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RESEARCH ARTICLE

Climate change-informed habitat suitability and conservation priorities for *Cinchona* species in eastern Democratic Republic of the Congo

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Abstract

Background and aims – *Cinchona* species, the botanical source of quinine, remain essential for treating severe malaria and support rural livelihoods in eastern Democratic Republic of the Congo. Yet, increasing climate stress and land degradation threaten its future habitat suitability. This study assessed current and mid-century habitat suitability for *Cinchona* in North and South Kivu provinces and prioritised areas for conservation and replanting.
Material and methods – Potential distributions were modelled with MaxEnt using 125 validated occurrences and ten environmental predictors (five bioclimatic, three topographic, two edaphic). To limit multicollinearity, we pre-selected variables with $|r| < 0.7$ and VIF < 10. Future projections used 2050s CMIP6 climates under SSP2-4.5 and SSP5-8.5.
Key results – Model performance was high. Thermal variability together with elevation most strongly explained suitability, indicating a preference for moderate thermal regimes at 1,400–2,300 m. Under current climate, high suitability covers 4.13% of the study area, moderate 6.49%, low 27.67%, and 61.71% is unsuitable. By the 2050s, high suitability contracts to 1.27% (SSP2-4.5) and 1.07% (SSP5-8.5), while unsuitable area expands to 81.72% and 83.90%, respectively. High-suitability zones cluster along the eastern escarpment, notably Lubero, Oïcha, Kabare, Walungu, and Butembo, whereas lowland territories such as Shabunda and Fizi become largely unsuitable.
Conclusion – Our results delineate micro-refugia for in situ protection, guide climate-resilient replanting toward highlands, and indicate where ex situ measures and assisted restoration will be needed under future climate conditions.

Keywords

Cinchona spp., climate change, conservation planning, eastern DRC, ecological niche, land-use planning, MaxEnt, species distribution modelling, SSP2-4.5, SSP5-8.5

INTRODUCTION

The genus *Cinchona* L. holds a strategic position at the crossroads of biodiversity conservation, economic development, and public health (Achan et al. 2011). Comprising 24 species in Rubiaceae and native to tropical Andean forests (Basuki and Edhi 2020; Verstraete et al. 2025), *Cinchona* yields bark rich in quinine and related alkaloids, still among the most effective treatments for severe malaria, especially across low- and middle-income countries. Beyond pharmacological value, *Cinchona* contributes to the structural and functional diversity of tropical montane forests.

In the Democratic Republic of the Congo (DRC), *Cinchona* is represented by a small number of introduced species, mainly *C. calisaya* Wedd. (including cultivated

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forms historically referred to as *C. ledgeriana* Moens ex Trimen) and *C. pubescens* Vahl, introduced primarily for quinine production (Ntore and Lachenaud 2022). *Cinchona* spp. have both ecological and socio-economic importance: the country contributes approximately 55% of global quinine production, with long-established plantations and remnant naturalized populations in North and South Kivu supplying domestic and international markets (Mekonnen et al. 2025). Local communities rely on quinine bark for livelihoods and healthcare, while montane stands support ecosystem stability.

Habitats of *Cinchona* species in their neotropical area of origin face growing threats from anthropogenic pressures and climate change, with several species now listed as Endangered on the IUCN Red List (García et al. 2022; Vergara et al. 2023). Eastern DRC, particularly North and South Kivu provinces are not exempt from the same challenges. Unsustainable harvesting practices, habitat degradation, and the escalating impacts of climate change are placing increasing stress on *Cinchona* populations (Mekonnen et al. 2025). Moreover, a regional assessment of forest disturbance in the Congo Basin using satellite time-series data estimated that 84% of forest disturbance area from 2000 to 2014 was due to small-scale, non-mechanized clearing for agriculture, and smallholder clearing in the DRC accounted for nearly two-thirds of total forest loss (Tyukavina et al. 2018). Climate-driven shifts in forest cover and plant disease emergence further heighten vulnerability in already over-harvested populations (Adegboye et al. 2021), while poverty and dependence on forest resources intensify pressure (Goldman et al. 2025).

One of the most critical challenges is the disconnect between conservation strategies and on-the-ground ecological realities. Biodiversity, climate change, and ecosystem-service considerations remain poorly integrated into land-use planning across the Congo Basin (Milena 2025). These socio-economic drivers intersect with environmental change: species worldwide are shifting their distributions in response to rising temperatures, with average shifts of about 11.8 km per decade toward higher latitudes and 9 m per decade upslope (Rubenstein et al. 2023). This persistent planning gap places additional pressure on species like *Cinchona* spp., which depend on humid, climatically stable montane ecosystems (Basuki and Edhi 2020). In the Albertine Rift, of which eastern DRC is part of, climate projections suggest that endemic species may lose over 30% of their range by 2080 under pessimistic scenarios (Ayebare et al. 2018).

Against this backdrop, spatial modelling tools are increasingly vital for assessing the future viability of species. In particular, Species Distribution Models (SDMs) enable researchers to estimate current and projected species ranges based on environmental variables such as temperature, precipitation, elevation, and soil characteristics. These approaches are becoming indispensable for conservation planning in biodiverse yet data-scarce regions such as the Congo Basin (Milena 2025). For example, recent studies in the DRC have applied SDMs to evaluate habitat suitability for threatened plant species under multiple climate scenarios (Imani wa Rusaati and Won Kang 2024), and their adoption is rising in regional conservation workflows.

Among the most widely used SDMs is the Maximum Entropy model, or MaxEnt. Introduced by Phillips et al. (2004), MaxEnt estimates species distributions using presence-only data and environmental predictors. The algorithm applies the principle of maximum entropy to generate the most uniform distribution consistent with the ecological constraints derived from the data, thereby providing robust inferences when occurrence information is limited.

Because of its user-friendliness, robustness with small datasets, and strong predictive performance, MaxEnt has become a cornerstone in conservation biogeography. It has been used across Africa to model current and future distributions of both plant and animal species under different climate change scenarios, including in the DRC (Cokola et al. 2020; Mugumaarhahama et al. 2020; Ngarega et al. 2021). These studies collectively demonstrate MaxEnt's capacity to identify climate refugia and regions at risk of habitat loss, even when data are minimal. For *Cinchona* spp., which inhabit fragmented, elevation-specific niches, this modelling approach is well suited to anticipating range shifts and informing proactive conservation strategies.

