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CROP MODELING TO SUPPORT CLIMATE CHANGE RESILIENCE IN KENYA

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Introduction

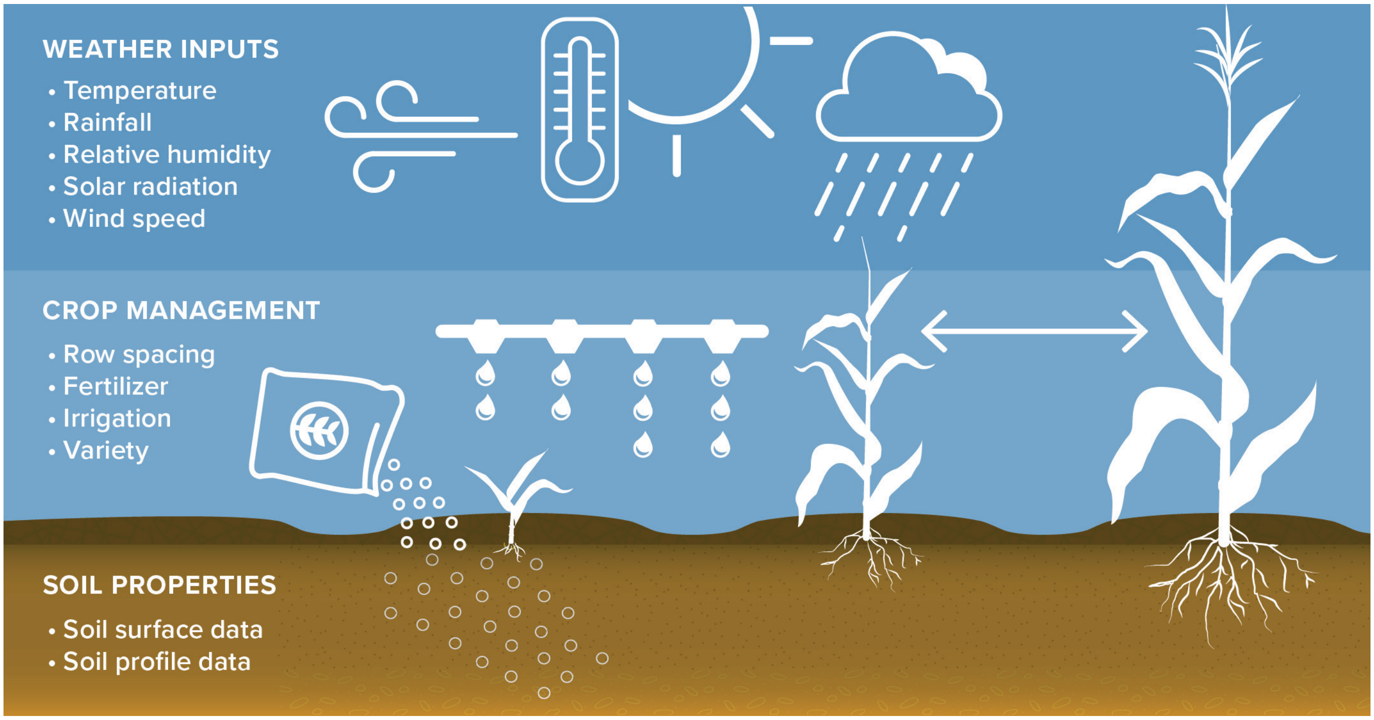
Food insecurity in Africa is growing, exacerbated by multiple overlapping and compounding crises. The United Nations estimated that in 2020 more than 2 billion people—close to one in three—did not have access to enough food (Food and Agriculture Organization [FAO] et al., 2021). In 2020, 281.6 million Africans were undernourished, an increase of 89.1 million over 2014. Since then, the COVID-19 pandemic, supply chain disruptions, and the war in Ukraine have led to further increases in food insecurity caused by the loss of many individuals' livelihoods and increases in food prices (Adjognon et al., 2020; Josephson et al., 2021; Kansiime et al., 2021; Maredia et al., 2022; Gebre & Rahut, 2021; Kogo et al., 2021).

