

Supplementary material: Methods

Model input: downscaled layers

Because models project bioclimatic variables for 2050 differently, choosing the best model to represent 2050 conditions is challenging. To dampen the influence of contrasting model assumptions, we averaged layers for a set of models (**table S1**). We adopted the list of models from de Sherbinin et al.'s (2014) study in Mali. We downloaded 5 arc-minute data from the Research Program on Climate Change, Agriculture, and Food Security (http://www.ccafs-climate.org/data_spatial_downscaling/). These layers represent downscaled AR5 RCP4.5 and RCP8.5. We did not need to do this averaging process for baseline data because those layers were based on observations, rather than models of 2050 climate conditions.

Table S1. Models averaged for input bioclimatic variables. (Source: de Sherbinin et al. 2014)

Model	Source
CanES M2	Canadian Centre for Climate Modelling and Analysis CCCMA (Canada)
CCSM4	National Center for Atmospheric Research NCAR (USA)
CNRM-CM5	Centre National de Recherches Meteorologiques and Centre Europeen de Recherche et Formation Avancees en Calcul Scientifique CNRM-CERFACS (France)
CSIRO-Mk3-6-0	Queensland Climate Change Centre of Excellence and Commonwealth Scientific and Industrial Research Organization CSIRO-QCCCE (Australia)
GISS-E2-R	NASA Goddard Institute for Space Studies NASA GISS (USA)
HadGEM2-ES	UK Met Office Hadley Centre MOHC (UK)
MIROC-ESM	University of Tokyo, National Institute for Environmental Studies and Japan Agency for Marine-Earth Science and Technology MIROC (Japan)
MIROC 5	University of Tokyo, National Institute for Environmental Studies and Japan Agency for Marine-Earth Science and Technology MIROC (Japan)
MPI-ESM-LR	Max Planck Institute for Meteorology MPI (Germany)
MRI-CGC M3	Meteorological Research Institute MRI (Japan)

Input data: MIRCA 2000

The MIRCA2000 dataset, used to represent cotton-growing areas, is derived from national and sub-national agriculture census data, represents crop area harvested in 1998-2002 (Portmann et al. 2010). We used annual rainfed cotton data at a 5 arc-minute resolution (cell size approximately 8,400 ha at this latitude). Sparse cotton production occurs across much of the study region: annual harvested area ranges from 1 to over 1,900 ha/cell, but with half of all non-zero cells have less than 30 ha. We excluded areas with less than 30 ha per 5-minute cell (0.34 percent of a cell). We used remaining areas to represent cotton production regions (0.34-22.7 percent of a cell, or 30 to 1,927 ha/cell).

Within this concentrated area, we then generated 500 random points, with a minimum separation of 5 km, to represent presence points within areas of relatively high production (Evangelista et al. 2013). In addition to using presence points, we generated 500 random pseudo-absence points as part of model implementation.

Model agreement

It is not possible to validate input climate layers for 2050 by comparing them to observations, but one way to assess confidence in models of future conditions is to evaluate agreement among them (de Sherbinin et al. 2014). Stronger agreement among climate models indicates convergence among GCM modelling groups in understanding of climate processes and their impacts. For our most important bioclimatic variables (section 2.4), we evaluated agreement by mapping the variation among the 10 climate models. To do this, we generated 5000 random points within the study area and sampled values of each of the 10 models at those 5000 points. We then calculated proportional difference between models at each point: that is, for each point location we identified the maximum and minimum values of the 10 climate models. We then calculated agreement as $((\max - \min) / \max)$. 2.7 Comparison to global regions.

In general, when diverse models converge on common agreement in outcomes, that supports confidence in those outcomes. We assessed the agreement among the 10 input models (**Table S1**) with a point sampling approach: We generated a random sample of 5,000 points within the study area and sampled all 10 models at each point. We then calculated $(\text{maximum} - \text{minimum value}) / \text{maximum}$ at each point.

For purposes of visualization, we then used inverse distance weighted interpolation to map the distribution of those values. Small values, approaching 0, represent small disagreement among models. Larger values, approaching 1, represent greater disagreement (**fig. S1**). Disagreement among downscaled models was greater for precipitation than for temperature variables. This difference is consistent with previous discussions of uncertainty around future precipitation regimes (Adeniyi 2016, USGS n.d., CILSS 2016).