The research effort presented here responds to a notable knowledge gap. While Vergara et al. (2023) used the MaxEnt algorithm to model current and future distributions of *Cinchona* spp. in Peru, comparable analyses for the eastern DRC remain lacking. In addition, conservation strategies and land-use planning in the Congo Basin rarely integrate biodiversity and climate data, despite the region's environmental sensitivity and socio-economic vulnerability (Youssoufa Bele et al. 2025). This lack of spatially explicit, climate-informed evidence limits informed conservation and land-use decision-making for *Cinchona* spp. in eastern DRC.

This study aims therefore to: (1) identify current and future suitable habitats for *Cinchona* spp. under projected climate scenarios; (2) determine the key environmental drivers shaping the species' ecological niche; and (3) translate these modelling results into actionable, evidence-based strategies for conservation, restoration, and land-use planning in eastern DRC. We hypothesize that suitable habitats will contract and shift upslope under future climate conditions, reducing the area available for both cultivation and conservation. By integrating geospatial modelling with climate projections, this work seeks to inform conservation priorities and promote sustainable land management for *Cinchona* spp. and the communities that depend on them.

MATERIAL AND METHODS

Study area

This study focuses on North and South Kivu provinces in eastern DRC, which straddle the equator and extend across the Albertine Rift between ~27° and 30°E, with a combined surface area of over 120,000 km^2 as illustrated in Fig. 1 (Ngalamulume et al. 2025). These provinces form part of the Albertine Rift, a core component of the Eastern Afromontane Biodiversity Hotspot and one of the most species-rich regions in continental Africa (Ayebare et al. 2018; Plumptre et al. 2021). Elevation ranges from 770 m in lowland valleys to over 5,000 m on volcanic and montane massifs. The region experiences a tropical humid climate, with mean annual temperatures between 17 and 24°C and distinct dry and wet seasons. Protected areas like Kahuzi-Biega National Park hold significant portions of its ecological diversity and carbon stock (Cirezi et al. 2025).

Occurrence data

A total of 456 unique presence points for *Cinchona* spp. were assembled from multiple sources, including field surveys conducted in 2024 across North and South Kivu, and validated datasets provided by local partners such as Pharmakina S.A. All occurrence coordinates were projected in WGS 84 (EPSG:4326) and duplicates and spatially imprecise records were removed to minimize sampling bias (Palacio et al. 2021; Davis et al. 2024). After processing, 125 high-confidence, georeferenced occurrence records were retained for integration with environmental predictor layers in the species distribution modelling framework (Suppl. material 1).

Environmental variables

Environmental variables were selected based on their documented ecological relevance to the distribution of *Cinchona* spp. along elevational climatic gradients typical of humid tropical montane forests (Ayebare et al. 2018; Coronel-Castro et al. 2024).

A total of 32 environmental variables were initially considered to model the potential distribution of *Cinchona* spp. in eastern DRC (Suppl. material 2). This dataset included 19 bioclimatic variables and one environmental variable (solar radiation), all obtained from WorldClim v.2.1 at a spatial resolution of 30 arc-seconds (~1 km) (Fick and Hijmans 2017; accessed on 21 Jun. 2025). Three topographic variables (elevation, slope, and aspect) were derived from the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM), downloaded from the CGIAR Consortium for Spatial Information (https://srtm.csi.cgiar.org; accessed on 21 Jun. 2025). Nine edaphic variables were extracted from SoilGrids (https://soilgrids.org; accessed on 21 Jun. 2025) at 250 m resolution. Future climate effects were evaluated using WorldClim v.2.1 CMIP6 ensemble projections for two mid-century scenarios in eastern DRC (SSP2-4.5 and SSP5-8.5) at 2050, defined as 2041–2060 (https://www.worldclim.org/data/cmip6/cmip6_clim30s.html; accessed on 21 Jun. 2025). All environmental predictors were resampled to 250 m with bilinear interpolation and aligned to EPSG:4326. Raster processing and data management were performed using QGIS v.3.34 (QGIS Development Team 2023) and R v.4.3.0 (R Core Team 2025).

Variable pre-processing and selection

To reduce multicollinearity among environmental predictors and enhance model reliability, a two-step variable selection procedure was implemented. First, pixel values for the 32 initial environmental variables were extracted at all 125 occurrence locations using the Point Sampling Tool in QGIS. Pairwise Pearson correlation analysis was then conducted to assess inter-variable relationships. Variables with correlation coefficients greater than 0.7 ($|r| > 0.7$) (Smith and Santos 2020) were considered redundant and excluded to minimize collinearity (Bradie and Leung 2017; Schnase et al. 2021).

In the second step, Variance Inflation Factors (VIFs) were computed on the reduced dataset using the vifstep function in the R package usdm v.2.1-7 (Naimi et al. 2014). Variables with VIF values exceeding 10 were iteratively removed until all remaining predictors met the threshold of VIF < 10 (Ab Lah et al. 2021; Kim et al. 2025; Lorenț et al. 2025). This process resulted in a final set of 10 predictors retained for MaxEnt modelling: bio2 (mean diurnal range), bio3 (isothermality), bio4 (temperature seasonality), bio16 (precipitation of wettest quarter), bio18 (precipitation of warmest quarter), elevation, slope, aspect, pH water, and coarse fragments. All the ten spatial layers were processed and formatted as ASCII grids compatible with MaxEnt software.

MaxEnt modelling

Species distribution modelling was performed using the Maximum Entropy algorithm implemented in MaxEnt v.3.4.4 (Phillips et al. 2025). The 10 environmental predictors retained after multicollinearity filtering (bio2, bio3, bio4, bio16, bio18, elevation, slope, aspect, pH water, and coarse fragments) were used as input. The modelling extent was restricted to the North and South Kivu provinces to avoid extrapolation into environmentally dissimilar areas. Model calibration used 125 georeferenced occurrences together with the ten predictors. Predictive performance was assessed by 10-fold cross-validation (ten replicates), with each fold trained on 90% of the occurrences and validated on the remaining 10%; replicates were generated independently (Ali et al. 2023; Kim et al. 2025). The background was defined within the study area, and the maximum iterations were set to 5,000 to ensure model convergence (Boussouf et al. 2023). Output was generated in logistic format on the [0,1] scale, producing habitat suitability scores

