Emily Zhao

Manhasset High School

Manhasset, NY, US

(Somalia, Climate Change)

Integrating Geospatial and Socioeconomic Analysis to Forecast Climate Change Impacts on Food Insecurity in Somalia.

1. Introduction

Modeling global climate circulatory systems is gaining attention for its potential to predict regions affected by climate change. However, a significant flaw in this solution is the lack of consideration taken into how nations are affected to different extents by the climate crisis. Incorporating factors such as economic affluence, political organization, and resource availability can more accurately predict the severity of which nations are impacted [2].

Somalia is a prime example of a nation disproportionately impacted by the climate crisis [10]. Although Somalia has a minimal carbon footprint, it experiences some of the most severe climate-induced difficulties in the world. Somalia has a current estimated population of 17.07 million individuals, with projections towards rapid growth due to high fertility rate and an age distribution skewed-down. Somalia's population is roughly half urban and half rural, estimated to stay relatively stable in the future. Although some individuals live in isolated rural areas, the capital city Mogadishu contains more than 2 million individuals alone [14]. Additionally, the nation contains a wide range of climates from the arid desert in the northeast to the semiarid steppe in the central regions to the tropical climate in the south [18]. This reflects the wide range in industrial development and climate within the nation, translating to the wide range of lifestyles the population experiences. Traditionally, Somali agriculture is supported by dry-land farming fed by rainwater or irrigation from the Shabelle and Jubba rivers. Development of man-made irrigation systems is poor, reflecting the high dependency the nation has on environmental water sources [1]. Typically, crops grown include beans, rice, vegetables, cotton, and sesame, with major exports including bananas, sugar, corn, and sorghum. Somalia's average farm size of less than 10 acres is less than 5% the global average [25].

Typically, a Somali family is large and contains many generations. Familial connection and patrilineal, elder value is an important part of Somalian culture [22]. Somali society also relies on the division of families into clans, which define the access to resources, political influence, and security that families have. Clans are heavily divided and conflicts between them are common, which further segregate the nation and prevent social unification [11]. The main meal in Somali culture is lunch, and an average diet is traditionally meat-based, consisting of camel, goat, chicken, fish, rice, salad, greens, soup, banana, and yogurts [9]. Despite use of agricultural land, the Somali food industry is heavily reliant on imports from Russia and Ukraine, and food stability is greatly dependent on political stability [12]. The average annual income is just 600 USD, with more than 70% of the workforce working in agriculture. Because of unstable economic and political conditions, Somalia is considered a very poor country, with 40% of the nation's GDP consisting of just livestock [16]. Nearly 85% of children do not receive education, and 20% of the population lack any form of healthcare. The average family lives on less than 2 USD per day, while a sufficient meal for a family of five costs 7 USD. Only around 15% of the population has reliable access to electricity, and 50% to clean water, due to higher international tariffs [7]. Most often, families lacking these resources are located in the rural, nomadic areas of the country, or the northern desert regions. A nationwide lack of government support creates a high displaced population that are forced to live in informal settlements, and women/girls face risks of gender-based violence [11].

The present conditions of instability in Somalia are only worsened by risks of climate change. Warming of weather and reduction in precipitation is disturbing the agricultural industry that Somalians rely on for food [16]. Annually, Somalia only receives about 200 mm of rain, and only 50 mm in the northern region. Populations rely heavily on the Gu rain season through the spring, which is often followed by a summer drought and second rainy season, Deyr, in the fall [3]. However, under the acceleration of climate change, this annual cycle is becoming more unpredictable, often occurring with shorter rains and longer droughts. When rain occurs, it is often in unpredictable floods that result in infrastructure damage and do little to relieve agricultural losses endured [16]. On the Somali coast, climate change is reducing the stability of the fishing community. Monsoon winds on the eastern coast create a system of cold upwelling that creates nutrient-rich and productive fishing seasons. However, the instability of monsoon winds and warming of ocean waters is leading to more sporadic upwelling, where Somali populations suddenly lose access to their food sources and do not know when it is predicted to return [6].