Climate change further increases the risks of food insecurity because of reductions in agricultural production and other factors. Climate variability and extreme weather increase pressure on already fragile lands, displacing people and driving conflict (Abel et al., 2019; Cappelli et al., 2022). The frequency of extreme weather events has increased substantially in Sub-Saharan Africa over the past four decades, and it has increased there at a faster pace than in the rest of the world. Relative to 1970–79, the frequency of droughts in the region nearly tripled by 2010–19 (Centre for Research on Epidemiology of Disasters, 2019). In fact, data from FEWSNET 2022 indicate that the Horn of Africa region will experience an unprecedented fourth consecutive drought, raising major concerns about the food security of vulnerable populations in Kenya and other countries in the Sahel region.

While the adverse effects of climate change are increasingly visible, major knowledge gaps limit policy makers' ability to predict and respond to food security threats caused by climate shocks. Remote locations, extreme weather, and conflict worsen the ability of policy makers and practitioners to rapidly generate and use data to make evidence-based, actionable decisions. In the absence of such data, it is critical that policy makers have access to reliable predictions on how climate change affects agricultural production. Reliable predictions can help stakeholders to develop response strategies for years of crop shortfalls, which could limit the likelihood of famine and food insecurity. Policy makers may consider crop modeling as a tool to contribute to global food and nutrition security. Crop models are in essence a mathematical representation of a cropping system (see Figure 1). This approach has the potential to create a better understanding of crop performance and yield gaps, genetic gains, more efficient irrigation systems, and optimized planting dates.

In this brief, we describe how a multidisciplinary crop simulation model developed by the American Institutes for Research (AIR) can rapidly generate reliable evidence on the effects of climate change on maize production in Kenya. It accounts for gene-based modeling and breeding selection; water use; greenhouse gas emissions; and long-term sustainability through the soil organic carbon and nitrogen balances. The model simulates both the physiological processes of plant development and the physical determinants of resources available in the whole soil–plant-atmosphere environment, highlighting the effects of the climate, soil, and crop management on crop growth, development, and production (Hoogenboom et al., 2004). Based on our analysis, predictions of maize yields using this model are comparable to the official maize production data from the Kenyan government and FAO.

Figure 1: Example of a Cropping System



PREDICTING MAIZE CROPS IN KENYA

Reliable estimates of maize production are critical because maize is the primary staple crop in Kenya and plays an important role in the livelihood of the local population. Its availability and abundance determine the level of welfare and food security in the country. However, maize production has not kept pace with population growth, despite exploitation by breeders and agronomists to boost its yield. Kenya's annual production target has been 40 million bags, or approximately 3.6 million tons, while the average annual food and other uses requirement is about 52 million bags (Kenya National Bureau of Statistics, 2022). The deficit is met through imports from elsewhere in the region—mostly Uganda and Tanzania—and intermittently from overseas during drought seasons.

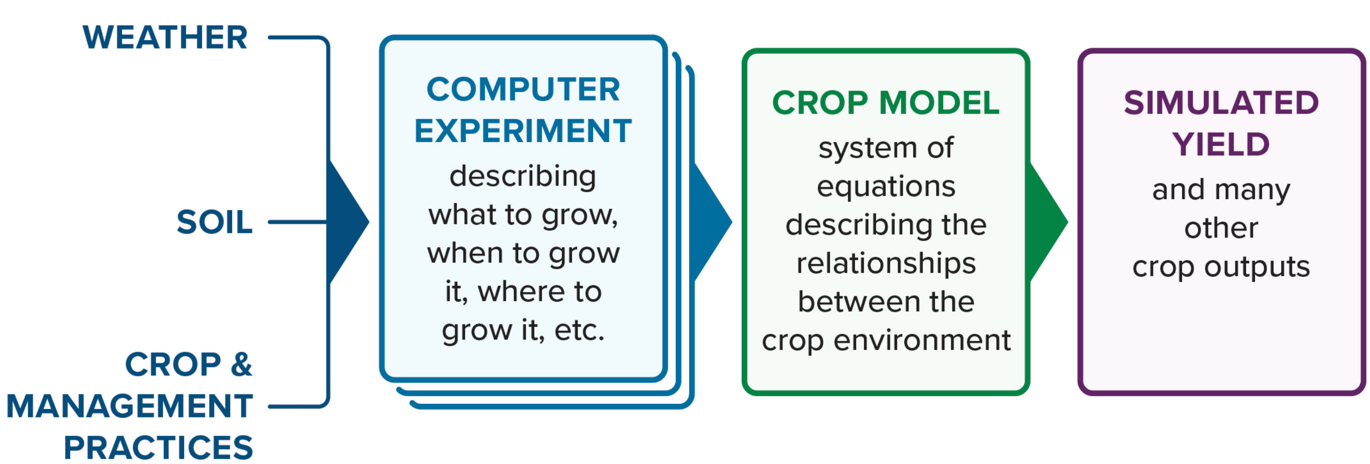
Because maize production in Kenya is predominantly rainfed, the production is heavily influenced by various climate-dependent abiotic factors, such as drought, waterlogging, heat, and frost, and biotic factors, such as disease, pests, and nematodes. In addition, Kenyan maize farmers' productivity has stagnated as:

