A Species Distribution Modelling Application to West African Rainfed Cotton

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Introduction

Species distribution models give important insights into likely range shifts for species, ecosystems, and biodiversity in response to climate change. This approach has also, to a lesser extent, been used to project climate impacts on agricultural production, in particular for pest species and key food crops. Cotton, which provides critical income for small-holder farmers in West Africa, has received relatively little attention, despite its importance in this fast-growing, agrarian region.

West Africa has begun to experience increasing variability in precipitation; at the same time, the region has rapidly growing populations dependent on small-scale farming.[1] Rainfed cotton is the principal income source for many farmers in this region of historically-reliable rainfall (fig. 1). Preliminary analysis indicated that among world cotton-producing regions, this region is likely to be among the most strongly affected by climate warming and shifts in precipitation regimes.

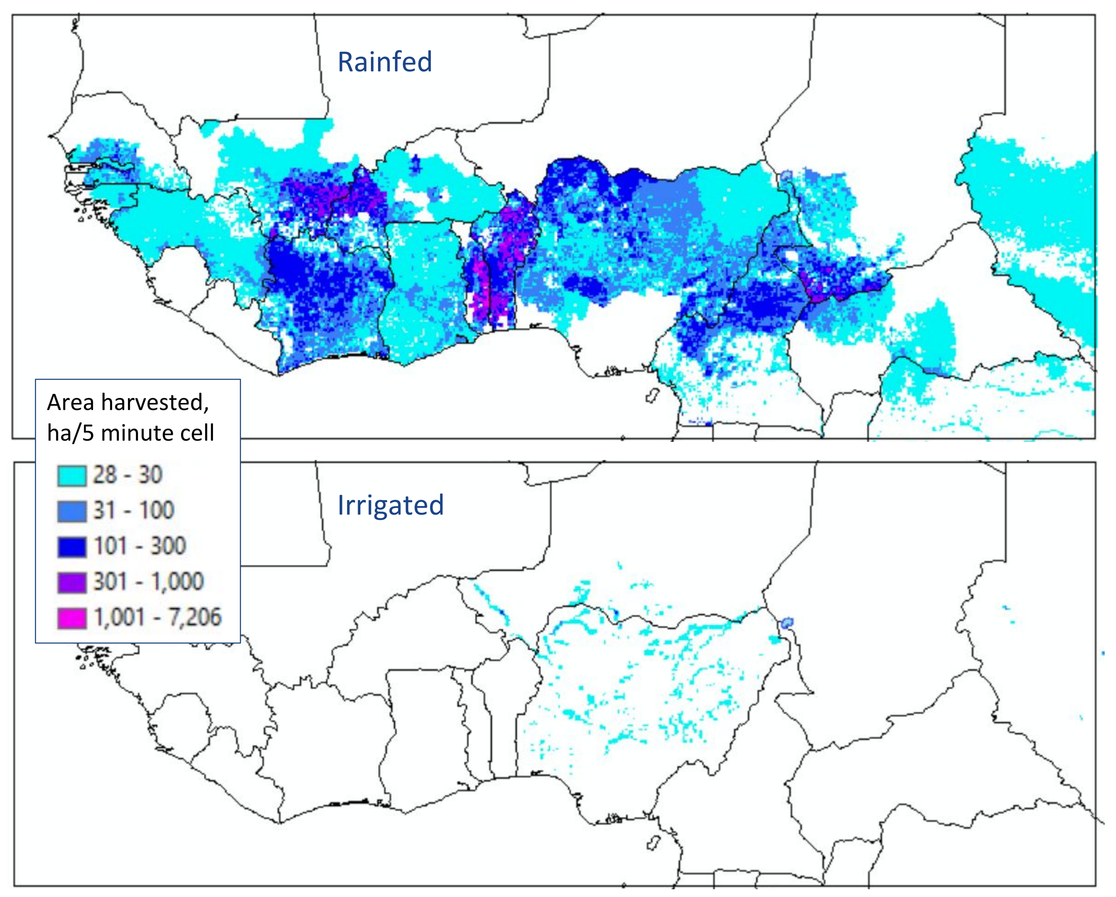


Figure 1. Distribution of rainfed (top) and irrigated (bottom cotton harvested (data source: Portmann et al. 2010, MIRCA2000[2]).

