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# Exploring the cooling effect of shading for climate change adaptation in coffee areas

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ABSTRACT

Rising air temperatures are the main reason for the expected reduction in land suitability for coffee cultivation under climate change in Central America. One of the reasons farmers use shade trees is to create a cooler microclimate in coffee plantations located in warming areas; therefore, adjusting the shade levels could alleviate future high temperatures. Even though data on expected climatic changes are available, no studies have addressed the cooling potential of shading in coffee production systems. In this study, we use regional climate information (RCP 4.5) and a simple shade model to explore the potential of shading as an adaptation practice in the coffee areas in Central America. A model was developed to estimate the required shade levels for *Coffea arabica* L. based on mean air temperature. Modeled and observed shade data were compared. Results indicate that compared to 2000, an overall increment of 23 ± 18% of shading would be required to alleviate the warming conditions by 2050. The shading will be more beneficial to coffee areas at medium and high altitudes than to areas at low ones. Also, the number of coffee areas that require dense shade levels (shading > 60%) may double by 2050. This would lead to a boost in tree biomass (carbon content) but also increase the competition for the coffee plants and consequently affect coffee yields. Trade-offs between adaptation, mitigation, and productivity objectives are expected in the coffee areas in the future.

## 1. Introduction

Coffee is part of many people's daily routines worldwide and provides livelihoods for farmers and communities in producer countries (Eakin et al., 2012). Coffee-producing countries on the American continent contribute more than half of worldwide production, and most of these countries have a recognized coffee quality profile in the international market (Wilson et al., 2012; Sepúlveda et al., 2016). Over the last decades, however, coffee farmers in Central America have experienced recurrent crises due to low market prices, rising production costs, and pests and disease problems such as outbreaks of coffee rust (Avelino et al., 2015; Bacon, 2005; PROMECAFE, 2018). In addition, climate change has become a major risk that is expected to lead to a decrease in the area suitable for coffee production and, consequently, negatively affect the sustainability of coffee systems in most producer countries (Byrareddy et al., 2021; Gay et al., 2006; Lara-Estrada et al., 2021; 2017; Pham et al., 2019; Schroth et al., 2014).

Until 2100, simulations of the representative concentration pathway (RCP) scenario 4.5 project rising temperatures between 2.5

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and 3.5 °C in most interior areas of Central America, and less precipitation in low-altitude coastal regions (Lyra et al., 2017). Most of the temperature changes are expected to occur in the middle of the century (Knutti and Sedláček, 2012). Since most coffee plantations are located inland at medium and high altitudes, rising temperatures are considered the main driver of decreasing climatic suitability for coffee production (Gay et al., 2006; Lara-Estrada et al., 2021). Identifying, evaluating, and promoting farming practices that alleviate the impacts of higher temperatures should be prioritized (Smith et al., 2014). Agroforestry is one of these practices (van Noordwijk et al., 2014; IPCC, 2014). The shade of trees modifies air temperature, wind speed, and relative humidity (Jose et al., 2004; Siles et al., 2010). Agroforestry can also help to improve physical and chemical soil properties, reduce soil losses, and diversify incomes. The trees in the coffee agroforestry system thus offer multiple benefits to farmers (Nair, 1993; Ombati et al., 2022; Somarriba 1990; Staver et al., 2013). In Central America, agroforestry systems are mainly used in coffee plantations at lower and medium altitudes to mitigate high temperatures. At higher altitudes, shading requirements are lower, and full-sun coffee systems are used. There are other benefits of shade trees, such as improvement of soil conditions and coffee quality (Beer et al., 1998; Muschler, 2001), but there are also potential drawbacks, such as an increased occurrence of fungal diseases due to (over)shading if weather and farming management are inadequate (Durand-Bessart et al., 2020; Villarreyna et al., 2020).

Studies have reported reductions in air temperature due to shading in coffee systems (Barradas and Fanjul 1986; Siles et al., 2010; Souza et al., 2012). However, few studies have attempted to look at the cooling effect of shading (Lin and Lin 2010; van Oijen et al., 2010). One study examined the benefits of shading in 2050 using a fixed shade value of 50% for coffee areas at different altitudes in Brazil (Gomes et al., 2020). However, the shade levels for coffee plantations need to be adjusted depending on altitude, responding to changes in the local warming conditions (Muschler 2001). In this study, we explore the potential of the cooling effect of shading as an adaptation strategy to temperature increases. We estimated the shade levels according to the local warming conditions in coffee areas (*Coffea arabica* L.) in Central America for the years 2000 and 2050 (RCP 4.5).

## 2. Material and methods

### *2.1. Study area*

The study area corresponds to the coffee areas in Nicaragua, which are located in the Pacific and Northcentral zones in the country (Fig. 1 (CATIE and MAGFOR, 2012)). Pacific coffee areas are located at lower altitudes with low to flat slopes and drier and warmer conditions than the areas located in the mountainous Northcentral zone (FAO, UNESCO, 1975; Hidalgo et al., 2017; Taylor and Alfaro,