- **FARM SIZES** have declined to uneconomical sizes;
- **SOIL QUALITY** has deteriorated; and
- **FARMERS COMMONLY USe** unsuitable varieties, infrequently use production inputs, and sub-optimally use inorganic fertilizers.

We used a four-step process to run and validate AIR's crop models. To run models on a national scale, we first divided the country into grid cells of 5 arcminutes (approximately 9.297 km) based on a geographic coordinate system. Second, we prepared a model using several explanatory variables:

- **WEATHER INPUTS**—Daily maximum and minimum temperature, rainfall, relative humidity, solar radiation, and wind speed data, collected from January 1983 to December 2022. For the remainder of 2022, we use the long-term daily average of the variables as the input to the model.
- **SOIL PROPERTIES**—Soil surface data include soil classification, surface slope, color, permeability, surface runoff curve number, and drainage class. Soil profile data by soil horizons include percentage of sand, silt, and clay content; bulk density; organic carbon; pH; etc.
- **CROP MANAGEMENT PRACTICES**—Variety, row spacing, plant population, fertilizer, and irrigation application dates and amounts as inputs for simulating growth, development, and yield (see Figure 2).

Figure 2: Crop Model Framework



Third, we ran a crop model for each individual grid cell or location. Fourth, we aggregated results of the simulations using gridded maize harvested area data layers to predict maize production in Kenya.

Our model allows policy makers to predict maize yields for each county or subcounty in Kenya. Users can run crop simulations over large areas and for many growing seasons using grid cells that each align with a specific location in Kenya. Using our model, policy makers can also simulate the results of many different decisions. For example, the model allows for making predictions about maize yields for rainfed high nitrogen-level maize production practice and comparing that with the results of irrigated high nitrogen-level, rainfed low nitrogen-level, or rainfed no nitrogen maize production practices in the long-rains growing season and short-rains growing season.

To generate predictions of maize production for a specific variety, we ran a two-stage simulation using a hybrid maize variety, H625. This variety grows in all six maize production zones (highland tropics, moist transitional, dryland transitional, moist mid-altitude, and dryland mid-altitude zones) in Kenya except for the lowland tropical zone (Hassan et al., 1998).

In the first stage, we conducted simulations without rainfall modification (i.e., normal rainfall) and with all crop management practices applied by farmers for both long and short rains. In the second stage, we modified our simulations with 50% less rainfall modification and with all crop management practices applied by farmers.

Figures 3a–3f and Figure 4 show the results of the simulations for each grid cell location for the long-rain season in 2020, showing that our model produces comparable results as officially reported maize production from the Kenya Ministry of Agriculture and FAO. At each grid cell location, we ran simulations for each year sequentially from 2010 to 2022.

