the extreme warming scenario indicates that suitability projections become less reliable as climate conditions diverge further from the historical baseline. There is need for cautious interpretation and flexibility in adaptation planning. The co-occurrence of high suitability and high uncertainty in parts of central and western Uganda suggests that, although these areas exhibit strong potential for future coffee production, their outcomes may be sensitive to local microclimatic variability. Consequently, site-specific assessments and microclimate-informed management will be essential for guiding investment and adaptation strategies in these high-value regions.

4.6 Study Limitations and Future Research Directions

While this study provides important insights into the climate–soil–agroforestry interactions shaping coffee suitability, several limitations remain. SDMs are sensitive to the quality and resolution of input data, model parameterization choices, and the reliability of future climate projections. These factors can contribute to overfitting or scale mismatches, potentially leading to overestimation or misrepresentation

of suitable areas. Future research would benefit from incorporating a broader set of high-resolution soil climate variables to improve the ecological interpretation of *C. canephora* suitability assessments.

5. Conclusions

This study evaluated the microclimatic shading effects of agroforestry on the future suitability of *C. canephora*. The modeled baseline suitability closely reflects the species' well-documented ecological range, confirming the robustness of the approach. Under projected climate change, substantial suitability shifts occur in both moderate and high emission pathways, illustrating the vulnerability of Uganda's coffee landscapes to warming. Incorporating microclimatic correction factors revealed a clear positive influence of agroforestry, with shading significantly enhancing net suitability gains—particularly under the moderate warming scenario. However, the strength of this buffering effect decreases under extreme warming conditions, indicating limits to the resilience that agroforestry alone can provide. Overall, the findings demonstrate that agroforestry meaningfully improves the climatic suitability of *C. canephora* and should be promoted as an effective adaptation strategy in coffee-growing regions, while recognizing that additional measures will be necessary under more severe climate futures.

Declarations

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Ethics Approval: This study did not involve human participants, animals, or sensitive personal data requiring ethical review.

Consent to Participate: All authors consented to participate in this research.

Consent for Publication: All authors provided consent for publication of this manuscript.

Availability of Data and Materials: All datasets used in this study are available from the corresponding author on reasonable request. Public datasets are accessible through their respective repositories.

Code Availability: The R scripts used for data processing and modelling are available from the corresponding author upon reasonable request.

Authors' Contributions: Conceptualization, Isaac T. Okurut; methodology, Isaac T. Okurut, Saul D. Ddumba, and D. Abigaba; validation, Saul D. Ddumba, C. Mulinde, D. Williamson, D. Waiswa; analysis, Isaac T. Okurut; investigation, Isaac T. Okurut; resources, D. Williamson and B. Fungo; data curation, Isaac

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Figures



Figure 1

Coffee monocropping system (left) showing open-field cultivation, compared with a coffee agroforestry system (right) where shade trees provide canopy cover and microclimate benefits.