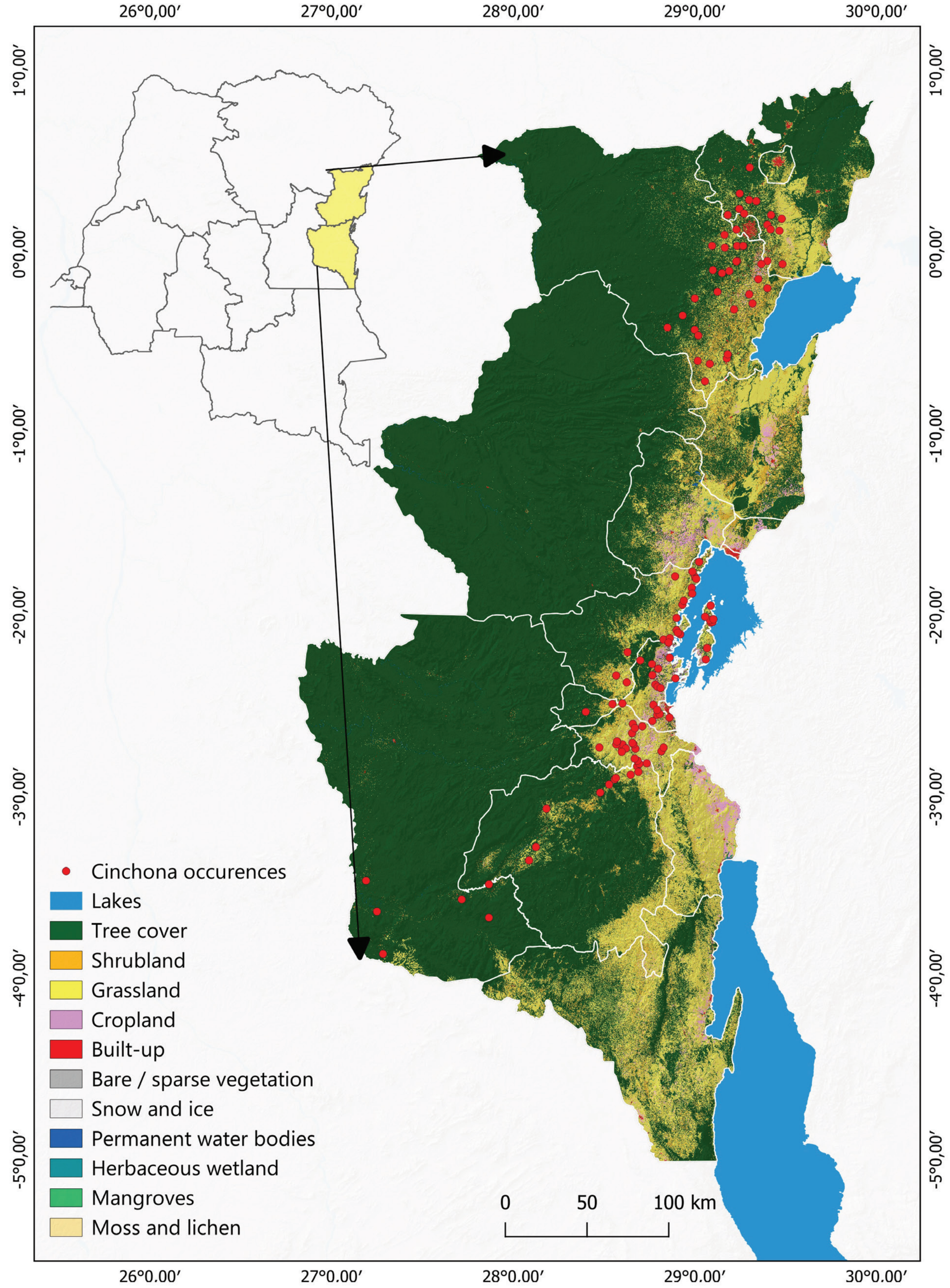

Figure 1. Study area showing North and South Kivu provinces in eastern Democratic Republic of the Congo, with *Cinchona* occurrence records overlaid on land-cover classes.

ranging from 0 (unsuitable) to 1 (highly suitable) (Xiao et al. 2024). For cartographic interpretation, the continuous logistic surface was reclassified into four suitability classes, following prior work adapted to our context (Vergara et al. 2023): very low (≤ 0.100), low (0.100–0.300), moderate (0.300–0.500), and high (> 0.500).

Model evaluation

Predictive performance was quantified with the threshold-independent Area Under the ROC Curve (AUC), a standard metric in ecological niche modelling (Fielding and Bell 1997; Jiménez-Valverde 2012). AUC values below 0.60 indicate very poor discrimination, values between 0.60 and 0.69 are considered poor, 0.70–0.79 satisfactory, 0.80–0.89 good, and ≥ 0.90 excellent (Lissovsky and Dudov 2021).

Analysis of variable importance

The contribution of each environmental variable to the MaxEnt model was assessed using jackknife tests and response curves. Jackknife tests quantified the gain reduction when each variable was omitted, identifying those with the highest unique explanatory power (Li et al. 2020; Vergara et al. 2023). Response curves were examined to characterize the relationship between habitat suitability and key predictors (Ab Lah et al. 2021; García et al. 2022). These analyses helped to interpret ecological drivers of *Cinchona* distribution and to compare our findings with those of earlier studies.

RESULTS

Model performance

Predictive performance was evaluated with 10-fold cross-validation (ten independent replicates; 90/10 splits). The model achieved high discrimination, with Test AUC = 0.8808 (SD = 0.0437) and Training AUC = 0.9036 (Suppl. material 3). For comparability, we report two threshold-dependent statistics from the average model: the 10th percentile training presence threshold (0.1552) yielded a test omission = 0.1352, while the maximum test sensitivity + specificity threshold (0.3196) yielded test omission = 0.1596. The ROC summarizing cross-validated performance is shown in Suppl. material 4; the omission-predicted area curve across cumulative thresholds is provided in Suppl. material 5.

Variable importance

Together, relative contributions and jackknife diagnostics indicate that a small set of predictors governs *Cinchona* distribution. Mean diurnal range (bio2) accounts for 37.6% of training gain but has low permutation importance (3.7%), which is consistent with overlap among temperature metrics. In contrast, elevation (17.1%) and temperature seasonality, bio4 (16.5%), show high permutation importance (20.2% and 23.2%, respectively), indicating substantial performance loss when perturbed in permutation tests (Suppl. material 6). Jackknife curves confirm that elevation carries the most unique information; it yields the highest "with-only" gain and its omission produces the largest decline (Suppl. material 7). Isothermality (bio3) contributes 8.2% yet attains the highest permutation importance (24.2%), revealing a strong non-redundant signal after accounting for collinearity. In 2050 projections under SSP2-4.5 and SSP5-8.5, this ranking (temperature regime: bio2/bio3/bio4 plus elevation) remains broadly stable, reinforcing the robustness of these drivers.