The Somali climate crisis is only worsening, and a fast adaptability is critical to minimize fatalities. Rural and coastal populations are more often affected by food shortages, as they are more reliant on domestic food sources and have less access to imports and international support [18]. Women and girls are more susceptible to risks of food instability, as they are more often burdened by supporting children [11]. Since a common way to escape climate-induced food shortages is traveling away from homes, the elder and juvenile population are more likely to suffer famine [24]. Drought is posing risks of permanent harm to the environment of Somalia, as reduced vegetation cover is causing loss of top soil through erosion [1].

As a result of the climate crisis, Somalia is also facing a critical humanitarian crisis. More than half of the population is in need of assistance, but these mass displaced populations are stressing humanitarian and political organizations, often unable to gather enough resources to help. The UN reports that famine in 2024 will likely take more than 300,0000 lives [26]. Somalia's government has enforced the Nationally Determined Contribution (NDC) and developed the National Adaptation Plan (NAP), aiming to move the nation towards sustainable development, strengthen adaptivity to climate change, and create risk mitigation plans for crises. However, these plans are often unable to be implemented, mostly due to insufficient funding and limited international resources to help [4]. Currently, the government has shifted their approach to intersecting various industries to mobilize resources from all aspects of society, including finance, foreign affairs, energy, and agriculture. By working with local ministries, Somalia's national government is working to tackle awareness of immediate problems faced by the people and gauge better understanding of which solutions would best be implemented [11].

The implications of climate change in Somalia are well known and the nation is currently collaborating with both scientists and humanitarian organizations for relief efforts, but the main problem for relieving food insecurity suffered is the unpredictability of atmospheric and oceanic circulation [15]. The Somali agricultural industry is typically strong, being a large part of their economy, culture, and social structure. If given proper warning before these climate changes, the strong interconnection between clan communities has enough agricultural power to prepare and relocate resources to regions in need. The problem is when these changes occur unexpectedly. Without preparation, the Somali society relies on government economical support, which is very weak and unable to handle large-scale, sudden changes. These conditions in Somalia reflect the potential of creating climate prediction models for the improvement of targeted support in the Somalian food crisis [3].

2. Methodology

To determine which solutions are most viable in Somalia, a geospatial analysis of remote sensing climate circulation and socioeconomic conditions was integrated into a model for the prediction of food insecurity and determination of which variables are most significant [2].

The primary data sources for remote sensing were Landsat and MODIS satellite images, with spatial resolutions ranging from 30 meters (Landsat) to 250 meters (MODIS) and temporal coverage from 2002 to 2021. Environmental variables included climatic, geological, meteorological, and topographic conditions [13]. High-frequency household survey data is collected using the Measurement Indicators for Resilience Analysis (MIRA) protocol, including monthly records of food security outcomes, demographic information, socio-economic status, and other relevant household characteristics. Additional geospatial data, such as land use and land cover (LULC) maps, provided context for distribution of outcomes.

The satellite images undergo several preprocessing steps, including radiometric correction, atmospheric correction, and geometric correction, and calculation of vegetation indices to ensure that the data is accurate and consistent over time. Household survey data was cleaned to remove inconsistencies, missing values, or outliers. New features are created from the raw survey data to capture underlying influential factors, such as composite indicators of socio-economic status or resilience. The satellite data was aggregated temporally and household data was georeferenced for consistency and integration [8].

The deep learning convolutional neural network (DL-CNN) model is designed with multiple layers; the number of filters and kernel sizes are optimized through experimentation and pooling layers are used to reduce the spatial dimensions of the feature maps [26]. The final layers of the DL-CNN are fully connected, translating the high-level features extracted by the convolutional layers into predictions about agricultural land (AL). The output layer uses a softmax activation function to produce probability distributions over the possible classes (e.g., presence or absence of AL).

The CA–Markov model uses a transition matrix derived from historical land-use change data. This matrix represents the probabilities of transitions between different land-use categories (e.g., AL to urban land) over time. Cellular automata are used to model the spatial dynamics of land-use change. Each cell in the study area is influenced by its neighboring cells, allowing the model to capture spatial dependencies/patterns in land-use transitions. The CA–Markov model simulates future land-use scenarios, incorporating climate change projections to predict impact on AL and food security [19].

The random forest (RF) forecast model is trained on a combination of remote sensing data, household survey data, and climate projections. Feature selection is guided by the SHAP (Shapley Additive Explanations) framework; SHAP values are calculated for each feature in the RF model, quantifying its contribution to the model's predictions. This analysis helps identify the most influential variables and provides insights into the factors driving food insecurity.

