Article

Climate metrics for modelling conditions on pilgrimages in Ethiopia

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Weather influences human actions, including cultural practices. The effects of climate change on intangible heritage are widely discussed, yet there has been little work that links specific drivers of environmental change to such outcomes. This study develops a set of climate metrics relevant for pilgrimages, focusing on Ethiopia. It assesses the sensitivity of metrics to seasonal windows using observed data (ERA5 reanalysis and CHIRPS) and the ability of three GCMs (HadGEM3-GC31-MM, CMCC-ESM2 and NorESM2-MM) to capture climate metrics for dry season pilgrimages. Results show the importance of using time-windows relevant to processes or social practices that might not map onto traditional three-month seasons. Five of eight climate metrics assessed (minimum and maximum temperature, rain days, windchill and heat index) were successfully captured by the GCMs. These metrics could be used to assess future impacts of climate change on the conditions experienced by pilgrims in Ethiopia.

Changes in climate have numerous implications and impacts on human actions influencing, for example, the locations of settlements and industries[1,2], agricultural yields[3,4] and how much time we spend out-of-doors[5,6]. Such changes also pose multiple threats to heritage. There has been a widening interest in studying these threats in relation to tangible heritage and historic buildings[7–9] which is emerging as the discipline of heritage climatology[10]. Furthermore, climate affects our experience of cultural practices and forms of intangible heritage, such as artistic or religious expressions[11]. However, even though they have been widely discussed, the effects of climate change on intangible heritage have been less frequently the subject of detailed climate analysis, with much of the body of research only engaging superficially with the physical processes and not linking specific drivers of environmental change to impacts or effects[12].

The effects of climate on many forms of intangible heritage and cultural practices can be subtle and complex and has to recognise the intersection of the environment and traditions[13]. For example, the effect of gradual shifts in the timing of seasonal events has been shown with weather conditions no longer coinciding with set festival dates. The Yayoi Festival in Japan now uses artificial cherry blossoms[14], and in many countries winterscapes associated with festivities around Santa Claus and Christmas are consigned to films and greeting cards even where snow has historically been present[15,16]. Such subtleties can make it challenging to define specific climate metrics that are important to many heritage practices.

Nevertheless, the effect of climate on cultural practice is particularly apparent in the case of pilgrimages[17,18]. People undertake pilgrimages from across the world and can travel long distances using a range of different forms of transport, and some are traditionally undertaken on foot. This means that pilgrims are exposed to external climates that have the potential to pose challenges. For example, high temperatures can cause heat stress for people walking without access to shade, particularly when coupled with high humidity[19], and persistent rain can cause mountain pass roads to become vulnerable to landslides and intense thunderstorms can affect air traffic (Tola and Adamu pers comm. 2023). The effects of current extreme weather events on pilgrimages have already been studied with pilgrims performing the Hajj in the Saudi Arabia facing heat-related risks with increasing with rising temperatures[17,20,21], and those travelling along the Camino de Santiago Francés being affected by the changing frequency of precipitation and heat waves[22].

While past and current effects of weather and climate events on pilgrimages can be studied using data from sources such as oral testimonies and observed weather conditions[23], assessing the future requires the use of models so future scenarios can be projected. Climate models provide a useful tool for assessing future scenarios as they (i) are likely to provide lengthy datasets with few gaps and (ii) can be tailored to metrics that relate to heritage impacts[24,25]. As pilgrimage is global practice, it would be helpful if the impact of future climates could be applied at a global scale. Global Climate Models (GCMs) potentially provide a useful dataset as they are spatially complete, but struggle to reproduce key climate features in some regions, such as Africa, where climate processes can occur at spatial scales smaller than the resolution of GCMs and extreme orography poses a challenge because models use average elevations[26,27]. Furthermore, as many pilgrimages are often associated with specific dates, small shifts in the seasonality of climate could notably affect pilgrims' experiences. Consequently, the standard time periods commonly used in climate science research (e.g.

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assessing seasonality by dividing the year into four, 3-month periods) are unlikely to align with the shorter time periods relevant to pilgrimages.

This study builds on our previous work[18] and aims to develop and test a set of climate metrics relevant for pilgrimages, focusing on Ethiopia. This is a useful test case as (i) numerous pilgrimages, often on foot, are undertaken in the region each year and (ii) the country poses a challenge to GCMs due to issues such as the complex, extreme orography of the Highlands of Ethiopia[28]. We assess: (i) the sensitivity of a range of climate metrics to the time period studied using observed data and (ii) the ability of three GCMs to capture climate metrics relevant to pilgrimages. Result from this study can be used to define metrics that are useful for national policy makers to assess current and future climate-based challenges facing pilgrims. Furthermore, the approach taken in this study provides a methodology that could be used to assess the ability for climate models to capture heritage climate metrics for cultural practices in other regions. As the importance of climate change on cultural heritage is increasingly recognised in climate policy, understanding the limits of climate models is becoming ever more important.

Methods
Pilgrimage in Ethiopia
Ethiopia is the most populous country in eastern Africa with over 120 million people, of which almost 80% live in rural areas[29]. In the north and centre of the country, the Ethiopian Highlands (1500–4550 m) dominate, with the higher altitudes exhibiting alpine climates and vegetation (Fig. 1). In contrast, in the northeast, east and southeast, lowlands are associated with dry, hot climates (Fig. 1b). Seasonal rainfall in Ethiopia is driven by the movement of the ITCZ, resulting in the following seasons based on rainfall: Bega, the dry season from October to February, Belg the short rains from March to May, and Kiremt the long rains from June to September[30,31]. Historically, Ethiopian climate has been highly variable as highlighted by the serious droughts in the late 1960s that resulted in reduced agricultural productivity[32,33].

The Bega season is an important time for pilgrimages. During this period, pilgrims travel to Dirre Sheikh Hussein for the Sheikh's birthday on January 1st, to sacred churches such as the rock-hewn churches at Lalibela for Genna, Ethiopian Christmas (7th January) and for Timket, Epiphany (19th January) at places such as Gondar (UNESCO, 2019). Pilgrims may walk more than 1000 km to reach these destinations, traversing mountainous regions and are exposed to low temperatures and heavy rain events (Brimblecombe et al., 2024; Tola, 2023 pers. comm.). The final destinations are located in a range of geographic and climate settings from cool mountain climates (e.g., Lalibela) to warm-dry lowland areas (e.g., Dirre Sheikh Hussein). A changing climate may alter the climate-based risks that pilgrims are exposed to on their journeys or affect their financial ability to undertake pilgrimages, particularly when harvests have been poor (Tola, 2023, pers. comm.). Understanding the extent to which climate models are able to capture these climate-based risks is an important first step for being able to then understand how such risks vary over time and space or might be sensitive to changes in seasonality.