Response curves further clarify the climatic, topographic, and edaphic controls on suitability. In the marginal curves (red = mean across 10 replicates; blue = ±1 SD; other predictors held at their means), suitability rises steeply with elevation and levels off at mid to high elevations; it increases monotonically with mean diurnal range (bio2) across the sampled range (to ~13°C) and declines with temperature seasonality (bio4). For edaphic predictors, both coarse fragments and pH water show sustained negative responses: suitability decreases as coarse fragment content increases, and declines with increasing pH. Taken together, these patterns support a composite thermal regime (bio2/bio3/bio4) coupled with an altitudinal constraint, rather than reliance on a single temperature metric (Fig. 2).

Current suitability

The modelling results provide a clear spatial baseline for anticipating climate change and land-use impacts on *Cinchona* habitats in eastern DRC (Fig. 3). High suitability (> 0.500) is concentrated along the eastern escarpment from Lubero in the north to Walungu and Fizi in the south, forming an elongated corridor where plantations coincide with remnant montane forests, thereby delineating landscapes where land-use choices directly intersect with suitable *Cinchona* habitats. This spatial configuration highlights a close overlap between optimal *Cinchona* habitat and montane landscapes shaped by long-term human land use, indicating that present-day land-use decisions strongly influence habitat persistence. Moderate suitability (0.300–0.500) surrounds these hotspots and extends into adjacent mid-elevation zones. Low suitability (0.100–0.300) covers much of the western foothills, reflecting transitional landscapes increasingly shaped by agriculture and settlement. Unsuitable areas (≤ 0.100) dominate the lowlands and interior plateaus.

Area statistics (Suppl. material 8) indicate that 4,799.31 km^2 (4.13%) of the study area falls in the high-suitability class, 7,533.39 km^2 (6.49%) in the moderate class, 32,142.64 km^2 (27.67%) in the low class, and 71,671.57 km^2 (61.71%) is unsuitable. High suitability is most extensive in Lubero (1,509.58 km^2), Walungu (811.17 km^2), Oicha (718.58 km^2), and Kabare (584.47 km^2), all located on montane ridges between roughly 1,400 m and 2,300 m above sea level, a narrow elevational band that constrains the spatial extent of optimal habitat. Moderate suitability is more widespread but largely confined to mid-elevation slopes, and only trace amounts of high suitability occur in lowland territories such as Shabunda and Fizi. These statistics confirm the restricted distribution of optimal *Cinchona* habitat under present conditions.

Future projections (2050)

Class totals

Under SSP2-4.5 (Suppl. material 9), high suitability decreases to 1,470.74 km^2 (1.27%), representing a 69.36% reduction relative to current conditions. Moderate suitability declines to 4,262.17 km^2 (3.67%) (-43.42%), while low suitability decreases to 15,493.90 km^2 (13.34%) (-51.80%). In parallel, unsuitable areas expand to 94,920.10 km^2 (81.72%), an increase of 23,248.53 km^2 (+32.44%), signalling a broad displacement of climatically favourable conditions away from large parts of the present landscape.

Under SSP5-8.5 (Suppl. material 10), contraction is stronger. High suitability falls to 1,240.56 km^2 (1.07%) (-74.15%). Moderate suitability declines to 2,858.08 km^2 (2.47%) (-62.08%). Low suitability decreases to 14,580.38 km^2 (12.56%) (-54.63%). Unsuitable area grows to 97,362.26 km^2 (83.90%), which is +25,690.69 km^2 (+35.86%) relative to the present. These changes indicate a marked shift from moderately suitable to unsuitable conditions.

Spatial patterns

By 2050, high suitability is largely confined to crest zones and becomes increasingly fragmented (Fig. 4). Under SSP2-4.5, the largest remnants persist in Lubero (474.56 km^2), Oïcha (298.07 km^2), Kabare (265.24 km^2), and Butembo (187.79 km^2), which together account for approximately 83% of the remaining high-suitability area, resulting in a strong spatial concentration within a few montane sectors.

A similar pattern emerges under SSP5-8.5, with Lubero (399.66 km^2), Oïcha (297.14 km^2), Butembo (172.46 km^2), and Walungu (165.45 km^2) again comprising about 83% of the total. In contrast, lowland territories become largely unsuitable: Shabunda reaches 99.78% unsuitable under both scenarios; Fizi reaches 98.89% under SSP2-4.5 and 84.50% under SSP5-8.5. Beni becomes majority unsuitable under SSP5-8.5 (55.31%). This pattern underscores an increasing spatial separation between lowland land-use zones and climatically suitable *Cinchona* habitats.