Methods

We used the species distribution modelling program Maxent[3] to examine likely range shifts in response to changes in climate conditions from the recent past (1970-2000) to projected 2050 (RCP 8.5, representing business-as-usual projections). For presence points, we randomly generated 500 points within a region defined by 5-min raster cells with > 30 ha of rain-fed cotton harvested (MIRCA2000[2]).

We used 19 bioclimatic variables acquired at 5 min resolution from Worldclim[4] (baseline) and CCAFS[5] (RCP 8.5, 2050). Ten models used by de Sherbinin et al[6] were averaged for input future model data. Twenty percent of points were reserved from training input for model testing.

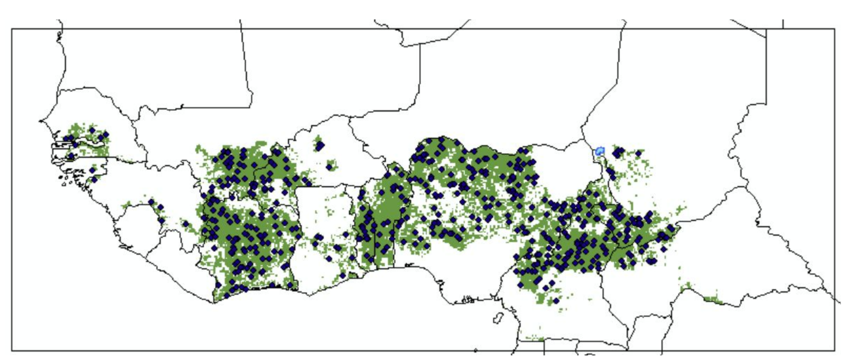


Figure 2. cells with > 30 ha of rainfed irrigated cotton harvested (green; data ca. 2000[2]) and randomly generated presence points within those cells (black dots).

Results

The area suitable for rainfed cotton declines sharply in 2050 modelled conditions. Variables explained distribution well: AUC = 0.86 for training data and 0.85 for test data (fig. 3). The most influential bioclimatic factor in this region was seasonal precip, followed by growing temperature seasonality; both constrain northern and southern extents of the study area. Most states lost nearly all suitable growing area (fig. 4, 5).