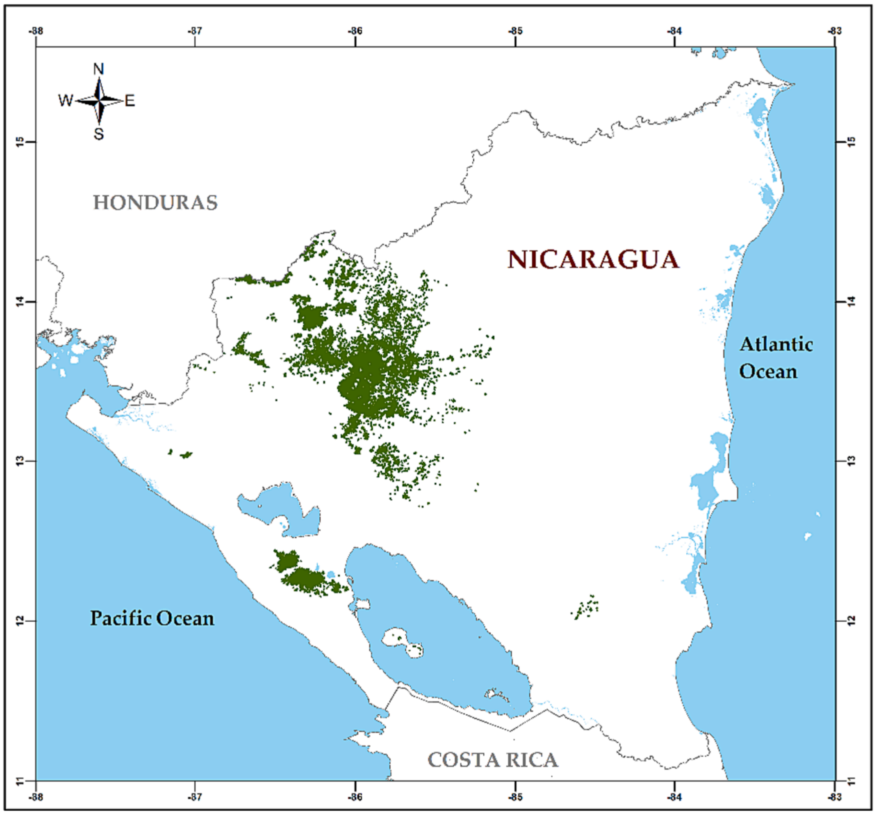


**Fig. 1.** Coffee areas in Nicaragua (CATIE and MAGFOR, 2012).

2005). Overall, the study area is representative of other coffee areas in Central America (Bornemisza et al., 1999; Lara-Estrada et al., 2017).

### 2.2. Shade functions

The optimal mean air temperature for coffee is around 20 °C, values above or below this temperature first become suboptimal and then unsuitable for coffee (DaMatta and Ramalho, 2006; Descroix and Snoeck, 2004; Montoya-Restrepo et al., 2009; Siles et al., 2010). Compared to unshaded conditions, shade trees in coffee agroforestry systems can reduce the air temperature by 1 to 5 °C, depending on the shading level (Barradas and Fanjul, 1986; Fanjul et al., 1985; Garedew et al., 2017; Mariño et al., 2016; Morais et al., 2006; Righi et al., 2008; Souza et al., 2012). The model Agroecological Land Suitability Evaluation for Coffea Arabica (ALECA) includes a suitability function for mean air temperature ($S$), which is an ecological response curve that assigns a quantitative suitability score to a given air temperature value under unshaded conditions (Table 1) (Lara-Estrada et al., 2017). Based on this function and the parameters reported in the literature for the cooling potential of shading in coffee systems, a new set of empirical functions were developed to estimate: 1) the shade level required ($Sh_r$) for coffee based on existing annual mean air temperature; 2) the corresponding air temperature reduction due to shading ($T_r$) compared to unshaded conditions; and 3) the air temperature suitability under shading ($S'$) (Table 1). The shade required ($Sh_r$) indicates the shade level that is needed to attain or come close to the optimal air temperature for coffee, and $S'$ scores how suitable the shade-adapted air temperature is for coffee cultivation.

### 2.3. Bayesian network model

Based on the functions in Table 1, a shade model was created using Bayesian Networks (BNs). BNs are multivariate models composed of 1) a graphical structure that depicts the dependencies between variables (parents → child) and defines how the information propagates across the variables of the model and 2) conditional probabilistic tables (CPTs) that quantify the cause-effect relationship between variables (parameters). Each variable has its own CPT. Expert elicitation, machine learning algorithms, equations, and parameters from the literature can be used to create the graphical structure and CPTs. BNs can deal with uncertainty and missing information by using certain or uncertain data in the inference (e.g., exact or interval values or Gaussian distributions). Furthermore, the BNs' graphical interface and the possibility of conducting *what-if* queries make their understanding and usage easy for practitioners and decision-makers (Aguilera et al., 2011; Harris et al., 2022; Uusitalo, 2007).

**Model graphical structure.** A node was created for each variable and linked according to the input–output relationship described in the functions in Table 1; the links describe causal relationships between nodes (Fig. 2A) (Kunimitsu et al., 2023). Next, variables were discretized in state values (ranges) as follows: first, maximum and minimum values for each variable were estimated from the corresponding functions (Table 1). Next, an equal state size was determined for each variable considering agronomical and practical factors and literature (Marcot et al., 2006). For example, shade values <10% are similar to the error of measurement (Bellow and Nair, 2003) and difficult to track or implement during shade pruning or shade level estimation in the field (first author personal observation); therefore, a range of 10% was used as the breakpoint for shade required. The discretization used for $S$ in ALECA was used in the model for $S$ and $S'$ (0–10, 20–30,…,80–90, 90–100%) (Lara-Estrada et al., 2017).

There could be situations where potential users of the model, such as farmers, agronomists, and other practitioners, do not have easy access to mean annual air temperature values for their locations. For these cases, we added the variables Altitude (m.a.s.l.) and Department (national administrative division) as proxy variables to infer the missing air temperature (Fig. 2). Altitude has a well-

**Table 1**
Functions to estimate the air temperature suitability with and without shading and their impact on air temperature suitability.

