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ABSTRACT

In Central America, coffee is mainly grown in agroforestry systems. This practice modifies the microclimate, which, in turn, influences coffee growth and development. However, modeling these microclimate modifications is a challenge when trying to predict the development of a disease in the understory crop, based on variables usually monitored in weather stations exposed to full sunlight. Furthermore, critical variables for plant disease development, such as leaf wetness duration and leaf temperatures, are generally not measured by weather stations. In our study, we sought to build models explaining daily minimum and maximum coffee leaf temperatures, daily coffee leaf wetness duration, and minimum and maximum air temperatures in agroforestry systems with a single shade tree species, which are common in Central America, and which were characterized by shade tree height, canopy openness and light gap distribution. The modeled variables were mainly explained by one or more meteorological variables provided by reference weather stations exposed to full sunlight. The presence of shade trees resulted in a buffer effect, reducing daily maximum air and leaf temperatures, and increasing daily minimum air and leaf temperatures. Moreover, except for the daily minimum air temperature under shade, shade tree characteristics affected these microclimatic variables. Indeed, the buffer effect on the daily maximum air temperature increased with shade trees 7 m tall or over, whereas for extreme leaf temperatures, this effect seemed to be further intensified by a dense and homogeneous canopy. The tallest shade trees also tended to provide conditions that reduced coffee leaf wetness duration. The coffee leaf stratum affected the daily maximum leaf temperature, with a top layer intercepting radiation for the lower strata, but had no effect on the daily minimum leaf temperature, detected at night. The models developed were simple equations allowing interpretation of shade tree height, the effects of canopy characteristics on the microclimate and were therefore useful for designing and managing agroforestry system. The more accurate models could be incorporated into an early warning system for coffee pests and diseases in the region.

Keywords: daily extreme temperatures, daily coffee leaf wetness duration, modeling, shade tree height, canopy openness, light gap distribution

INTRODUCTION

Agroforestry is a cropping practice that consists in combining one or more tree species with a crop production based on annual or perennial plants. While the word agroforestry is recent, this practice is traditional for certain crops, such as coffee. Since the 1970s, the modernization of coffee cultivation has led to a significant conversion of traditional diversified agroforestry systems into agroforestry systems with fewer tree species and even monoculture systems (Perfecto et al. 1996; Jha et al. 2014). These modernized full-sun systems have increased yields through the introduction of high-yielding varieties and increased use of chemical inputs that are all the more useful since the crop is fully exposed to sunlight. However, production costs have also increased significantly, which probably explains why coffee is still mainly grown under shade in regions where smallholders are mostly represented, such as Central America (Fernandez 1984). In this area, more than 40 species of trees are used in coffee agroforestry systems (Dix et al. 1999).

Agroforestry offers many benefits: food security through income diversification and self-consumption of products from the farm (wood, fruit), improved coffee quality, reduction of coffee production bienniality, biodiversity conservation including pollinators, regulation of certain diseases and pests, improved soil water status, increased light use efficiency and carbon sequestration (Perfecto et al. 1996; Muschler 2001; DaMatta 2004; Lin 2007; Jha et al. 2014; Charbonnier et al. 2017; Avelino et al. 2018; Schnabel et al. 2018). This practice is therefore considered to be an agroecological practice that promotes the resilience of agroecosystems (Hillel and Rosenzweig 2010; Lasco et al. 2014). However, disadvantages to its use have also been reported since shade trees compete with coffee plants for light, nutrients (Campanha et al. 2004; Stigter 2015) and even for water under certain conditions (Padovan et al., 2015), thus hampering blossoming and the achievement of high yields (DaMatta and Rena 2002). Agroforestry also influences the dynamics of coffee diseases and pests in different directions, mainly through its effects on the microclimate (Schroth et al. 2000; Staver et al. 2001; Avelino et al. 2011; Allinne et al. 2016; Avelino et al. 2018). Most studies have demonstrated the overall effect of coffee-based agroforestry systems on different microclimate variables (Butler 1977; Barradas and Fanjul 1986; Gutierrez and Vaast 2002; Morais et al. 2006; Siles et al. 2010; Pezzopane et al. 2011; Coltri et al. 2019). Air, leaf and soil temperatures are buffered, leaf wetness is increased, wind speed and solar radiation are reduced, rainfall is intercepted and redistributed, and raindrops have a higher kinetic energy (Monteith et al. 1991; Stigter 2015; Vezy et al. 2018; Avelino et al. 2020). However, only a few studies have modeled how the microclimate is affected by different characteristics of these agroforestry systems, such as planting density and shade tree height, or canopy opening rate and light gap distribution (van Oijen et al. 2010a; Vezy et al. 2020). At present, simulation models based on physical phenomena are available to simulate flows involved in the major coffee growth mechanisms of photosynthesis, respiration and transpiration (van Oijen et al. 2010a; Rodríguez et al. 2011; Charbonnier et al. 2013; Vezy et al. 2018, 2020), and even coffee canopy temperatures under shade trees (Vezy et al., 2018). However, these process models are based on physical phenomena whose descriptors, such as the global radiation extinction coefficient of the trees and tree leaf area index (Taugourdeau et al. 2014), are difficult to measure. Some studies developed simple equations to forecast minimum night crop temperatures, with a view to predicting frost events (Georg 1978; Lhomme and Guilioni 2004), but these models were still using complex parameters that were difficult to measure. Alternatively, to process models that are useful for research but difficult to apply widely, empirical equations using only easy-to-measure characteristics would offer several interesting perspectives and allow large-scale applications. Indeed, in order to regulate the microclimate to suit the seasonal needs of the crop and improve disease and pest management, practices such as shade tree pruning could help to adjust these easy-to-measure characteristics when needed (Niether et al. 2018). In addition, the ability to estimate the microclimate under different agroforestry systems based on their characteristics and data from weather stations fully exposed to sunlight would improve the accuracy of crop growth model predictions and pest and disease forecasts (Merle et al. 2020), which would be an important achievement prior to their introduction in a warning system (van Maanen and Xu 2003).

In our study, we investigated the relative importance of different simple agroforestry system characteristics to explain the microclimate in the understory, considering meteorological data provided by nearby weather stations fully exposed to sunlight. To that end, we set up six trials at six sites in an altitudinal gradient, where the microclimate of several agroforestry systems was recorded along with that of full sun conditions. We focused on different agroforestry systems with a single shade tree species, which are common in Central America. Shade tree height, canopy openness and light gap distribution were measured.

MATERIALS AND METHODS

Location of the studied coffee-based single-species agroforestry systems

This study was carried out in Costa Rica from July 2018 to January 2019 in seven coffee plantations distributed in a gradient ranging from 740 to 1400 m a.s.l. The selection of these plantations was based on the possibility to establish a coffee plot fully exposed to sunlight used as a reference and a minimum of two coffee plots in agroforestry systems with a single shade tree species, considering a minimum plot radius of 20 m. Four plantations were selected in Cartago province and three in San Jose province (Table 1).

The first plantation in Cartago province was located in Pavones at an altitude of 740 m a.s.l. and included two plots with the Catimor coffee variety grown in agroforestry systems with a single shade tree species, namely *Erythrina poeppigiana* and *Cordia alliodora*. The second site was located in Palomo at an altitude of 770 m a.s.l. and included a plot planted with the Catimor coffee variety grown in an agroforestry system with *C. alliodora*. Due to its altitude close to that of the Pavones site and the availability of only one agroforestry system, this site was not studied over the whole duration of the test (Fig. 1). The third plantation studied in Cartago province was located near the town of El Guayabo at an altitude of 840 m a.s.l. and provided three plots with the Catimor coffee variety cultivated in agroforestry systems with a single shade tree species, namely *E. poeppigiana*, *Musa* spp. and *Gliricidia sepium*. The last plantation studied in this province was located near the village of Cachí at an altitude of 1140 m a.s.l. and had two plots with the Caturra coffee variety cultivated in agroforestry systems with the species *E. poeppigiana* and *Musa* spp alone.