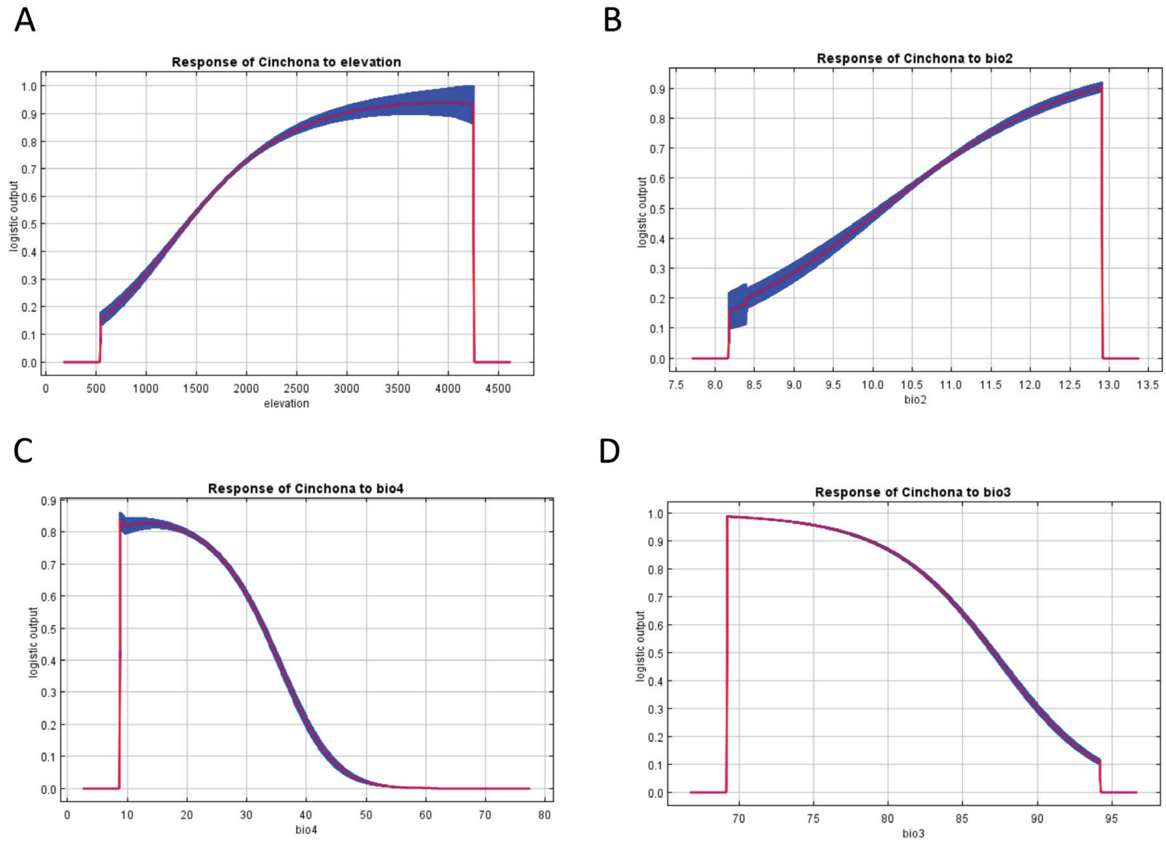

Figure 2. Response curves key predictors. **A**. Elevation: suitability rises quickly from ~540 m, reaches a near-plateau around ~2000–2500 m, and remains high up to > 4000 m. **B**. Mean diurnal range/bio2: suitability increases monotonically across the full range, highest near 12.909°C. **C**. Temperature seasonality/bio4 (8.774–71.280): suitability declines steadily as seasonality increases, high around ~9–20. **D**. Isothermality/bio3 (69.162–94.228%): suitability is highest at lower–moderate values (~69–80), lowest near ~94.

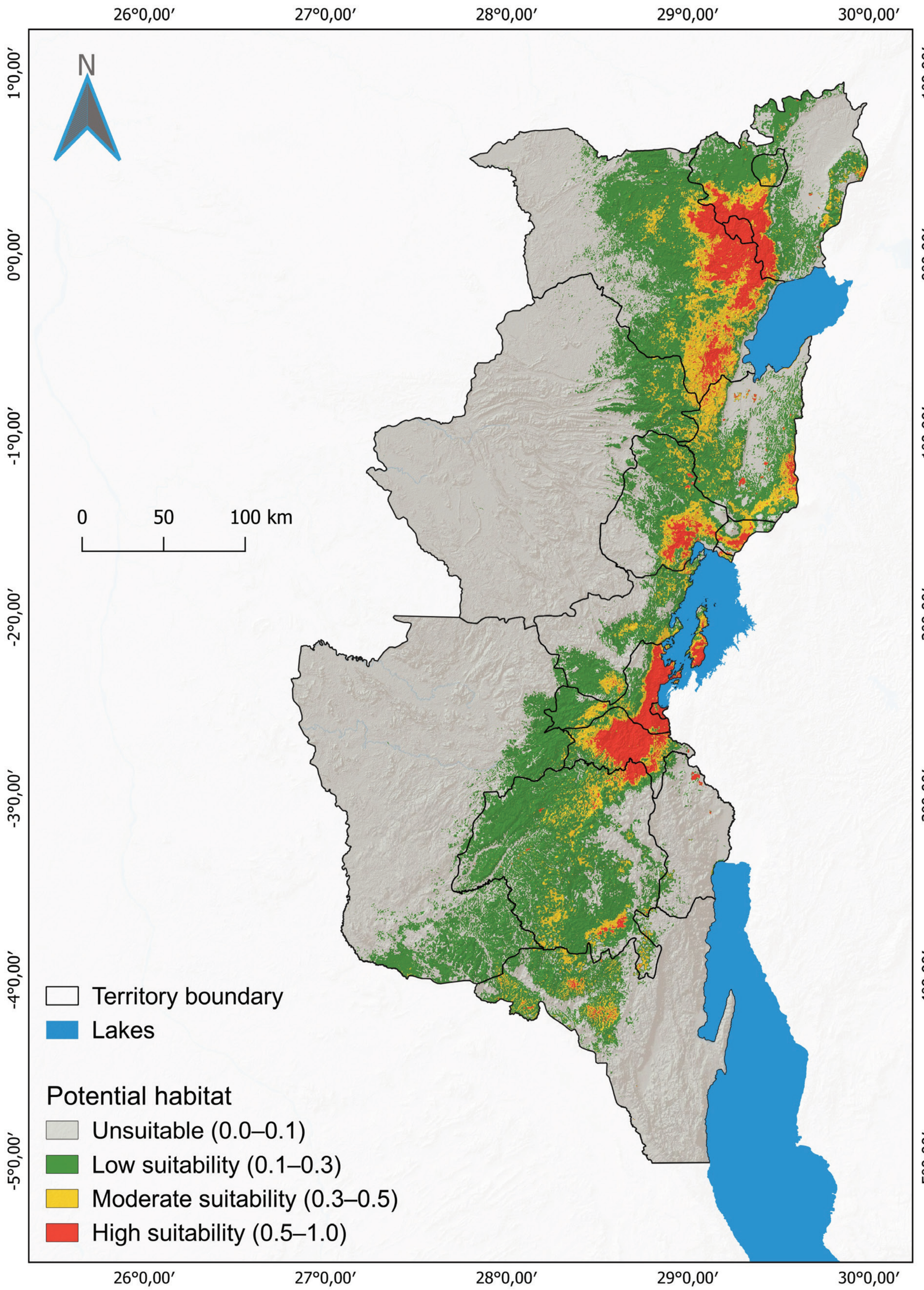

Figure 3. Current habitat suitability for *Cinchona* spp. in North and South Kivu derived from MaxEnt (logistic output reclassified into four classes: ≤ 0.100, 0.100–0.300, 0.300–0.500, > 0.500). Warmer colours indicate higher suitability. District boundaries are shown for orientation.