| Variables | Equations |
|---|---|
| Shade required ($Sh_r$) [%] | $Sh_r = \begin{cases} 0; \ if \ T_i \leq 20\,°\text{C}; \\ [(T_i - 20) \div 0.0444] + 0.023, \quad if \ T_i \leq 30\,°\text{C}; \\ 90; \ otherwise \end{cases}$ Where $Sh_r$ is the shade level required (%) and $T_i$ is the annual mean air temperature (°C). $T_i = 20$ °C is assumed as 100% suitable; below this value, no shading is required. If $T_i > 24$, the shade level is fixed to 90 % |
| Temperature reduction ($T_r$) [°C] | $T_r = \begin{cases} 0; \ if \ Sh_r < 10\%; \\ (0.0444 * Sh_r) - 0.023; \end{cases}$ Where $T_r$ is the mean air temperature reduction (°C) due to shading. Maximum $T_r = 4$ °C |
| Suitability function ($S'$) for $T_i$ under the shade of trees [%] | $S' = \begin{cases} S; \ if \ T_i \leq 20\,°\text{C}; \\ T_i \sim N[(\mu - T_r), \sigma^2] \div T_\mu \sim (\mu, \sigma^2) \cdot 100; \quad if \ T_i \leq 30\,°\text{C}; \\ 0; \ otherwise \end{cases}$ Where $S'$ is the suitability score (0-100 %, where 100% is excellent suitability) for a given annual mean temperature $T_i$ (°C) considering the $T_r$ under the $Sh_r$; where $T_i$ that has a normal distribution with mean $\mu = 20$ and variance $\sigma^2 = 3.89$; $T_\mu = \mu$. |
| Suitability function ($S$) for $T_i$ under unshaded conditions [%](Lara-Estrada et al. 2017) | $S = T_i \sim N(\mu, \sigma^2) \div T_\mu \sim (\mu, \sigma^2) \cdot 100$ Where $S$ is the suitability score (0-100 %, where 100% is excellent suitability) for a given annual mean temperature $T_i$ (°C). that has a normal distribution with mean $\mu = 20$ and variance $\sigma^2 = 3.89$; $T_\mu = \mu$. |

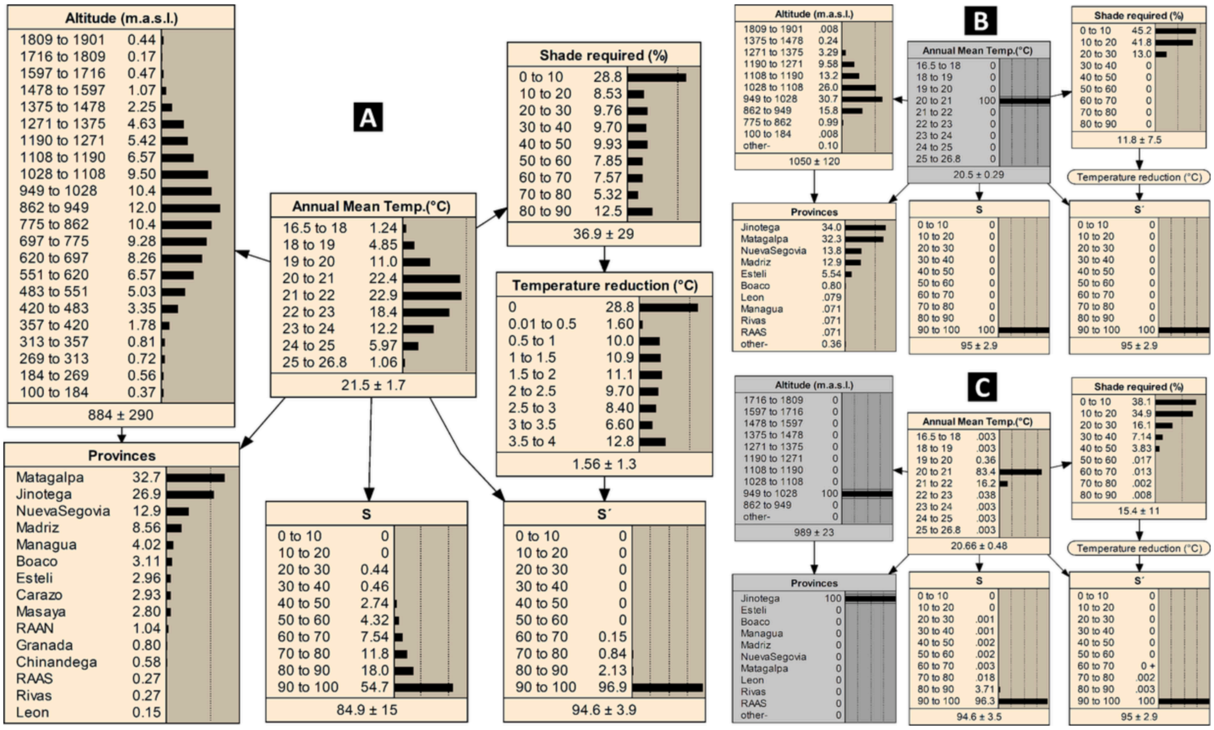


**Fig. 2.** Shade model. *S* and *S'* are the air temperature suitabilities under unshaded and shaded conditions (%), respectively. A) Model compiled using current data (2000) for coffee areas in Nicaragua (CATIE and MAGFOR, 2012; Hijmans et al., 2005). B) Inference when air temperature ($T_i$) is known. C) Inference when the air temperature is missing, and Altitude and Department information are used to infer the air temperature.

known negative correlation with air temperature (Barry, 2008) and is commonly used as a proxy for climate suitability for coffee cultivation (Avelino et al., 2005; ICAFE-CICAFE, 2011; Muschler, 2001; Pineda, 2001). Department captures the possible effects of location (latitude, longitude) and landform on air temperature. For example, the Department of Masaya is located in the flat Southeast