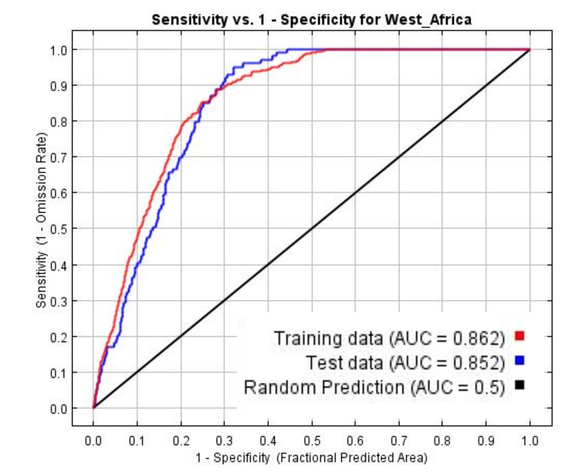


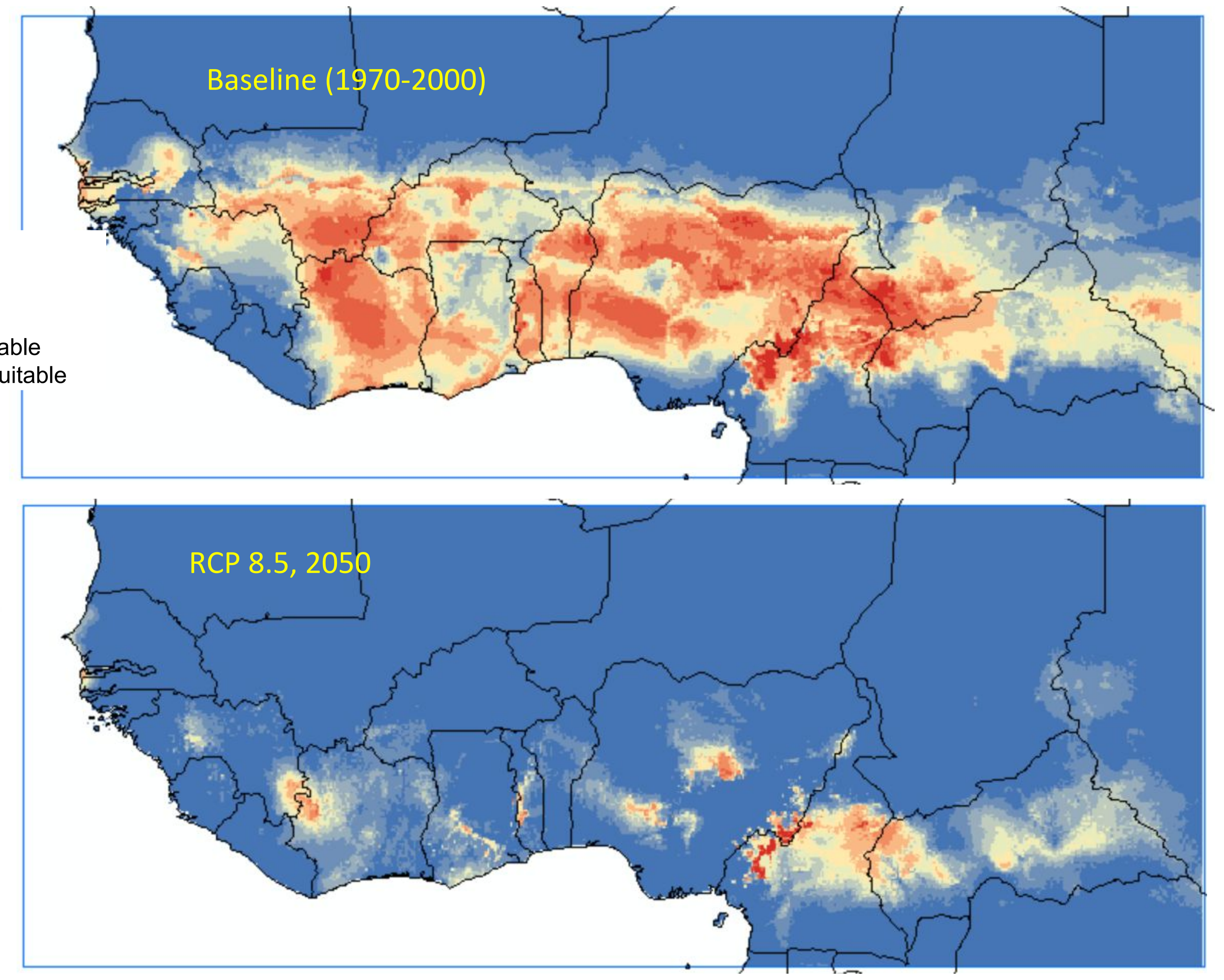
Figure 3. ROC curve

Variable	Variable	Percent contribution	Permutation importance
Annual precipitation	bio_12	60.1	22.7
Temperature seasonality (std dev)	bio_4	18.5	19.1
Precipitation of warmest quarter	bio_18	7.9	9.3
Isothermality (diurnal range/annual range)	bio_3	4	25.6

Figure 4. Suitability

1 = very suitable
0 = very unsuitable

0.91 - 1
0.81 - 0.9
0.71 - 0.8
0.61 - 0.7
0.51 - 0.6
0.41 - 0.5
0.31 - 0.4
0.21 - 0.3
0.11 - 0.2
0 - 0.1