On the Fizi-Mwenga highlands (Minembwe plateau), only limited suitability persists by 2050: in Mwenga, high suitability is 1.61 km^2 under SSP2-4.5 and 1.37 km^2 under SSP5-8.5, with moderate suitability of 49.03 km^2 and 69.44 km^2, respectively. In Fizi, high suitability is 0.00 km^2 under SSP2-4.5 and 0.74 km^2 under SSP5-8.5, with moderate suitability of 0.06 km^2 and 74.04 km^2. Areas that remain suitable under both scenarios are also consistently selected across the 10 MaxEnt cross-validation replicates, pointing to a small set of montane locations that remain stable across model runs.

DISCUSSION

Ecological drivers

The composite climatic niche of *Cinchona* in eastern DRC is governed by a cool, thermally stable regime combined with a clear altitudinal constraint. Our MaxEnt model highlighted diurnal temperature range (bio2), isothermality (bio3), and temperature seasonality (bio4) as key climatic predictors, with elevation acting as a major non-climatic driver. Diurnal range (bio2) accounted for 37.6% of training contribution but only 3.7% permutation importance and was not supported by the jackknife test (Suppl. material 7). This discrepancy is consistent with collinearity among temperature variables, since percent contribution can be inflated when predictors are correlated (De Marco and Corrêa Nóbrega 2018; Feng et al. 2019). Permutation importance, by contrast, assesses how much predictive power is lost when a variable is permuted, and is generally less biased in the presence of correlated variables (Hooker et al. 2021). The high contribution but low permutation of bio2 therefore indicates that mean diurnal range strongly co-varies with other temperature variables; it helps fit the training data but carries little unique information. The jackknife results confirm this: removing bio2 caused only a small drop in gain, whereas the model built with elevation alone had the highest gain and the largest drop when excluded. We therefore interpret bio2 as part of a composite thermal regime (bio2/bio3/bio4) rather than a uniquely driving factor. Elevation (17.1% contribution; 20.2% permutation) and the two indices of temperature variation (bio3 and bio4) provided non-redundant signals. Bio3 (isothermality) had moderate contribution (8.2%) but the highest permutation importance (24.2%), indicating that the ratio of diurnal to annual temperature range is critical for predicting suitable sites; bio4 (seasonality) followed closely (16.5% contribution; 23.2% permutation). This coincides with the findings of García et al. (2022), who also demonstrated that elevation, isothermality (bio3), and temperature seasonality (bio4) were among the most influential predictors of *Cinchona* distribution in Peru.

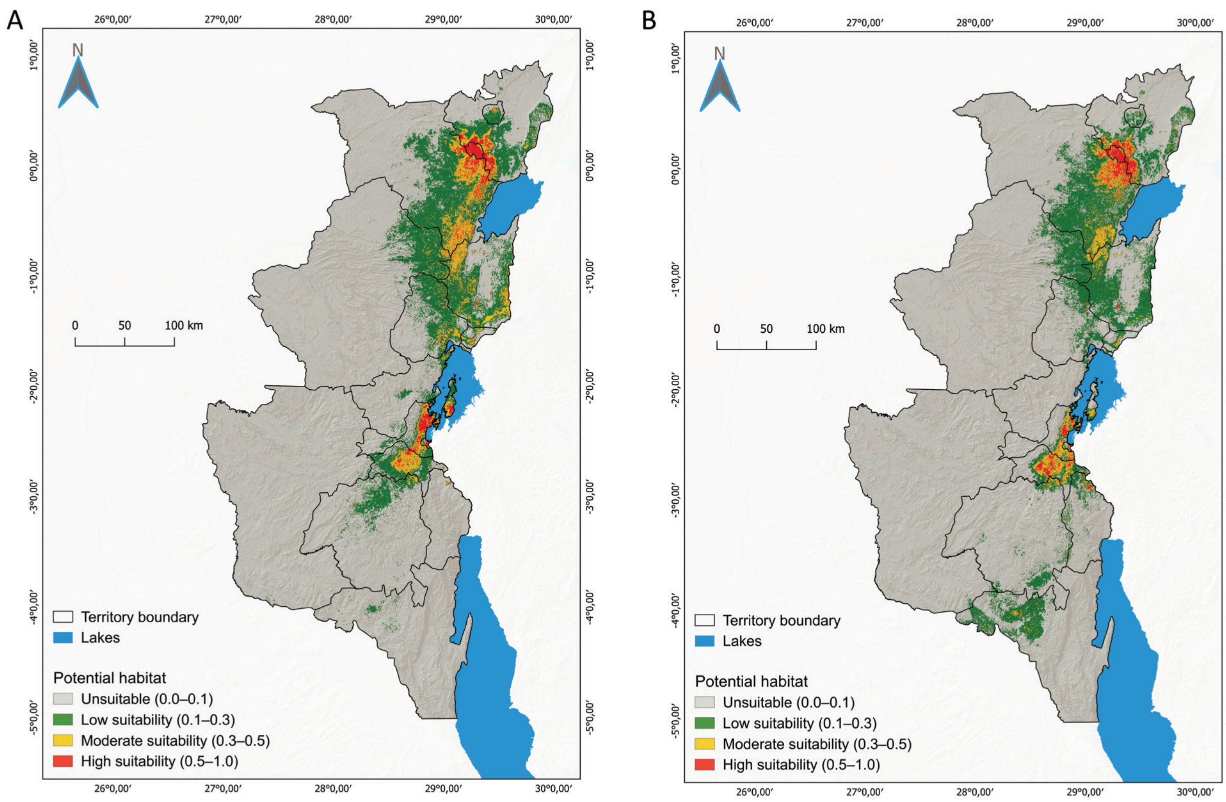

Figure 4. Projected habitat suitability for *Cinchona* spp. by 2050 under (**A**) SSP2-4.5 and (**B**) SSP5-8.5 scenarios (logistic output reclassified into four classes). High-suitability areas (red) retreat to isolated montane refugia, while unsuitable conditions expand into the lowlands.

Their study similarly emphasized the ecological relevance of thermal stability and altitudinal gradients in shaping the species' niche, reinforcing the robustness of our model across distinct biogeographic contexts. Comparable results were reported by Coronel-Castro et al. (2024) in north-eastern Peru, where bio3 and bio4, alongside edaphic factors such as cation exchange capacity (CEC), emerged as key contributors to the distribution of multiple *Cinchona* species.