Climate metrics
Pilgrims may experience extremes in temperature and precipitation conditions, which can make their journey difficult. In Ethiopia, low temperatures can make sleeping at night uncomfortable and strong winds could lower the temperature experienced by pilgrims during their travels on foot[34]. High temperatures can make walking during the day exhausting, especially when coupled with high humidity as this impacts the body's ability to perspire[35]. We have opted to use wind chill and the heat index, rather than recently developed indices such as the Universal Thermal Climate Index (UTCI)[36], on the basis of greater familiarity with the traditional indices, especially beyond climatology and some lingering concerns about new indices for wind chill[37]. Rainfall events may hinder both pilgrims travelling by foot or by car as it makes paths and roads muddy and in extreme cases, impassable (Tola and Adamu pers. comm. 2023). Based on information from oral testimonies[18], we assess the following eight metrics to capture climate conditions that are challenging for pilgrimages in Ethiopia:

- Minimum daily temperature (°C): The mean minimum daily temperature for a given period.
- Days below 5 °C: The number of days within a given period where the daily minimum temperature falls below 5 °C.
- Maximum daily temperature (°C): The mean maximum daily temperature for a given period.
- Days above 35 °C: The number of days within a given period where the daily maximum temperature exceeds 35 °C.
- Maximum daily rainfall (mm): The maximum rainfall that fell on a single day within a given period.
- Rain days above 1 mm: The number of days where rainfall exceeds 1 mm within a given period.
- Wind chill: The experienced temperature accounting for the cooling effect of wind calculated using Eq. 1 [38].
- Heat Index: Combines temperature and relative humidity to calculate the temperature as it feels to the human body[39] calculated by Eq. 2 and adjusted, where required, by Eq. 3 [40].

$$Wind\ chill = 13.12 + 0.6215\mathrm{T_{min}} - 11.37\mathrm{v}^{0.16} + 0.3965\mathrm{T_{min}}\mathrm{v}^{0.16}$$

$$(1)$$

Where Tmin is the minimum temperature (°C) and v is the wind speed (mph).

$$Heat\ Index = 0.5(T_{max} + 61.0 + 1.2(T_{max} - 68.0) + 0.094Rh)$$
$$\text{When T max} < 80$$

$$Heat\ Index = -42.379 + 2.04901523T_{max} + 10.14333127Rh - 0.22475541T_{max}Rh$$
$$- 0.00683783T_{max}^2 - 0.05481717Rh^2 + 0.00122874T_{max}^2Rh$$
$$+ 0.00085282T_{max}Rh^2 - 0.00000199T_{max}^2Rh^2$$
$$\text{When T max} \geq 80$$

$$(2)$$

Fig. 1 | Topography and climate of Ethiopia.
a Topographic map of Ethiopia where green is low land and white is highland areas, **b** the 30-year mean average temperature, °C where dark red indicates warmer regions and (c) total rainfall, mm (1984–2014) where dark blue indicates wetter regions during the Bega season (here considered 1st December–15th February). Climate data is calculated using the ERA5 reanalysis for temperature and CHIRPS for rainfall[42].
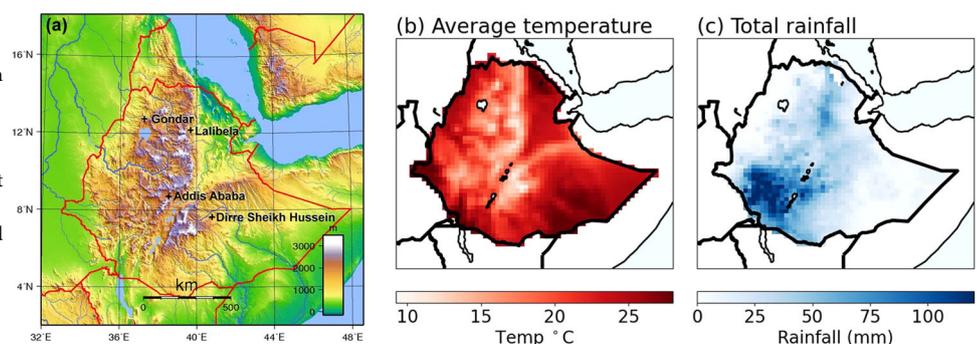
$$\text{Heat Index} = \text{Eq2} - \left(\frac{13 - Rh}{4} \sqrt{\frac{17 - ABS(T_{max} - 95)}{17}} \right)$$
$$\text{When } 80 < T_{max} < 112 \text{ and } Rh < 13$$

$$\text{Heat Index} = \text{Eq2} + \left(\frac{Rh - 85}{10} \frac{87 - T_{max}}{5} \right) \qquad (3)$$
$$\text{When } 80 < T_{max} < 87 \text{ and } Rh > 85$$

Where Tmax is the maximum temperature (°F) and Rh is the relative humidity (%).

For days below 5 °C, days above 35 °C and rain days above 1 mm, the metrics are normalised to a 30-day period to enable comparison between periods of different lengths.

A wide range of values for these eight metrics are present across Ethiopia during the Bega season (Fig. 2). Cooler temperatures are evident in a north-south band down the middle of Ethiopia (Fig. 2a), while the number of days with temperatures less than 5 °C occur only at isolated points in the Highlands (Fig. 2b). Maximum daily temperatures of more than 30 °C can be found in the eastern areas (Fig. 2c) near Dirre Sheikh Hussein[41]. However, temperatures only occasionally exceed 35 °C, even in arid eastern parts of Ethiopia (Fig. 2d). Although Bega is the dry season, there is a broad band of wetter conditions that runs across the country in a diagonal that encompasses the Highlands (Fig. 2e). Here maximum daily rainfall can exceed 20 mm. Rain days are more frequent in the southwest (Fig. 2f), with fewer rain days in the northeast around Lalibela, and little rain is expected in the east near Dirre Sheikh Hussein. Wind chill is severest in the Highlands (Fig. 2g) while the heat index is highest in the lowland areas of Ethiopia (Fig. 2h).

Time periods
Three periods were used to assess the climate metrics' sensitivity to duration of time. These three periods fit within the Bega season and are centred around key times of pilgrimage in Ethiopia: (i) 14 days from the 1st to 14th January, (ii) 48 days from the 15th December to 31st January and (iii) 77 days from the 1st December to 15th February. For simplicity, these time periods are referred to as short, medium and long, respectively. The three temporal durations were chosen as they cover various times that pilgrims might need to use in the travel to the celebrations and return home. The time periods have been determined for the 30-year interval from December 1984 to February 2014. All values presented in the figures are a mean for the 30-year interval.