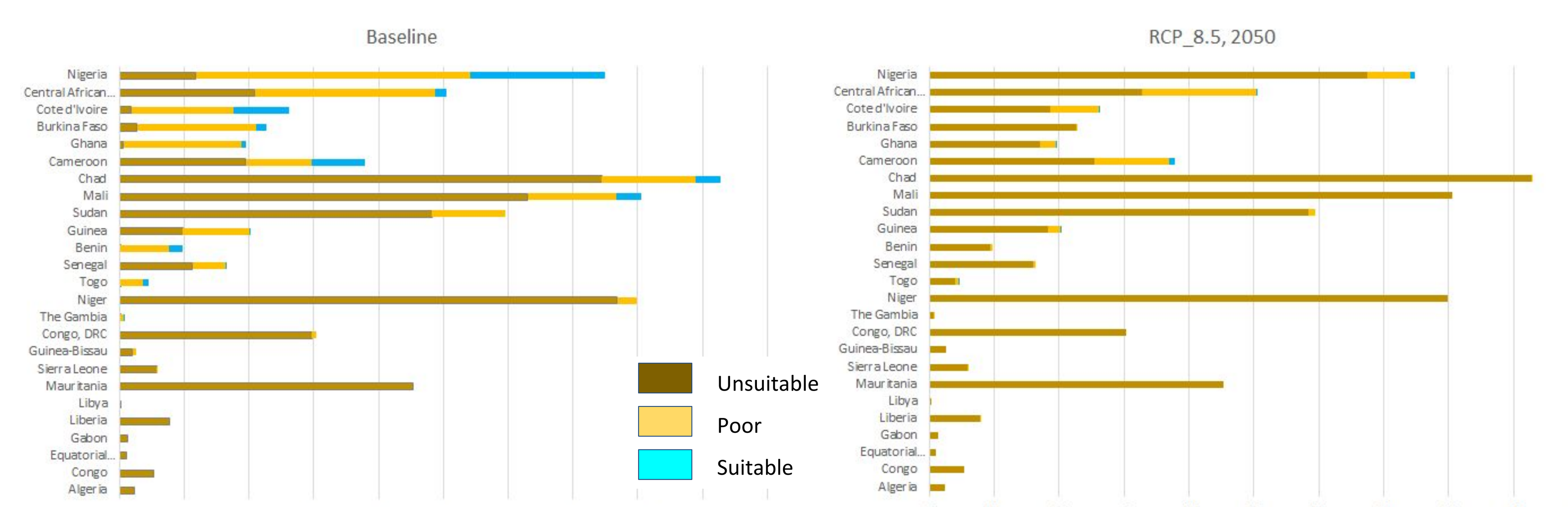


Figure 5. Count of cells classed for present purposes as "suitable" (suitability index values 0.66-1.0), "poor" (0.33 - 0.66) or "unsuitable" (0 - 0.33), by state. These cutoff values are subjective and provisional.

Uncertainty

Assessing and communicating uncertainty in future models is an challenge for species distribution modelling, and projections should be interpreted with caution, even while they use the best available information.[7] Maxent uses an information theoretic approach that takes a conservative approach to confidence, and the AUC indicates good confidence in model fit.[3] In addition, while areas outside the range of input values should be interpreted with caution (red shading, fig. 6), these areas were generally outside of both observed and projected areas of high suitability.

The greatest uncertainty in this approach lies in our inability to test 2050 conditions against observations. Consequently the model results here can be posited as an expected outcome of business-as-usual changes. Testing these expectations against production observations in future years is the only way to have clear certainty in model output.[7] However, climate projections have often been observed to under-predict change.[8]