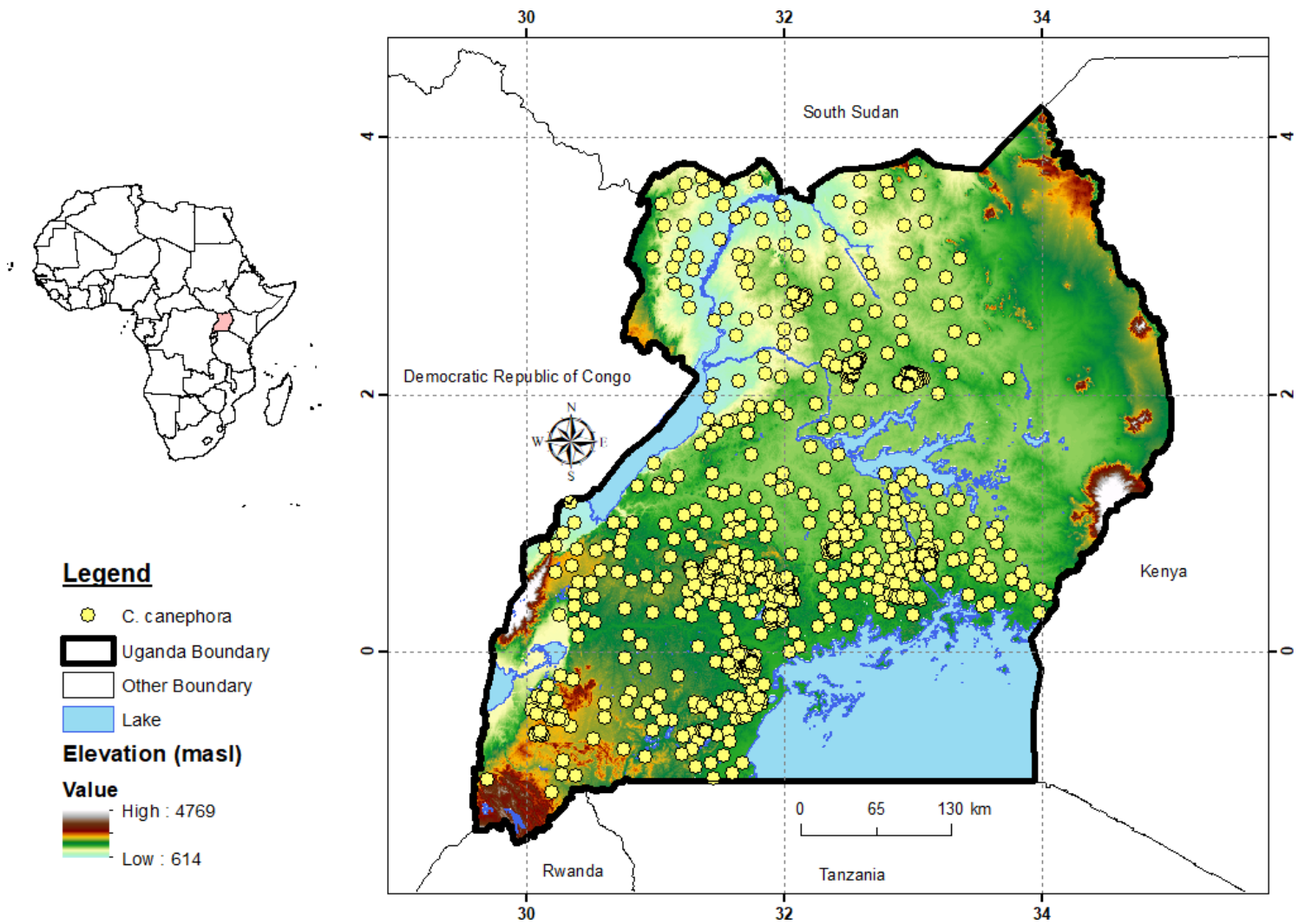


Figure 2

Map of the study area, Uganda, showing the distribution of coffee presence points used in the suitability modeling.

