

The understory microclimate in agroforestry now and in the future – a case study of Arabica coffee in its native range

Francesco Zignol^{a,b,*}, Erik Kjellström^{c,b}, Kristoffer Hylander^{a,b}, Biruk Ayalew^{a,b},
Beyene Zewdie^{a,b}, Alejandro Rodríguez-Gijón^{a,d}, Ayco J.M. Tack^{a,b}

^a Department of Ecology, Environment and Plant Sciences, Stockholm University, SE-106 91 Stockholm, Sweden

^b Bolin Center for Climate Research, Stockholm University, SE-106 91 Stockholm, Sweden

^c Rossby Centre, Swedish Meteorological and Hydrological Institute, SE-601 76 Norrköping, Sweden

^d Science for Life Laboratory, SE-171 65 Stockholm, Sweden

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ABSTRACT

Climate change is having a major impact on crop production and food security worldwide, and particularly so for smallholder farmers. As agroforestry is common with smallholder farmers, it is important to not only model the macroclimate, but also the microclimate that crops experience below the canopies. However, there are few high-resolution spatiotemporal climate projections for forest understories, because of constraints related to the lack of i) development of models for downscaling global climate projections, ii) high-resolution gridded datasets of environmental factors influencing microclimate, and iii) spatially replicated in-situ microclimate measurements. We focused on a landscape in southwestern Ethiopia where Arabica coffee originated, and, in the present day, is commonly grown as a shade crop. We first examined the relative contribution of in-situ field measurements vs. GIS-derived estimates of vegetation and topographic features in explaining in-situ microclimate. Second, we used a statistical downscaling approach to obtain past and future microclimate maps at 30-meter spatial resolution for the part of the landscape that is covered by trees. Predictive models using in-situ variables performed equal to models with GIS variables, indicating that remote sensing data might substitute for in-situ field measurements. Vegetation and topographic features were both important in explaining microclimatic variation. Our spatiotemporal projections of the microclimate indicate that coffee farming might have to relocate to higher altitudes due to increasing temperatures, that vegetation might buffer the macroclimate at middle altitudes to some extent, and that decreasing trends in relative humidity at the beginning of the wet season might become problematic for coffee production. Taken together, our findings demonstrate that we can rely on remote sensing data to create microclimate maps in landscapes where in-situ field measurements are challenging, and we suggest how these microclimate projections can be used as a tool to promote climate-resilient agriculture at the local and landscape levels.

1. Introduction

Forest microclimate regulates many biophysical processes that take place within and below the tree canopy, and its physiological and ecological importance have been widely recognized, including in agroforestry systems (Chen et al., 1999; von Arx et al., 2013; Hylander et al., 2022). As global and regional climates are warming at a fast pace, microclimate spatiotemporal variation in the understory below trees is also expected to change, with potential strong impacts on food production in agroforestry systems and thus on smallholder farmers'

livelihood (Morton, 2007; Lin et al., 2008). However, we lack insights into how understory microclimate dynamics will respond to the predicted macroclimate warming (De Frenne et al., 2013; Jucker et al., 2018; De Frenne et al., 2021). Indeed, while the general macroclimate conditions of the free atmosphere (e.g., air temperature, vapor pressure deficit, intensity of light) certainly influence microclimate, differences in the understory microclimate also result from the spatiotemporal heterogeneity of topographic and vegetation features (von Arx et al., 2012; Lembrechts et al., 2019; Kermavnar et al., 2020). With satellite-driven estimates of topography and vegetation becoming more

* Corresponding author.

E-mail addresses: francesco.zignol@su.se, francesco.zignol@gmail.com (F. Zignol).

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accurate in terms of spatial and temporal resolution and complementing in-situ observations, new insights into forest microclimate modelling can be gained, which is essential to obtain long-term high-resolution mapped time series of key microclimate variables, such as air temperature and humidity (Zellweger et al., 2019b; De Frenne et al., 2021). These cartographic products can be used in prediction of the impacts of forest microclimate changes on agroforestry crops, and will help identify global warming adaptation strategies that can be implemented by smallholder farmers at the local level (Meineri and Hylander, 2017).

The field of microclimate modelling has advanced over the last decade primarily due to the advent of inexpensive loggers that can record multiple climate variables and the availability of remote sensing products at ever-higher spatiotemporal resolution (Pan et al., 2017; Greiser et al., 2018). In predictive models, logger data are mostly used for calibration and validation purposes, whereas remote sensing data and in-situ observations of environmental features generally serve as predictors (Nechad et al., 2010; George et al., 2015; Balsamo et al., 2018). Remote sensing data allows estimating microclimate variability over continuous surfaces. On the other hand, in-situ measurements can provide a more detailed description of the local environment, but collecting such data can be time-consuming and requires more economic resources, especially in remote areas. Despite the increasing spatiotemporal resolution and improved algorithms, remote sensing products should be tested for accuracy based on analogous data collected on site.

Spatiotemporal microclimate patterns in forests are determined by the interaction of several climatic and environmental factors, which can contribute in different ways depending on the microclimate variable and spatiotemporal scale considered (Zellweger et al., 2019a). Most drivers of understory microclimate can be grouped into three broad categories: the macroclimate outside the forest, the landscape topography, and the vegetation structure and composition (Chen et al., 1999; De Frenne et al., 2021). The seasonal large-scale atmospheric patterns and the prevailing meteorological conditions outside the forest clearly have a major impact on the understory microclimate. Topography also influences microclimate spatial variability due to pooling of cold air in depressions, exposure to winds, variation in incoming solar radiation attributable to aspect and slope, variation in soil moisture, and the adiabatic lapse rate caused by altitudinal gradients (Jucker et al., 2018; Rita et al., 2021). Finally, vegetation strongly affects microclimate by canopy shading, evaporative cooling, providing shelter from wind and heavy rainfall, and buffering macroclimate temperature extremes. Examples of vegetation predictors that have been used to model forest microclimate include distance to forest edge, canopy cover, basal area, plant area index, leaf area index, tree age distribution, and forest edge orientation (Greiser et al., 2018; De Frenne et al., 2021). Understanding the interplay of different climatic and environmental drivers for target microclimate variables is essential in that it might enable a farmer to manage some of these factors to buffer the impacts of global warming and induce more favorable crop-specific microclimates (Wang et al., 2017; Hylander et al., 2022).

In addition to understanding the mechanisms that drive microclimate, several studies have attempted to map microclimate in forested areas at different spatial and temporal scales for a variety of purposes (George et al., 2015; Greiser et al., 2018; Haesen et al., 2021). While many of them have focused on predicting maximum and minimum air temperatures, only few have modelled other relevant microclimate variables, such as air humidity (e.g., von Arx et al., 2012; Klimes et al., 2022). Seasonal dynamics of atmospheric humidity, however, can be very important; for example, it has a major impact on the flowering and berry development of Arabica coffee (DaMatta et al., 2007; Jayakumar et al., 2016). Moreover, mapping explicitly future microclimate has received little attention in the field of ecology (De Frenne et al., 2021). Downscaling global climate projections to obtain gridded maps of future microclimate in forest understories is crucial for smallholder farmers and local governments to identify measures and undertake actions in the effort of adapting to climate change.