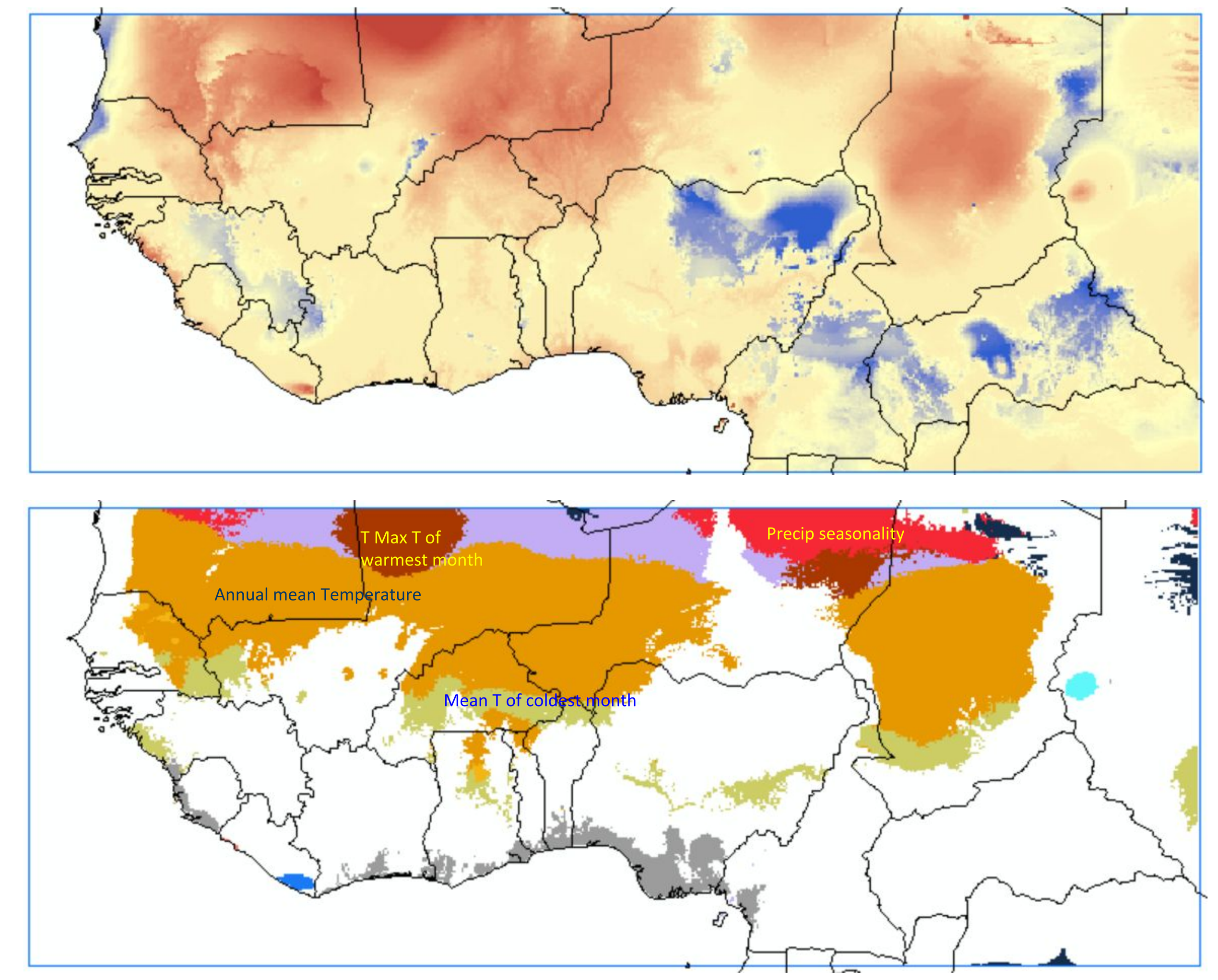


Figure 6: Values outside the range of training values. Areas in red (top) have values out of range and should be treated with caution. Primary variables outside of range are indicated (bottom).

Implications

A species distribution modeling approach can provide insights into the effects of climate change on crops and agricultural communities. While farmers and crop breeders are innovative, climate limits are likely to constrain production, especially where capital or water for irrigation is limited. While adaptation of agriculture is a known need, changes found here point toward substantial shifts in production systems, possibly advantaging relatively capital-intensive, irrigated systems (if high temperatures allow crop growth). This could imply shifts regimes and ownership of production, with relatively higher vulnerability for smallholders.

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