In the province of San José, two plantations were selected at altitudes of 1000 m a.s.l. and 1400 m a.s.l. near the town of San Marcos. In the 1000 m a.s.l. plantation, three plots were studied: one plot with the Obata coffee variety grown in agroforestry systems based on *Vochysia guatemalensis* and two plots with the Catuaí rojo coffee variety grown in agroforestry systems based on *Musa* spp. and *E. poeppigiana* alone. Finally, the last site of the province of San José was located near the town of Aserrí at an altitude of 1270 m a.s.l. and the plots studied were three agroforestry systems with a single shade tree species, namely *Acrocarpus fraxinifolius*, *E.*

poeppigiana and *Musa* spp. At this site, the Catimor variety was grown in the shaded plot with *A. fraxinifolius* and the variety Catuaí rojo in the other two plots. Most of the studied shade tree species are commonly found in agroforestry systems in Central America (Staver et al. 2001; van Oijen et al. 2010b).

Microclimatic data recording

Since we had a total of 12 dataloggers, it was decided that a maximum of 2 to 3 sites could be equipped simultaneously and that each site would have weather stations during three separate 21-day recording periods (Fig. 1). The three recording periods of 21 days carried out in the six sites represent a total of approximately 380 days of recording. At the Palomo site, the weather stations were installed for only one recording period as explained previously.

Each of the weather stations included eleven to twelve sensors connected to a Campbell CR1000 or Campbell CR1000X (Campbell Scientific) datalogger to measure daily microclimatic variables that are drivers of coffee leaf rust disease caused by *Hemileia vastatrix*, one of the most harmful diseases of the coffee tree (Merle et al. 2020). The stations were placed in the center of each plot and included an air temperature and relative humidity sensor positioned 1.5 meters from the ground (HMP45C), four leaf wetness sensors 1.2 meters from the ground, oriented in four opposite directions (Dielectric LWS) and six T-type thermocouples (copper/constantan) placed at three different heights on two coffee plants. Each thermocouple was subdivided into four secondary thermocouples placed in contact with leaf laminas on the underside of four leaves from the same stratum (Miller 1971). The leaf temperature measurements were therefore an average of four leaves. Only the stations located in the reference plots with full sun exposure had a rain gauge placed above coffee trees 2 meters from the ground (TE525MM, accuracy 0.1 mm). The dataloggers recorded data every five seconds and stored average, minimum and maximum values every fifteen minutes. Data were retrieved from the dataloggers weekly using PC200W 4.5 Datalogger Support Software (Campbell Scientific).

Characterization of plot shade tree height and canopy openness

To account for shade tree growth due to seasonal microclimatic variations as well as pruning practices, we chose to measure shade tree height and canopy openness above the coffee plants, which vary along year, rather than focusing on seedling density (Table 1). We measured the shade tree height with a clinometer. Canopy openness (%) was calculated by using hemispherical photographs analyzed with Gap Light Analyzer software (Frazer et al. 1999). The hemispherical photographs were taken using a GoPro camera placed above the coffee plants and equipped with a fish eye lens allowing the capture of images with an ultra-wide angle (Fig. 2). The software then estimated the percentage of canopy openness for different angles by manually classifying the pixels with a software feature that manages the contrast level. Given that this classification is arbitrary, it was operated by a single person (Weiss et al. 2004).

Description of variables

Given our objective of using the models in warning systems based on a network of weather stations fully exposed to sunlight, we decided to work on daily variables, which is the most common format used to process weather data. Leaf wetness duration and leaf temperatures are important for predicting fungal foliar diseases (Magarey et al. 2005). However, leaf wetness and leaf temperature are not usually measured in unshaded weather stations. For that reason, in addition to modeling the microclimate in the understory of agroforestry systems as a function of shade tree characteristics, we decided to model these microclimatic variables as a function of others, usually recorded in weather stations. Specifically, we chose to develop five models for:

the daily leaf wetness duration (*HoursLW*), the minimum and daily maximum leaves temperatures (*MinTleaf* and *MaxTleaf* respectively), the daily minimum and maximum air temperatures under agroforestry systems (*MinTairShade* and *MaxTairShade* respectively). The daily leaf wetness duration was calculated by averaging the duration per hour of the four leaf wetness sensors, and then by summing these hourly durations. The daily minimum and maximum leaves temperatures was calculated by averaging the values recorded by the two thermocouples of each coffee stratum. The daily minimum and maximum air temperatures under agroforestry systems was the values provided by the air temperature and relative humidity sensor placed in these systems.

To explain these five microclimatic variables, we chose to use only variables usually measured by the weather station networks of the region. Thus, we selected only the daily minimum and maximum air temperatures (*MinTairSun* and *MaxTairSun* respectively), the daily average relative humidity (*RHSun*) and the total daily precipitation (*RainfallSun*), provided by the reference weather station that we had placed in the full sun exposed plot at each site.

The plots were classified according to a factor characterizing their agroforestry system, named *classAgroforSyst*. It included eight modalities representing the combination of two levels of canopy openness, two levels of light gap distribution, and two levels of shade tree height (Table 2). A ninth modality, representing plots fully exposed to sunlight, was created for the models explaining the variables *HoursLW*, *MinTleaf* and *MaxTleaf*. Canopy openness was considered low when <50% and high when ≥50%. To characterize the level of light gap distribution, we chose four lines of gap fractions from the zenith rather than the larger angle to exclude the tops of neighboring coffee plants and only characterize the shade provided by the trees (Fig. 2 C). As an estimation of light gap distribution, we then used the standard error of the ratios of canopy openness and the area of the 80 gap-fractions included in the four lines. The higher the standard error, the more irregular was the light gap distribution. To create two classes for the variables of light gap distribution and shade tree height we used the *party* package (Hothorn et al., 2006) in R 3.6.1 (R Development Core Team 2019), which builds a tree-based regression by recursive binary partitioning (Table 2).

The *MinTleaf* and *MaxTleaf* variables had the particularity of being measured on three leaf strata of the coffee plant. We studied the effect of coffee leaf strata in these two models (*CoffeeLeafStratum*: *Bottom*, *Middle*, *Top*).

Statistical analysis

For each of the five variables *HoursLW*, *MinTleaf*, *MaxTleaf*, *MinTairShade* and *MaxTairShade*, we first studied the distributions of the microclimatic variables to focus on domains of definition with a sufficient number of observations. We then used the boosted regression tree analysis to evaluate the linearity of relationships and obtain a relative ranking of all the variables tested for each model (Table 2). This machine learning algorithm is increasingly being used in ecological modeling due to the flexibility of regression trees, which enables complex ecological responses to be modeled (Elith et al., 2008; Bhatt et al., 2013). The model consisted of a linear combination of regression trees. The relative importance of each variable was estimated using the number of times a variable was selected for splitting, weighted by the squared improvement of the model following each splitting, and averaged over all regression trees (Friedman, 2001; Williams et al., 2010). The linearity of the dependence is checked using the partial dependence function showed the marginal effect of each variable on the count response after averaging the effects of all the other variables (Bhatt et al., 2013).

The five dependent variables were then fitted to a Gaussian distribution using generalized linear models (GLM) and keeping the independent variables with the greatest relative level of influence only (Table 3), the sum of whose influences accounted for 95% of the dependent variable. To compare factor modality effects, we used Tukey's multiple comparison post hoc test.

In order to assess the validity of the equations on an independent dataset, two plots were excluded from the entire construction of the model (BRT and GLM), the plot of the site at the altitude of 770 m, under shade provided by tall shade trees, and the plot of the banana agroforestry system at the altitude of 1140 m. In these two plots, the predicted and observed values were then compared using the root mean square error. The extreme values excluded from the model building stage were similarly used for evaluation purposes. All the statistical analyses were performed with R 3.6.1 (R Development Core Team 2019) and with an alpha level of 0.05. Boosted regressions trees were constructed using the *gbm* package version 2.1.5 (Greenwell et al, 2019) and the *dismo* package (Hijmans et al., 2017). GLM were fitted using the *lme4* package version 1.1-21 (Bates et al., 2015), and we carried out Tukey's multiple comparison post hoc test using the *multcomp* package version 1.4-12 (Hothorn et al. 2020).