Agreement among models was stronger for temperature variables than for precipitation variables (**fig. S1**). Strong agreement among models of temperature variables, which supports confidence in the direction of temperature limitations. For mean temperature of hottest month (Bio 10), climate model values varied by less than 10 percent. This strong agreement suggests good confidence in temperature projections. For precipitation variables, within the area where cotton occurs, differences for precipitation variables were 20 to 40 percent for both RCP4.5 and RCP8.5. This greater disagreement indicates lower confidence in precipitation projections. Because three of our five variables represent temperature factors, and because agreement was good in the area where presence points occurred, it is reasonable to have confidence that our model represents a good understanding of available understanding of future climate conditions. However, uncertainty in precipitation projections is important to recognize when assessing risk for rainfed crops.

In general, agreement was greater for temperature variables and poorer for precipitation variables, especially in the arid northern reaches of the study area. Here precipitation is low, so changes of a few mm comprises a large proportional change in the arid northern reaches of the study area.

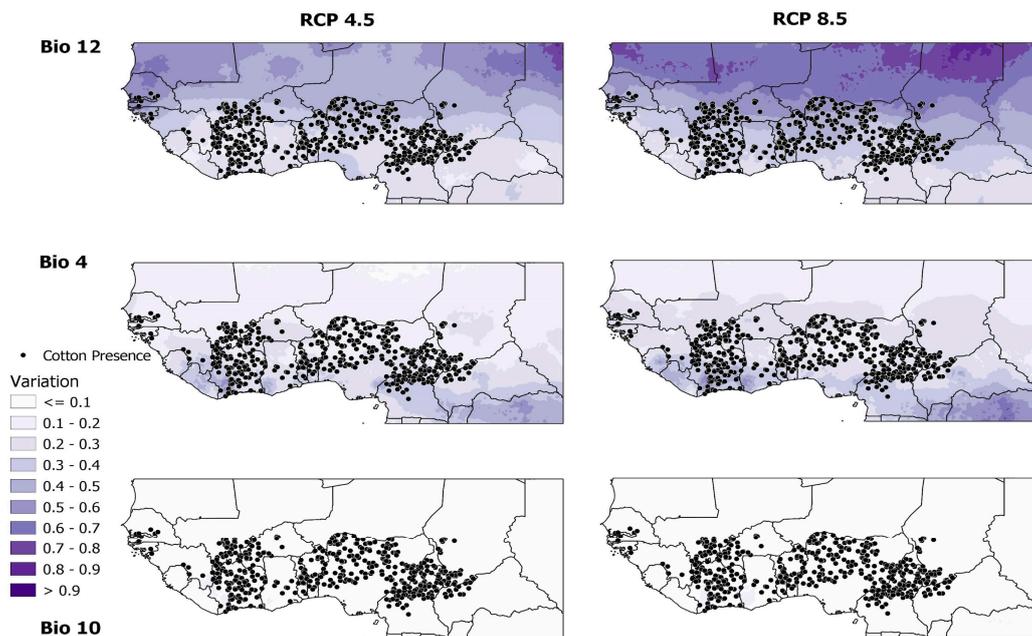


Fig. S1 Disagreement (variation) among 10 input models for three of our model layers. Values represent (the largest model value – the smallest model value) / the largest model value. Large values represent greater difference in model projections. Variables shown are annual precipitation, mm (Bio 12); temperature seasonality (std dev; Bio 4); and mean temperature of warmest quarter, °C (Bio 10).

Projected changes in bioclimatic variables by 2050

To evaluate how individual bioclimatic variables influenced changes in cotton distribution (from baseline years to 2050), we mapped values for our input layers using ranges of Cloglog likelihood output. That is, SDM output produced a curve showing likelihood of cotton occurrence points across a range of each variable. We used these ranges to classify areas as too hot/dry, suitable, or too cool/wet. For the purpose of visualization, we designated values corresponding to a Cloglog likelihood of cotton presence greater than 0.7 (strongly suitable variable values), greater than 0.5 but less than 0.7 (moderately suitable), and below 0.5 (less suitable).

For baseline conditions, we mapped the ensemble average input layers (used in Maxent). To show changes, we used class breaks corresponding to likelihood of occurrence of cotton presence points, as shown in Maxent Cloglog output. For each of the variables plotted, we identified the variable range corresponding to high, medium, and low likelihood of cotton occurrence in recent past conditions (**fig. S2a**). We show here the two strongest contributors to the Maxent model, Bio 12 and Bio 4, and the two seasonal temperature variables, Bio 10 and Bio 9.