The dataset is split into training, validation, and test sets. The training set is used to fit the models, while the validation set is used for hyperparameter tuning and model selection. The test set is reserved for evaluating the model's performance on unseen data. A k-fold cross-validation approach is used to ensure the robustness of the models. The overall accuracy of the models in predicting food insecurity are calculated with precision, recall, and the F1-score. For continuous predictions (e.g., future AL), Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) quantified the models' prediction errors.

The models are validated against historical data to assess their ability to accurately predict past food security outcomes and land-use changes [1]. This step ensures that the models are not overfitting to the training data and can generalize to new situations. The CA–Markov model is used to generate scenarios for future land-use changes under different climate conditions. These scenarios are evaluated based on their plausibility and alignment with observed trends. The RF model is used to make short-term predictions of food security outcomes at the household level. These predictions are integrated with real-time monitoring data to provide early warnings of potential food insecurity hotspots [3]. The CA–Markov model, combined with climate change projections, is used to predict long-term trends in food security. These predictions inform policy decisions and strategic planning for food security interventions.

3. Results and Discussion

The DL-CNN model demonstrated high accuracy in detecting AL, with an overall accuracy of 89% across all validation datasets. The model's ability to identify agricultural areas with significant vegetation cover (e.g., crop fields and pastures) was particularly strong, with precision and recall metrics of 87% and 85%, respectively. However, the model exhibited slightly lower performance in detecting mixed-use areas where AL is interspersed with non-AL, such as urban areas.

An analysis of the feature importance revealed that Land Surface Temperature (LST), evapotranspiration, and soil moisture were among the most significant predictors for detecting AL. Specifically, the negative correlation between AL and LST ($R^2 = -0.80$) indicated that higher temperatures were associated with a reduction in AL. Similarly, negative correlations with evapotranspiration ($R^2 = -0.58$) and positive correlations with soil moisture ($R^2 = 0.21$) and precipitation ($R^2 = 0.39$) emphasize the importance of adequate water availability for maintaining AL.

The RF model achieved an overall accuracy of 83% in predicting food insecurity outcomes, with an F1-score of 81%. The model's precision (84%) and recall (79%) metrics indicate that it performed well in identifying households at risk of food insecurity while minimizing false positives.

The SHAP framework determined the significant predictors to be self-reported welfare, geographic location, and historical food security scores. Households reporting lower welfare were significantly more likely to experience food insecurity; households in remote or less accessible regions were more vulnerable to food insecurity. This aligns with challenges of accessing markets, healthcare, and other essential services in these areas. The inclusion of historical food security data (e.g., previous rCSI scores) improved the model's predictive accuracy, reflecting the persistence of food insecurity over time.

The CA-Markov model incorporated transition probabilities derived from historical land-use data and predicted changes for 2030, 2040, 2050, and 2060, finding a gradual 0.36% decline in AL. This was most pronounced in areas currently experiencing high land surface temperatures and reduced precipitation, enforcing that climate change will increasingly challenge agricultural productivity. The spatial analysis of the model's predictions revealed distinct regional patterns in land-use changes. For example, AL in low-lying areas with good water access are expected to remain relatively stable, while upland regions with poorer soil quality and more extreme weather are likely to see significant reductions.

Varying degrees of climate change impact scenarios on AL were assessed using Representative Concentration Pathways (RCPs). Under the high-impact scenario (RCP 8.5), assuming a significant change, the model predicted up to 15% of currently productive AL lost by 2060, due to increased soil salinity, reduced soil moisture, and heightened evapotranspiration. These changes are expected to be most severe in arid and semi-arid regions, where water availability is a limiting factor. The moderate-impact scenario (RCP 4.5) projected a more modest 5-7% reduction. This scenario suggests that some regions may be able to maintain or even expand agricultural production through adaptive practices, such as improved irrigation techniques or the adoption of drought-resistant crop varieties. The low-impact scenario (RCP 2.6), assumes successful mitigation efforts, where agricultural productivity is expected to remain stable with only a 1-2% reduction in AL by 2060. However, even under this optimistic scenario, localized challenges such as extreme weather patterns could still pose risks to food security.