Figure 3: Maize Production Model Simulations, 2020

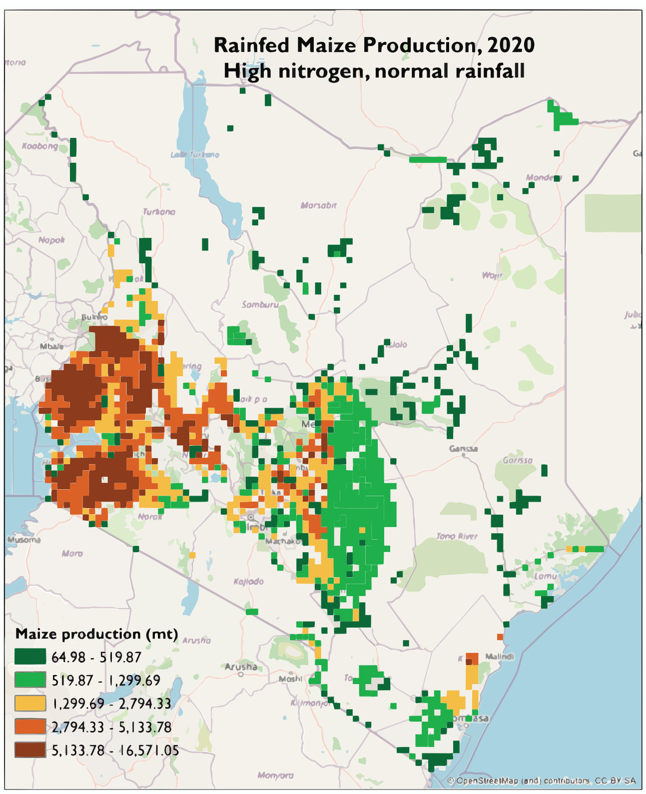


Figure 3a

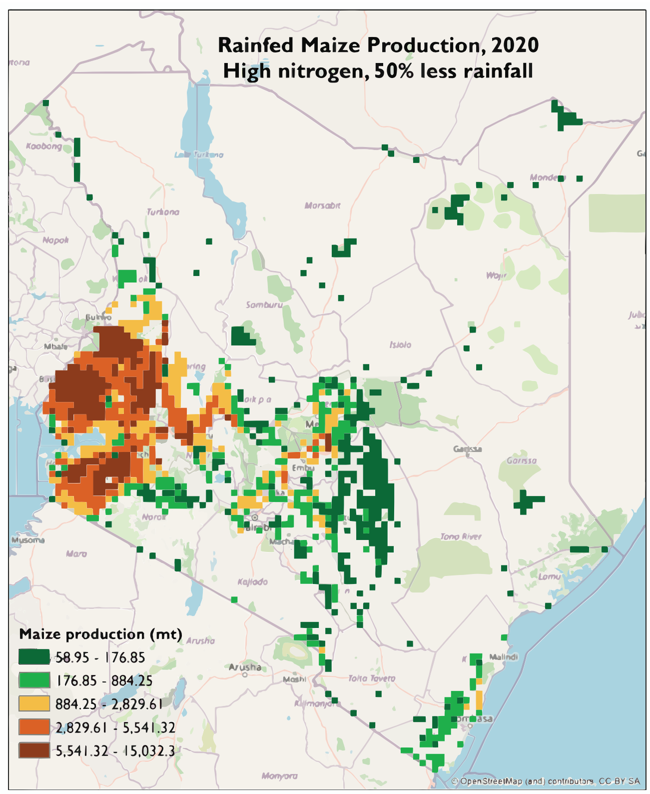