RESULTS

Description of the study microclimate and shade tree characteristics

Thanks to the altitudinal gradient, we could measure a wide range of microclimatic conditions. On the total of 380 days of recording, we observed a good distribution of rainy days with 120 days without rain, 80 days with rainfall between 0.1 and 1 mm, 58 days with rainfall between 1 and 5 mm and 122 days with rainfall ranging from 5 to 103 mm (Fig. 1). In terms of air temperature, we observed minimum and maximum temperatures ranging from 8.0 to 20.4 °C and from 18.4 to 34.1 °C respectively (Table 2). The temperature of the coffee leaves varied from 7.3 to 20.4 °C for the minimum daily temperature and from 17.7 to 48.8 ° C for the maximum daily temperature. Regarding the leaf wetness duration, it varied from 0 to 24 hours per day with an average duration of 17 hours (Annex).

Tree height in the agroforestry systems we studied ranged from 2.8 m to 26.5 m and canopy openness from 12 to 90% depending on the tree species, date of establishment and pruning applied. Indeed, during the study, a tree pruning was carried out in several plots that included *E. poeppigiana* or *Musa* spp., increasing canopy openness, light gap distribution sometimes and decreasing shade tree height (Table 1).

Model of the daily minimum and maximum air temperatures under agroforestry systems

The results of the exploratory analysis carried out using the boosted regression tree approach enabled us to classify, in order of importance, the variables tested in the models explaining the daily minimum and maximum air temperatures in agroforestry systems (*MinTairShade* and *MaxTairShade* respectively) (Table 3).

Considering only the variables with the highest level of influence and representing about 95% of the dependent variable, the only variable selected was *MinTairSun,* with a relative importance rate of around 95%, and its effect on *MinTairShade* was significantly positive ($p < 0.001$) (Equation 1 whose parameter values are presented in table 4). The variables *MaxTairSun*, *RHSun*, *RainfallSun* and *classAgroforSyst* had negligible effects.

Equation 1: $MinTairShade = \alpha_1 + \alpha_2 \times MinTairSun$

On the model definition domain, i.e. at minimum air temperatures in full sunlight between 12 and 20°C, the temperature of the air under shade is always higher than that in full sunlight with a difference of less than 1°C.

The comparison of predicted and observed values gave root mean square errors of 0.46 on the data used to build the model, 0.96 on the extreme data excluded from the data set and 0.71 on the independent data set (Fig. 3A, C and E).

The exploratory analysis showed that the *MaxTairSun* variable described about 79% of the *MaxTairShade* variable. The variables *MinTairSun* and *classAgroforSyst* represented together a relative influence of around 17% and the other variables had importance levels below 5% (Table 3). These three independent variables were selected to build the *MaxTairShade* estimation model, but *MinTairSun* did not show a significant effect ($p = 0.056$). Thus, *MaxTairSun* had a positive effect ($p < 0.001$) and the effect of the factor *classAgroforSyst* illustrated a negative effect of taller shade trees (Equation 2 whose parameter values are presented in table 4).

Equation 2: $$MaxTairShade = \beta_1 + \beta_2 \times MaxTairSun + \beta_{3,classAgroforSyst}$$

For this model, only a few cases, mainly for low maximum temperatures in agroforestry systems based on short trees, showed a higher maximum air temperature under shade than in full sunlight. Indeed, in the range of definition of this model, i.e. maximum air temperatures in full sunlight from 23 to 33°C, only 25% of the values were found below 28°C. For very high maximum air temperatures with full sun exposure, the maximum air temperature under shade could be 4°C lower.

This model was less efficient in terms of prediction accuracy than the model of *MinTairShade* estimation. Indeed, the root mean square error between predicted and observed values used to build the model was 1.11 (Fig. 3B). In addition, the validation on extreme values, excluded from the analysis, and on the independent dataset showed that predicted and observed values were linked by root mean square errors of 1.22 and 1.23, respectively (Fig. 3D and F).

Model of the daily minimum and maximum leaf temperature

By using the boosted regression tree approach, we determined the relative importance of the variables tested in the models explaining the daily minimum and maximum leaf temperatures (*MinTleaf* and *MaxTleaf* respectively) (Table 3). *MinTleaf* was described mainly by *MinTairSun*, then in decreasing order of importance by the variables *classAgroforSyst, MaxTairSun*, *RHSun*, *RainfallSun*, and *CoffeeLeafStratum*. With respect to the *MaxTleaf* variable, the maximum value of the full sun temperature (*MaxTairSun*) was the most important variable but, unlike the *MinTleaf* variable, the following variables also had a major weight: *CoffeeLeafStratum*, *classAgroforSyst, MinTairSun*, *RainfallSun* and *RHSun*.

Considering only the variables with the highest level of influence and representing about 95% of the dependent variable, we selected the variables *MinTairSun*, *classAgroforSyst*, *MaxTairSun*, and *RHSun* for the model explaining *MinTleaf.* From these variables, the subsequent model development phase resulted in the conservation of three variables that had a significant effect on *MinTleaf*: *MinTairSun*, *RHSun* and *classAgroforSyst*.

Considering quantitative microclimatic variables, *MinTairSun* and *RHSun* had a positive effect on *MinTleaf* ($p < 0.001$ and $p = 0.026$ respectively). In terms of factors, we found a significant influence of *classAgroforSyst* showing a positive effect of all of the agroforestry systems compared to the full sun exposure ($p < 0.001$). The result of the pair-wise comparison of the different modalities of *classAgroforSyst* did not show a clear difference related to any of the three characteristics: shade tree height, canopy openness and light gap distribution (Equation 3 whose parameter values are presented in table 4). However, agroforestry systems combining a low canopy openness and a regular light gap distribution were responsible for a greater increase in the daily minimum leaf temperature.

Equation 3: $MinTleaf = \gamma_1 + \gamma_2 \times MinTairSun + \gamma_3 \times RHSun + \gamma_{4,classAgroforSyst}$

To explain *MaxTleaf,* we selected all the tested variables because the least influential variable had a relative influence of 8% (Table 3). In this model, the variables conserved for their significant effect were *MaxTairSun* for its positive effect ($p < 0.001$), *RHSun* for its negative effect ($p < 0.001$), *MinTairSun* for its negative effect ($p = 0.020$), and the factors *CoffeeLeafStratum* ($p < 0.001$) and *classAgroforSyst* ($p < 0.001$). Conversely, the variable *RainfallSun* did not have a significant effect ($p = 0.34$). We found significant differences between the three modalities of *CoffeeLeafStratum* with a positive effect of the upper strata (Equation 4 whose parameter values are presented in table 4). The pair-wise comparison of the different modalities of *classAgroforSyst* highlighted that the modality with short shade trees, high canopy openness and a regular light gap distribution was not significantly different from the modality of full sun exposure, unlike the other modalities.

Equation 4: $MaxTleaf = \delta_1 + \delta_2 \times MaxTairSun + \delta_3 \times MinTairSun + \delta_4 \times RHSun + \delta_{5,classAgroforSyst} + \delta_{6,CoffeeLeafStratum}$

Under shade, the daily minimum leaf temperature was higher than in full sunlight, with a difference of 0.18 to 1.04°C, while the daily maximum leaf temperature was often lower with a difference of 1.62 to 4.91°C. According to the model generated, the leaves of the upper stratum of the coffee plant had a maximum temperature 2°C higher than those of the intermediate stratum, and 5.95°C higher than those of the lower stratum.

The minimum leaf temperature estimation model gave better prediction results with a root mean square error of 0.67 between predicted and observed values (Fig. 4A) compared to 3.01 for the maximum leaf temperature estimation model (Fig. 4B). The evaluation of these models on the extreme values extracted from the definition domain also resulted in a better predictive accuracy of the *MinTleaf* estimation model compared to the *MaxTleaf* estimation model, with root mean square errors between predicted and observed values of 1.06 and 3.16 respectively (Fig. 4C and D). The validation on the independent dataset illustrated the same trend with root mean square errors of 0.72 for *MinTleaf* and 2.93 for *MaxTleaf* (Fig. 4E and F).