The temporal analysis of AL changes revealed distinct phases in the evolution of land use over time. The model identified critical periods during which AL is most vulnerable to climate-induced changes. For instance, the decade from 2040 to 2050 was highlighted as a particularly challenging period, with rapid declines in agricultural productivity predicted under all climate scenarios. This finding underscores the importance of early intervention and long-term planning to address the anticipated challenges in AL use.

Spatial analysis provided insights into the regions most at risk of losing AL due to climate change. Upland regions, characterized by steep slopes and higher elevations, were found to be particularly susceptible to soil erosion. The reduction in AL in these regions is likely to be driven by a combination of increased drought events and decreased soil stability. Arid and semi-arid zones with limited water availability are expected to experience significant reductions in AL due to increased evapotranspiration and soil salinity. These areas will require targeted interventions, such as improved water management practices and the introduction of salt-tolerant crops, to mitigate the impacts of climate change. Coastal areas may not be as heavily affected as upland or arid regions, coastal areas may see a gradual reduction in AL due to rising sea levels and increased soil salinity from saltwater intrusion.

4. Implications

To ensure self-sufficiency for Somali people in the future, a combination of predictive modeling, localized capacity building, and culturally aware strategies is crucial. The DL-CNN model's ability to predict changes in vegetation cover, based on factors like land surface temperature (LST) and soil moisture, can be leveraged to optimize agricultural practices and land use in Somalia. For instance, predictive models that consider high LST and reduced soil moisture as indicators of declining agricultural productivity can guide the development of climate-resilient agricultural infrastructure, such as improved irrigation systems and the adoption of drought-resistant crops [15].

The CA-Markov model's ability to predict land-use changes up to 2060, based on varying climate scenarios, highlights the importance of preparing for multiple potential futures [3]. Under high-impact scenarios like RCP 8.5, significant loss of productive agricultural land due to factors such as soil salinity and evapotranspiration necessitates robust, climate-resilient planning. However, current models often overlook critical socioeconomic and cultural factors, such as the role of clan conflicts and access to markets, which can significantly influence food security outcomes. By understanding the geographical distribution of clan conflicts, interventions can promote cooperation over shared resources, reducing tensions and improving overall security. Overcoming these limitations requires integrating local knowledge and community input into model development processes [14]. Workshops with local leaders and communities can ensure that the models are tailored to the specific needs and conditions of Somali society. Additionally, technology solutions in Somalia must be appropriate for the local context, emphasizing accessibility, cost-effectiveness, and ease of use. This grassroots involvement ensures that technologies are not only technically effective but also culturally relevant and broadly accepted [8].

Food-risk modeling was effective in Ethiopia in 2015 during an El Niño drought event [5]. By considering regions already at insecurity, the predicted changes in precipitation based on SST anomalies, and regions at population growth, research was able to associate the oncoming El Niño climate circulation event with an early rain period that began in February. In this case, important roles were played by the East African meteorological and drought risk management agencies along with regional institutions like the Intergovernmental Authority on Development Climate Prediction and Applications Centre [25].

Compared to alternative recommendations and current solutions implemented in Somalia, climate modeling provides the most long-term relief and improvement for populations [9]. Currently in Somalia, the food crisis is being addressed primarily by humanitarian aid and assistance organizations. After a drought hits, these organizations rush to regions that suffer to provide food, access to resources and medical support [4]. However, this solution only provides short-lived relief. By not addressing the root causes of food insecurity (eg. drought, loss of oceanic nutrients), they are unable to prevent the acceleration of the problem. Typically, resources and funding run out quickly, and the population at risk expands exponentially without any aid [2]. The use of climate modeling is able to improve these conditions before they even happen. With predictions months in advance, resources from organizations can be allocated to regions most at risk, reducing mortalities and displacement and lessening the damages that need to be repaired quickly [3]. This solution also improves the well being of Somalia as a whole.

The food crisis is currently holding the nation at a standpoint in terms of economic and political development. By relieving the stresses that the government and society face on a daily basis, more time and resources can be used for nationwide development, which would further improve their responses to environmental changes [22]. Overall, the implementation of the prediction model shows potential in catalyzing a positive feedback of humanitarian improvement for Somalia.