Figure 3b

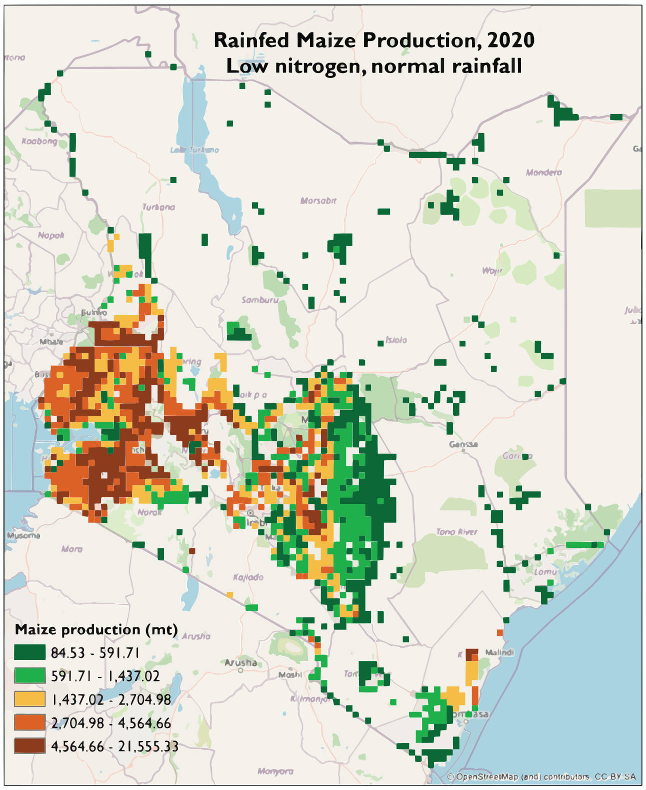


Figure 3c

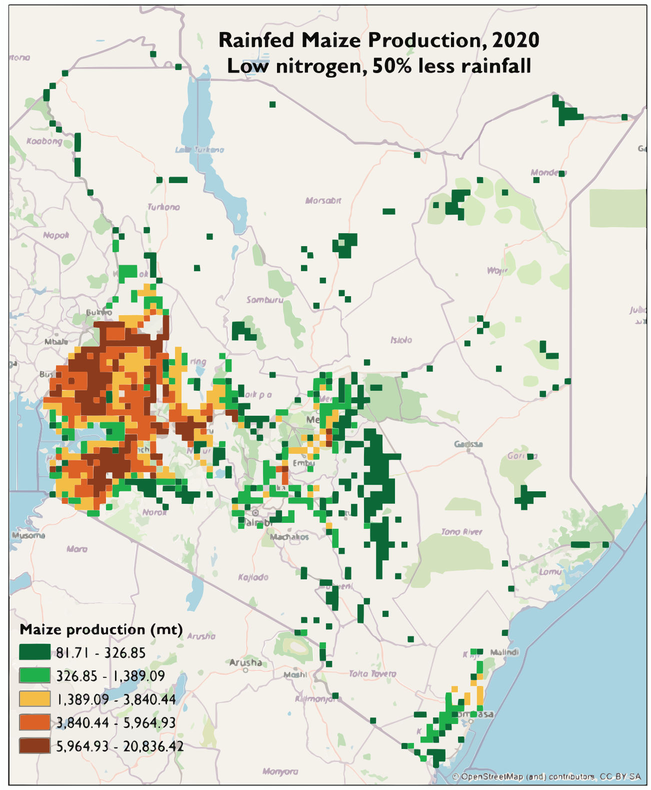


Figure 3d