Model of the daily leaf wetness duration

The exploratory phase of the analysis revealed that the variable *HoursLW* was mainly explained by the variables *RHSun*, *classAgroforSyst*, *MaxTairSun, RainfallSun* and *MinTairSun* (Table 3).

The model building stage for *HoursLW* resulted in the conservation of four variables with a significant effect. *RHSun* had a positive effect ($p < 0.001$), *MaxTairSun* had a negative effect ($p < 0.001$), *RainfallSun* had a weak positive effect ($p = 0.020$) and *classAgroforSyst* showed a tendency of taller shade trees to decrease more the number of hours with leaf wetness than systems with shorter shade trees. Indeed, among the agroforestry systems with smaller shade trees, the system with a high canopy openness and an irregular light gap distribution was the only one that showed a significant difference from the system with full sun exposure, whereas among the agroforestry systems with taller shade trees, there was only one system showing no difference with the system with full sun exposure (Equation 5 whose parameter values are presented in table 4).

Equation 5: $HoursLW = \varepsilon_1 + \varepsilon_2 \times RHSun + \varepsilon_3 \times MaxTairSun + \varepsilon_4 \times RainfallSun + \varepsilon_{5,classAgroforSyst}$

In the agroforestry systems with tall trees, the leaf wetness duration was higher than in the full sunlight systems, with a maximum difference of up to 2 hours.

A comparison of the model's predictions provided root mean square errors of 2.87 with the data used for its construction (Fig. 5A), of 3.73 with the extreme values excluded from model building (Fig. 5B), and 2.38 with the independent dataset (Fig. 5C). The model inaccuracy was higher for non-rainy days since the RMSE was 3.50 versus 2.59 for rainy days.

DISCUSSION

The main drivers for predicting the microclimate in agroforestry systems were the variables provided by weather stations located in full sunlight and nearby. However, except for the daily minimum air temperature in these systems, the data provided by the stations in full sunlight were not sufficient to predict the microclimate under shade. Indeed, different agroforestry systems in terms of tree height, canopy openness or even regularity of light gap distribution showed different effects on the microclimate. This could explain the different effects of agroforestry systems on the development of coffee pests and diseases (Merle et al. 2019). Therefore, predicting their development only using data from stations in full sunlight, without taking into account the particularities of agroforestry systems, could lead to significant prediction inaccuracies.

Estimated daily minimum temperatures of air under shade and of coffee leaves

The daily minimum coffee leaf temperature and air temperature under shade were mainly determined by the daily minimum air temperatures in full sunlight. Although this variable was sufficient to predict the minimum daily air temperature under shade, the minimum daily temperature of coffee leaves was explained by other microclimatic variables, but also by the characteristics of the agroforestry systems. Indeed, the positive effect of the daily mean relative humidity in full sunlight on the daily minimum leaf temperature may have been due to the fact that relative humidity is lower on cloudless days and the absence of cloud leads to a greater cooling of temperatures at night. The buffer effect we found for the presence of shade trees compared to full sun exposure on the minimum temperature of coffee leaves has already been observed (Morais et al. 2006; Soma 2015). We also found that agroforestry systems with a dense and homogeneous canopy displayed a greater buffer effect, increasing the daily minimum coffee leaf temperature. We suggest that this effect is due to the canopy uniformity preventing exchanges with the outside air. The fact that the coffee leaf stratum had no effect on the daily minimum leaf temperature was certainly due to the absence of radiation intercepted by the top stratum at night when the minimum temperature was detected. In their definition domain, both models showed that the minimum temperatures of air and coffee leaves were higher under agroforestry systems with differences of around 1°C (Siles et al. 2010).

Estimated daily maximum temperatures of air under shade and of coffee leaves

The daily maximum temperatures of air under shade and of coffee leaves were mainly explained by the daily maximum air temperature in full sunlight. With respect to the daily air maximum temperature under shade, the strong overall buffering effect of trees on the maximum air temperature under shade is well known (Barradas and Fanjul 1986; Jaramillo-Robledo and Gómez-Gómez, 1989; Siles et al. 2010; López-Bravo et al. 2012; Sida et al. 2018). However, in our study, it was mostly explained by one factor of agroforestry systems: shade tree height. Tall trees made it possible to isolate a larger layer of air, which therefore heated up less easily than the shallow layer of air delimited under short trees. This buffer effect was also observed in the case of the daily maximum temperature of coffee leaves, but it seemed to be related both to the height of the trees (Muschler 1998; Siles et al. 2010; Soma 2015; Vezy et al. 2018) and to the density and regularity of the canopy. A dense canopy with a regular light gap distribution made it possible to isolate a layer of air that was less easily heated than a system with an irregular canopy openness (Renaud and Rebetez, 2009). This phenomenon resulted in a lower temperature of the air surrounding the leaves. The upper coffee leaf stratum probably acted as a layer protecting the lower ones from radiation (Siles et al. 2010; Ngao et al. 2017), thus reducing their daily maximum temperature.

The weak negative effect of the daily minimum air temperature in full sunlight and the negative effect of the relative humidity in full sunlight on the daily maximum leaf temperature could be related to the fact that lower relative humidity induced stomatal closure that stopped plant transpiration resulting in leaf heating (Lange et al. 1971). The effect of the minimum air temperature in full sunlight on the daily maximum leaf temperature was possibly due to cloudy days responsible for an increase in this minimum temperature and a decrease in the maximum temperature because of a lower level of radiation.

These two models predicting maximum temperatures exhibited less accuracy than models predicting minimum temperatures (Ferrez et al. 2011), doubtless because of the very heterogeneous sunlight conditions interacting with the coffee leaf angle and orientation on the plant (Miller 1971; Butler 1977). Another phenomenon that could partially explain this inaccuracy is the increase or decrease in wind speed depending on the agroforestry system, which are responsible for air conductance changes (Judd et al. 1996; Stigter et al. 2002; Pezzopane et al. 2011).

Estimated daily leaf wetness duration

The daily leaf wetness duration was mainly explained by a positive effect of the daily average relative humidity in full sunlight, as described by other studies (Smith 1958; Shaw 1973; Sentelhas et al. 2008). Actually, rainfall only showed a weak positive effect on the daily leaf wetness duration, which can be attributed to three causes. The first cause is the nature of the variable being measured, since daily rainfall is a sum of rainfall over 24 hours that does not consider rain distribution. From that point, daily rainfall does not provide as much information as average relative humidity on the duration of rainy periods during the day and therefore on leaf wetness duration (Sentelhas et al. 2008). The other causes are related to tree effects on precipitations in the understory, which reduces the effect of rains on leaf wetness, as rain interception by shade trees (Siles et al., 2010) and the probable reduction of dew formation by night under shade (Marrou et al. 2013), as minimum coffee leaf temperature is higher in this condition. Leaf wetness is also under the influence of temperatures. The maximum air temperature in full sunlight had a negative effect on the daily leaf wetness duration, indicating that warmer conditions are conducive to leaf wetness drying. In addition, trees hinder leaf drying by intercepting light (Charbonnier et al. 2013) and reducing wind speed (Stigter et al. 2002;

Pezzopane et al. 2011; Gagliardi et al. 2020). However, these effects that occur during the day, seem secondary, as taller shade trees tended to decrease the daily leaf wetness duration compared to full sun exposed plots. We verified, with the data at hand, that the reduction of dew formation at night in the understory was a key factor reducing coffee leaf wetness. Coffee leaves took longer to be wetted by dew under tall shade trees. The second effect of trees could be on wind. Indeed, it has been shown that turbulence, which can enhance leaf drying, can be observed within the canopy, particularly when windbreak solidity is high (Judd et al. 1996).

Our equation gave less accurate results probably because we used the daily average, commonly provided by a weather station, rather than the number of hours of relative humidity above 90%. In addition, it is possible that the absence of a very pronounced dry season during the trial was responsible for a higher model inaccuracy for non-rainy days. Despite its inaccuracy, our equation had the advantage of estimating the daily coffee leaf wetness duration in full sunlight like Sentelhas et al. (2006), but also in agroforestry systems.