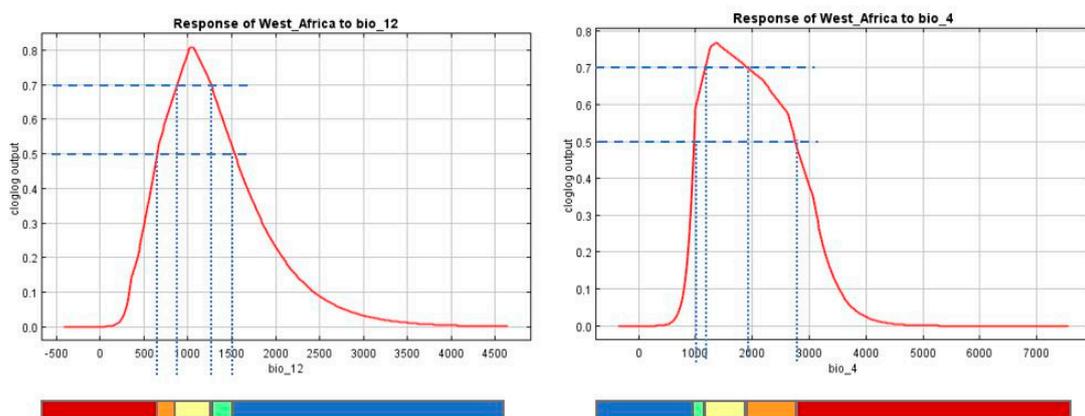


Fig. S2a Method of designating optimal ranges for variables from Cloglog graphs in Maxent output. For annual precipitation (Bio12), a Cloglog likelihood greater than 0.7 (upper dashed line) corresponds to precipitation between 900 and 1300 mm (vertical dotted line). A Cloglog likelihood of presence greater than 0.5 but less than 0.7 corresponds to precipitation greater than 600 mm and less than 1500 mm. Colors in fig. S2b and S2c correspond to value ranges that are above 0.7 (yellow) between 0.5 and 0.7 (orange or green), and below 0.5 (red or blue). Red corresponds to hotter or drier conditions; blue corresponds to wetter or cooler conditions.

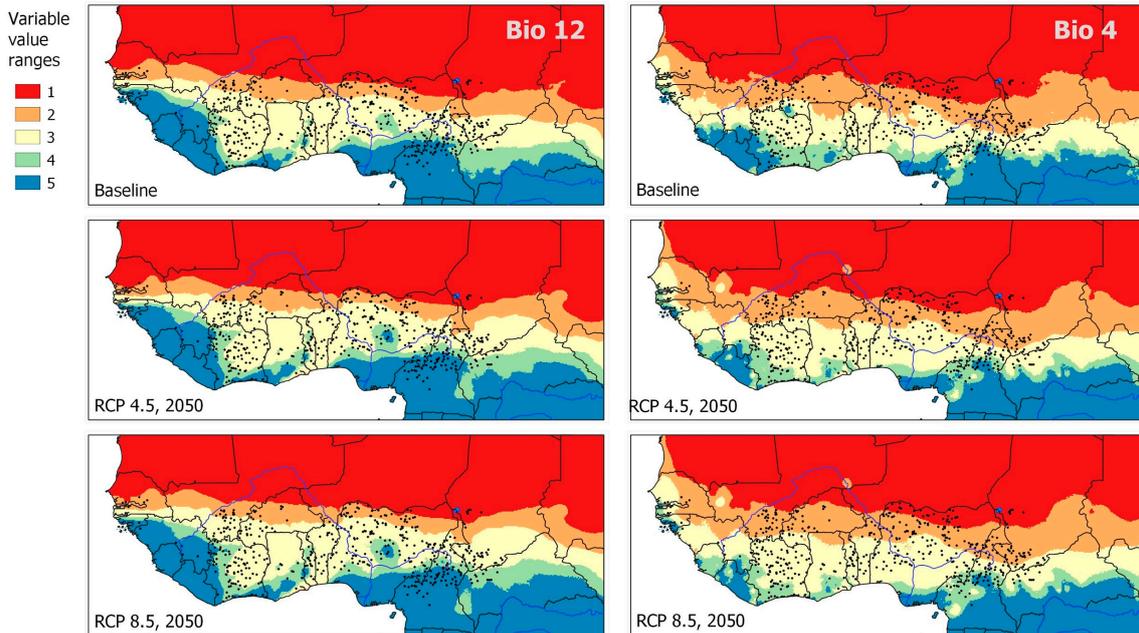


Fig. S1b Change from baseline to RCP4.5 and RCP8.5 for input layers annual precipitation (Bio12) and temperature standard deviation (Bio4). Colors represent the range of variable values that have a Cloglog likelihood greater than 0.5 or 0.7 (see fig. S2a). Red corresponds to hotter or drier conditions; blue corresponds to wetter or cooler conditions.