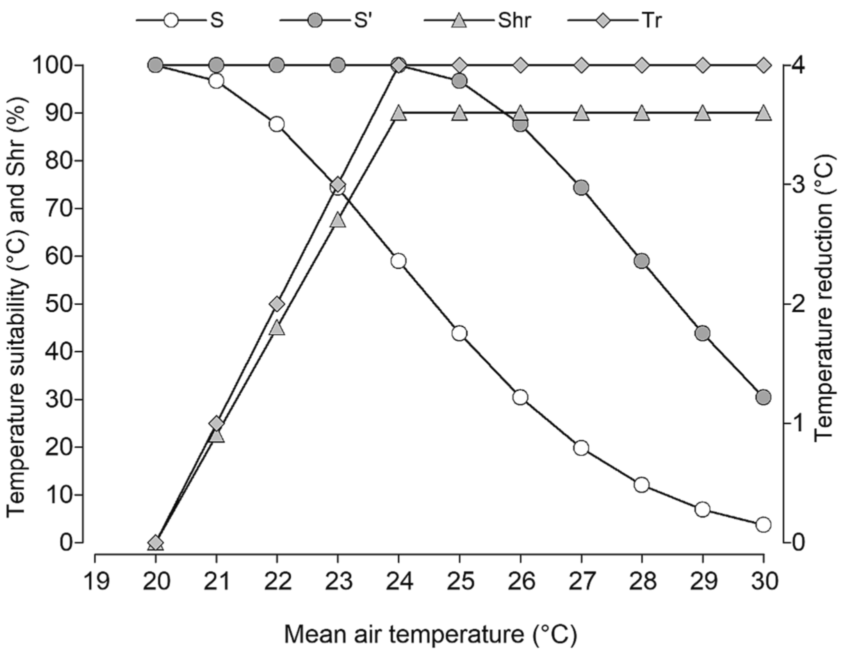


**Fig. 3.** Functions shade level required ($Sh_r$), air temperature reduction ($T_r$), and air temperature suitability under unshaded and shaded conditions (*S* and *S'*, respectively).

region of Nicaragua and is influenced by the Pacific Ocean, whereas Jinotega, which is located in the Northwest mountain central region, is influenced by the Atlantic (Barry, 2008; Linacre and Geerts, 2002; Taylor and Alfaro, 2005). After selecting air temperature as the target variable, the structural machine learning algorithm Tree Augmented Naïve Bayes was implemented to create the links between the variables air temperature, altitude, and department (Friedman et al., 1997; Hijmans et al., 2005; Norsys, 2022; Sucar, 2015). Similarly, Lara-Estrada et al. (2018) inferred relative humidity using other climate variables as proxies. The altitude and air temperature data used in the structural machine learning were extracted from the Worldclim dataset (1 km resolution) for the study area (CATIE and MAGFOR, 2012).

**Conditional probability tables.** After the graphical structure was defined, the CPTs for all the variables in the model were learned from data and equations. For the variables altitude, department, and air temperature, the data extracted from the datasets Worldclim and coffee map (CATIE and MAGFOR, 2012; Hijmans et al., 2005) were used to populate the CPTs of the variables using the Counting-Learning Algorithm (Norsys, 2022). For the rest of the CPTs of the variables, the functions from Table 1 were implemented in each variable (node); then, using the feature "equation to table" available in the software Netica (Norsys, 2022), the CPTs were populated for each of those variables. Once all the CPTs were populated, the model was compiled and ready to use.

**Model assumptions.** No shading is needed at optimal or lower temperatures. Under these conditions, *S* and *S'* are identical (Fig. 3). If the air temperature rises above the optimal value, the shade level will increase to alleviate the warming conditions until the maximum temperature reduction ($T_r$) due to shading is reached. The maximum $T_r$ is reached at an environmental air temperature of 24 °C, after which *S'* starts to decrease (Fig. 3). For the modeling purpose of this study, we assumed that air temperature is the only variable that determines the shade level, however, in reality, more factors influence a farmer's decision on the shade levels in their plantation. Since *Coffea arabica L.* covers over 99.6% of the coffee area in Nicaragua (CATIE and MAGFOR, 2012), all suitability functions are based on the optimal mean air temperature for this species, and we did not include coffee varieties in our analysis.

An additional benefit of including altitude and departments to infer air temperature is that it enables users to explore the existing coffee temperature suitabilities of each department. For example, most coffee areas with high air temperature suitability are found in the departments of Matagalpa, Jinotega, Nueva Segovia, and Madriz. Coffee areas in Jinotega, e.g., are located at altitudes of 962 ± 260 m.a.s.l., with a mean annual temperature of 20.80 ± 1.50 °C, and require shade levels of 25.90 ± 25%. Coffee areas with lower temperature suitabilities due to higher air temperatures (≥24 °C) are located in the departments of Masaya, Carazo, Managua, and Granada. In Masaya, e.g., coffee areas are located at altitudes of 538 ± 160 m.a.s.l. with higher air temperatures (24 ± 1.10 °C) and require mean shade levels of 79.20 ± 14%.

**Model evaluation.** We used the metric Spheric Payoff to evaluate the performance of altitude and department in predicting air temperature. The metric considers the predicted probabilities for the correct and the predicted state and the overall mean value for the cases tested. The metric values range from 0 to 1, where 1 is the best performance (Marcot, 2012). Our model scored 0.8, which indicates a good performance. A sensitivity analysis using the metric Variance Reduction (VR) was used to evaluate the influence of air temperature, altitude, and department on shade required (target variable). A sensitivity analysis shows how the variations in the posterior probability distribution of a given target variable are affected by changes in the states of the other variables, resulting in a ranking of variables (VR scores). VR values range from 0 to 100%; a value of 0% indicates that a change in the state of one variable does not have any impact on the target variable, meaning the variables are independent; scoring close to 100% indicates a strong influence on the target variable (Chen and Pollino, 2012; Marcot, 2012; Norsys, 2022). The obtained VR values indicate that the most influential variable on shade required is air temperature (VR = 94.20%), then altitude (80.70%), and lastly, department (30.10%). In a second sensitivity analysis, we evaluated the influence of altitude and department on air temperature (as the target variable), and similar values were obtained for altitude (82.20%) and department (29%). In BNs, knowing the states of all the parent variables enhances the prediction of their children; entering information on both altitude and department instead of only one will thus improve the inference of air temperature.

The variable shade required was evaluated by comparing estimated and observed shade values using the metric spherical payoff. Observed shade values were taken from a survey conducted on coffee plantations in Northcentral coffee areas in Nicaragua (n = 66). The shade was measured using a spherical densiometer. The observed shade values ranged from 0 − 91% at altitudes of 630 to 1350 m. a.s.l. The air temperature values for each of the surveyed coffee plantations were extracted from the Worldclim dataset and used in the model to infer the shade values for each plantation.