East Africa is one of the regions with the highest vulnerability to climate change due to significant development constraints, such as governance challenges and limited access to basic services and resources, violent conflicts, poverty, and high levels of climate-sensitive livelihoods (IPCC, 2022). Coffee smallholder farmers in southwestern Ethiopia, for example, heavily rely on a narrow range of climatic and environmental conditions to produce high-quality coffee and sustain their livelihoods (Teketay, 1998; Davis et al., 2012; Moat et al., 2017). The moist forests of the Ethiopian Highlands, the main center of origin of Arabica coffee, have provided these conditions for centuries, making coffee not only one of the main sources of Ethiopia's export earnings, but also a fundamental component of Ethiopian culture (Petit, 2007; Davis et al., 2012). However, macroclimate warming is posing a threat to coffee production in this region, with some impacts already experienced by local farmers, such as an increase in coffee diseases and decrease in coffee yield (Moat et al., 2017). For these reasons, studying microclimate changes in the agroforestry system of the Ethiopian Highlands in the context of climate change is particularly relevant. In addition, the heterogeneity of topographic and vegetation features makes this landscape an interesting case study from a microclimate modelling perspective.

We investigated spatiotemporal variation in microclimate in the tree-covered part (forests and agroforests) of a representative landscape in the southwestern Ethiopian highlands with a gaze on past, present, and future conditions, and aimed at uncovering some of the environmental factors that drive this variability. By quantifying the relative importance of macroclimate, topography, and vegetation in explaining understory air temperature and relative humidity across different seasons in a tropical forest landscape, and by creating future projections of microclimate for the study landscape, we intended to provide insight into potential climate change adaptation strategies related to coffee production. Our specific aims were: (i) to assess the relative contribution of in-situ measurements and remote sensing data in modelling microclimate, (ii) to examine the relative importance of macroclimate, topography, and vegetation drivers in modelling microclimate, and (iii) to predict monthly microclimate at 30-meter resolution for the period 1979–2100 by considering different climate change scenarios. We expected that remote sensing data of both topographic and vegetation features are essential to model the spatial variation of understory microclimate. We also anticipated that the predicted global warming (IPCC, 2022) will modify the current understory microclimate in the southwestern Ethiopian highlands, with potential drastic consequences for coffee cultivation at lower altitudes.

To test these hypotheses, we focused on two climate variables that strongly influence coffee plant physiology: air temperature (both daily maximum and daily minimum) and relative humidity (daily mean); hereinafter we refer to these variables when using the term “microclimate”. From a methodological point of view, we first analyzed temperature and relative humidity data that were recorded between 2018 and 2020 through hundreds of loggers located at 60 sites representative of different environmental conditions across an area of about 3,350 km². Then, we developed a landscape-specific spatiotemporal model that predicts monthly temperatures and relative humidity based on weather station daily time series and a variety of in-situ measured and remote sensing variables of topographic and vegetation features. Finally, we derived historical estimates and future projections of temperature and relative humidity by driving the landscape-specific spatiotemporal model with statistically downscaled reanalysis data and global climate model outputs according to different climate change scenarios.

2. Material and methods

2.1. Study area

We focused on a 67 × 50 km landscape in Jimma zone, Oromiya region, in southwestern Ethiopia (Fig. 1). The study area used to be

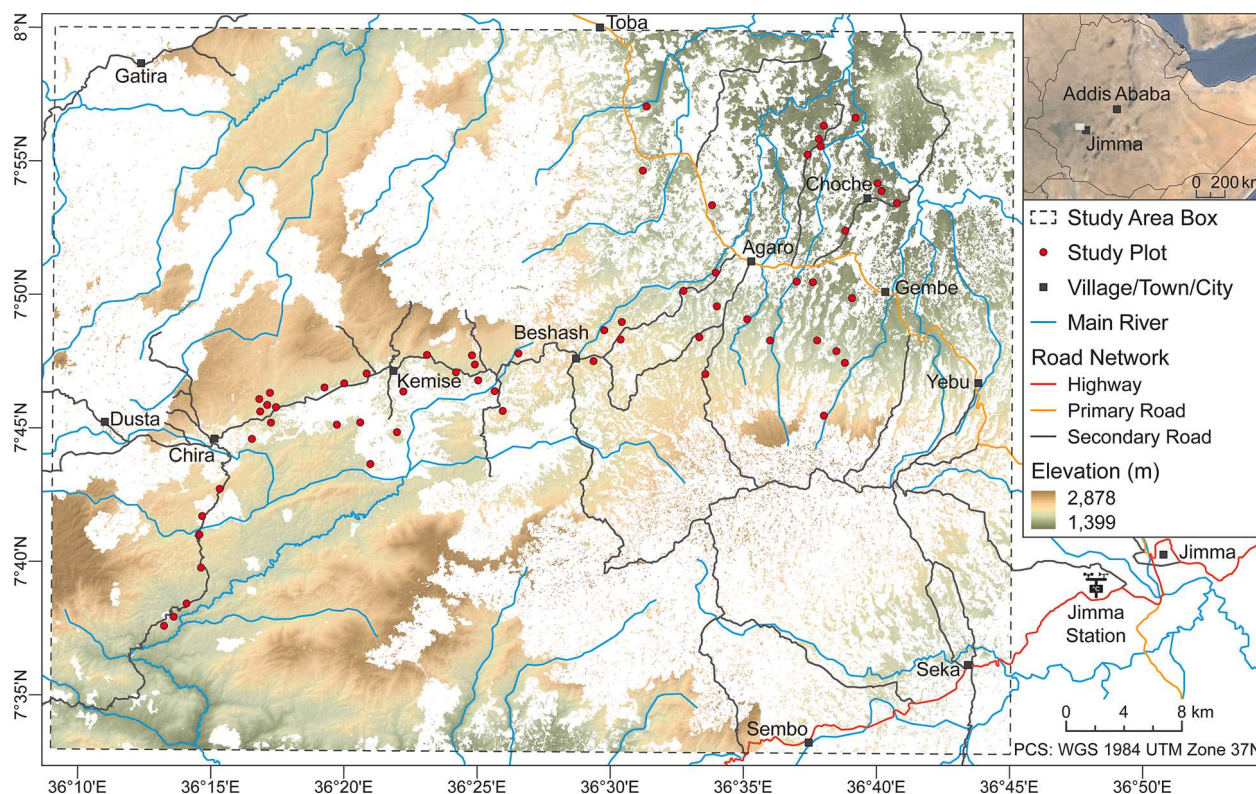


Fig. 1. Overview of the study area in Jimma zone, southwestern Ethiopia. Displayed in the top right is an inset map of Ethiopia, with the study area northwest of Jimma indicated by a white rectangular box. Elevation is shown only for the area covered by trees (forests and agroforests), where microclimate is modelled. The map also illustrates the main roads, rivers, and settlements as well as the 60 study plots where microclimate was measured and the Jimma meteorological station that provided the long-term climate time series needed for statistical downscaling.

dominated by moist Afromontane forest, where Arabica coffee grew wild in the understory along an elevational range from 1200 to 2000 m (Gole et al., 2008; Friis et al., 2010; Moat et al., 2017). Nowadays, it is a mosaic landscape consisting of extensive natural forests with coffee growing with little or no management in the interior of the forest and more intensive management along forest margins, forest fragments that in most cases are dominated by coffee agroforestry, a few commercial coffee plantations, tree-rich home gardens, grazing lands, and annual croplands (Lemessa et al., 2013; Zewdie et al., 2020; Beche et al., 2022). Based on records from the Jimma meteorological station (see Fig. 1) for the period 1985–2014 (see Table S1), the average of the total annual rainfall is 1557 mm, whereas the annual averages of daily minimum and maximum temperatures are 11.7°C and 27.6°C, respectively (see Fig. S1). The main wet season is from June to September (mean rainfall of 895 mm), while the main dry season is from December to February (mean rainfall of 122 mm), with a mean relative humidity of 81% and 68% during the wet and dry season, respectively (see Fig S1).