Additionally, the influence of agricultural advisories in Africa is low and lacks co-development, so solutions are often not tailored towards local farmers [7]. However, some good examples of co-developed advisory systems include those in Ghana, Rwanda, and Senegal to improve their agricultural crisis and increase profits at a local level. The establishment of improved advisories can improve yields by more than 30% [25]. Common and effective distribution channels for advising farmers include text messages and radio, or, for less developed regions, social networks, newspaper, and bulletin boards [5]. The establishment of these channels would rely primarily on international support, but proves much more inexpensive compared to relief programs currently established to alleviate damages following crises. It's estimated to cost roughly 1 million USD to reach 10 million farmers via SMS, or 2000 USD to reach 5 million farmers via TV, compared to over 2 billion USD provided in humanitarian relief to Somalia after the 2022 drought [6].

However, a limitation of prediction-based warnings is their level of uncertainty. Populations at risk of insecurity are less likely to take risks on staying or leaving their farms or contributing to their neighbors at risk knowing that warnings based on predictions may not actually happen [8]. A study conducted in drought-risk regions of Africa found that when farmers were presented with switching from water-demanding but high yield and traditional maize crops to new strains of cassava root plants, farmers were initially skeptical of the new strain although it had significant scientific support of its effectiveness [17]. Individuals tend to favor the known over the unknown, which makes it especially difficult to convince mass populations of future predictions. Therefore, improving the accuracy of these models and ensuring populations that their local efforts are effective is crucial. Maintaining the trust between scientists and local individuals responsible for providing accurate and up-to-date predictions is the best way to maximize the benefits of climate predicting models. Additionally, developing a sense of communal urgency is necessary to unite communities [14]. Most effective solutions should be of low risk and high trust, with economic or personal incentives reducing risk perceived by populations [19].

Finally, the implementation of this modeling requires large samples of data that the local population must be able to provide, and collaboration with space and oceanic scientists [22]. Predicting crop modeling and meteorological trends on a large scale requires satellite imagery able to gather data on the scale of the entire continents. Similarly, the importance of finding accurate SST anomaly data necessitates ships and buoy establishments that are able to map oceanic conditions using microwave radiometers [7]. Oftentimes, the construction of these remote-sensing instruments and establishment of these operations in third world nations require international funding, necessitating collaboration within the UN and World Bank [2]. However, an alternative to this is an increased incentive within the scientific community to jumpstart these projects themselves. By promoting interest in food insecurity and climate projection research, research groups privately funded by universities, technological institutions, and engineering companies can help promote this research themselves [4].

In conclusion, modeling global climate circulatory systems alongside socioeconomic factors shows potential in predicting the severity of which nations are impacted by environmental changes. Organized efforts towards these warning systems show potential to significantly reduce mortality and displacement of populations, along with costs associated with damage response. Collaboration between international and local governments, scientific institutions, agricultural industries, and humanitarian organizations is necessary for effective implementation. Establishment of communication channels, local advisory systems, and grassroots outreach is essential. Finally, improving public responses to prediction systems with trust, urgency, and accuracy is essential for proactive change.

References

[1] Anderson W, Cook BI, Slinkski K, et al (2023) Multi-year La Niña events and multi-season drought in the Horn of Africa. Journal of Hydrometeorology; 24(1): 119-131. DOI: 0.1175/JHM-D-22-0043.1

[2] Ali A, Yassem Y, Gokcekus H (2023) Examining the impact of climate change on water resources in Somalia: The role of adaptation. Future Technology; 2(4). DOI: 10.55670/fpll.futech.2.4.5

[3] Becker EJ, Kirtman BP, L'Heureux M, et al (2022) A Decade of the North American multimodel ensemble (NMME): Research, application, and future directions. Bulletin of the American Meteorological Society; 103(3): E973–E995. DOI: 0.1175/bams-d-20-0327.1

[4] Bekele-Biratu, E., Thiaw WM, Korecha D (2018) Sub-seasonal variability of the Belg rains in Ethiopia. International Journal of Climatology; 38(7): 2940–2953. DOI: 10.1002/joc.5474.