**Climate scenarios and modeling.** The high-resolution interpolated air temperature from the WorlClim dataset was used for 2000 (Hijmans et al., 2005). The data on projected air temperature in the year 2050 was taken from simulations with the model MPI-ESM (ECHAM5) under scenario RCP 4.5 (Jungclaus et al., 2006; Ramirez-Villegas and Jarvis, 2010). Both datasets have a 1 km × 1 km resolution. The MPI-ESM model was selected because it has a better performance for the Central American Region than the average of 20 other climate models (Conde et al., 2011; Fuentes-Franco et al., 2015; Maloney et al., 2013; Schaller et al., 2011). The RCP 4.5 was selected because it represents an intermediate warming scenario and because a previous study on shading conducted for Brazil used the same RCP scenario (Gomes et al., 2020), thus enabling comparability and building a knowledge base for the region. The air temperature data was narrowed down to the study areas (CATIE and MAGFOR, 2012) and used to estimate shade required ($Sh_r$), air temperature suitability under unshaded conditions (*S*), and air temperature suitability under shaded conditions (*S'*). The inferred results for each variable correspond to the expected value, which is the weighted mean value of the variable's states per their probability of occurrence (Norsys, 2022).

## 3. Results and discussion

### 3.1. Observed vs. Estimated shade values

We estimated the shade required for commercial coffee plantations located at different altitudes and departments in Nicaragua to achieve the highest possible air temperature suitability score. Observed and estimated shade levels show the same general tendency of increasing at higher temperatures and reducing at lower ones (Fig. 4). The comparison displays a close agreement between observed and estimated shade levels at the lower and higher end of the temperature range with an SP of 0.57 for $Ti < 20$ °C, and 0.50 for $Ti \geq 22$ °C. At the middle-temperature values ($Ti = 20–21$ °C), observed shade values were higher than the estimated required ones (SP = 0.06).

The observed agreement between the estimated and observed shade levels under warmer and colder conditions was expected. Full-sun coffee systems are mostly recommended at colder high altitudes, whereas higher shade levels are used at low altitudes to decrease temperatures to more suitable levels, extend the lifetime of the coffee plants, and improve coffee quality (Bertrand et al., 2012; Muschler, 2001). At mid-level altitudes with temperatures from 20 to 21 °C (optimal for coffee plants), farmers have more freedom in the shade usage. We believe that the differences in shading between the estimated and observed values under these conditions are due to agronomical, socio-economical, and financial factors that influence farmers' decision-making (Bacon, 2005). For example, farmers may increase the shading to control fungal diseases (e.g., *Cercospora coffeicola*), reduce the abundance of weeds (Soto-Pinto et al., 2002; Staver et al., 2001), or increase the density of some tree species (e.g., musaceas and timber trees) for income diversification (Somarriba 1990; Staver et al., 2013). If coffee prices are low, farmers increase the shading to reduce the fertilizer requirements of the coffee plants and reduce maintenance costs (Bacon, 2005). This high shade/low input strategy has been reported for coffee plantations in Central America (Méndez et al., 2009; Meylan et al., 2013; Villarreyna et al., 2020) and is the most likely reason for the differences observed here, as the shade survey was conducted in 2005 when the coffee sector was at the end of a price-crisis (Wilson, 2010).

### 3.2. Required shade levels and temperature suitability under climate change

We estimated the shade required and the air temperature suitability under unshaded and shaded conditions for coffee areas in Nicaragua for the years 2000 and 2050 (Fig. 5). At the country level, the temperature suitability under unshaded conditions will decrease from 82% in 2000 to 66% in 2050. Consequently, the required shade levels will need to increase from 44% in 2000 to 68% in 2050. Under shade conditions, the temperature suitability will improve by 17% (2000) and 31% (2050) in comparison to the temperature suitability under unshaded conditions (Fig. 6). This downgrade in the air temperature suitability will negatively affect the quantity and quality of the coffee produced in the country. In a climate change impact study, Gay et al. (2006) found a negative correlation between high summer air temperatures and coffee yields in coffee plantations in Mexico, setting the coffee production equal to zero at temperatures greater or equal to 28.29 °C. Organoleptic and physical coffee quality are also negatively correlated to temperatures (Bertrand et al., 2012; Kath et al., 2021; Pham et al., 2020). Bertrand et al., found that coffee plantations cultivated under unshaded conditions at higher temperatures negatively affect the development of the coffee beans and, therefore, the final organoleptic quality. In this sense, another benefit of shading coffee plants under higher temperatures – and even temperatures closer to the optimal temperature – is that the physical and organoleptic coffee quality is improved compared to unshaded plantations under the