Niche response patterns

Marginal response curves help translate these statistics into ecological interpretations. Elevation showed a rapid increase in suitability from ~540 m, with a plateau between 2,000 and 2,500 m above sea level. This plateau coincides with the crest zones of the Albertine Rift, where montane forests and subalpine grasslands provide cool, moist microclimates (Martin and Burgess 2023). Although bio2 contributed substantially to model fit, its low permutation importance and lack of jackknife support suggest that it does not act independently. Nevertheless, the marginal response shows monotonic increases within the observed window (8.173–12.909°C). The response to bio4 declined steeply from 8.77 to 71.28, indicating that high temperature seasonality reduces suitability. Similarly, suitability declined with increasing isothermality (bio3) beyond 69.16%, suggesting preference for climates where daily variability does not dominate the annual range. Suitability remains high across acidic soils (pH $\lesssim$ 5.5–6) and declines steadily towards neutral–slightly alkaline conditions (up to ~7.8), indicating a preference for moderately acidic substrates (Nair 2010). Suitability declines sharply with increasing coarse-fragment content. Suitability is highest at very low contents ($\lesssim$ 2–4%), drops to moderate levels around ~8–10%, and approaches zero above ~25%, consistent with a preference for fine-textured, stone-poor substrates. Together, these patterns depict an ecological niche defined by cool, seasonally stable montane climates at mid-to-high elevations, with moderate day–night thermal variation, relatively low isothermality, and fine-textured, moderately acidic, stone-poor soils.

Spatial reconfiguration under climate change

The present suitability map shows a continuous corridor of high to moderate suitability along the eastern escarpment, notably in the territories of Lubero, Walungu, Oïcha, Kabare, and around Butembo. Climate projections under SSP2-4.5 and SSP5-8.5 suggest profound habitat contraction and upslope fragmentation by 2050. This shift from moderate and low suitability to unsuitability reflects the combined effects of warming, increased temperature seasonality and edaphic stress, pushing the niche upslope and constricting its extent.

Spatially, the continuous corridor breaks into isolated patches on crest zones. High suitability persists in parts of Lubero, Oïcha, and Kabare, but these areas contract and shift upslope. Walungu exhibits a local persistence signal: under SSP5-8.5, a few crest-linked cells remain above the 0.5 threshold, consistent with topographic buffering and potential microrefugia at high elevations. In contrast, lowland territories such as Shabunda and Fizi become almost completely unsuitable, with Shabunda being ~99.8% unsuitable under both scenarios and the Fizi-Mwenga highlands retaining only residual suitable patches. These shifts mirror broader ecological predictions that montane species must track cooler conditions upslope, losing area as mountain surfaces narrow (Conniff 2018). Afrotropical montane birds provide a parallel: upslope shifts of lower elevational range limits combined with restricted dispersal lead to range contractions in fragmented forests (Neate-Clegg et al. 2021). Comparable patterns have been documented for indigenous montane flora of the Albertine Rift, where plant species distributions are strongly constrained by elevation and increasingly fragmented by land-use change, as shown by regional niche-based conservation planning analyses (Ayebare et al. 2018; Plumptre et al. 2021). The fragmentation observed in our projections implies that *Cinchona* may experience a similar "escalator to extinction" effect (Conniff 2018), if dispersal and regeneration cannot keep pace with climatic changes.

Implications for conservation and land-use planning

The spatial reconfiguration of suitable habitat has direct consequences for conservation and land-use planning in the eastern DRC. Our projections indicate that future climatic suitability for *Cinchona* will be increasingly restricted to crest-linked montane areas, reinforcing the importance of identifying and safeguarding climatic refugia. Such refugia are widely recognised as critical components of climate-adaptation strategies, as they provide relatively stable microclimatic conditions that can buffer species against regional warming (Hannah et al. 2014; Morelli et al. 2016).

By 2050, most high-suitability areas lie on ridge crests around Lubero, Oïcha, Kabare, and parts of Walungu. These small refugia should be prioritised for strict protection. These areas are also subject to strong land-use pressure, as montane zones in the Albertine Rift are increasingly targeted for agriculture and settlement, often overlapping with climatically resilient habitats. Prioritising crest-linked refugia for conservation therefore requires their explicit integration into provincial land-use plans and forest zoning frameworks. We recommend establishing a network of 10–50 ha micro-reserves around the remaining high-suitability patches, either as strictly protected nature reserves or as legally recognised community-managed conservation areas, depending on local land tenure and governance contexts, with formal legal recognition and community-based co-management, particularly in fragmented landscapes (Neate-Clegg et al. 2021). Management should also preserve montane forest canopy to maintain microclimate stability, as canopy cover lowers understorey temperatures and limits soil evaporation (Watts et al. 2022).

As the climate warms, suitable habitat shifts uphill. Without connections, high-elevation patches become isolated. We recommend elevational corridors that link low, mid, and high zones, especially between 1,400 and 2,600 m identified by our response curves. Maintaining such altitudinal connectivity is increasingly recognised as a core element of climate-wise conservation planning, as it facilitates dispersal, gene flow and adaptive range shifts in mountainous landscapes where available habitat narrows with elevation (Hilty et al. 2020). This reduces dispersal barriers and supports gene flow. Evidence from Afrotropical montane birds shows that fragmented forests block upslope shifts and cause range losses (Neate-Clegg et al. 2021). In the Albertine Rift, corridor-based conservation would also complement existing transboundary initiatives and regional biodiversity strategies.

Many suitable areas overlap with settled highlands where *Cinchona* is already cultivated. Agroforestry can buffer heat, stabilise soils, and diversify livelihoods. In such human-dominated landscapes, strict protection alone may be neither feasible nor socially acceptable, making climate-smart agroforestry a necessary complement to reserve-based conservation. Shade trees can lower air temperature by ~4°C and soil temperature by 6–10°C, while regulating humidity and improving soil moisture (Watts et al. 2022). We recommend integrating diverse canopy species such as *Ficus* spp. and native *Albizia* spp. with *Cinchona* plantations, as well as using mulching and organic amendments to improve soil structure. Avoid coarse-fragment and high-pH soils, and conserve moist valley bottoms where microclimates are more stable.