Datasets
The eight climate metrics were calculated using observed and modelled datasets. The observed results were calculated using the ERA-5 reanalysis for the four temperature metrics, wind chill and the heat index. The Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) Version 2[42] was used for the two rainfall metrics. Both datasets were interpolated onto a common 0.25° x 0.25° grid. We used the hourly 2 m surface temperature from ERA-5 to determine the daily minimum and maximum temperatures and the total daily rainfall from CHIRPS was used to calculate the rainfall metrics. The metrics were calculated using the observed data for each of the three time periods defined in "Time periods".

The eight metrics were also calculated using the mean output from an ensemble of three CMIP6 models[43]: HadGEM3-GC31-MM, CMCC-ESM2 and NorESM2-MM. Given the well-documented challenges of reproducing climate over Africa with GCMs[26,36], these three models were selected as they have been found most effective in reproducing climatological features across the area[28] and had daily precipitation, minimum and maximum 2 m surface temperature, relative humidity and surface wind speed values for the period 1984 to 2014. Daily temperature, relative humidity, wind speed and precipitation data were obtained from the Centre for Environmental Data Analysis (CEDA) archive for the CMIP6 historical period (CMIP experiment), using only model runs with the simulation variant r1i1p1f*. Models were interpolated to a common 1° x 1° grid to facilitate model comparison[44].

Statistical analysis
The sensitivity of each of the eight climate metrics to the time period used was assessed by spatially calculating (i) the difference in the mean values over a 30-year period and (ii) the significance of the difference within a 30-year period. The significance was determined using the nonparametric Wilcoxon signed rank test to calculate p-values.

The difference between the observed and modelled climate metrics is spatially mapped and the association between the modelled and observed results in each of the modelled grid cells was tested using Pearson's r-value. The root mean square error (RMSE) was used to calculate the average difference between the predicted and observed values from our regression models. A RMSE value of 0 would indicate that all modelled values exactly mapped onto the observed values, while a value of for example, 2 would tell us that the difference between the modelled and observed values was 2 units.

Results
Sensitivity of metrics to period length
Results calculated using the observed datasets show that the four temperature metrics are sensitive to period length in some areas of Ethiopia (Fig. 3). Minimum daily temperatures (Fig. 3a) are typically warmer when longer periods are considered (Fig. 3b, d), although the difference is not statistically significant in the Highlands (Fig. 3c, e). The Highlands receive the greatest number of days <5 °C per 30-days (Fig. 3f). Results show that there are more of these cold days when longer durations are considered (Fig. 3g, i), the significance is low i.e., $p > 0.1$ (Fig. 3h, j). The maximum daily temperatures (Fig. 3k) are higher when longer periods are considered in all but the southwest of the country at the border with Kenya (Fig. 3l, n). These differences are not statistically significant in the central regions of the country, but are significant in eastern (Fig. 3m, o) and northern (Fig. 3o) areas. The differences in days with temperatures > 35 °C remains the same across most of the country irrespective of the period (Fig. 3q, s). However, in areas where a difference is noted, it tends to be significant (Fig. 3q-t).

Rainfall is greatest in the southwest of the country (Fig. 4a, f). The maximum daily rainfall increased when longer periods were considered (Fig. 4b, d), and these differences were significant across most of the country (Fig. 4c, e). The influence of longer time periods on the number of rain days greater than 1 mm is spatially noisy (Figure g), and only significant in isolated patches (Fig. 4h), although this becomes more significant when comparing the long time period with the short time period (Fig. 4j).

Wind chill is severest in the Highland regions of Ethiopia with temperatures dropping below 5 °C (Fig. 5a). The wind chill was greatest in almost all areas of the country when longer time periods were considered (Fig. 5b, d). This difference was found to be significant only in the northwest for the medium period (Fig. 5c) but over a larger area of the low lying regions for the long period (Fig. 5e). The heat index was highest in the low lying areas of the north east and south east as well as in the southwest of the country (Fig. 5f). Similarly to the wind chill, the heat index increased when longer seasonal windows were considered (Fig. 5g, i). This difference was significant in the south west for both the medium and long periods (Fig. 5h, j) and in the non-central areas for the long period (Fig. 5j).

Comparing observed and modelled results
Due to the sensitivity of the climate metrics to the time period, we present the results comparing the observed and modelled results for the short time period (14 days from the 1st to 14th January) as this aligns most closely with the main periods of pilgrimage to Lalibela and Dirre Sheikh Hussein.

For minimum daily temperature, the lowest temperatures are found in the Highlands of Ethiopia (Fig. 6a), and here the modelled values are warmer than the observed values (Fig. 6b). The reverse is seen in the warmer areas of eastern Ethiopia, where the modelled temperatures can be up to 10 °C lower than the observed values. However, when comparing the two datasets, there is a strong positive association (Fig. 6c). The RMSE for Fig. 6c is 2.07 indicating that the average distance between the modelled and actual values is just over 2 °C.