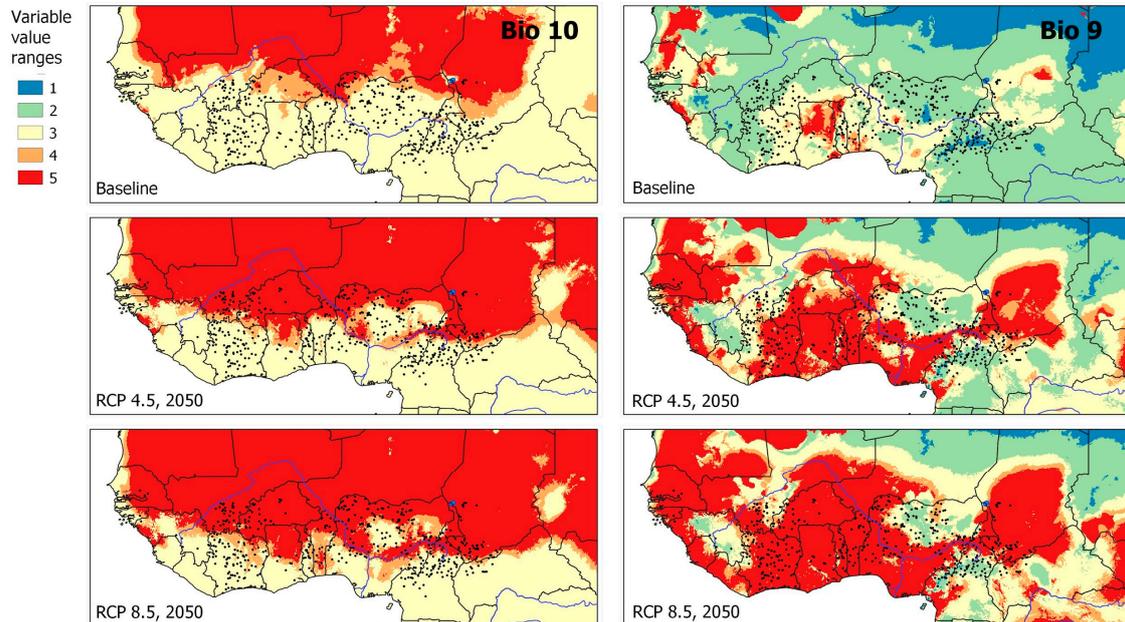


Fig.S2c Change from baseline to RCP4.5 and RCP8.5 for input layers mean temperature of warmest quarter (Bio10) and mean temperature of driest quarter (Bio9). Colors represent the range of variable values that have a Cloglog likelihood greater than 0.5 or 0.7 (see fig. S2a). Red corresponds to hotter conditions; blue corresponds to cooler conditions.

Global cotton producing regions

To compare climate conditions in West Africa to other study regions, we identified areas where cotton production was greater than 30 ha per cell globally. We note that cell size varies across this region, but this generalized cutoff allowed us to distinguish major production areas from sparse production areas. With this threshold, cotton production clustered into seven major regions, outlined by boxes in **fig. S3**. We plotted baseline and future climate conditions for these regions in fig. 5 in the main body of the paper.

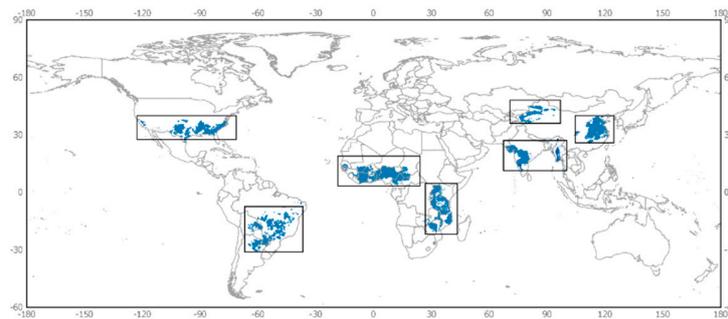


Fig. S3 Areas with annual rainfed cotton production > 30 ha/cell in MIRCA2000 data. These regions were evaluated in fig. 5.

Comparison of baseline projections from different algorithms

Many approaches to SDMs exist. We compared several algorithms to assess variation in output and test statistics. While models varied in details, the general prediction of suitability for current suitable conditions was broadly similar among models (**fig. S4**). We therefore selected the model with strongest AUC and TSS metrics for subsequent analysis (see table 1 in the main paper).