2.2. Climate and environmental data

As for climate data, we monitored air temperature and relative humidity in each of the 60 sites from March 2018 to September 2020 using iButton (model DS1921G-F5, Maxim Integrated, San Jose, CA, USA) and LASCAR dataloggers (LASCAR EL-USB-2), respectively. The iButton and LASCAR dataloggers were placed to avoid direct sunlight, and were set to record every three hours and every hour, respectively. iButton dataloggers were attached to branches of coffee at a height of approximately 1.5 m above the ground using an iButton wall mount (Maxim Integrated), and LASCARs were attached to shade tree branches approximately 2 m above the ground using ty-wraps. We run a comprehensive quality check on the 1560 time series collected over the entire study period, including visually inspecting each of them independently. We

also acquired daily long-term (1981–2020) time series of air maximum temperature, air minimum temperature, air relative humidity, and rainfall from the Jimma weather station, which is located about 40 km east of the center of the study area (Fig. 1). Finally, we used reanalysis data from the European Centre for Medium-Range Weather Forecasts (ECMWF) Atmospheric Reanalysis Fifth Generation (ERA5; Hersbach et al., 2020) dataset and Global Climate Model (GCM) data from the Coupled Model Intercomparison Project Phase (CMIP6; Eyring et al., 2016) dataset. We downloaded both reanalysis and GCM data from the Canadian Centre for Climate Modelling and Analysis (CCCma) at the daily time scale for the periods 1979–2014 and 2015–2100, respectively (ECCC, n.d.). All daily data were provided at the same atmospheric horizontal resolution ($2.8125^\circ \times \approx 2.8125^\circ$ based on a 64×128 latitude-longitude global Gaussian grid) and normalized over the period 1981–2010 (ECCC, n.d.).

Regarding environmental data, we included the in-situ variables elevation, slope, canopy cover, number of large trees, and number of canopy layers, as well as the GIS-derived variables Digital Elevation Model (DEM), direction to forest edge, distance to forest edge, distance to sink, Enhanced Vegetation Index (EVI), Fraction of Photosynthetically Active Radiation (FPAR), Leaf Area Index (LAI), Normalized Difference Moisture Index (NDMI), relative elevation, solar radiation, tree height, and Topographic Wetness Index (TWI). We obtained the forest layer (i.e., the area covered by trees; Fig. 1) based on overlaying two 30-m spatial resolution datasets, namely the global forest canopy height map (Potapov et al., 2021) and the EVI (Huete et al. 2002) derived from two contiguous Landsat 8 scenes, using a threshold of 7 m and 0.22, respectively. For a detailed description of these variables, methods used to measure the in-situ variables, and the estimation behind the GIS variables, see Table S2.

2.3. Methodological workflow

Understory microclimate results from the interactions of innumerable factors, which can be grouped into three main categories: the climate of the open space outside the forest (hereinafter called local climate), the topographic characteristics of the terrain of the focal site, and vegetation traits, such as vegetation structure and greenness of the canopy (Fig. 2). In our simulations, the local climate at the Jimma station, which, in turn, is driven by the macroclimate of the free atmosphere, provided the dynamic inputs for the microclimate predictive models (Fig. 2). On the other hand, the spatial distribution of topographic and vegetation features was assumed constant over time and contributed to the spatial variability of the modelled microclimate (Fig. 2). To predict spatiotemporal variations in understory microclimate over a long temporal scale, we designed a three-step approach as follows. First, we created a landscape-specific spatiotemporal model that predicts understory microclimate in 2019/2020 across the study area using a variety of predictors falling into the three aforementioned categories, namely local climate, topography, and vegetation. Second, we derived historical estimates and future projections of air temperature and relative humidity at the Jimma station by statistically downscaling reanalysis data and GCM outputs, respectively. Third, we combined the current landscape-specific spatiotemporal model with the local-climate projections to obtain future microclimate maps of the forests and agroforests in the region (Fig. S1 describes the three steps).

LANDSCAPE-SPECIFIC SPATIOTEMPORAL MODEL – To predict the observed maximum temperature, minimum temperature, and relative humidity at the 60 study sites, we used the corresponding climate variables recorded at the Jimma station and a variety of in-situ measurements and GIS-derived variables as predictors. We developed a series of monthly and annual models using the forest-based classification and regression tool in ArcGIS Pro, which relies on the Leo Breiman's random forest algorithm (Breiman et al., 2017). Because of the relatively low number of recording sites (i.e., 60) and the lack of continuous time series both for the Jimma station and the loggers, we combined the spatial and temporal information to increase the statistical power of this supervised

machine-learning method. Specifically, we employed daily and monthly time series in monthly and annual models, respectively. We created twelve monthly models and one annual model from March 2019 to February 2020 (when most logger data were available) for each climate variable (i.e., maximum temperature, minimum temperature, and relative humidity) and each category of predictors (i.e., only variables measured on site, only GIS-derived variables, and a combination of both), for a total of 117 models (i.e., 3 climate variables $\times$ 3 predictor categories $\times$ [12 monthly + 1 annual models]). We calculated the relative importance of predictors by means of the Gini coefficient (Gini, 1912). As a measure of accuracy, we produced 100 ensembles for each model by randomly selecting at each round 90% of the dataset to build the model and the remaining 10% of the dataset to validate it.

STATISTICAL DOWNSCALING MODEL – To obtain historical estimates and future projections of maximum temperature, minimum temperature, relative humidity, and rainfall at the Jimma station, we statistically downscaled reanalysis and GCM data using the open-source software Statistical DownScaling Model (SDSM; Wilby et al., 2002; Wilby and Dawson, 2013). SDSM relies on robust statistical downscaling procedures, namely a regression-based transfer function and a stochastic weather generator. The regression-based method involves identifying an empirical relationship between a set of regional-scale climate predictors and a site-specific climate variable, called predictand; under the assumption of stationarity (i.e., model parameters do not change over time), this relationship is then transferred to other periods for which equivalent predictors are available. The stochastic weather generator produces ensembles of synthetic daily time series of local climate variables with statistical properties that are derived empirically from the underlying distribution (Mearns et al., 2014). This serves as a means to estimate the prediction error associated with the downscaling process. After a data quality check, we created four statistical downscaling models (one for each climate variable) using a variety of coarse-resolution atmospheric predictors at different pressure levels (i.e., 1000, 850, and 500 hPa) and at the surface level from the ERA5 dataset for the period 1985–2014. We selected half of the dataset (odd years) for calibrating the model and the second half (even years) for