Fig. 2 | Climate conditions relevant to pilgrimages.
The distribution of observed (**a**) daily minimum
temperature where black indicates cooler temperatures and yellow indicates warmer temperatures,
b days below 5 °C where black indicates fewer days
and yellow indicates great days when the condition
is present, **c** maximum daily temperature where
black indicates cooler temperatures and yellow
indicates warmer temperatures, **d** days above 35 °C
where black indicates fewer days and yellow indicates great days when the condition is present,
e maximum daily rainfall where yellow indicates less
rainfall and blue indicates greater rainfall (**f**) rain
days > 1 mm where yellow indicates less rainfall and
blue indicates greater rainfall, **g** windchill where blue
indicates cooler values and yellow indicates warmer
values and **h** heat index in Ethiopia where blue
indicates cooler values and yellow indicates warmer
values, for the period 1st December to 15th February
(1984–2014) using ERA5 (temperature, relative
humidity and wind speed) and CHIRPS (rainfall)
datasets.
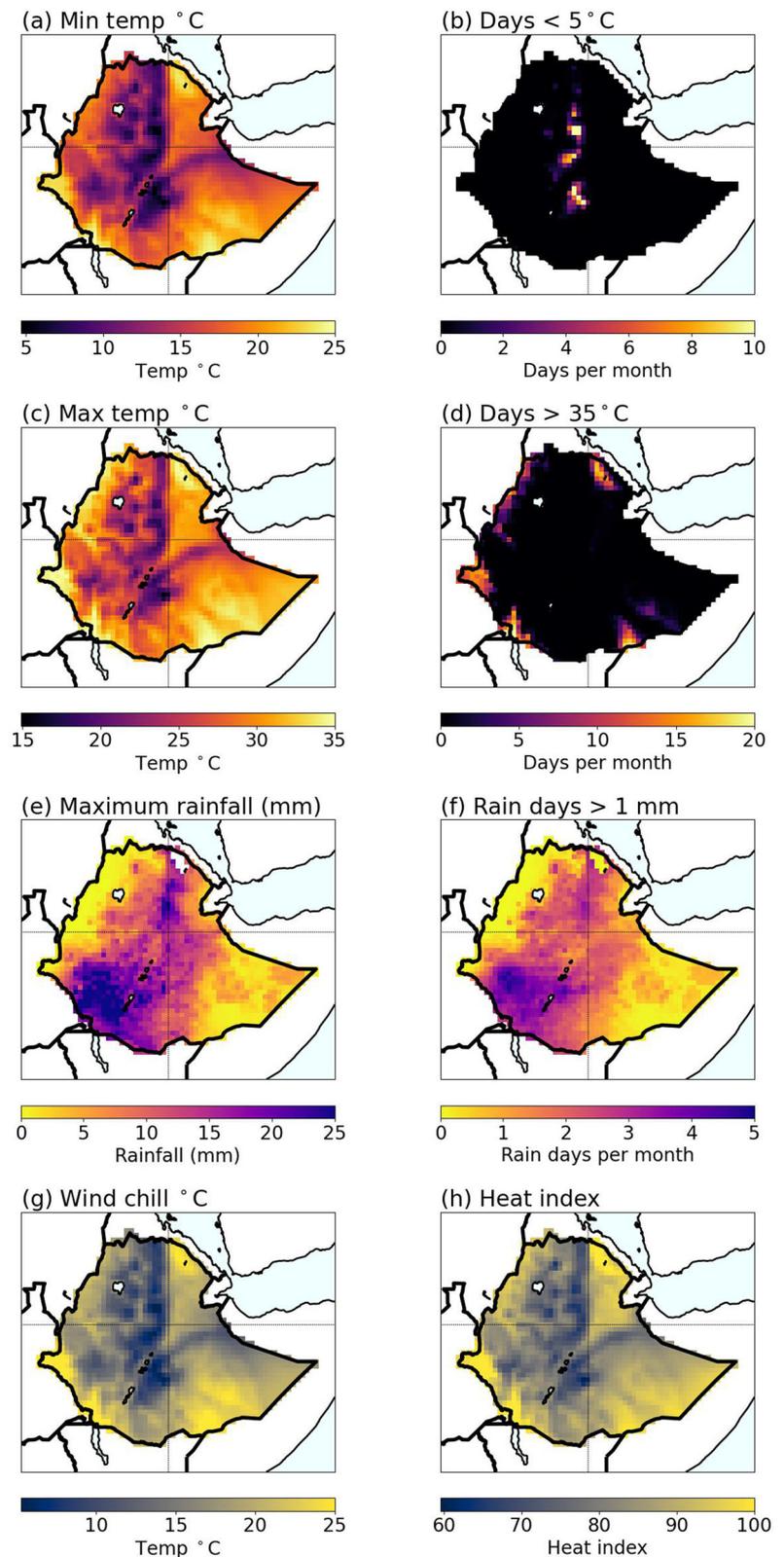
Days below 5 °C are tightly constrained to the highland areas in the observed data (Fig. 6d). However, the modelled data can underestimate the frequency of cold days in these highland areas by up to 10 days per month (Fig. 6e). The modelled data also projects the occurrence of these low temperature days to be spread across a much wider area than seen in the observed data, resulting in a poor association between the number of days below 5 °C in the observed and modelled data (Fig. 6f).

The maximum daily temperature, which can exceed 35 °C in lowland areas of Ethiopia (Fig. 6g), is underestimated by the modelled data in the eastern half of Ethiopia (Fig. 6h). However, results showed a strong positive correlation between the observed and modelled data for maximum daily
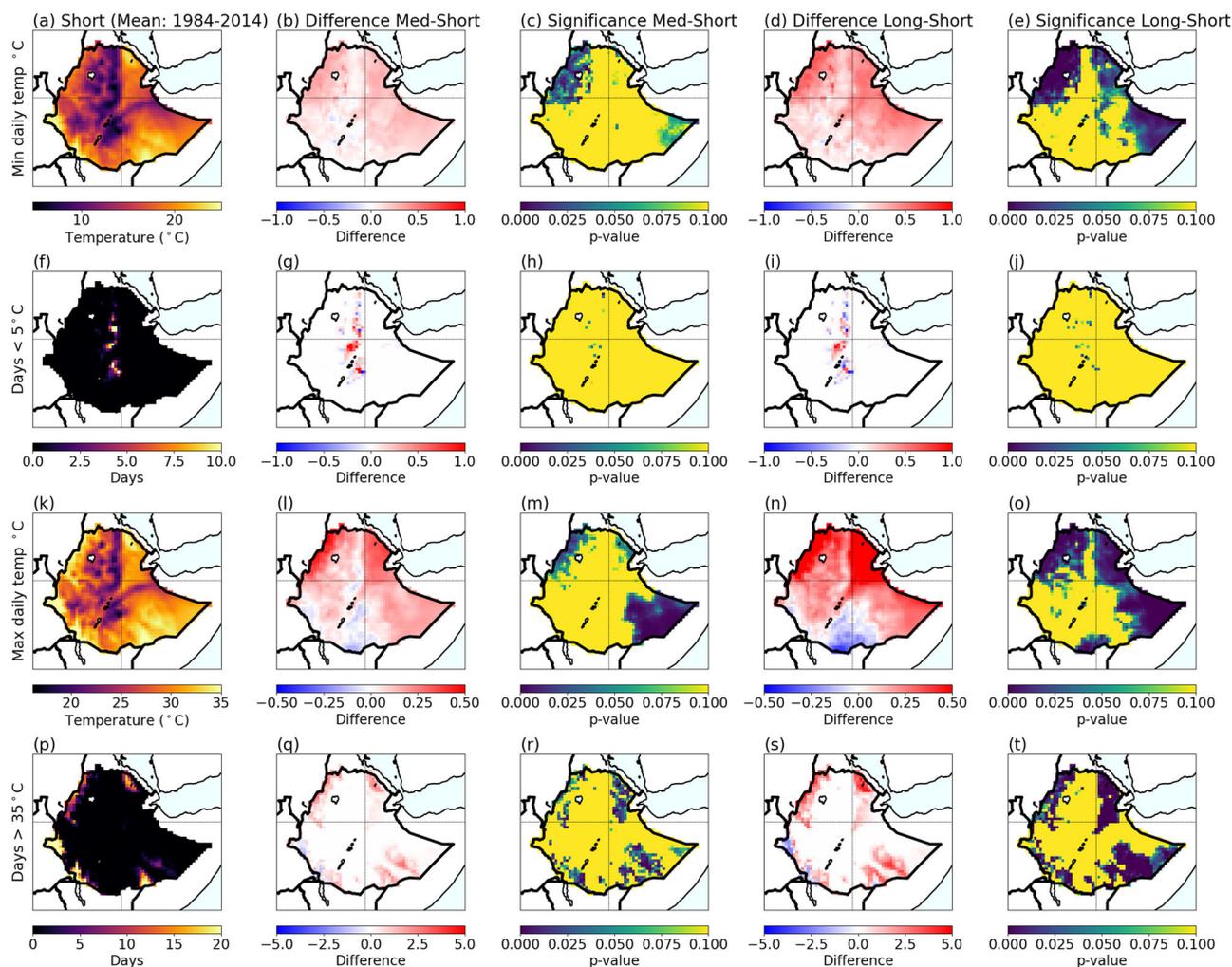
Fig. 3 | Temperature metrics from the ERA5 data 1984-2014. a–e Minimum daily temperature, **f–j** days below 5 °C, **k–o** maximum daily temperature and **p–t** days above 35 oC. **a, f, k, p** show the parameter mean for the period 1st to 14th January over the 30-year interval, where black indicates cooler temperatures and yellow indicates warmer temperatures, **b, g, l, q** show the difference between the medium (15th December to 31st January) and short (1st to 14th January) period, with