CONCLUSION

In our study, simple equations were developed to estimate five variables that are useful in predicting the development of plant fungal diseases (Magarey et al. 2005) in plantations exposed to full sunlight and in agroforestry systems. These models were based on (1) meteorological variables commonly provided by reference weather stations located in full sunlight and (2) easily measurable characteristics in agroforestry systems. Models estimating the daily maximum leaf temperature and the daily leaf wetness duration did not show high accuracy, but highlighted the importance of indicating the presence and height of shade trees to reduce estimation error. By identifying tree height, canopy openness and light gap distribution as the main agroforestry system factors influencing the studied microclimatic variables, our equations offer opportunities to optimize agroforestry system design and management, for example, by carrying out pruning to modify the canopy openness and the light gap distribution, and help manage coffee leaf rust. By deciding to use only weather variables commonly provided by weather station networks, easy-to-measure shade tree characteristics and to model daily variables, we sought to promote their use in warning systems. However, incorporating meteorological variables such as wind and cloud cover could improve the accuracy of the leaf wetness duration and maximum leaf temperature models and are therefore variables that deserve to be more commonly measured by weather station networks in the region. To evaluate the suitability of these equations for disease and pest predictions under mono-specific shade in Central America, it would be valuable to compare predictions given by pest and disease models using modeled microclimatic variables under shade to predictions using models based on meteorological variables in full sun. Lastly, it would be interesting to complete these results by carrying out such a study in diversified systems with several shade tree species and incorporate these equations into a local disease warning system that would improve prediction by considering the cropping system of each coffee producer.

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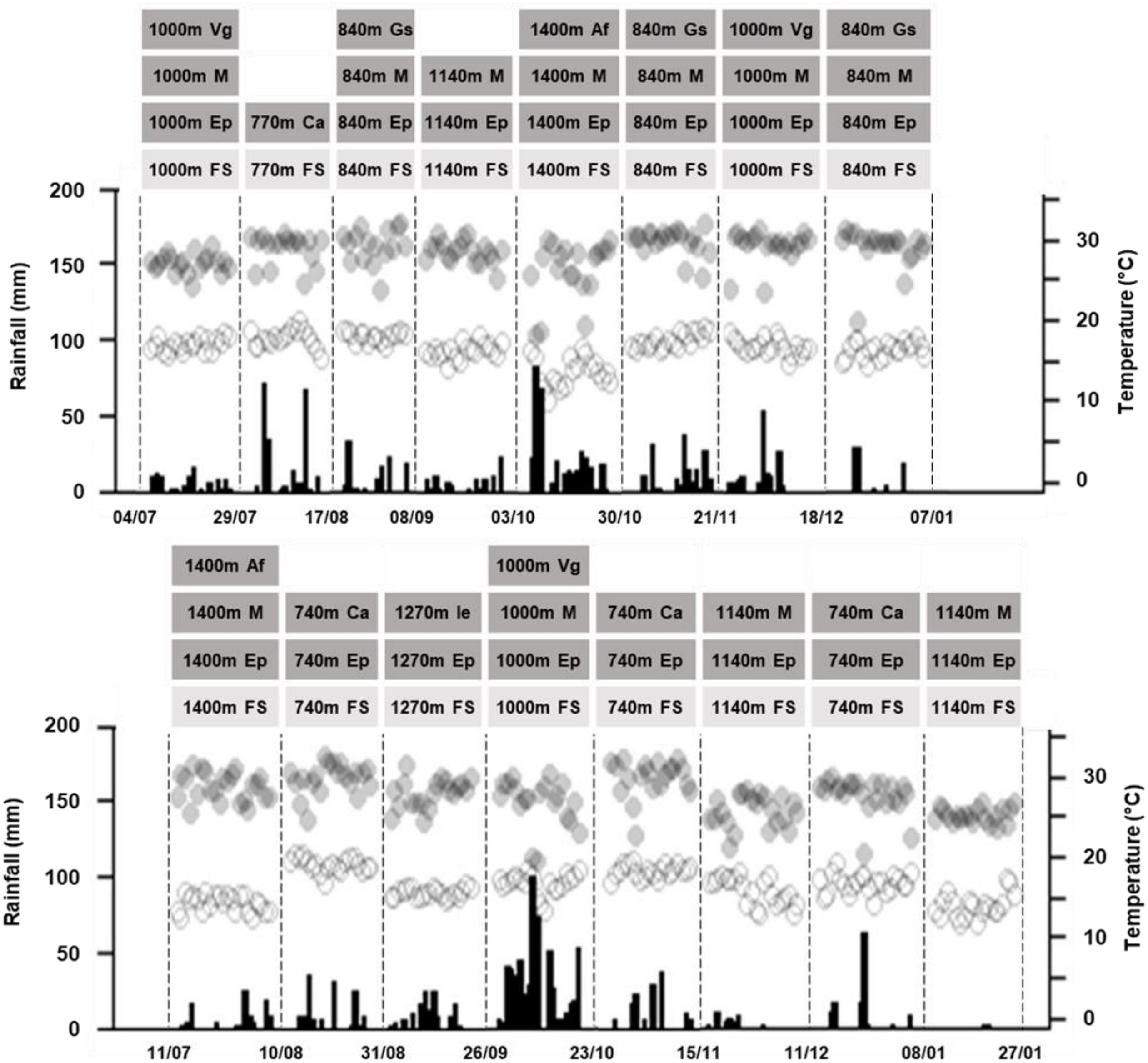
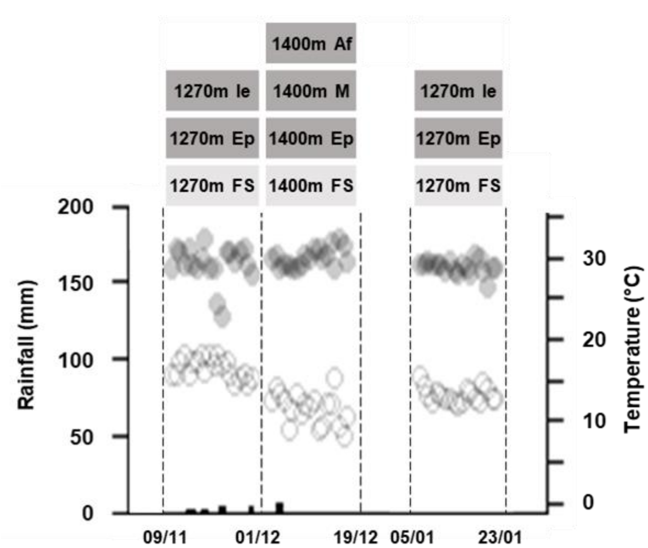


Fig. 1. Organization of the successive installations of weather stations on the plots of each site from July 2018 to January 2019 and data of daily rainfall (black bar plot), daily minimum temperature (empty dots) and daily maximum temperature (full dots) of the weather stations in the full sun reference plot.