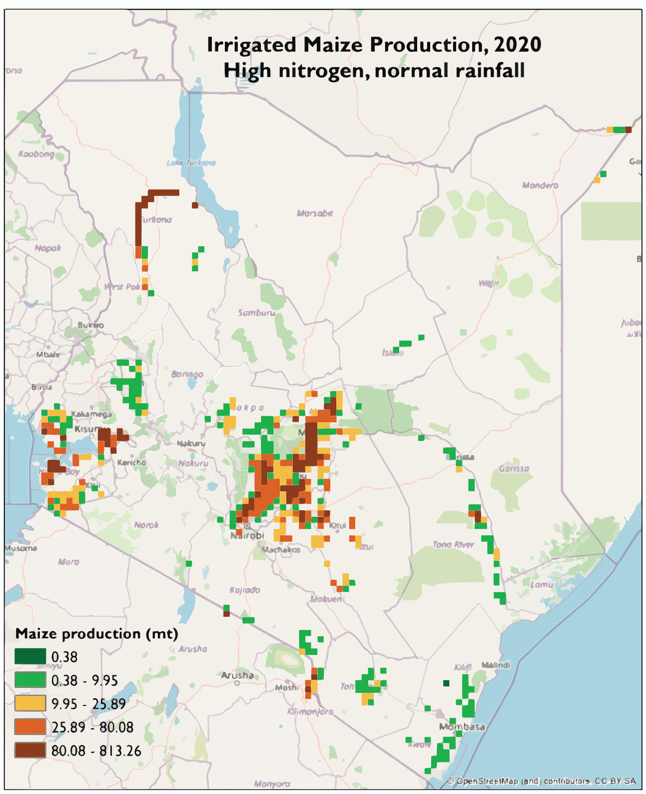


Figure 3e

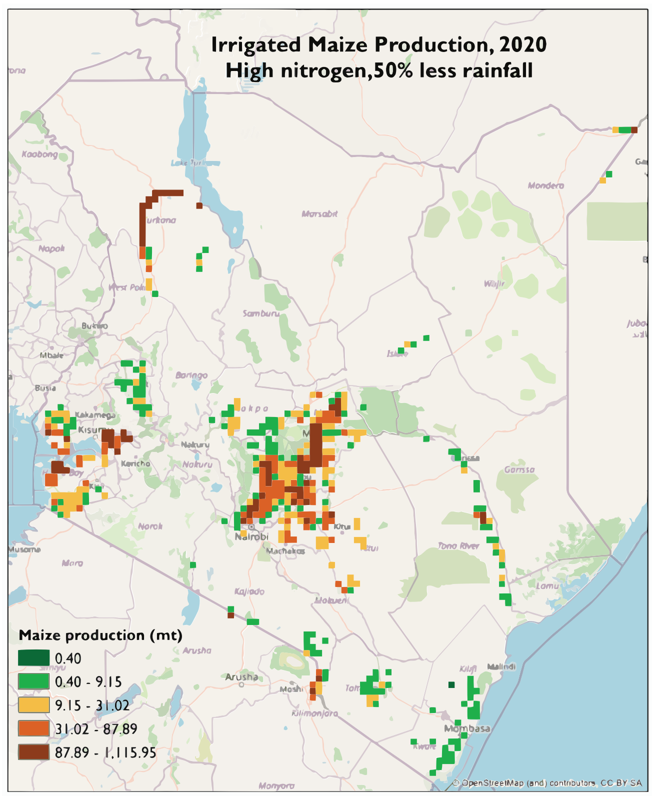
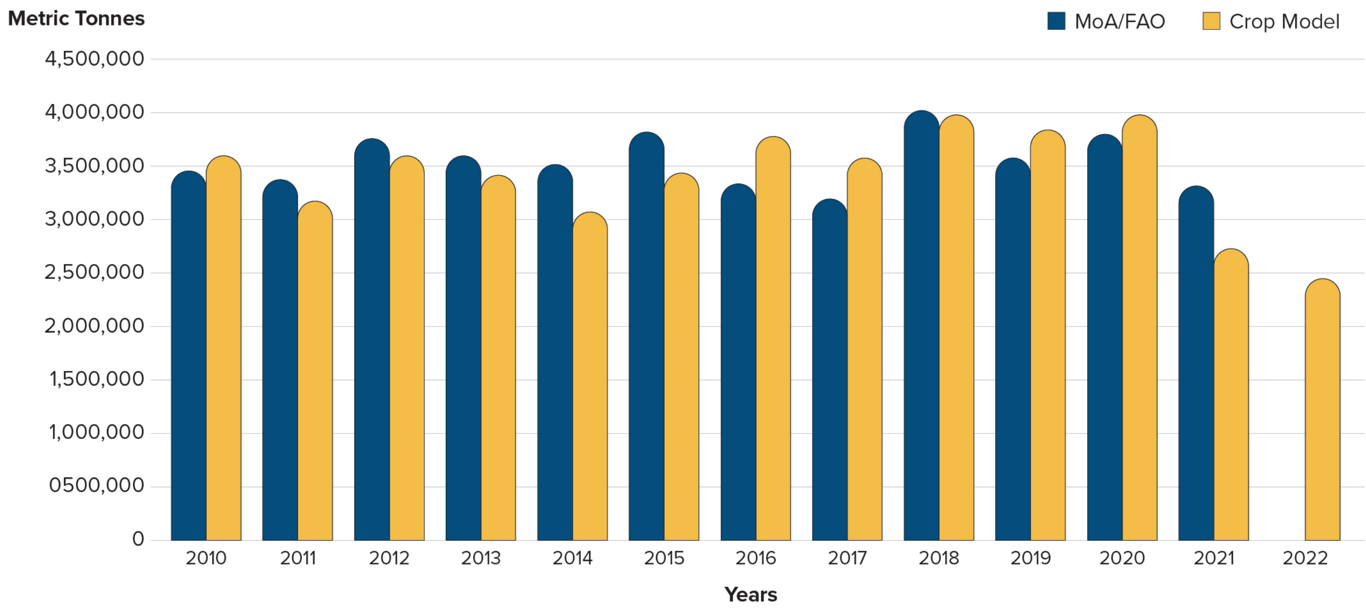