c, h, m, r showing the significance of this difference (Willcoxon signed rank test, $n = 30$), **d, i, n, s** the difference and **e, j, o, t** the significance of the difference between the long (1st December to 15th February) and short (1st to 14th January) period. In **b, d, g, i, l, n, q, s** red indicates that the long or medium period is warmer than the short period. In **c, e, h, j, m, o, r, t** dark blue indicates a low p-value and yellow indicates a p-value > 0.01.

temperature (Fig. 6i) with an RMSE of 2.12. Days where the temperature is above 35 °C are constrained to the border regions of Ethiopia (Fig. 6j), but there was little agreement between the observed and modelled values (Fig. 6k, l), in spite of a high degree of correlation that is driven by the agreement between datasets in the cooler areas where both observed and modelled datasets indicate that there are no days above 35 °C. It should be noted that the high r-value for this metric (Fig. 6l) is strongly influenced by the large area in central Ethiopia where both the observed and modelled datasets show with no days above 35 °C. As such, the predictive power of this relationship is likely to be lower than the r-value would suggest for regions that experience temperatures exceeding 35 °C.

In the case of the rainfall metrics, the maximum daily rainfall is greatest in southwestern Ethiopia (Fig. 7a). Across almost all of Ethiopia the modelled maximum daily rainfall is less than that calculated using the observed data (Fig. 7b). The inability for the modelled data to capture heavy rainfall events is highlighted in Fig. 7c, where the maximum daily rainfall ranges between 0 and 15 mm in the observed dataset, but only 0 and 3 mm in the CMIP6 dataset. Even though a high r value of 0.75 has been calculated, a modelled value of say 2 mm could relate to an observed value between 0 and 12 mm, making this linear model of limited value in comparing the two datasets. In contrast, there is a stronger association between

the observed and modelled data for the number of rain days > 1 mm (Fig. 7d–f). The modelled outputs are higher than the observed in the highland and eastern regions, but lower than the observed datasets in the northeast and central regions (Fig. 7e). Overall, there is a strong positive trend with some notable variability around the line of best fit, with an RSME of 0.78 (Fig. 7f).

Wind chill temperatures are the lowest in the central area of Ethiopia (Fig. 8a). Here the modelled data sets tend to not capture the severity, with modelled wind chill temperatures being up to 10 °C warmer than when the wind chill is calculated using the observed data sets. In contrast, in eastern Ethiopia the modelled wind chill temperature is cooler than the observed wind chill temperature. Nevertheless, there is a strong correlation (r = 0.75) between the observed and modelled values with an RSME of 2.46 suggesting an average difference of 2.46 °C between the modelled and observed values (Fig. 8c).