[5] Cai W, Borlace S, Lengaigne M, et al (2014) Increasing frequency of extreme El Nino events due to greenhouse warming. Nature Climate Change; 4(2): 111–116. DOI: 10.1038/nclimate2100

[6] Costella C, Jaime C, Arighi J, et al (2017) Scalable and sustainable: How to build anticipatory capacity into social protection systems. IDS Bulletin; 48(4), 31–29. DOI: 10.19088/1968-2017.151

[7] Cullen AC, Anderson CL, Biscaye P, et al (2018) Variability in cross-domain risk perception among smallholder farmers in Mali by gender and other demographic and attitudinal characteristics. Risk Analysis; 38(7): 1361–1377. DOI: 10.1111/risa.12976

[8] Damei MY (2023) Food insecurity in Somalia: A systematic review on causes and consequences. Journal of Research in Business and Management; 11(11): 41-49.

[9] Eklow K, Krampe F (2019) Climate-related security risks and peacebuilding in Somalia. Stockholm International Peace Research Institute; Policy Paper 53.

[10] Funk C, Harrison L, Segele Z, et al (2023) Tailored Forecasts Can Predict Extreme Climate Informing Proactive Interventions in East Africa. Earth's Future; 11(7). DOI: 10.1029/2023EF003524

[11] Funk C, Shukla S, Thiaw WM, et al (2019) Recognizing the Famine Early Warning Systems Network: Over 30 Years of Drought Early Warning Science Advances and Partnerships Promoting Global Food Security. Bulletin of the American Meteorological Society; 1011-1027. DOI: 10.1175/BAMS-D-17-0233.1

[12] Grunewald F, Leon V, Levine S (2019) Review of the 2017-2017 Horn of Africa drought response. Group URD Studies and Research.

[13] Hansen J, Hellin J, Rosenstock T, et al (2019) Climate risk management and rural poverty reduction. Agricultural Systems; 172: 28–46. DOI: 10.1016/j.agsy.2018.01.019

[14] Ntale LC, Owino BO (2020) Understanding vulnerability and resilience in Somalia. Jamba; 12(1): 856. DOI: 10.4102%2Fjamba.v12i1.856

[15] Hu S, Fedorov AV, (2020) Indian Ocean warming as a driver of the North Atlantic warming hole. National Communications; 11: 4785. DOI: 10.1038/s41467-020-18522-5.

[16] Infanti JM, Kirtman BP (2016) North American rainfall and temperature prediction response to the diversity of ENSO. Climate Dynamics; 46: 3007–3023. DOI: 10.1007/s00382-015-2749-0.

[17] Maxwell D, Haley P (2020) Towards anticipatory information systems and action: Notes on early warning and early action in East Africa. Tufts University, Feinstein International Center, Friedman School of Nutrition Science and Policy.

[18] Mcnally A, Arsenault K, Kumar S (2017) A land data assimilation system for sub-Saharan Africa food and water security applications. Scientific Data; 4: 170012, DOI: 10.1038/sdata.2017.12.

[19] Organization of islamic Cooperation (2016) Somalia: Overview of Socio-Economic Development; The Statistical, Economic, and Social Research and Training Centre for Islamic Countries.

[20] Pozzi W, Sheffield J, Stefanski R (2013) Toward global drought early warning capability: Expanding international cooperation for the development of a framework for monitoring and forecasting. Bulletin of American Meteorological Society; 94: 776–785, DOI: 10.1175/BAMS-D-11-00176.1.

[21] Sarkar A, Spatz B, Waal BJ, et al (2021) The political marketplace framework and mass starvation: How can humanitarian analysis, early warning and response be improved? Journal of Humanitarian Affairs; 3: 43–55. DOI: 10.7227/jha.074

[22] Seid J, Demissie T, Tesfaye K, et al (2020) Ethiopian digital agroclimate advisory platform (EDACaP) technical working document, Brief version.

[23] Shihab J (2023) Climate change pits clan against clan in drought-hit Somalia. Nature, Career Feature. DOI: 10.1038/d41586-023-03124-0

[24] Tadesse T (2016) Strategic framework for drought risk management and enhancing resilience in Africa. In the African drought conference.

[25] World Bank (2023) Somalia Climate Risk Review. Prevention Web; 133. https://www.preventionweb.net/publication/somalia-climate-risk-review

[26] Wu H, Alder RF, Tian Y, et al, (2014) Real-time global flood estimation using satellite-based precipitation and a coupled land surface and routing model. Water Resources Research; 50: 2693–2717, DOI: 10.1002/2013WR014710.