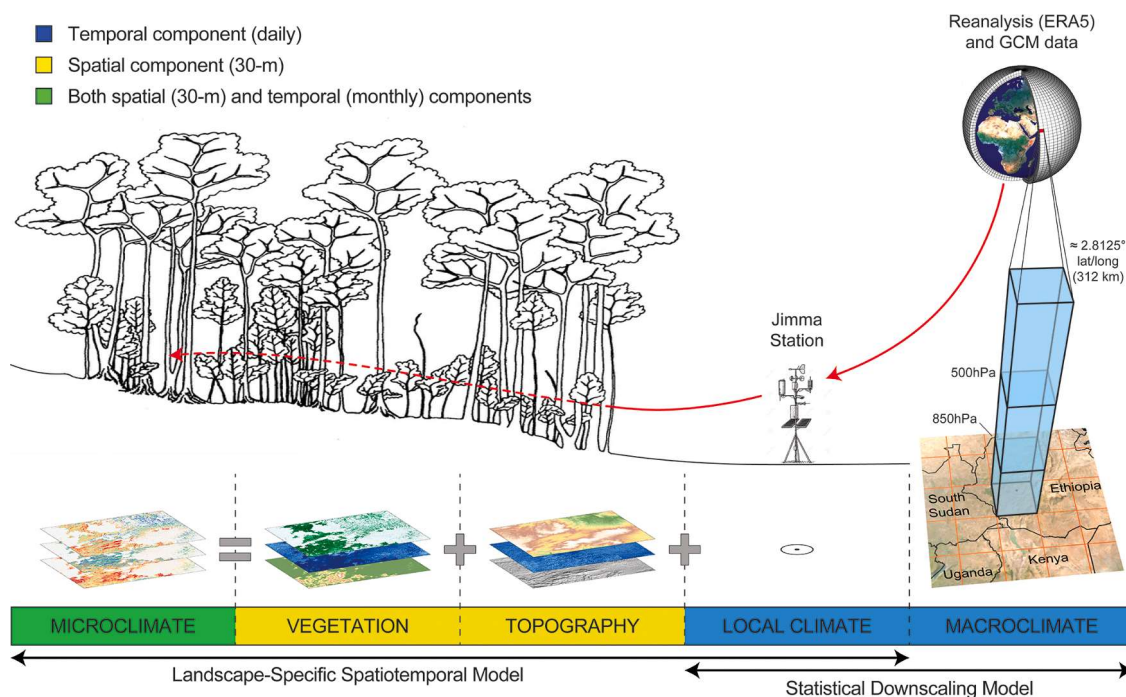


Fig. 2. Graphical representation of the three main drivers influencing forest microclimate: i) the climate outside the forest (i.e., the local climate), which, in turn, is driven by the macroclimate of the free atmosphere, ii) the topographic characteristics of the terrain where the forest grows, and iii) vegetation traits, such as vegetation structure and greenness of the canopy.

validating it (see Table S2 for dataset specifications). Once the models were validated, we imputed missing records of the Jimma daily time series starting from 1979 (i.e., the earliest year for which ERA5 data were available) and we estimated daily values up to 2100 (i.e., the latest year for which GCM data were available). To downscale future climate

variables, we chose three CMIP6 GCMs spanning a range of Equilibrium Climate Sensitivity (ECS): the Canadian Earth System Model version 5 (CanESM5; Swart et al., 2019) with relatively high ECS, the Higher Resolution version of the Max Planck Institute Earth System Model (MPI-ESM1.2-HR; Müller et al., 2018) with medium ECS, and the

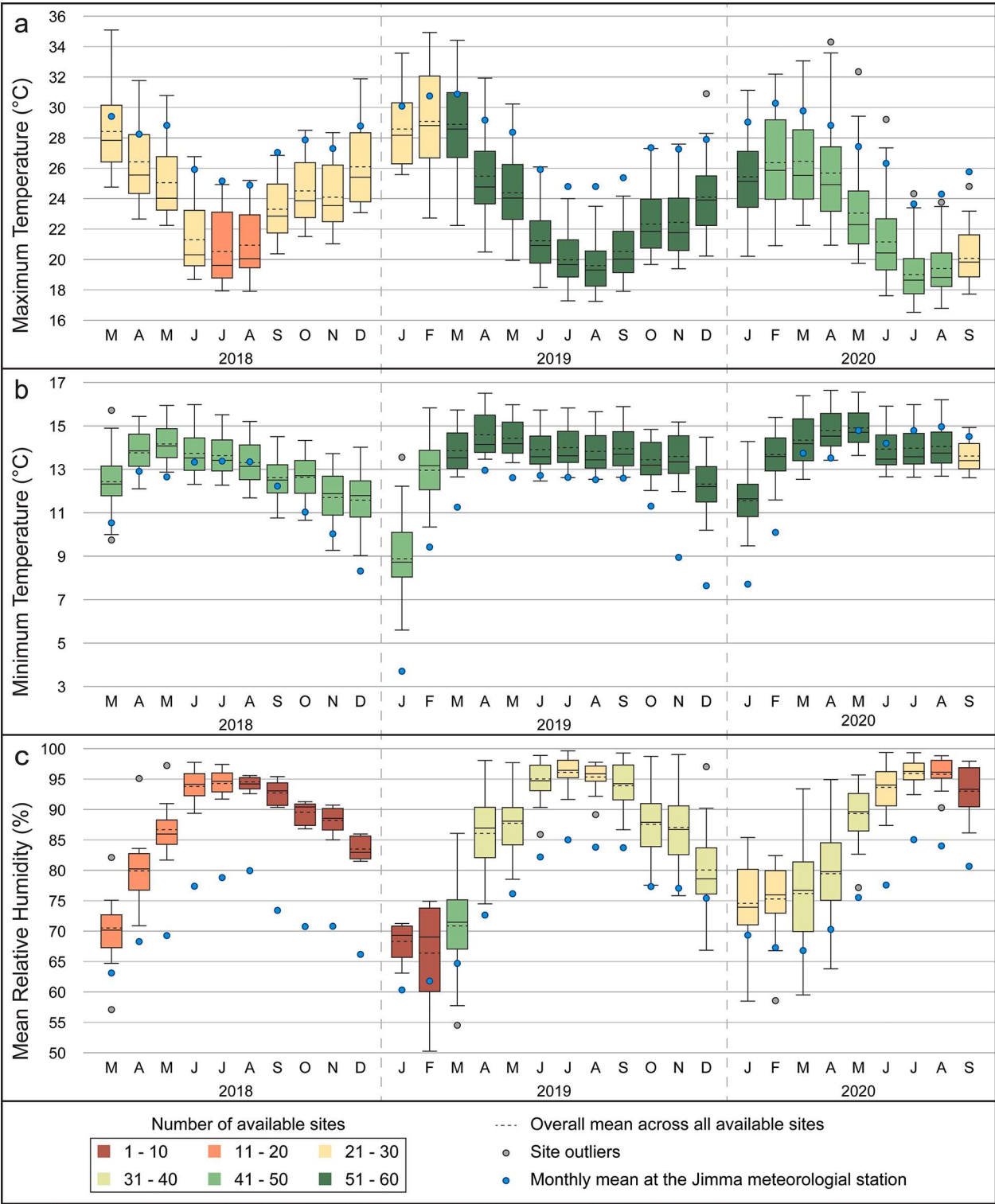


Fig. 3. Spatial variation of monthly averages of daily a) maximum temperature, b) minimum temperature, and c) mean relative humidity across the 60 study sites in southwestern Ethiopia from March 2018 to September 2020. Shown are box plots, with median values (heavy horizontal line), mean values (dotted horizontal line), first and third quartiles (box bottom and top), whiskers (showing either the minimum and maximum value or 1.5 times the interquartile range of the data, whichever is smaller), and, if present, outliers (gray circles). The number of available sites per month is indicated through a color code (see figure legend). As a reference, monthly means at the Jimma meteorological station are also displayed (blue circles).