The heat index shows a similar spatial pattern to wind chill temperatures with lowest observed heat index values found in the Highland regions, but these values are underestimated by the modelled data (Fig. 8d, e). There is also a strong correlation between the observed and modelled values (r = 0.73) with modelled outputs tending to overestimate cooler values, and underestimate warmer values, with an RSME 4.45 (Fig. 8f).
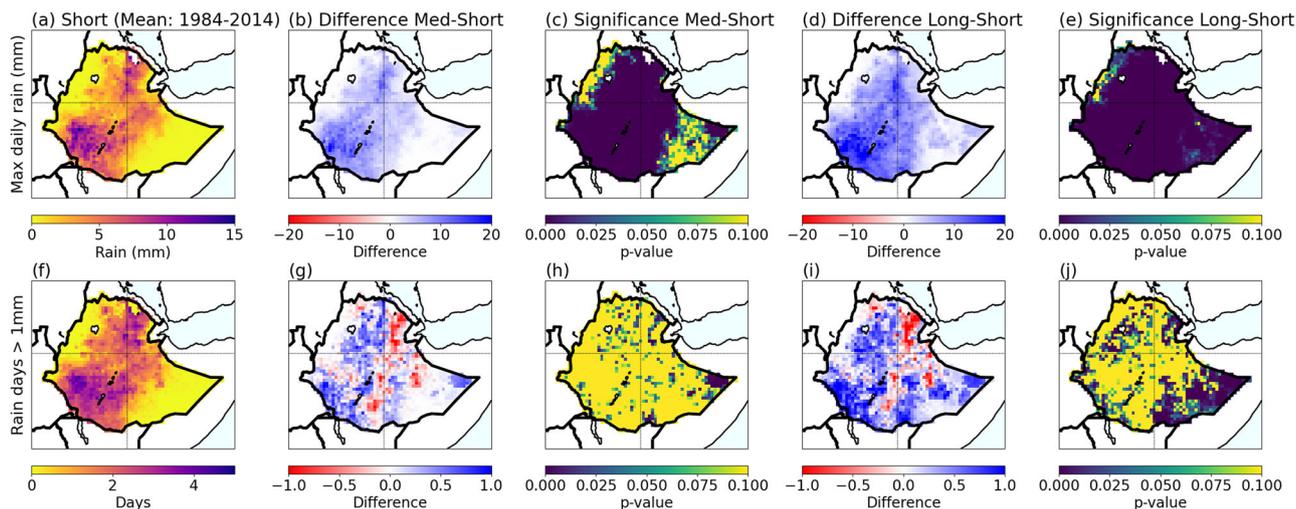
Fig. 4 | Rainfall metrics derived from the CHIRPS data 1984-2014. a–e Maximum daily rainfall, and **f–j** number of rain days greater than 1 mm. **a**, **f** show the parameter mean for the period 1st to 14th January over the 30-year interval, where yellow indicates low rainfall and blue indicates greater rainfall (**b**, **g**) the difference between the medium (15th December to 31st January) and short (1st to 14th January) periods with **c**, **h** showing the significance of this difference (Willcoxon signed rank test, n = 30), **d**, **i** the difference and **e**, **j** shows the significance of the difference between the long (1st December to 15th February) and short (1st to 14th January) period. In **b**, **d**, **g**, **i** blue indicates that the medium or long period is wetter than the short period. In **c**, **e**, **h**, **j**) dark blue indicates a low p-value and yellow indicates a *p*-value > 0.01.
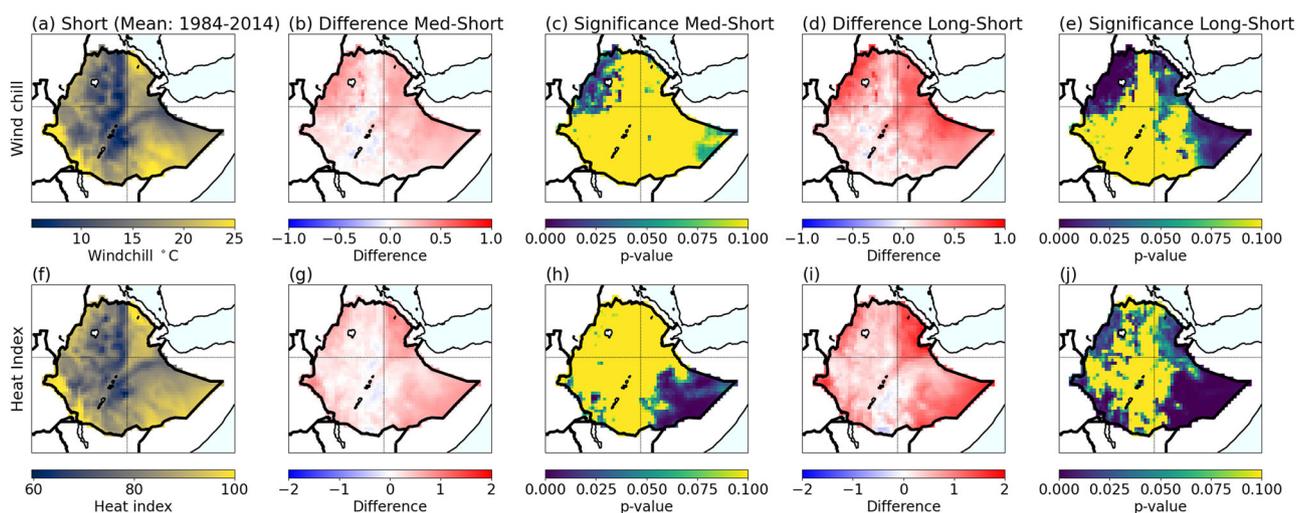

Fig. 5 | Combined metrics. a–e Wind chill and **f–j** heat index calculated using ERA5 data 1984-2014. **a**, **f** show the parameter mean for the period 1st to 14th January over the 30-year interval, where blue indicates cooler values and yellow indicates warmer values (**b**, **g**) show the difference between the medium (15th December to 31st January) and short (1st to 14th January) period, with **c**, **h** showing the significance of this difference (Willcoxon signed rank test, n = 30), **d**, **i** the difference and **e**, **j** the significance of the difference between the long (1st December to 15th February) and short (1st to 14th January) period. In **b**, **d**, **g**, **i** red indicates that the long or medium period is warmer than the short period. In **c**, **e**, **h**, **j** dark blue indicates a low p-value and yellow indicates a *p*-value > 0.01.

Discussion

Meteorological metrics commonly reported or evaluated in the climate science literature are not necessarily those most relevant to the weather phenomena that influence the day-to-day lives of people. In this study, we have combined climate and heritage science to explore the extent to which eight climate metrics relevant to pilgrimage are sensitive to the time period studied and the ability for them to be captured by observed and modelled datasets.

The commonly used division of the year into four 3-month periods (typically Dec–Feb, Mar–May, June–Aug and Sep–Nov) may helpfully map onto the seasons that occur in many western countries, but is less useful for regions where the inter-annual climate variability does not fit this pattern. Our results highlight the importance of using time periods that are appropriate to the process being studied. The use of region-specific seasons, such as those used by Taye et al. [45] to analyse their results within the context of the Ethiopian rainy seasons, means that interpretation can be tightly focused on a locally relevant climate process rather than being constrained by an arbitrary 3-month period. These findings demonstrate that when assessing climate impacts on cultural practices, such as pilgrimages, generic time periods (e.g., annual or three-month seasons) are likely to not capture the full extent of the impact. This is an important consideration for policymakers, especially as climate impacts on heritage are increasingly included in climate change policy.