Af = *Acrocarpus fraxinifolius*; Ca = *Cordia alliodora*; Ep = *Erythrina poeppigiana*; FS = Full sun; Gs = *Gliricidia sepium*; Ie = *Inga edulis*; M = *Musa* spp.; Vg = *Vochysia guatemalensis.*



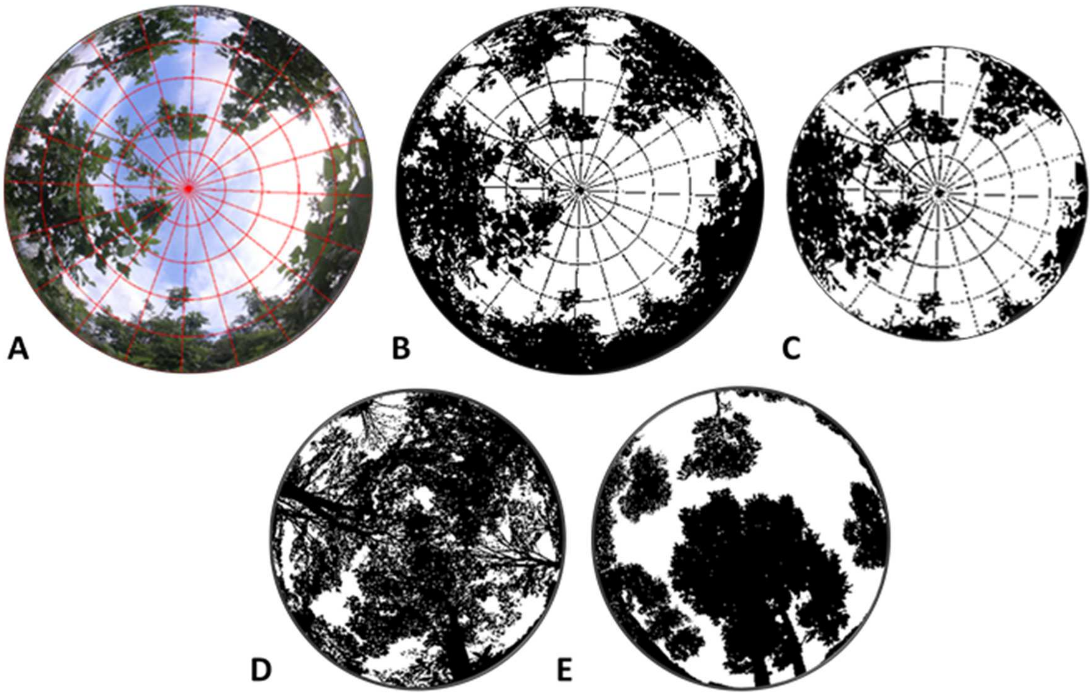


Fig. 2. Hemispherical photographs analyzed with Gap Light Analyzer software (A), which classified the pixels using the contrast level (B) to compute the canopy openness of four lines of gap fractions from the zenith (C). Examples of a regular light gap distribution (D) and an irregular light gap distribution (E). Photographs by Rogelio Villarreyna-Acuña

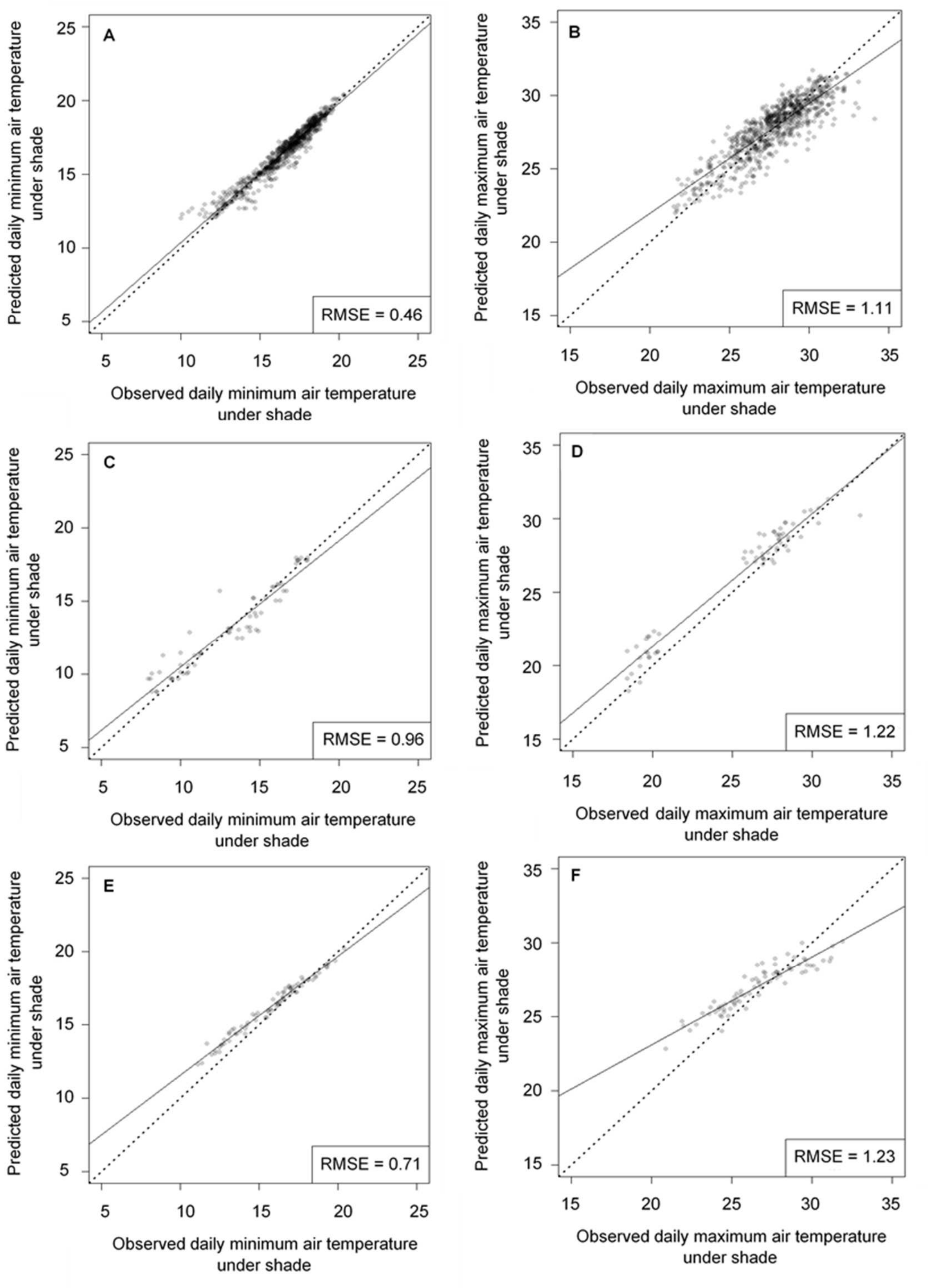


Fig. 3. Graphs illustrating predicted daily minimum and maximum air temperatures under shade as a function of the observed values on the dataset used to build the model (A and B), on the extreme values from the domain of definition excluded from the model building stage (C and D) and on the independent dataset including the site at an altitude of 770 m a.s.l. and the coffee plot with a banana agroforestry system at the site at an altitude of 1140 m a.s.l. (E and F); RMSE = root mean square error.