Norwegian Earth System Model version 2 (NorESM2; Seland et al., 2020) with relatively low ECS. Also, we considered multiple Shared Socioeconomic Pathways (SSP; Riahi et al., 2017), ranging from a more sustainable, very low emission scenario (SSP1-1.9; CO₂ emissions cut to net zero around 2050) to a fossil fuel oriented, very high emission scenario (SSP5-8.5; CO₂ emissions close to triple by 2075).

MAPPING UNDERSTORY MICROCLIMATE – To obtain past and future microclimate maps at 30-meter spatial resolution over the entire forest-covered study area (see Fig. 1), we combined model outputs from the previous two steps (see Fig. 2 and Fig. S1). Specifically, we ran the landscape-specific spatiotemporal models at the annual temporal scale using current topographic and vegetation-related GIS data and monthly averages of the daily local-scale climate estimates at the Jimma station as predictors. This process was computationally demanding in terms of storage space and processing time. We ran three different models (one for maximum temperature, one for minimum temperature, and one for relative humidity) using thirteen different combinations of GCMs and emission scenarios for each year between 1979 and 2100, for a total of 4758 runs. In each run, the spatiotemporal model had to predict about 20 million values, as the forest-covered area encompassed almost 1.7 million pixels, whose values had to be calculated for all twelve months. We finally calculated monthly and annual normals over four 30-year periods (1981–2010, 2011–2040, 2041–2070, and 2071–2100) to summarize the results. In this article, we present a representative subset of microclimate maps derived from downscaling MPI-ESM1.2-HR SSP3-7.0, but all maps are made publicly available at the Bolin Centre Database of the Bolin Centre for Climate Research.

3. Results

3.1. Observed microclimate variability

The data from the loggers showed that monthly averages of daily maximum temperature, daily minimum temperature, and daily mean relative humidity ranged from 19°C to 29°C, 9°C to 15°C, and 66% to 96%, respectively (Fig. 3). Seasonal patterns followed expectations, with lower maximum temperature, higher minimum temperature, and higher relative humidity during the wet season from June to September than during the dry season from December to February. The combination of low maximum temperatures and high minimum temperatures during the wet season resulted in small daily temperature variations, while the opposite is seen for the dry season, with large daily temperature fluctuations (Fig. 3ab). The among-site variation in maximum temperature was higher than the among-site variation in minimum temperature, and the among-site variation in maximum temperature, minimum temperature, and relative humidity were lower during the wet season than during the rest of the year (Fig. 3).

3.2. Predicting observed microclimate

The observed spatiotemporal variability of maximum temperature, minimum temperature, and relative humidity was generally predicted well by the monthly and annual models ($R^2 > 0.5$; Fig. 4). Predictive power was higher for maximum temperature (mean $R^2 = 0.77$) than for minimum temperature and relative humidity (mean $R^2 = 0.65$), and higher for the annual models than for the monthly models (Fig. 4). Models with only in-situ predictors, only GIS predictors, or a combination of both explained a similar amount of variation for each climate variable (Fig. 4), with only minor differences (up to 7%) in predictive power between the models in specific months. Despite similar R^2 values, the relative importance of predictors varied depending on the type of model considered. Overall, topography explained the majority of variation (mean $R^2 = 0.28$), followed by local climate (mean $R^2 = 0.23$) and vegetation (mean $R^2 = 0.19$). Local climate and vegetation contributed relatively more to the site-based models, topography more to the GIS-based models, and vegetation to the combined models. The relative

importance of predictors also varied by month and climate variable (Fig. 4). For example, vegetation explained 45% of the variation (mean $R^2 = 0.37$) in maximum temperature during the peak of the dry season in January, which resulted in a higher predictive power than the other months and variables (Fig. 4).

3.3. Downscaling future climate

The predictions from the statistical downscaling model for the Jimma station matched closely the observed values (Fig. S2, Tables S2 and S3; see Fig. 5 for the atmospheric variables used as predictors in the downscaling procedure). When downscaling the climate variables for 2071–2100, projections varied strongly among GCMs and emission scenarios. For each of the three GCMs it is clearly seen that the emission scenario had a central role in determining the long-term response. Depending on GCM and variable, scenarios started to diverge at different points in time in the first few decades. At the end of the century, comparing to 1981–2010, annual mean changes ranged from less than 1°C increase in temperature, and no change in relative humidity, according to the SSP1-2.6 scenario with the Norwegian GCM to more than 4°C increase in temperature, and 6% increase in relative humidity, in the SSP5-8.5 scenario with the Canadian GCM (Fig. 5). When looking across the study area, the increments in maximum and minimum temperature were usually higher at lower elevations in the northeast and southwest compared to the high altitudinal area in the west (Fig. 6ab). Monthly changes in relative humidity were also larger at lower elevations, but the direction of the change in relative humidity differed among months (Fig. 6c and Fig. S5). For all three climate variables, the absolute change is usually larger in areas that experience the highest temperatures and lowest relative humidity over the reference period (i.e., 1981–2010; Fig. 6). Regarding landscape features, the increments in maximum and minimum temperature were highest – while relative humidity tended to decrease (at least during parts of the year) – along forest edges, rivers, and roads (Fig. 6; see also Fig. 1 as a reference). The increment in maximum temperature (up to 4°C) was generally larger than the increment in minimum temperature (up to 1°C; Fig. 6a, b). The increment in minimum temperature was particularly small from May to September, a pattern that was consistent across the entire study area (< 0.1°C; Fig. 6b). Relative humidity decreased at the beginning of the wet season in June and increased just before the dry season in November, whereas it did not change during the peak of the wet season in July and August (Fig. 6c and Fig. S5).

4. Discussion

In this study, we estimated the future understory microclimate in the forests and agroforests of a representative landscape in southwestern Ethiopia to better understand potential consequences of climate change for agroforestry by smallholder farmers. We used a combination of in-situ microclimate observations, spatially-explicit information of the landscape characteristics, and statistically downscaled GCM projections to develop a series of maps of air temperature and relative humidity at 30-meter spatial resolution and monthly temporal resolution up to 2100 under multiple climate change scenarios. Below we discuss the key findings that emerged from our analysis by focusing on each of the three study aims in turn.

We found that in-situ landscape measurements and remote sensing data were equally good in explaining understory microclimate at 30-meter spatial resolution. Few studies have directly compared the ability of remote sensing estimates and ground measurements in predicting microclimate, but their results are similar to ours (e.g., Kašpar et al., 2021). If these findings are generalizable to other regions, it means that we can predict the microclimate in less accessible areas where in-situ variables are difficult to measure and/or funding is lacking, such as in many areas of the Global South. This finding is particularly timely given the increasing spatial and temporal resolutions of global remote sensing