Our results suggest that using time frames that cover longer periods of the Bega season broadly represent climatic conditions occurring at a given time within the period (Figs. 5, 6). However, narrowing the time frame means that the results are most likely to be representative of those experienced by people engaged in social practices, such as a pilgrimage. The timing of this period is likely to be important at times of year when regions experience large changes in climate over short periods of time. As such,
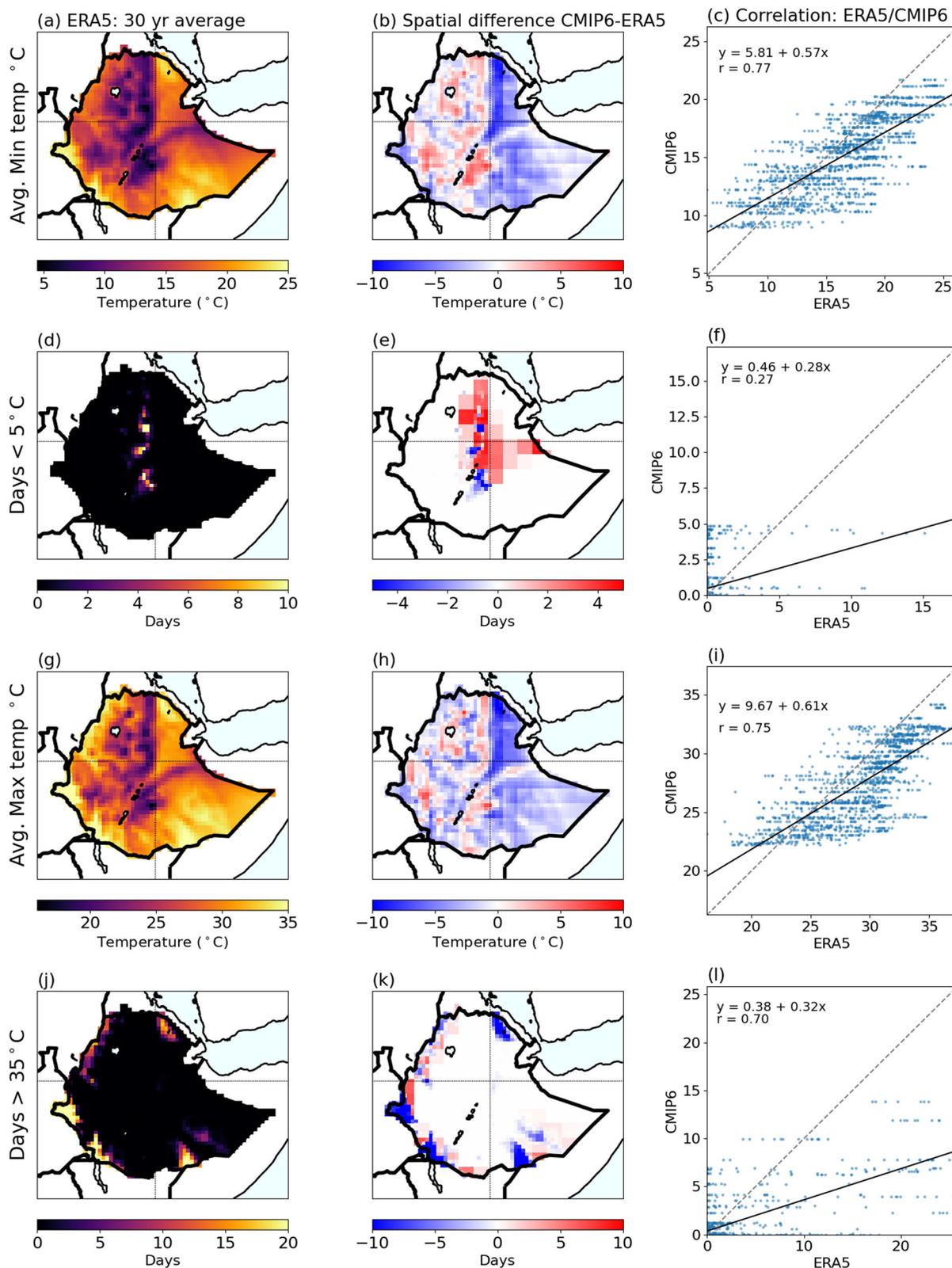
Fig. 6 | A comparison of the modelled and observed temperature metrics.
a–c Minimum daily temperature, **d–f** days below 5 °C, **g–i** maximum daily temperature and **j–l** days above 35 °C. These are calculated using: **a**, **d**, **g**, **j** the observed data, where black indicates cooler temperatures and yellow indicates warmer temperatures; **b**, **e**, **h**, **k** the difference between the modelled and observed data and **c**, **f**, i, **l** the association between the observed and modelled data. In **b**, **e**, **h**, **k** blue indicates that the modelled data is cooler than the observed data. The grey dotted line shows a one-to-one relationship. The black line shows the line of best fit.
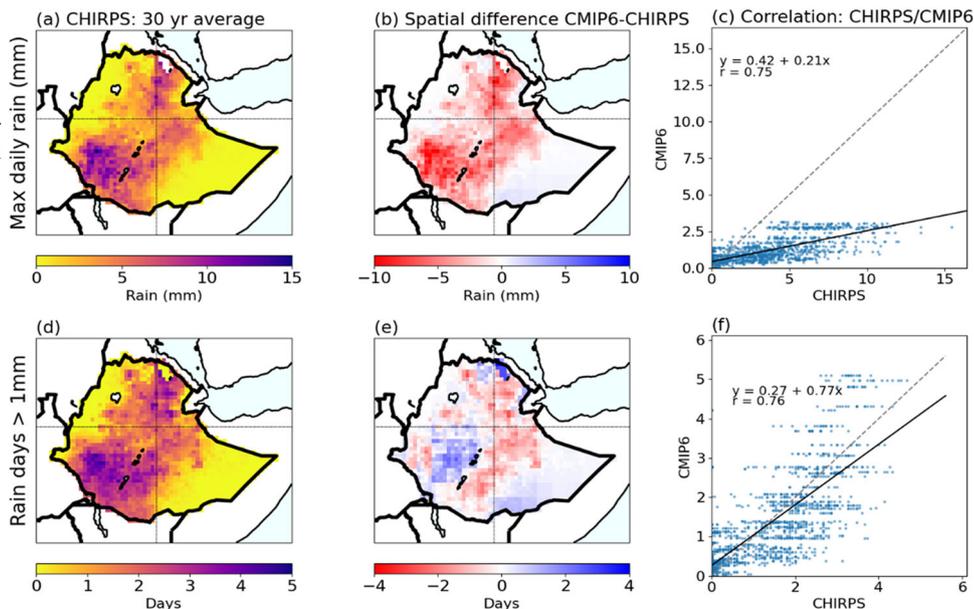
Fig. 7 | A comparison of the modelled and observed precipitation metrics. a–c Maximum daily rainfall and d–f rain days > 1 mm. These are calculated using: **a**, **d** the observed data, where yellow indicates less rainfall and blue indicates greater rainfall, **b**, **e** the difference between the modelled and observed data and **c**, **f** the association between the observed and modelled data. In **b**, **e** red indicates that the modelled data is drier than the observed dataset. The grey dotted line shows a one-to-one relationship and the black line the line of best fit.