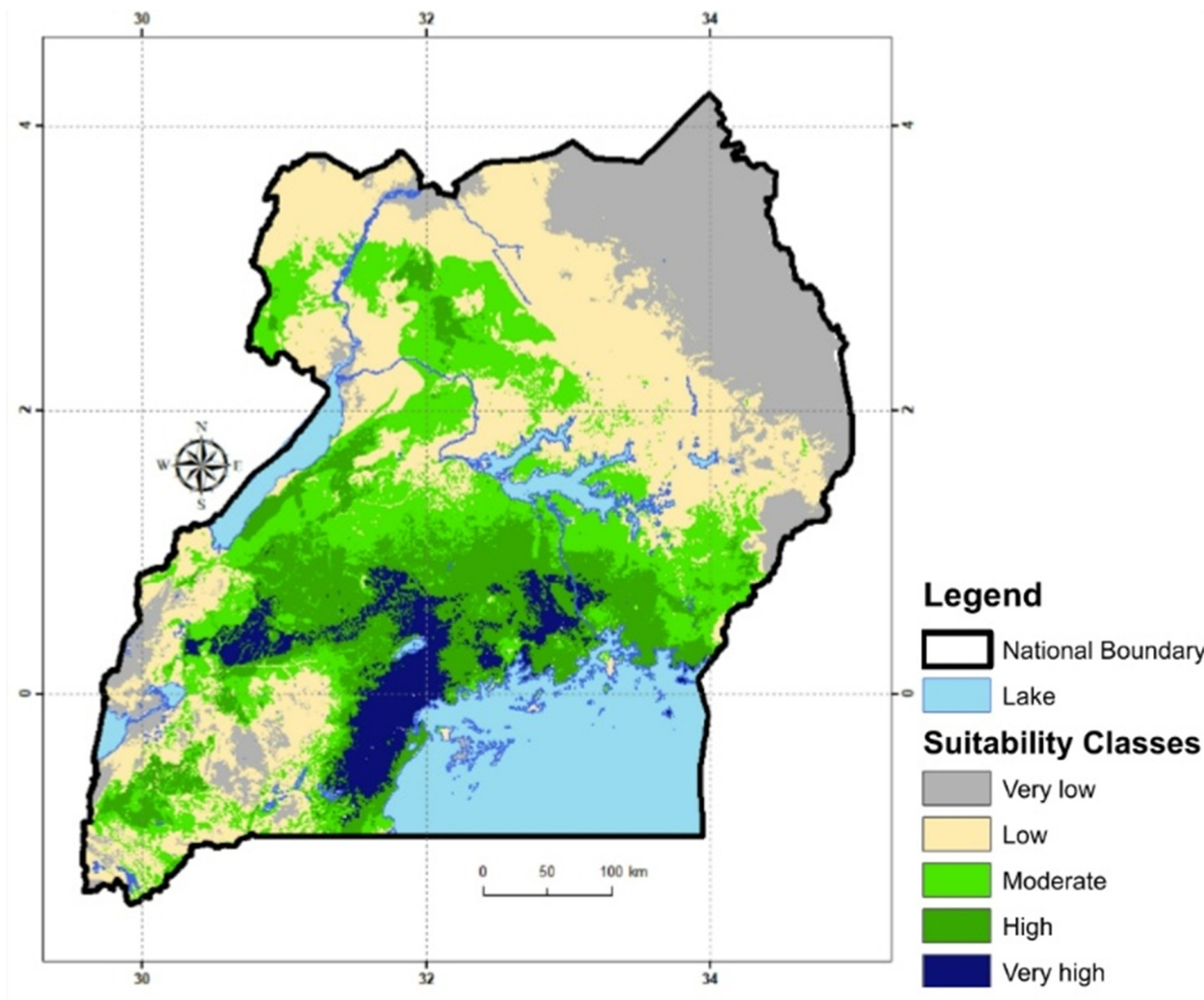


Figure 3

Current suitability for *C. canephora* in Uganda.

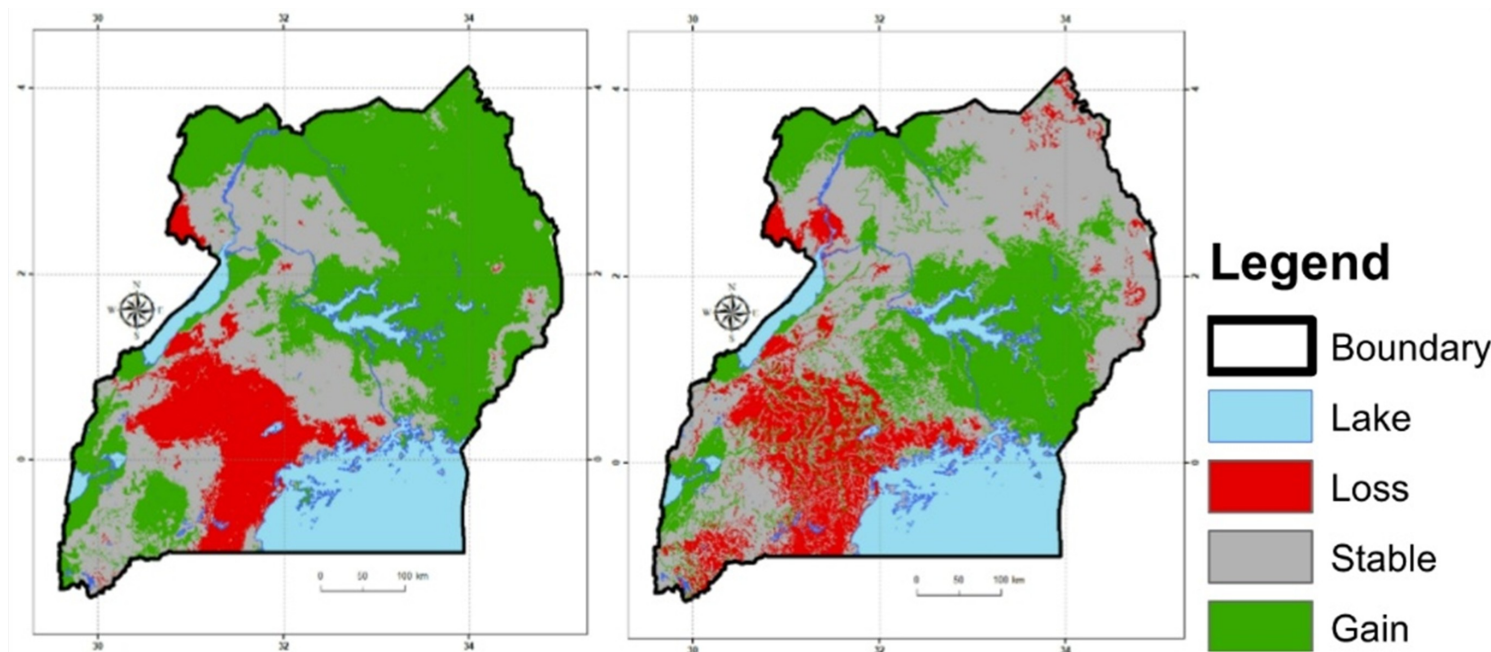


Figure 4

Net effect of agroforestry under SSP2-4.5 (L) and SSP5-8.5 (R) in 2050.

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