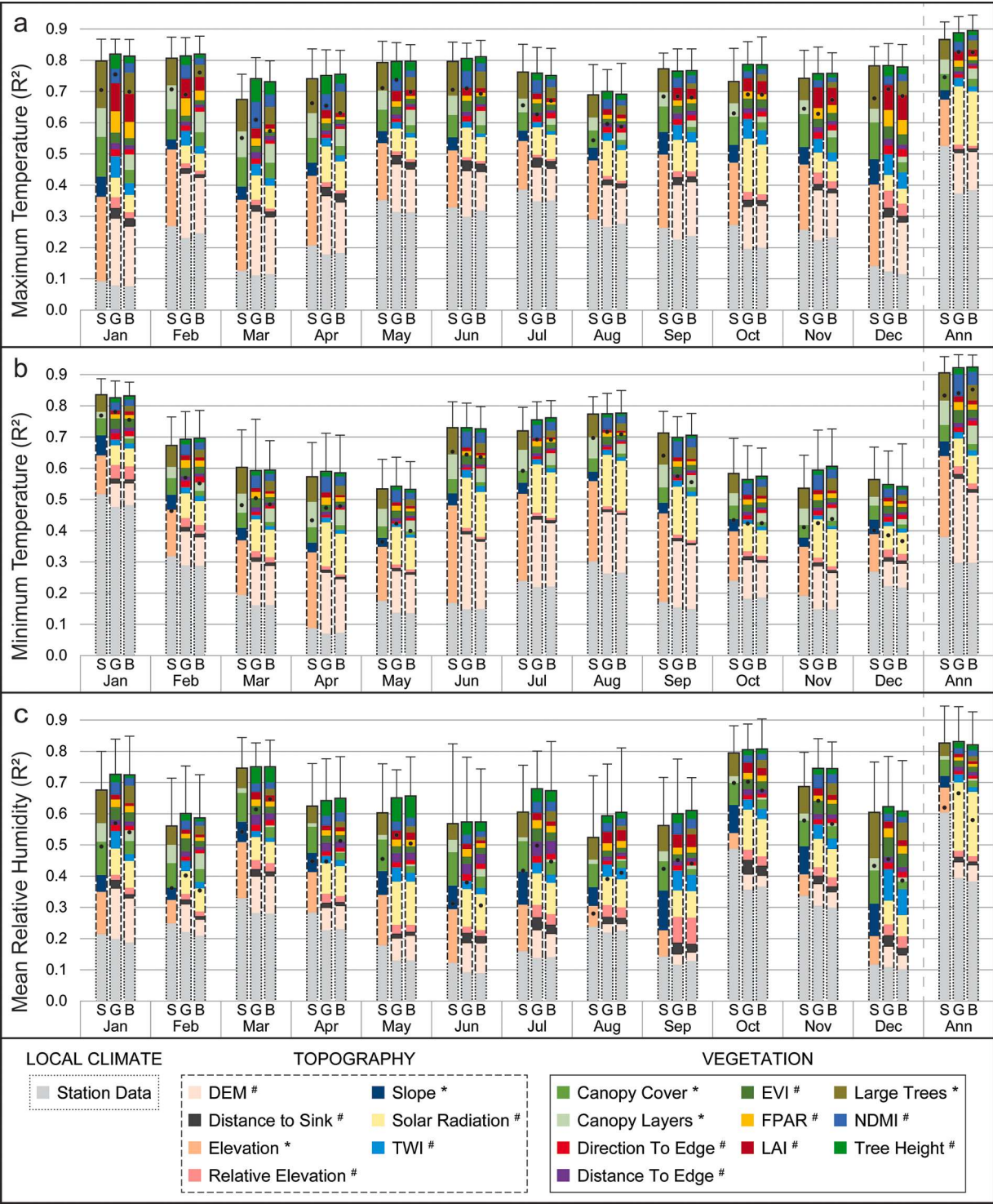


Fig. 4. Relative importance of predictors for monthly and annual models of daily time series of a) maximum temperature, b) minimum temperature, and c) mean relative humidity in 2019/2020 across 60 agroforestry sites. Results are displayed by model type: S, models comprising in-situ predictors (these variables are marked with an asterisk on the figure legend); G, models comprising GIS-derived predictors (these variables are indicated with a hash symbol on the figure legend); and B, models comprising both types of predictors together. Elevation and slope that were measured on site are not included in the combined models because of the presence of GIS predictors that provide analogous information (DEM and solar radiation, respectively). Weather station data are included in all three model types. The total R^2 displayed in each column represents the mean value of 100 validation ensembles that were generated by randomly selecting at each round 90% of the dataset to build the model and the remaining 10% of the dataset to validate it. In each column, the cap of the black vertical bar and the black point represent the ensembles with the highest and lowest R^2 , respectively.