Fig. 8 | A comparison of the modelled and observed combined metrics. a–c Windchill and d–f heat index using: **a**, **d** the observed data, where blue indicates cooler values and yellow indicates warmer values; **b**, b the difference between the modelled and observed data and **c**, **f** the association between the observed and modelled data. In **b**, **e** blue indicates that the modelled data is cooler than the observed data. The grey dotted line shows a one-to-one relationship. The black line shows the line of best fit.
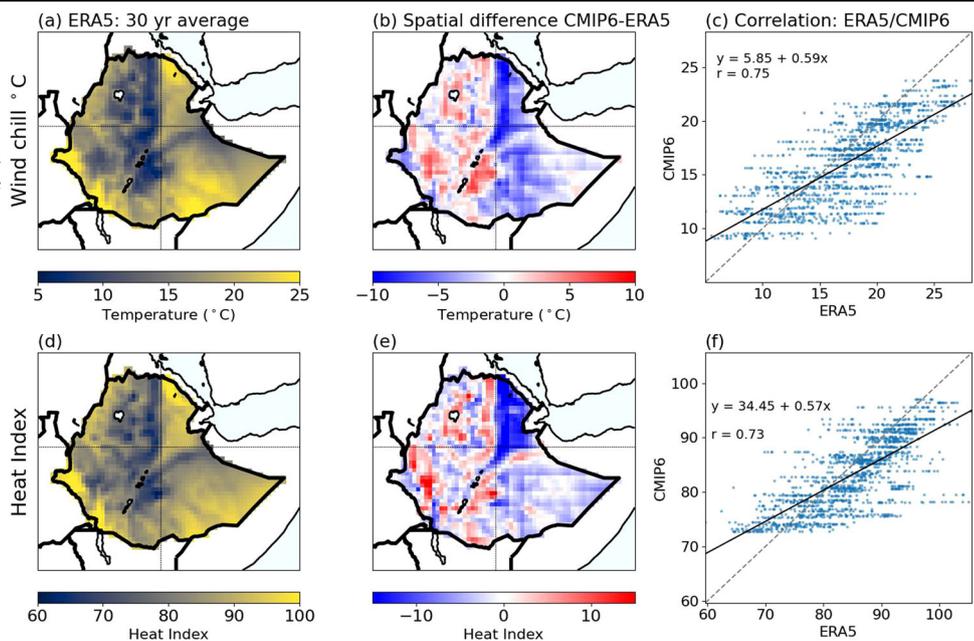
periods that bridge the rainy and dry seasons will likely need careful consideration by researchers and policymakers to properly represent that experienced by pilgrims. Studies of climate and heritage could follow the lead shown by some research undertaken within an agricultural context. Here, the timing of planting, thinning and harvesting can be very specific, such that small changes in climate, or the dates of specific climate events, can have large knock-on impacts, e.g., short cold snaps can damage crops or limit pollination[46,47].

Previous work has shown that modelling the Ethiopian climate is challenging[41], with large-scale GCMs struggling to capture precipitation extremes and future trends in precipitation amounts[26,48]. However, our study shows that for Ethiopia, the CMIP6 ensemble of models used here are able to capture a selection of climate metrics useful for understanding climate conditions during pilgrimages in the Bega season (Figs. 5, 6).

The CMIP6 models were able to better represent the two temperature metrics related to minimum and maximum daily temperature, wind chill and heat index, than those metrics that counted the number of days below 5 °C or above 35 °C. Climate metrics that describe transitions across a set threshold can lead to errors as even small biases within the dataset can cause a particular threshold to be crossed more or less often[25]. In the Ethiopian highlands, the spatial resolution of GCMs, which can be 10 s to 100 s of kilometres, fail to account for the complex orography[49], because an average elevation is used for each grid cell, which means that mountain peaks and valley floors are smoothed over. As temperature is linked to elevation[26,49], it is hardly surprising that these threshold metrics were not adequately captured.

The warm or cold biases present in the CMIP6 data is also important to consider in the context of when the climate metric represents a condition that poses the greatest challenge to pilgrims. For example, wind chill is important when it is cold while the heat index is of particular importance

when it is hot. As such, modelled data is likely to underestimate the challenge faced by wind chill in the mountainous regions (Fig. 8c) but overestimate the severity of the impact of warm humid temperatures in the lowland regions (Fig. 8f).

Rainfall has been notoriously difficult to estimate in climate models for Ethiopia[26,28,49]. This problem was also seen in our study, with the poor agreement between modelled and observed data for the maximum daily rainfall (Fig. 7). It arises from constraints to the parameterisation of rainfall processes within these models, such that GCMs have been found to simulate low rainfall events too frequently, yet fail to simulate high intensity events[50–52]. Results in Fig. 7c, clearly show that CMIP6 models predict more low rainfall events that occurred, but failed to generate a rainfall event more than 3 mm on any given day, yet the observed data showed that these could reach up to 15 mm. Interestingly, and very usefully, the precipitation parameter assessing the number of rain days above 1 mm showed a much stronger association between the observed and modelled values (Fig. 7f). As this parameter removes all values below 1 mm, it reduces the impact of the CMIP6 model biases, which cause an overestimation of low rainfall days. Thus, this parameter reduces the problem caused by the CMIP6 models' inability to accurately simulate very high rainfall events.

Our results show that five of the eight heritage climate metrics could be applied to GCMs for assessing how climate might affect the experience of people undertaking pilgrimages in Ethiopia. We suggest that minimum and maximum daily temperature, wind chill, heat index and the number of rain days greater 1 mm are most reliable in the modelled data for the present period. When applying these metrics to future climate projections, the higher confidence of future projections of temperature means that temperature-based metrics are likely to be associated with a greater level of certainty than metrics based on precipitation or windspeed – although rapid developments in convection permitting models and neural GCMs are likely to improve the representation of rainfall in climate models in future. Therefore, as individual metrics might give only a partial picture of the climate pressures on cultural practices, a collection of metrics such as those presented here that are effectively captured by models and account for the human experience of weather should be used by researchers and policy makers.

Higher spatial resolution output available from regional climate models (RCMs) might better simulate metrics that were not effectively captured by the GCMs. However, RCMs have also faced limitations in their ability to represent rainfall and precipitation over Ethiopia[53,54]. Thus, high-resolution convection-permitting models might be needed to resolve such metrics more effectively.

Our research also highlights the range of approaches and ideas that need to be brought together to better understand the effect of climate and climate change on cultural practices. It requires technical knowledge to engage with climate data that needs to be coupled with an understanding of the heritage in a given area. This is seen in the use of special climatological metrics that are adapted to represent potential threats to heritage[10]. Collaboration and dialogue between people and disciplines would help improve climate analysis when considering the way climate change and heritage, which is often overlooked in many studies.

The impact of climate and climate change on cultural heritage, although widely discussed, is rarely evaluated quantitatively. Here we assess the sensitivity of observed datasets and the ability of modelled datasets to capture climate metrics that are relevant to climates experienced by people undertaking pilgrimages in Ethiopia during the dry season (Bega). Results show the importance of adjusting the length of the period in question rather than using temperate seasons traditionally used in many western cultures, making it more relevant to the process or practice being studied. In our study, five of eight climate metrics were successfully captured by the three CMIP6 GCMs selected for this study (minimum and maximum daily temperature and the number of rain days greater than 1 mm). While this means we have to be selective about the climate metrics that can be used, it at least provides us with some tools with which we can assess future impacts of climate change on the climate experienced by pilgrims.

Data availability

The raw data supporting the conclusions of this article will be made available by the authors on request.

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Author contributions

Both authors contributed to the study conception, design, data interpretation, drafting and finalising. Data processing and analysis were performed by JR. Both authors read and approved the final manuscript.

Competing interests

The authors declare no competing interests.

Additional information