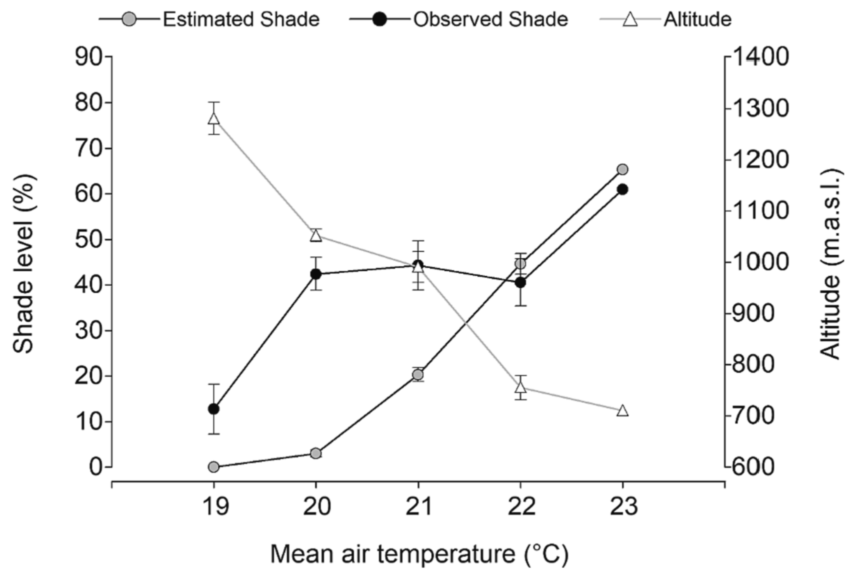


**Fig. 4.** Comparison of observed and estimated shade levels in coffee plantations. Error bars indicate standard error.

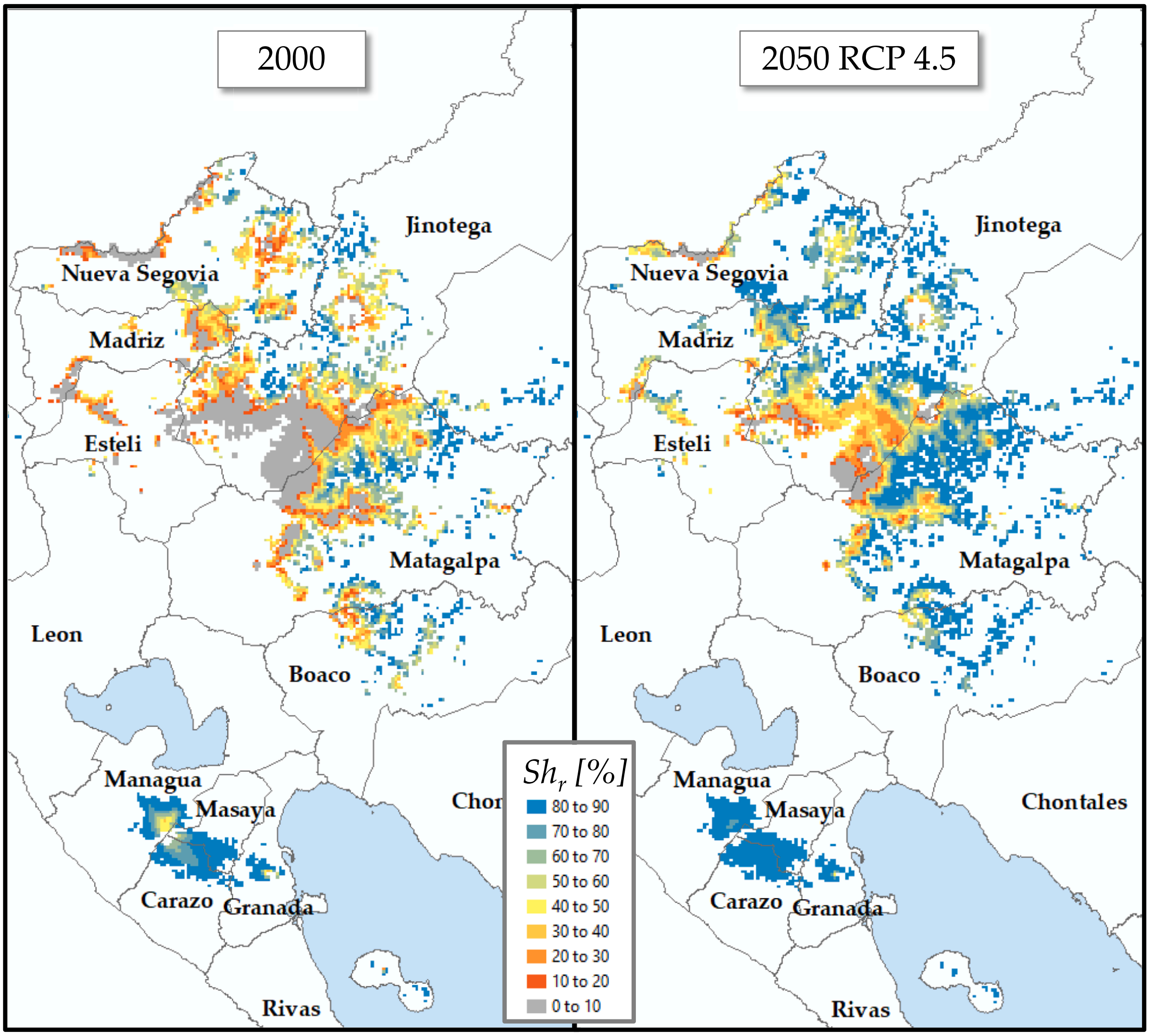


**Fig. 5.** Required shade levels ($Sh_r$) for coffee areas in Nicaragua for 2000 and 2050 (RCP 4.5).

same conditions (Muschler, 2001; Vaast et al., 2005).

A matrix of change is provided in Table 2 to track the changes in the shade required between the two periods. The shade values for 2000 describe a quasi-uniform distribution with peaks at the lowest and highest shade levels. For 2050, a dominant peak occurs only at the highest shade level. Areas requiring high shading ($Sh_r \geq 60$ %) increased from 36% in 2000 to 67% of the total coffee areas by 2050. Coffee areas requiring no or low shading ($Sh_r \leq 10$%) decreased from 22% to 5% (Table 2). If we observe the changes for coffee plantations that needed shade ≤ 10% in 2000, from the 100% of those plantations, only 21.11 % still need shade ≤ 10% by 2050. This value corresponds to the number of plantations that in 2000 had lower than the optimal air temperature and did not require any or only low levels of shading (Table 2 and Fig. 5). On these plantations, the rising in air temperature under climate change is still not enough to require higher shade levels. Most of the other coffee areas will have to adjust their shade levels by 2050 (Fig. 5).

At the local level, increasing the shading under climate change will be more effective for coffee plantations at altitudes ≥ 700 m.a.s.l. than for plantations at low altitudes of < 700 m.a.s.l. At low altitudes, coffee areas require high shade levels to mitigate the warmer temperatures even in 2000, leaving little margin to increase the shade level (Fig. 7A). This seems to be the main reason that the temperature suitability under shaded conditions *S'* is lower in 2050 than in 2000 (Fig. 7C). Coffee areas at medium altitudes will need to increase their shade levels, and the areas at higher altitudes (>1100 m.a.s.l.) that did not require shading in 2000 will do in 2050 (Fig. 7A). It can be observed that at these altitudes, the temperature suitability is lower in 2000 than 2050 (Fig. 7B and C). The reason is that in 2000, average temperatures were lower than 20 °C (suboptimal because of the coldest conditions), whereas, in 2050, temperatures come closer to the optimal coffee growing temperature of 20 °C, so the air temperature suitability increases.