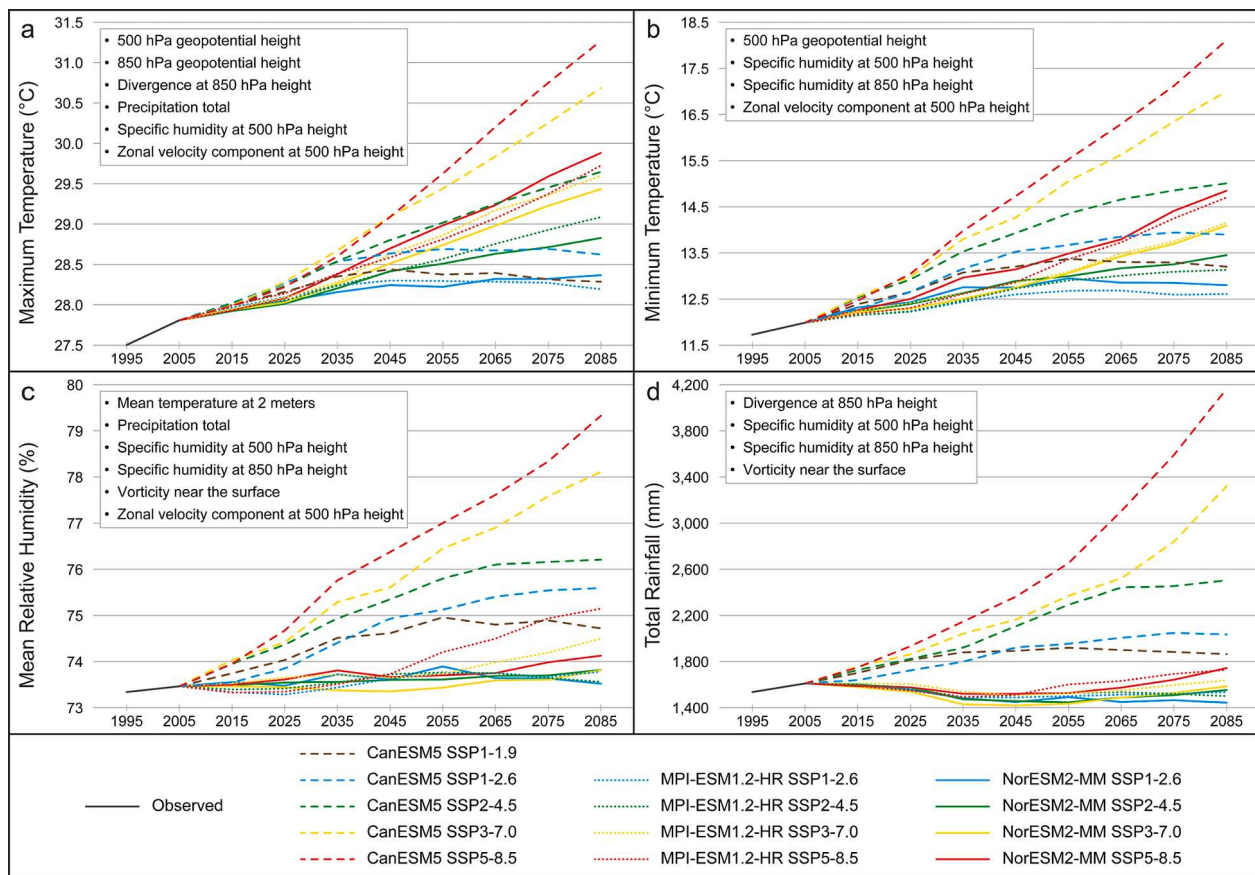


Fig. 5. Trend in 30-year annual normals of daily time series of a) maximum temperature, b) minimum temperature, c) mean relative humidity, and d) total rainfall at the Jimma meteorological station according to three Global Climate Models (GCMs) from the Coupled Model Intercomparison Project Phase 6 (CMIP6). The selected GCMs span a range of Equilibrium Climate Sensitivity (ECS) values from very high (CanESM5) and low (NorESM2-MM) to in-between (MPI-ESM1.2-HR) and are driven by different Shared Socio-economic Pathways (SSPs) representing a range of radiative forcing levels from very high (SSP5-8.5) and very low (SSP1-1.9) to in-between (SSP2-4.5). The marks (i.e., years) on the x-axis represent the midpoints of the 30-year normals starting from 1981-2010 (labeled as 1995) to 2071-2100 (labeled as 2085). Shown in the top left of each graphic is the list of large-scale predictors used for statistically downscaling the corresponding climate variable.

datasets and increasing computational power of data processors, which can make GIS-derived datasets an inexpensive and viable alternative to the more costly and time-consuming field measurements (Zellweger et al., 2019a). For example, the Global Ecosystem Dynamic Investigation (GEDI), which monitors the Earth's forests and topography from the International Space Station (ISS) at a very high spatial resolution using LIDAR technology, will allow for a three-dimensional reconstruction of the surface topography and forest structure (i.e., canopy height, canopy cover, and vertical structure metrics) at the global level, including remote areas or dense forests where in-situ measurements are challenging and landscape information are commonly lacking. We caution, however, that many microclimate models, including our own, are at least to some extent dependent on the specific site of application, rather than on generalizable processes and parameters, which means that in-situ measurements of key microclimate variables are still important for calibrating and validating GIS-based microclimate models (George et al., 2015; Man et al., 2022).

While the relative importance of predictors in explaining spatio-temporal variation in the understory microclimate was dependent on the climate variable being modelled and differed among months, both topography and vegetation contributed significantly to predicting microclimate, with topography often being slightly more relevant than vegetation. This matches the general notion that topography is one of the most important factors in affecting microclimate spatial variability, especially in mountainous regions (Dobrowski, 2011; Ward et al., 2018). In line with other studies (e.g., Aalto et al., 2017), not only elevation but also solar radiation, as a function of slope and aspect, strongly

influenced microclimate variability, which perhaps is surprising given the proximity to the equator (Åström et al., 2007). Similarly, soil moisture, represented here by TWI, was an important predictor for maximum temperature, possibly buffering high temperatures during the warmer months (e.g., Greiser et al., 2018). The importance of vegetation as a driver of understory microclimate and its buffering effect are also well documented (Jucker et al., 2018; Christiansen et al., 2022; De Lombaerde et al., 2022). It is interesting to note that, in the case of maximum temperature, the relative importance of vegetation is higher and the buffering effect is stronger during the dry season when the intra-monthly fluctuations in maximum temperature are larger (see also De Frenne et al., 2019). In the context of a warming climate and increasing climate extremes, these results reiterate that the topography of the region is probably the most important factor in determining where it will be possible to grow coffee in the future, with higher elevations becoming more suitable for agroforestry, and demonstrate that the forest structure can be a crucial factor in buffering climate extremes that would otherwise be critical for coffee plants.

For centuries, the humid forests of the Ethiopian Highlands have provided optimal climatic and environmental conditions for Arabica coffee to grow naturally under the canopy of native shade trees, and nowadays the livelihoods of many smallholder farmers is dependent on coffee (Gole et al., 2008). Because of global warming, the microclimate below the forest canopy is changing, which poses a serious threat to coffee production in a region where coffee represents the farmers' most important source of income and is a key component of their culture and everyday life. Our results indicated that air temperature is most likely to

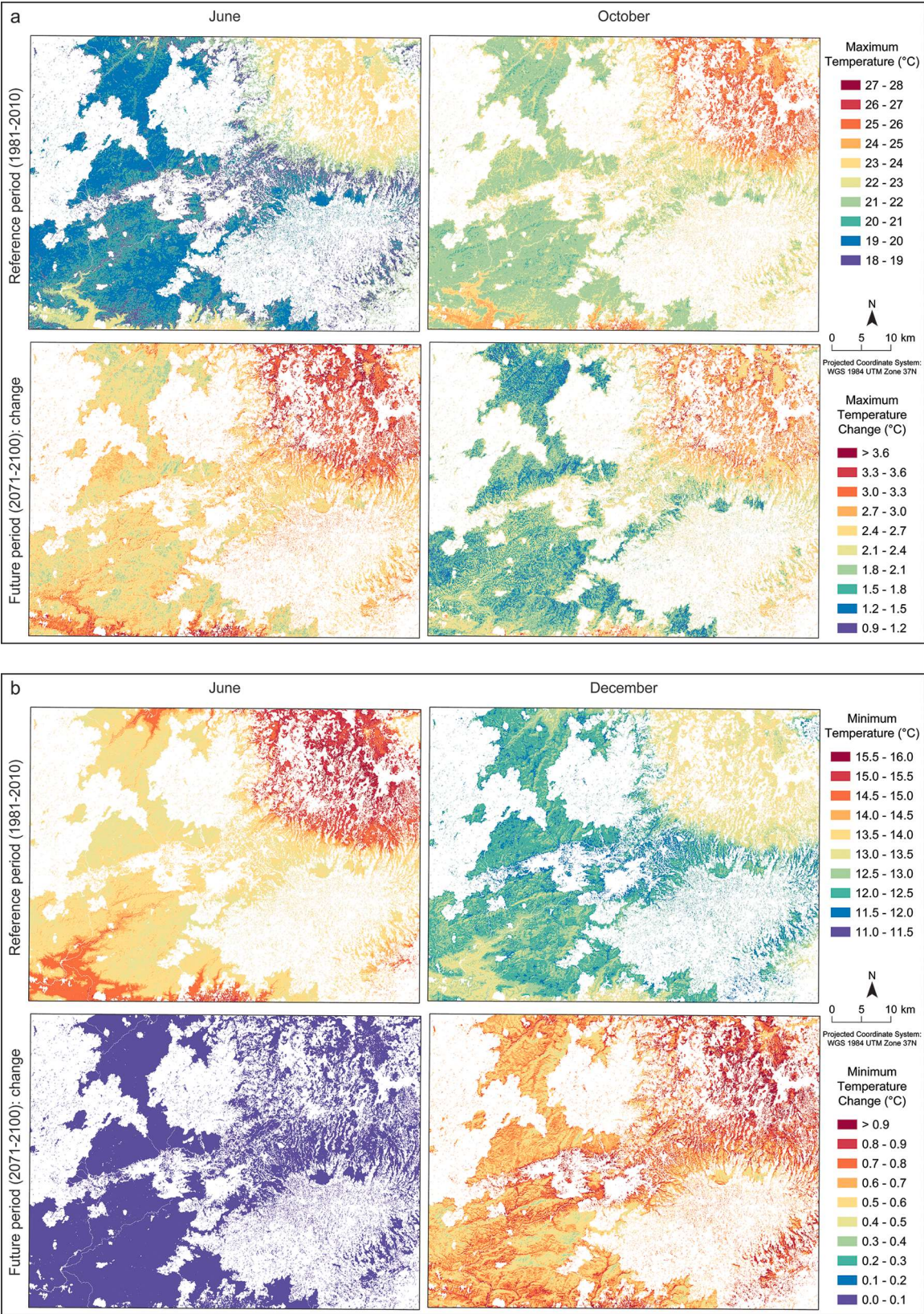


Fig. 6. Monthly normals for the reference period (1981-2010) and differences between the reference period and future period (2071-2100) for a) maximum temperature, b) minimum temperature, and c) relative humidity across the forested part of the landscape in southwestern Ethiopia. Two representative months are shown for each climate variable. All maps have a 30-meter resolution and are driven by the MPI-ESM1.2 under the SSP3-7.0. For the full set of maps of all months, see Figures S3, S4, and S5 (difference between reference period and future period).