More broadly, our results demonstrate the relevance of species distribution models as decision-support tools for land-use policy and climate adaptation. Climate-informed suitability maps can guide environmental impact assessments, restoration planning, and the spatial targeting of national climate frameworks such as REDD+ and National Adaptation Plans. Embedding such spatially explicit ecological information into planning and governance processes would strengthen anticipatory decision-making and enhance the long-term effectiveness of conservation and land-use policies in eastern DRC (Guisan et al. 2013; Pavón-Jordán et al. 2015; Babanezhad and Naqinezhad 2025 and references therein).

Uncertainty, limitations, and future research

Several sources of uncertainty qualify our conclusions. First, the occurrence data may be biased towards accessible areas such as roads and villages, a well-known accessibility bias in species distribution modelling. This well-documented accessibility bias (Meyer et al. 2015) may lead to overrepresentation of human-modified habitats and under-sampling of remote regions. As a result, model predictions may not fully capture the species' ecological breadth. Future work could address this by applying bias correction techniques such as spatial filtering or background manipulation (Kramer-Schadt et al. 2013).

Second, 10-fold cross-validation used here assumes that presence records are independent and identically distributed. Random cross-validation can overestimate model performance because spatial autocorrelation violates this assumption, leading to optimistic statistics (Tziachris et al. 2023). Spatially blocking data into non-overlapping subsets is recommended to reduce this bias (Koldasbayeva and Zaytsev 2025). Future studies should evaluate alternative partitioning strategies (spatial blocking, environmental clustering) and report sensitivity of AUC and omission rates to these methods.

Third, collinearity among temperature variables complicates the interpretation of variable importance. Metrics such as percent contribution can be skewed by correlated predictors, whereas permutation importance more accurately reflects each variable's unique influence. In this study, we reduced redundancy by applying Variance Inflation Factor (VIF) and Pearson correlation analysis to retain only five relatively uncorrelated predictors (bio2, bio3, bio4, bio16, and bio18). Nevertheless, residual collinearity may persist, and its potential influence cannot be entirely excluded. Future research could explicitly compare the effectiveness of different dimensionality-reduction approaches, such as VIF/Pearson filtering versus Principal Component Analysis (PCA) (De Marco and Corrêa Nóbrega 2018), to assess which better minimizes multicollinearity while preserving ecological interpretability.

Finally, beyond technical limitations, it is crucial to consider the socio-ecological context shaping species distributions. Research should explore socio-economic drivers of land-use change and the potential for incentive schemes (e.g. payment for ecosystem services) to support conservation. By addressing these interconnected ecological, methodological, and socio-economic uncertainties, future studies will enhance the reliability and policy relevance of GeoAI and climate-informed species distribution models in the eastern DRC.

CONCLUSION

By integrating species distribution modelling with mid-century climate projections, we provide a decision-ready picture of *Cinchona*'s current and future niche in eastern DRC. High discrimination and coherent response curves indicate a cool, stable montane niche, structured by elevation and thermal variability, with edaphic constraints penalising stony, higher-pH soils. By 2050, suitable habitat contracts markedly and fragments into ridge-linked patches concentrated in Lubero, Oïcha, Kabare, Butembo, and parts of Walungu, while most lowlands become unsuitable. These dynamics call for pragmatic, place-based action: micro-reserves of 10–50 ha to safeguard refugia, elevational corridors to support upslope migration and connectivity, and climate-smart agroforestry in settled highlands to buffer heat, stabilise soils, and diversify incomes. Beyond their ecological value, these measures have direct socio-economic implications for local communities that depend on *Cinchona* cultivation for medicinal use and supplementary income. Maintaining climatic suitability through agroforestry and landscape connectivity can help secure production systems, reduce climate-related yield risks, and support household resilience in montane farming communities.

Empowering local farmers through training in propagation and integrated soil and pest management will be essential to sustain *Cinchona* cultivation and landscape restoration. Such capacity-building initiatives can enhance local stewardship, strengthen knowledge transfer, and promote equitable participation in conservation efforts, thereby aligning biodiversity objectives with rural development priorities. Recognising uncertainties related to accessibility bias, spatial autocorrelation, and residual collinearity, future work should implement spatial corrections and alternative partitions, and test dimensional-reduction approaches. Models that incorporate socio-economic drivers and species-specific responses will enable conservation strategies better tailored to *Cinchona* spp., while providing a transferable framework that could inform studies on other montane plant species in agroforestry contexts. Even so, our results provide a robust basis for aligning conservation priorities with land-use planning in the Albertine Rift and for guiding the sustainable management of medicinal plants under climate change.

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SUPPLEMENTARY MATERIALS

Supplementary material 1

Occurrence records of *Cinchona* spp. in eastern DRC used for MaxEnt modelling. Records: 125 georeferenced occurrences from field surveys and curated sources. Geography: North & South Kivu, eastern DRC (Albertine Rift). CRS: WGS84, EPSG:4326; coordinates in decimal degrees (lat, lon). Cleaning: duplicates removed, obvious spatial errors corrected.

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Supplementary material 2

Overview of environmental variables and data sources used in the MaxEnt modelling.

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Supplementary material 3

Cross-validation summary.

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Supplementary material 4

Cross-validated receiver operating characteristic (ROC) for *Cinchona* spp. across 10-fold cross-validation. The solid curve shows the mean ROC; the shaded band denotes ± 1 standard deviation across folds. The diagonal line represents random discrimination.

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Supplementary material 5

Omission-predicted area vs cumulative threshold. The Predicted area curve shows the fraction of the landscape retained as the threshold increases. The mean omission on test data curve reports the proportion of independent test presences falling below each threshold, with shaded bands denoting ± 1 SD across folds.
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Supplementary material 6

Variable importance (MaxEnt; averages over 10 replicates).
https://doi.org/10.5091/plecevo.176900.suppl6

Supplementary material 7

Jackknife of variable importance (AUC on test data).
https://doi.org/10.5091/plecevo.176900.suppl7

Supplementary material 8

Area and within-unit percentage in each suitability class under current climate by administrative unit (territory/city).
https://doi.org/10.5091/plecevo.176900.suppl8

Supplementary material 9

Area (km^2) and percentage of each suitability class under future scenarios (SSP2 4.5) by administrative unit (territory/city).
https://doi.org/10.5091/plecevo.176900.suppl9

Supplementary material 10

Area (km^2) and percentage of each suitability class under future scenarios (SSP5 8.5) by administrative unit (territory/city).
https://doi.org/10.5091/plecevo.176900.suppl10