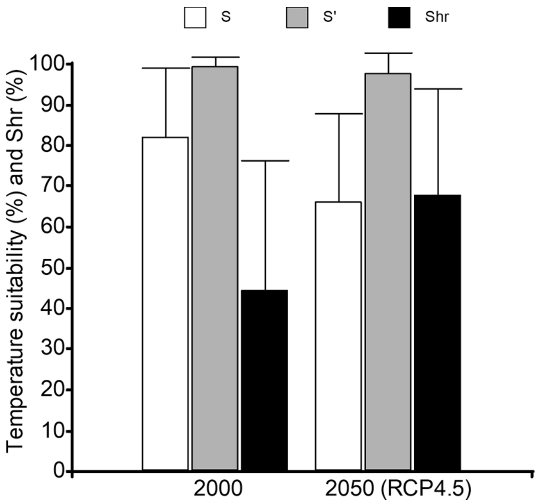


**Fig. 6.** Mean air temperature suitability under unshaded ($S$) and shaded conditions ($S'$) and the required shade levels ($Sh_r$) for 2000 and 2050 (RCP 4.5) for coffee areas in Nicaragua.

**Table 2**
Matrix of changes between different required shade levels ($Sh_r$) from 2000 to 2050 (RCP 4.5). The bold values indicate the remaining amount of area under the same shade level class by 2050. The other values show which proportion of coffee areas moved from the shade class observed in 2000 to the new shade class. In the first line, e.g., 28.24% of areas with a shade level of 0–10% in 2000 will require a shade level of 30–40% in 2050. The total coffee area shares (%) for each shade level in 2000 and 2050 are given in the last column and last row, respectively.

| | **$Sh_r$ (%)** | **2050 (RCP 4.5)** | | | | | | | | | **Total area (2000)** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 0 to 10 | 10 to 20 | 20 to 30 | 30 to 40 | 40 to 50 | 50 to 60 | 60 to 70 | 70 to 80 | 80 to 90 | |
| | *Changes in this direction →* | | | | | | | | | | |
| | 0 to 10 | **21.11** | 7.13 | 19.17 | 28.24 | 20.42 | 3.46 | 0.48 | | | 22.14 |
| | 10 to 20 | | **0.00** | 0.31 | 7.10 | 51.23 | 32.10 | 8.64 | 0.62 | | 4.96 |
| | 20 to 30 | | | **0.00** | 1.39 | 11.98 | 42.53 | 37.50 | 5.03 | 1.56 | 8.83 |
| | 30 to 40 | | | | **0.00** | 1.64 | 8.74 | 53.01 | 32.42 | 4.19 | 8.41 |
| **2000** | 40 to 50 | | | | | **0.14** | 1.70 | 16.17 | 48.23 | 33.76 | 10.80 |
| | 50 to 60 | | | | | | **0.00** | 1.33 | 14.58 | 84.09 | 8.09 |
| | 60 to 70 | | | | | | | **0.32** | 1.42 | 98.26 | 9.70 |
| | 70 to 80 | | | | | | | | **0.40** | 99.60 | 7.65 |
| | 80 to 90 | | | | | | | | | **100.00** | 19.41 |
| **Total area (2050)** | | 4.67 | 1.58 | 4.26 | 6.73 | 8.27 | 7.03 | 10.19 | 9.76 | 47.50 | 100.00 |

The increment in the shade required for 2050 implies a rise in tree biomass per area and, therefore, in the carbon stock of the coffee plantations. This higher biomass could be achieved by reducing the number and severity of the prunings on the existing shade trees, planting more trees, changing tree species, or a combination of all of them. The rise of the shade levels or tree planting density is likely to lead to an increment in the competition between trees and coffee plants for light, water, and nutrients and, consequently, a decline in annual coffee productivity (Haggar et al., 2021; Méndez et al., 2009; Vaast et al., 2005). Coffee quality, however, is generally increased by shading, but it is unclear if the change in shading levels will allow coffee plantations to keep their 2000 s coffee quality profile in the future; more research needs to be done on this.

It is important to note that our results on required shade levels are based on mean annual air temperature only. The locally optimal decision on the implemented shade level should also consider factors such as the farmer's production strategy (high or low intensification, diversification, coffee quality), and the coffee plantation conditions (e.g., prevalence of pest and diseases, soil conditions, coffee plantation age). If a higher shade level is implemented, agroforestry design and planning will play a relevant role in optimizing the additional tree biomass by selecting tree species that increase the land profitability, which may compensate for the drawbacks of higher competition between trees and coffee plants. Diversification or specialization of the coffee tree component can provide multiple goods such as fruit, fuelwood, or timber to generate more income from coffee plantations (Peeters et al., 2003; Somarriba 1990; Staver et al., 2013). Also, shade systems can be adjusted to favor conservation objectives and secure better coffee prices by farmers joining sustainable certification schemes like Rainforest Alliance, Fairtrade, Organic, and others. Haggar et al. (2017) found that coffee farms with Rainforest Alliance certification have a high density of trees, basal tree area, carbon stock, and coffee prices, but also that there is a negative correlation between tree density and tree species diversity with coffee productivity. However, the farmers were able to compensate for the negative tree-crop competition effects by achieving higher prices for their coffee due to the certification. Another alternative could be to use coffee varieties better adapted to shaded conditions that can compete more efficiently for light and