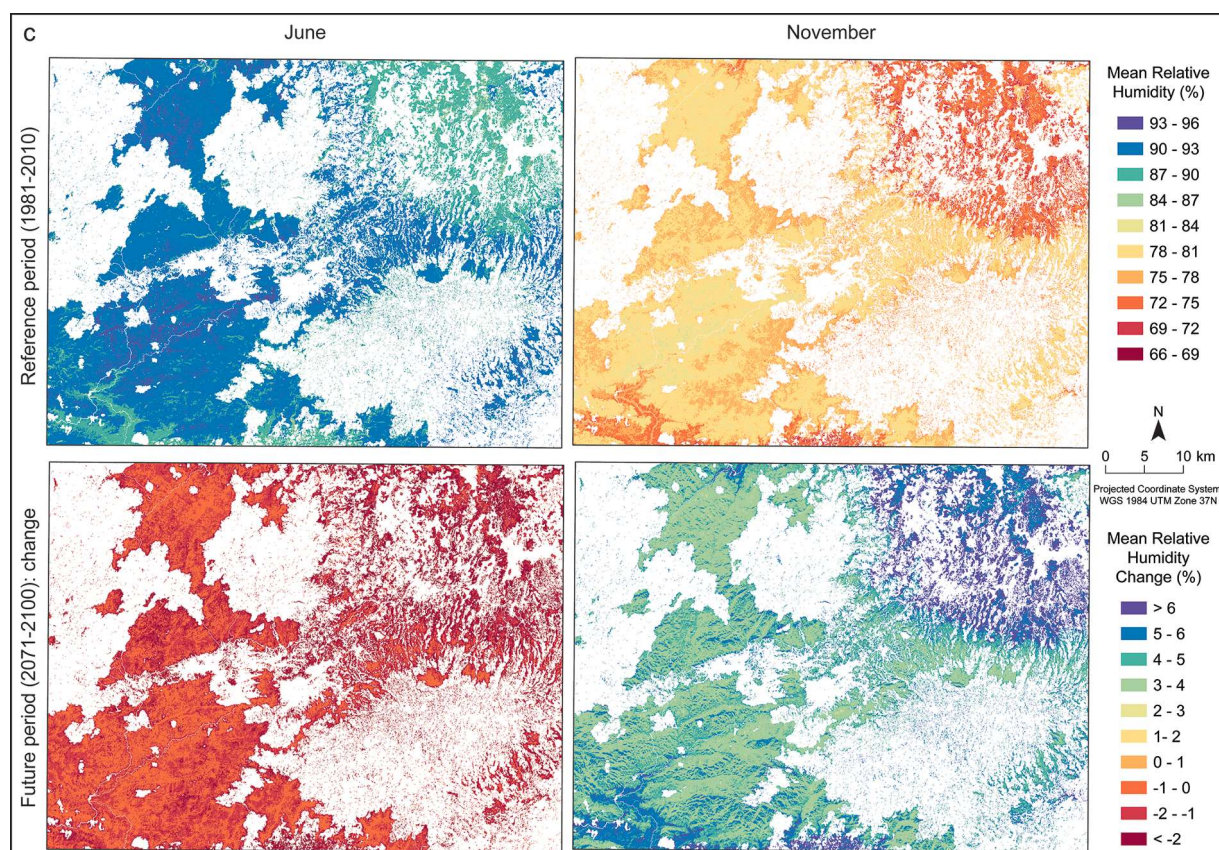


Fig. 6. (continued).

increase in the future, especially at lower altitudes and along forest edges, rivers, and roads. The expected increment in air temperature is higher for the daily maximums than the daily minimums and follows specific seasonal patterns, with maximum temperature increasing most during the months preceding the main wet season (April to June) and minimum temperature increasing most in the dry season, while remaining almost unaltered in the wet season. Based on these projections, the majority of coffee farms will experience a shift towards higher temperatures, as these cultivations are usually located close to the forest edge for accessibility reasons, but the magnitude of the change is altitude-dependent. In order to find climatic conditions suitable for growing coffee plants, relocating coffee production towards higher altitudes will probably be the only option. Coffee farms currently located at lower elevations may need to change to other crops (Davis et al., 2012; Corato and Ginbo, 2021), since temperatures in these areas are not only currently highest, but the predicted rate of climate change is also highest. Intensifying shade cover or modifying vegetation structure might be an alternative for middle-altitude farms (Lin et al., 2008; Koutouleas et al., 2022). Our results showed a more complex pattern for relative humidity, as it is expected to remain unaltered during the main wet season, decrease at the beginning of the wet season, and increase at the beginning of the dry season. In addition, the magnitude of the change, either positive or negative, is likely to be larger at lower altitudes and along forest edges, rivers, and roads. In these areas, the reduction of relative humidity together with the increment in maximum temperature during the months preceding the main wet season would affect coffee flowering, fruit initiation, and early fruit development stages, whereas the increase in relative humidity at the beginning of the dry season would be problematic for coffee harvesting. This means that changes in air relative humidity – which are less commonly modelled than air temperature – might be equally or more detrimental to future coffee production than changes in air temperature, and it is imperative

to understand what interventions can be made to alleviate negative consequences of such changes. Although our results showed that vegetation can be an important factor in explaining the microclimate spatiotemporal variability, explicitly modelling the interventions on forest structure to modulate the link between macroclimate and microclimate was beyond the scope of the study, but this could be an interesting aspect to investigate in the future. Similarly, we suggest that complementary high-resolution atmospheric dynamic models could be implemented for further validation. The microclimate maps produced in this research are made publicly available and can be used as a tool to plan climate change adaptation measures at the local and landscape levels and support climate-resilient agroforestry systems in south-western Ethiopia.

5. Conclusions

This work is a collaborative effort that brings together ecologists and meteorologists to advance our understanding of the complex relationship between macroclimate and forest microclimate in the context of global warming in a coffee agroforestry system. By combining methods and datasets that traditionally belong to either ecology or meteorology, this study is among the first to produce monthly microclimate maps for such a long period of time (1979-2100) and across multiple climate change scenarios. We showed that it is possible to predict future microclimate in agroforestry systems through the support of easily accessible remote sensing estimates of topographic and vegetation features, field logger time series of key microclimate variables, and statistically downscaled global reanalysis and GCM projections of most common atmospheric variables. Overall, the resulting maps revealed clear patterns and trends of air temperature and relative humidity that can be used as guidelines to develop long-term adaptation strategies to climate change at the local and landscape levels.

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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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at [doi:10.1016/j.agrformet.2023.109586](https://doi.org/10.1016/j.agrformet.2023.109586).

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