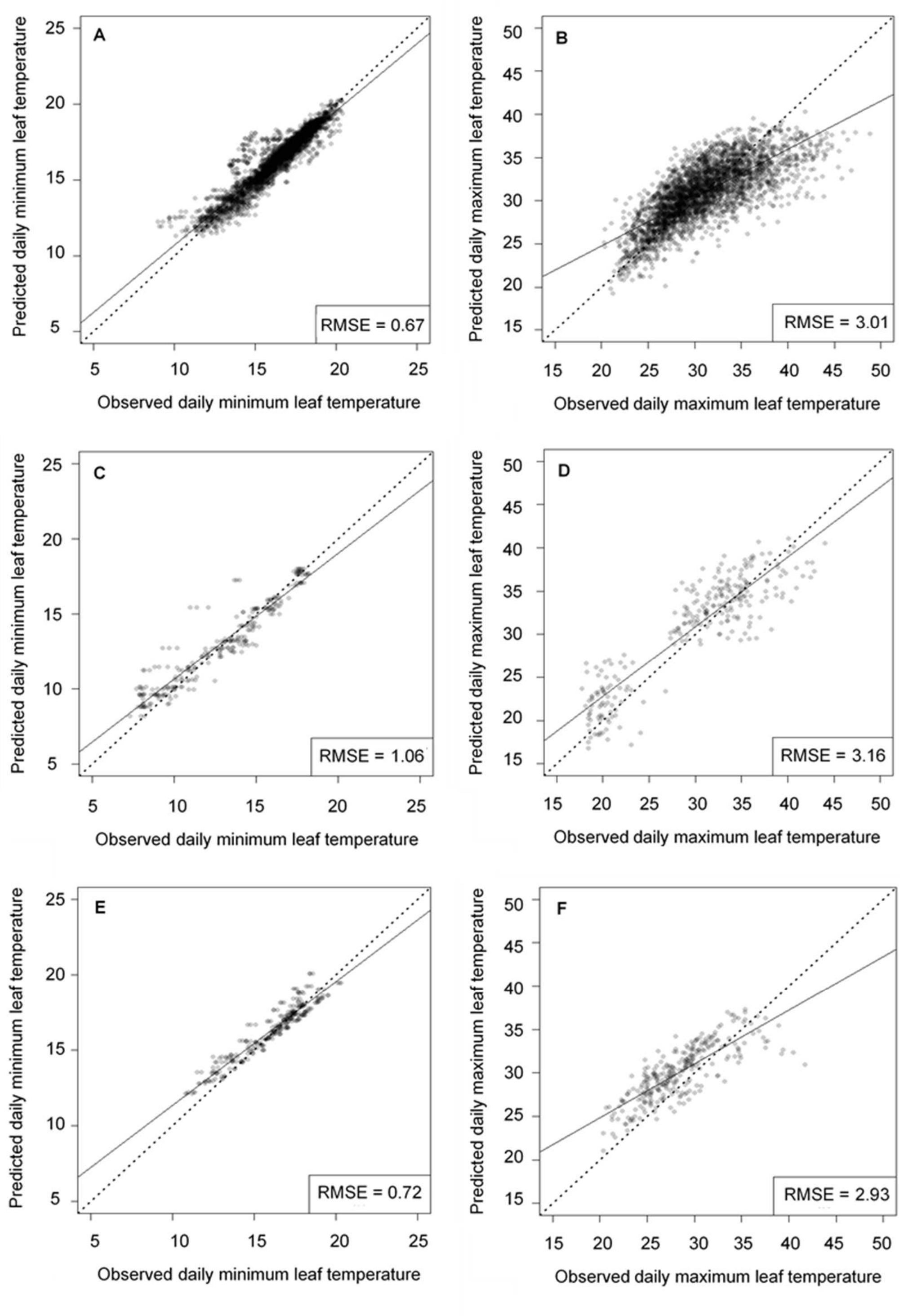


Fig. 4. Graphs illustrating predicted daily minimum and maximum leaf temperatures as a function of the observed values on the dataset used to build the model (A and B), on the extreme values from the domain of definition excluded from the model building stage (C and D) and on the independent dataset including the site at an altitude of 770 m a.s.l. and the coffee plot with a banana agroforestry system at the site at an altitude of 1140 m a.s.l. (E and F); RMSE = root mean square error.

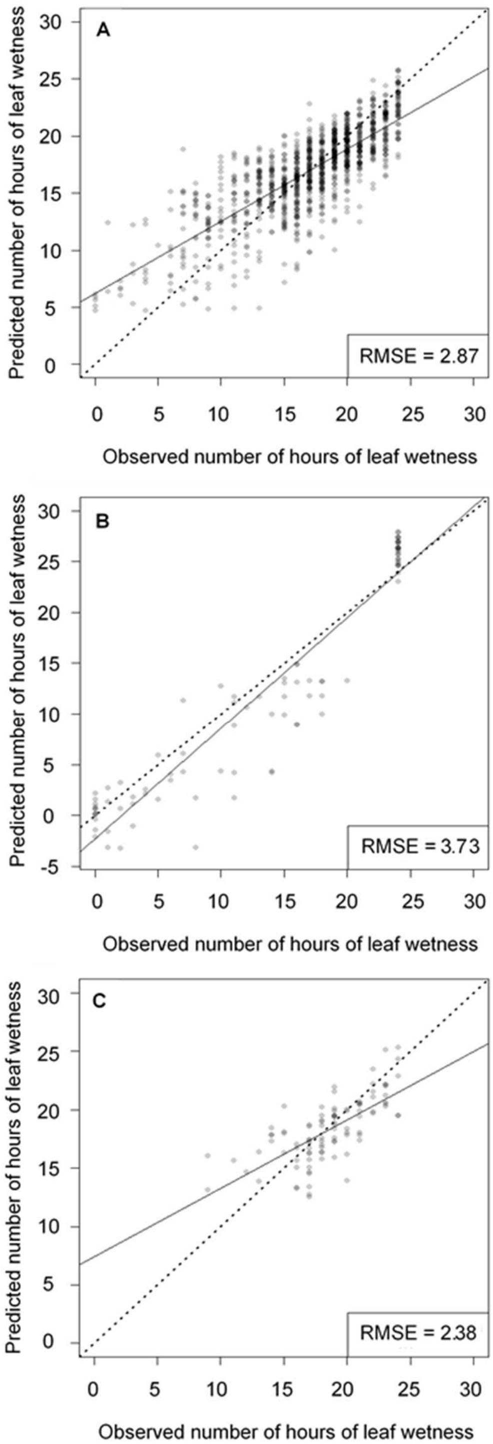


Fig. 5. Graphs illustrating predicted daily leaf wetness duration as a function of the observed values on the dataset used to build the model (A), on the extreme values from the domain of definition excluded from the model building stage (B) and on the independent dataset including the site at an altitude of 770 m a.s.l. and the coffee plot with a banana agroforestry system at the site at an altitude of 1140 m a.s.l. (C); RMSE = root mean square error.

TABLE 1. Studied coffee plots GPS data, altitude, shade tree species, shade tree height, canopy openness and light gap distribution (R=Regular and I=Irregular) during the three periods of recording (P1 = 1st period, P2 = 2nd period and P3 = 3rd period)

Site (Province)	GPS data	Altitude (m a.s.l.)	Shade tree species	Shade tree height (m)			Canopy openness (%)			Light gap distribution		
				P1	P2	P3	P1	P2	P3	P1	P2	P3
Pavones (Cartago)	9º54´34´´ N 83º37´55´´ W	740	-	-	-	-	-	-	-	-	-	-
			Erythrina poeppigiana	3.8	4.1	4.1	57	63	40	I	I	I
			Cordia alliodora	14.6	14.8	14.8	64	57	51	I	I	I
Palomo (Cartago)	9º59´27´´ N 83º38´14´´ W	770	-	-	-	-	-	-	-	-	-	-
			C. alliodora	18.5	-	-	56	-	-	I	-	-
El Guayabo (Cartago)	9º57´25´´ N 83º39´50´´ W	840	-	-	-	-	-	-	-	-	-	-
			E. poeppigiana	6.5	7.9	7.9	67	21	21	I	I	I
			Gliricidia sepium	4.8	5.5	12,5*	79	71	48	I	I	I
			Musa spp.	6.6	6.1	6.1	61	50	50	I	I	I
San Marcos (San Jose)	9º35´36´´ N 84º01´29´´ W	1000	-	-	-	-	-	-	-	-	-	-
			E. poeppigiana	5.8	2.8	3.5	74	90	59	I	R	I
			Musa spp.	7.0	7.0	7.0	53	47	37	I	I	I
			Vochysia guatemalensis	10.5	10.8	10.9	36	32	27	I	I	I
Cachí (Cartago)	9º48´38´´ N 83º49´20´´ W	1140	-	-	-	-	-	-	-	-	-	-
			E. poeppigiana	6.8	7.2	7.2	16	12	27	R	R	R
			Musa spp.	6.9	6.2	6.2	37	44	46	I	I	I
Aserrí (San Jose)	9º46´8´´ N 84º06´30´´ W	1270	-	-	-	-	-	-	-	-	-	-
			E. poeppigiana	21.2	21.2	21.2	37	25	40	R	R	I
			Inga edulis	4.4	4.8	4.8	76	45	20	I	I	R
San Marcos (San Jose)	9º39´29´´ N 84º02´44´´ W	1400	-	-	-	-	-	-	-	-	-	-
			Acrocarpus fraxinifolius	26.4	26.5	26.5	51	59	69	R	R	I
			E. poeppigiana	6.9	7.8	7.8	62	70	53	I	I	I
			Musa spp.	7.2	5.8	5.8	56	88	73	I	R	I