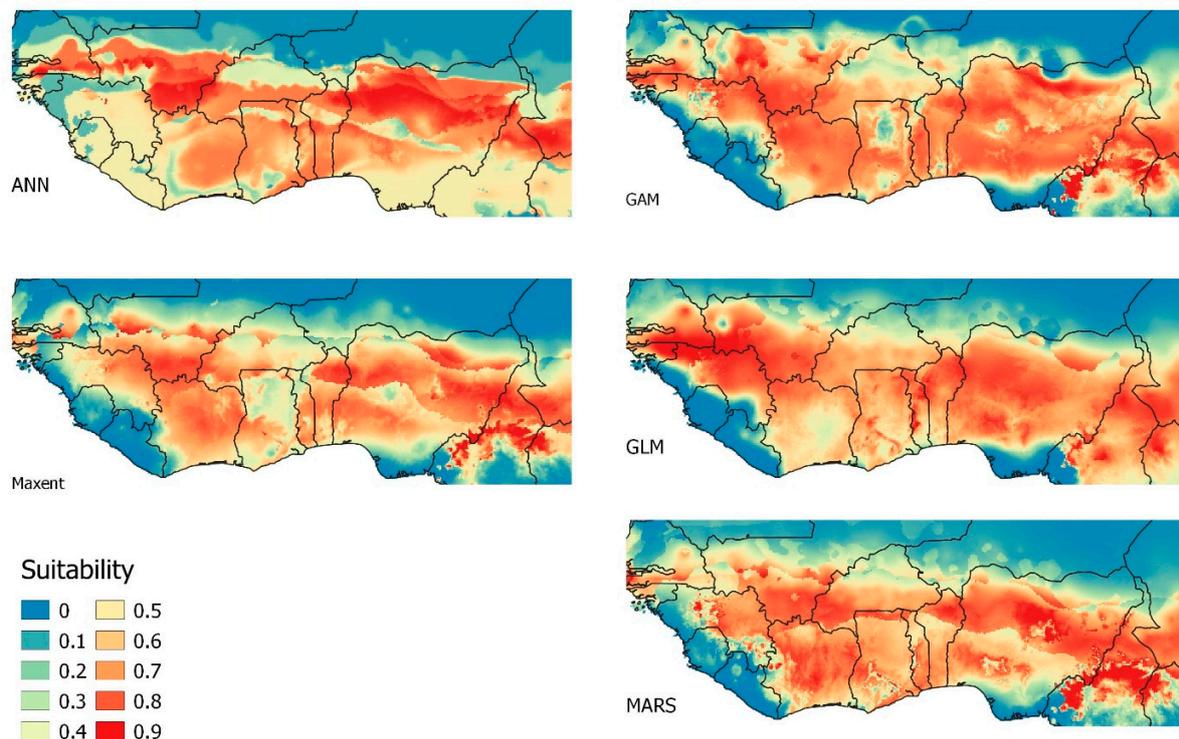


Fig. S4 Baseline projection of suitable area for rainfed cotton, from 5 algorithms. Algorithms are Artificial neural network (ANN), Maximum entropy (Maxent), Generalized additive model (GAM), Generalized linear model (GLM), and Multiple adaptive regression spline (MARS). AUC and TSS statistics are given in table 1 in the main paper. The poorest performing algorithm for our data, boosted regression tree, is omitted.

Jackknife results

While the full model ranked variables in importance, jackknife output gives further detail regarding the independent contribution of each variable. In this analysis, all five of the input variables provided good explanation, with an AUC > 0.6 for each (**fig. S5**). For discussion of the Maxent jackknife analysis, see Philips et al. 2006.

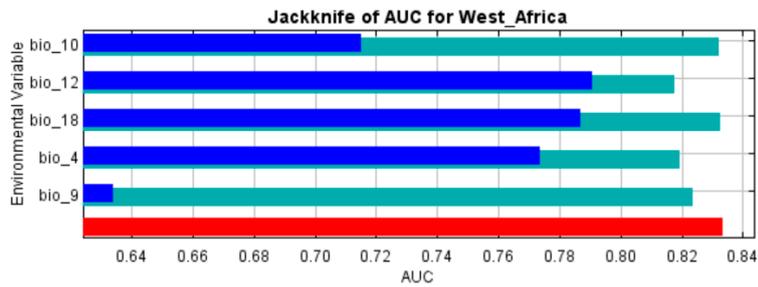


Fig. S5 Maxent jackknife output showing AUC for each variable in a model using only that variable (blue), compared to a model excluding that variable (green). Strong individual-variable AUC indicates that Bio 10 provides explanation by itself, despite low ranking in the full model.

References cited

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