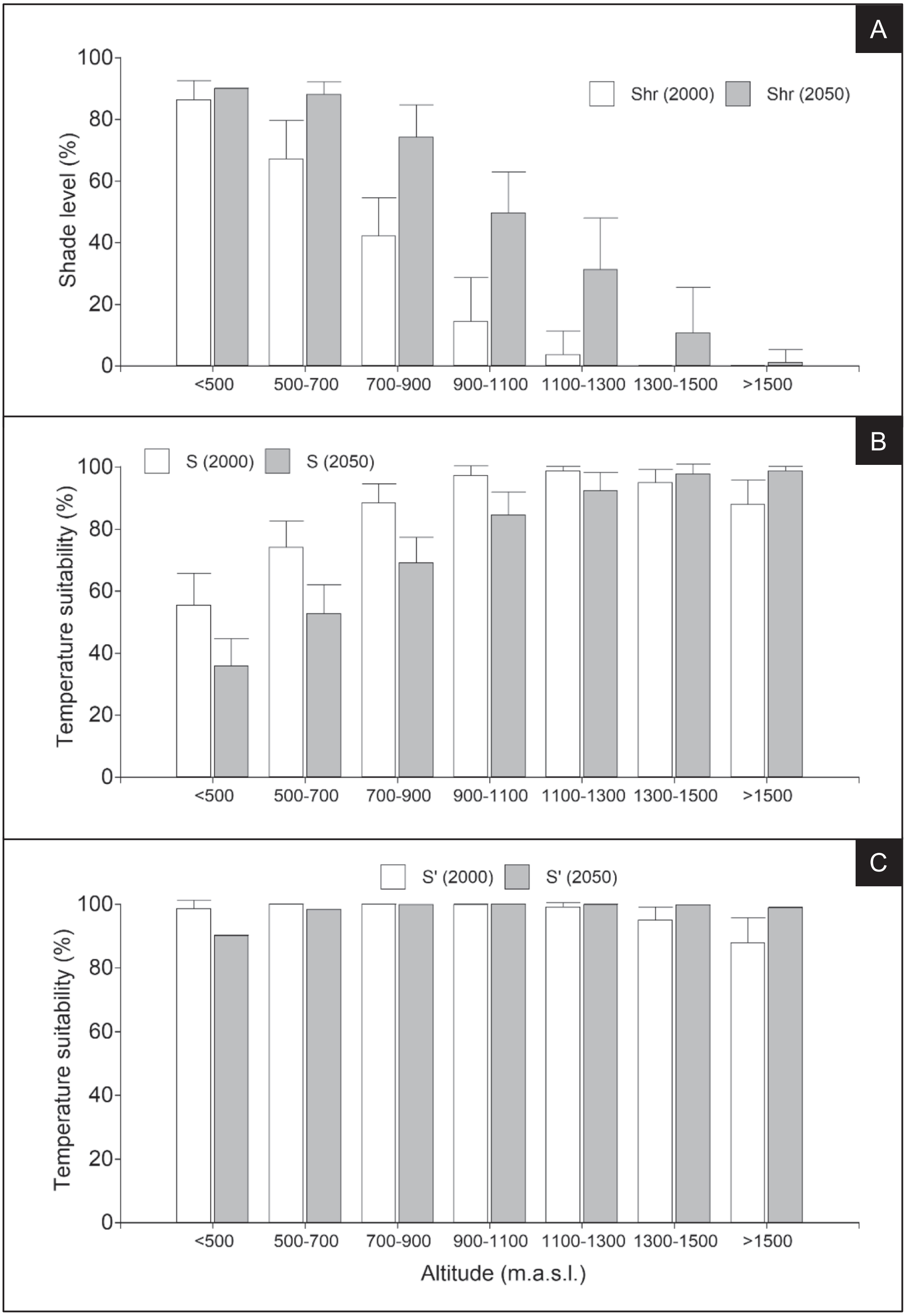


**Fig. 7.** Required shade levels ($Sh_r$) and air temperature suitability under unshaded and shaded conditions (*S* and *S'*, respectively) for coffee areas in Nicaragua. A) Average required shade levels in 2000 and 2050, B) Average temperature suitability for coffee under unshaded conditions in 2000 and 2050, and C) Average temperature suitability for coffee under shaded conditions in 2000 and 2050.

nutrients. This could stabilize or increase yields under the expected increase in required shade levels, which would, in turn, lead to sustainable intensification of coffee production by increasing coffee productivity without losing the services and goods that trees provide (Bertrand et al., 2011; Haggar et al., 2021). In areas where shading is not enough to deal with warmer conditions, switching to coffee varieties better adapted to warming conditions is an option. This includes changing to other coffee species like *Coffea canephora* or *Coffea stenophylla*; the first is more productive, and the second has better quality (Davis et al., 2021).

## 4. Conclusions

In this study, we introduce a simple shade model that uses climate information to generate agronomical information for coffee systems. The tool uses mean air temperature to estimate the required shade levels and the air temperature suitability for coffee under shaded and unshaded conditions. Under RCP 4.5, increasing the required shade level has the potential to alleviate the warming conditions in coffee areas by 2050. Coffee areas at different altitudes need different shade levels; the changes are of such magnitude that coffee areas under dense shade levels (Shr $\geq$ 60%) may double by 2050. Even though a higher density of shading trees can negatively affect coffee yields due to light and resource competition, increasing the shade levels is also an opportunity to diversify income via a judicious selection of tree species, enabling farmers and communities to build coffee production systems more resilient to crises and unexpected events. An increment in shade levels can furthermore increase carbon stocks and biodiversity in coffee systems, thus synergizing adaptation and mitigation to climate change and biodiversity conservation objectives.

The challenge climate change poses to the coffee areas is an opportunity to rethink, redesign, and plan more resilient and sustainable coffee systems, and knowing the shading needs is essential in these processes.

Even if other adaptation practices or technologies, such as better-adapted coffee varieties, may become available on time, not all farmers will have the financial resources to take advantage of them. Adjusting or planting shade trees thus remains the first response practice against upcoming warming conditions. This paper provides information on and a tool to explore shade requirements to be used by coffee institutions, agronomists, and farmers.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Data will be made available on request.

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