* change for a plot with older shade trees

TABLE 2

Description of the five microclimatic dependent variables and their tested independent variables, including microclimatic quantitative variables provided by a weather station exposed to full sunlight and plot characteristic factors

Variables	Description	Unit	Range
Dependent			
HoursLW	Daily number of hours of leaf wetness	-	[0; 24]
MinTleaf	Daily minimum leaf temperature	°C	[7.3; 20.4]
MaxTleaf	Daily maximum leaf temperature	°C	[17.7; 48.8]
MinTairShade	Daily minimum air temperature under agroforestry	°C	[8.0; 20.4]
MaxTairShade	Daily maximum air temperature under agroforestry	°C	[18.4; 34.1]
Independent			
Microclimatic quantitative variables			
MinTairSun	Daily minimum air temperature in full sunlight	°C	[8.1; 20.4]
MaxTairSun	Daily maximum air temperature in full sunlight	°C	[18.4; 32.7]
RHSun	Daily average relative humidity in full sunlight	%	[61; 100]
RainfallSun	Daily rainfall in full sunlight	mm	[0; 103]
Characteristic factors			
classAgroforSyst	Type of agroforestry system:		
	Shade tree height ≥ 7m, canopy openness ≥ 50% and light gap distribution (> 2.6)		
	Shade tree height ≥ 7m, canopy openness ≥ 50% and light gap distribution (≤ 2.6)		
	Shade tree height ≥ 7m, canopy openness < 50% and light gap distribution (> 2.6)		
	Shade tree height ≥ 7m, canopy openness < 50% and light gap distribution (≤ 2.6)		
	Shade tree height < 7m, canopy openness ≥ 50% and light gap distribution (> 2.6)		
	Shade tree height < 7m, canopy openness ≥ 50% and light gap distribution (≤ 2.6)		
	Shade tree height < 7m, canopy openness < 50% and light gap distribution (> 2.6)		
	Shade tree height < 7m, canopy openness < 50% and light gap distribution (≤ 2.6)		
	Full sunlight (modality specific to **HoursLW**, **MinTleaf** and **MaxTleaf**)		
CoffeeLeafStratum	Coffee leaf stratum: Bottom; Middle; Top (specific to **MinTleaf** and **MaxTleaf**)		

TABLE 3

Relative levels of influence (%) of each independent variable on the dependent variables provided by the boosted regression tree analysis

	Dependent variables				
Independent variables	MinTairShade	MaxTairShade	MinTleaf	MaxTleaf	HoursLW
MinTairSun	95.3	9.2	84.2	9.3	6.3
MaxTairSun	1.4	78.6	2.8	30.0	7.8
RHSun	1.5	3.2	2.3	7.9	66.3
RainfallSun	0.6	2.2	1.8	6.1	7.1
classAgroforSyst	1.2	6.8	7.8	22.2	12.5
CoffeeLeafStratum	-	-	1.1	24.5	-

TABLE 4

Description of the parameter estimates of the models *MinTairShade*, *MaxTairShade, MinTleaf, MaxTleaf* and *HoursLW*

		Models								
		MinTairShade	MaxTairShade		MinTleaf		MaxTleaf		HoursLW	
Independent variables		Parameter value [±standard error]	Parameter value [±standard error] [b]		Parameter value [±standard error] [b]		Parameter value [±standard error] [b]		Parameter value [±standard error] [b]	
Intercept		$\alpha_1 = 1.23$ [± 0.14]	$\beta_1 = 3.84$ [± 0.63]	-	$\gamma_1 = 0.28$ [± 0.21]	-	$\delta_1 = 18.6$ [± 1.64]	-	$\varepsilon_1 = -37.07$ [± 2.69]	-
MinTairSun		$\alpha_2 = 0.94$ [± 0.0087]	-	-	$\gamma_2 = 0.92$ [± 0.0071]	-	$\delta_3 = -0.074$ [± 0.033]	-	-	-
MaxTairSun		-	$\beta_2 = 0.77$ [± 0.021]	-	-	-	$\delta_2 = 0.86$ [± 0.031]	-	$\varepsilon_3 = -0.16$ [± 0.049]	-
RHSun		-	-	-	$\gamma_3 = 0.0058$ [± 0.0026]	-	$\delta_4 = -0.13$ [± 0.014]	-	$\varepsilon_2 = 0.66$ [± 0.021]	-
RainfallSun		-	-	-	-	-	-	-	$\varepsilon_4 = 0.023$ [± 0.0097]	-
classAgroforSyst [a]	A	-	$\beta_3 = 1.13$ [± 0.22]	b	$\gamma_4 = 0.62$ [± 0.039]	d	$\delta_5 = -2.79$ [± 0.]	b	$\varepsilon_5 = -1.69$ [± 0.29]	a
	B	-	$\beta_3 = 0$	a	$\gamma_4 = 0.18$ [± 0.11]	ab	$\delta_5 = -4.01$ [± 0.47]	ab	$\varepsilon_5 = -1.42$ [± 0.77]	ab
	C	-	$\beta_3 = 1.54$ [± 0.22]	c	$\gamma_4 = 0.76$ [± 0.038]	cf	$\delta_5 = -3.12$ [± 0.17]	b	$\varepsilon_5 = -1.02$ [± 0.28]	a
	D	-	$\beta_3 = 0.77$ [± 0.24]	b	$\gamma_4 = 0.87$ [± 0.048]	ef	$\delta_5 = -4.91$ [± 0.22]	a	$\varepsilon_5 = -1.95$ [± 0.37]	a
	E	-	$\beta_3 = 2.70$ [± 0.22]	e	$\gamma_4 = 0.58$ [± 0.033]	d	$\delta_5 = -1.65$ [± 0.15]	c	$\varepsilon_5 = -1.81$ [± 0.26]	a
	F	-	$\beta_3 = 2.99$ [± 0.28]	e	$\gamma_4 = 0.56$ [± 0.071]	cd	$\delta_5 = 0.40$ [± 0.32]	d	$\varepsilon_5 = -1.09$ [± 0.53]	ab
	G	-	$\beta_3 = 2.71$ [± 0.25]	e	$\gamma_4 = 0.52$ [± 0.064]	bd	$\delta_5 = -1.62$ [± 0.29]	c	$\varepsilon_5 = 0.34$ [± 0.40]	b
	H	-	$\beta_3 = 2.46$ [± 0.29]	e	$\gamma_4 = 1.04$ [± 0.075]	e	$\delta_5 = -3.78$ [± 0.34]	ab	$\varepsilon_5 = -0.49$ [± 0.56]	ab
	I	-	-	-	$\gamma_4 = 0$	a	$\delta_5 = 0$	d	$\varepsilon_5 = 0$	b
CoffeeLeafStratum	Bottom	-	-	-	-	-	$\delta_6 = 0$	a	-	-
	Middle	-	-	-	-	-	$\delta_6 = 2.01$ [± 0.13]	b	-	-
	Top	-	-	-	-	-	$\delta_6 = 4.95$ [± 0.13]	c	-	-

[a]: A: Shade tree height ≥ 7m, canopy openness ≥ 50% and irregular light gap distribution (> 2.6)
B: Shade tree height ≥ 7m, canopy openness ≥ 50% and regular light gap distribution (≤ 2.6)
C: Shade tree height ≥ 7m, canopy openness < 50% and irregular light gap distribution (> 2.6)
D: Shade tree height ≥ 7m, canopy openness < 50% and regular light gap distribution (≤ 2.6)
E: Shade tree height < 7m, canopy openness ≥ 50% and irregular light gap distribution (> 2.6)
F: Shade tree height < 7m, canopy openness ≥ 50% and regular light gap distribution (≤ 2.6)
G: Shade tree height < 7m, canopy openness < 50% and irregular light gap distribution (> 2.6)
H: Shade tree height < 7m, canopy openness < 50% and regular light gap distribution (≤ 2.6)
I: Full sun exposure

[b]: by model and by factor, the modalities that do not share a letter are significantly different