Figure 3f

Figure 4: Predicted Maize Production for the Year 2020 Versus Official Figures



The different regions in Kenya each face different climatic conditions. From east to west, the lowland tropics on the coast and dry mid-altitude and dry transitional zones around Machakos (figures 3a–3d) are zones characterized by low yields.

Although they cover 29% of Kenya's maize area, they only produce 11% of the maize. These are drought-prone maize areas of Kenya as depicted by drought scenarios—50% less rainfall modification (figures 3b and 3d). Central and Western Kenya are dominated by the High Tropics, bordered to the west and east by the moist transitional zone, which is between mid-altitude and highland. These zones have high yields and produce 80% of Kenya's maize on 30% of Kenya's maize area. Finally, the area around Lake Victoria is the moist mid-altitude zone, with moderate yields.

Conclusion

This brief shows how crop simulation models can generate reliable predictions of maize crop yields in Kenya. We combined traditional data with globally available datasets to provide quantifiable information that can guide stakeholders in making decisions that contribute to agricultural production and food security in Kenya.

Using our model, policy makers can make predictions of maize production for distinct policy scenarios for different growing seasons in Kenya. Policy makers can run in-season crop yield forecasting using seasonal weather forecasts for early warning planning of food security. These predictions can help stakeholders develop strategies for years of crop shortfalls and thus contribute to policy makers' ability to reduce the likelihood of famine and food insecurity in Kenya.

Future research could focus on combining the crop simulation model with data from large-scale surveys, as well as data on dietary diversity, including gender-disaggregated data. While large-scale surveys to collect data on agricultural outcomes are costly and labor-intensive, they remain critical to provide reliable information about agricultural production and food security in Kenya and other low-and middle-income countries. We do not consider our model a replacement for such surveys. Instead, we consider crop simulation models and large-scale surveys as two complementary methods that can generate synergies for maximizing learning about how to improve climate resilience.

In addition, it is critical to combine the model with gender-disaggregated data and data on dietary diversity and nutrition. At this moment, the model produces reliable estimates of maize production in Kenya. However, it is not yet clear how various levels of maize production have differential effects on food security for men, women, boys, and girls in Kenya. For this reason, it is critical to combine the results from the simulations with data on women's agency and dietary diversity of different household members, as well as children's stunting and wasting, to generate lessons about how climate change affects women's empowerment, dietary diversity, and nutrition outcomes. Finally, it is critical to validate the model in other contexts and for different crops, including in other settings in Sub-Saharan Africa and South Asia. In doing so, we may learn about how the results of the models interact with contextual characteristics.

Evidence-based decisions to improve agricultural production and food security in Kenya will become ever more important in a context with climate variability, extreme weather, and multiple, overlapping, and compounding crises. Adding data on women's empowerment, dietary diversity, and children's nutrition outcomes will broaden the application of AIR's crop model, enabling policy makers to use crop simulation models for a larger variety of objectives. In this way, crop simulation models can contribute to policy makers' ability to improve the welfare of farmers in Kenya and various other low- and middle-income country settings.

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