**Predicting Food Security with Machine Learning**

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**Abstract**

Hunger is on the rise throughout Africa, with famine threatening millions in several countries. Identifying food insecurity crises rapidly and accurately can enable humanitarian responses to mitigate casualties from hunger and save lives. We develop a predictive model based on readily available, spatially granular data on prices, geography, and demographics. Using machine learning techniques, we are able to improve the accuracy of predicting those villages that face a potential threat of hunger. As with any rare event, one challenge with predicting food insecurity is the thankfully low rate of severe food insecurity in the baseline data; we use different approaches to address this imbalance. We apply our procedure to three sub-Saharan African countries: Malawi, Tanzania, and Uganda to predict food security in out-of-sample villages. We correctly identify 69-88 percent of the food insecure clusters, which is 10 - 90 percent higher than the baseline model using a logistic regression. We further explore which data splits perform best under the spatial-temporal correlations between observations in the panel dataset to reduce overfitting in actual implementation. …Our result shows that a data-driven model with the help of machine learning methods can significantly improve its performance on capturing the food insecure households despite the imbalance in the data. Our paper demonstrates that this approach could be used in a scalable, automatically updated prediction model that could enhance the current famine early warning systems.

**Keywords:** food insecurity, machine learning, early warning, Sub-Saharan Africa, famine

**Predicting Food Security with Machine Learning**

1. **Introduction**

Hunger crises are increasing in frequency and severity in many parts of the world. Identifying the scale and scope of these crises in a timely and accurate fashion is essential for providing food aid and organizing humanitarian responses to mitigate the long-run effects of food insecurity. Without the information required to identify the right populations to target programming and resources, the food aid often fails to arrive the areas in time where the assistances are needed the most (Barrett and Headey 2014). One of the many reasons that prevent building a successful early warning system is that data are scarce, and data collection is costly (Hutchinson 1991). The data gap hinders the efforts to effectively target the population in need and calls for the use of data and method that are cost-effective and accurate. Currently, governments and NGOs in the sub-Saharan Africa region use the Integrated Food Security Phase Classification System (IPC) as the early warning system. The IPC uses a Delphic system that requires detailed on-the ground data and is updated quarterly for each livelihood zones, making it difficult to identify specific villages that might be at risk of hunger in the near term.

The recent increase in available data related to geography, weather, and market price for food staples provides us with the opportunity to predict food security more frequently at a finer geographic level. Nightlights data (Chen and Nordhaus 2011; Henderson et al. 2012) can serve as a proxy for economic activity but variations in the nightlight intensity are too low in remote rural or better off urban areas to detect any substantial changes in economic outcomes. Mobile phone data (Blumenstock et al.,2015; Steele et al., 2017) also hold potential for identifying economic outcomes and are more frequent and less expensive than census surveys. However, geocodes are often limited to cell towers, and the biases associated with using relying on cell phone-sourced information to infer population statistics are as of yet, not well understood. Very high-resolution satellite imagery is becoming cheaper but the lack of labeled data in the imageries makes it challenging to extract structured information from the raw images (Engstrom et al., 2017; Donaldson and Storeygard, 2016). Recent studies using a Convolutional Neural Network (CNN) and transfer learning (Jean et al., 2016; Babenko et al. 2017) make promising progress utilizing the information in satellite imageries. These models can explain up to 60% - 75% of the variation at the village level wealth and asset measures in several sub-Saharan Africa countries. However, the reliance on the information in the satellite imagery (specifically, building size, roof type, road conditions) limits its performance for time-varying development indicators. Head et al. (2017) finds that the prediction performance of the Jean et al. method degrades quickly on health and nutrition outcomes to no better than random guessing in some cases. The reliance on nightlight data in this approach also limits the prediction accuracy when applied in countries with different socioeconomic conditions. The external validity and interpretability of this deep learning-based approach call for a method tailored for food security predictions.

To the best of our knowledge, Lentz et al. (2019) is one of the few papers that combines spatially and temporally granular data that are publicly available to predict the food security status that greatly improves the prediction accuracy without significant cost in data collection and model training. Building on the framework in Lentz et al. (2019), in this paper, we construct a prototype of an early-warning system that is automatically updated, generalizable, scalable, and cost-effective in predicting areas of potential food shortage. Like Lentz et al., we incorporate data of different sources, dimension, and scales into a single predictive model of food security status. We use machine learning models to predict cluster-level food security status for targeting, aid purposes in times of food shortage. Variables in the model include the market price of food staples, weather shocks in growing seasons, and geospatial features around clusters. We combine data techniques such as oversampling and data segmentation with the machine learning models to improve prediction performance on the food insecure categories specifically. The models correctly capture 69-88 % of food insecurity categories among the three countries for different food security measures. The main contribution of this paper is to improve the prediction of clusters with potential food crisis in an imbalanced data setting with spatial-temporal correlations in the data. We are able to achieve this by choosing the right measurement of model success, data sampling, data split, and data segmentation.

Instead of predicting the overall accuracy of food security status in previous studies, this study focuses on correctly detecting the clusters that are actually food insecure. Similar to a fraud detection problem, severe food insecurity crises are rare but too valuable to miss, even for a single one of them. The failure of identifying villages with food shortage is more costly than falsely sending food assistance to areas that do not have a shortage of food. Therefore, we focus more on identifying all the insecure clusters to maximize the recall rate in classification, where the recall rate is defined as percent of actual insecure households correctly captured by the model. We care less about minimizing the number of secure clusters misclassified as unsafe. In technical terms, we put a higher weight on the recall rate than the precision rate for classifying the food security categories. Choosing the right criterion to optimize matters for model selection and parameter tuning. Ultimately, we want the model to correctly detect the minority classes that are food insecure. This paper uses a cost-sensitive learning approach to maximize the recall without too much sacrifice on precision.

Along with choosing the optimization criterion, we also explore the effect of different up and down sampling approaches to identify the food-insecure groups. Various sampling techniques are used to create a balanced data-set that forces the classifiers to learn about the characteristics of the minority class. One such method is merely oversampling the minority class at the risk of model overfitting. SMOTE creates synthetic new data of the minority class by forming convex combinations of neighboring points, as a way to reduce the overfitting in oversampling.

Data split and data segmentation also matters to creating a balanced and representative training and testing data set, with more discussion in the methodology section. With spatial and temporal correlations between observations in the panel data, the training and testing dataset may not hold the independent assumption. Without consideration of these correlations, we are inclined to choose more complex models and appear to have higher accuracy than actual; according to Robert et al. (2017). This paper contributes to the literature of food security prediction in panel dataset by emphasizing the importance of addressing and correcting for the spatial-temporal correlations among observations in order to reduce overfitting.

As a natural extension to Lentz et al. (2019), this study expands the study areas to Malawi, Uganda, and Tanzania with more years of data to test the framework with more heterogeneity in geography, environment, and socioeconomic status. For example, Uganda has two growing seasons, and the main food staples are matoke and cassava while most areas in Malawi and Tanzania have only one growing season and rely on maize as the staple food. This means adjustments to the local climate and agricultural markets, such as having the weather variables during local growing seasons, grabbing markets data on the staples that take up a more significant share in the household budget in that specific area. The machine learning algorithms and data techniques used for prediction are the same kinds for the three countries, but the hyperparameters are tuned on the training dataset of each country separately. This procedure makes the model generalizable for application in other data-scarce countries and areas with some previous household survey data (LSMS or DHS) and frequently updated market price for food staples. At the same time, the model remains flexible and adaptable enough to capture the differences between countries such as climate, crops, and road infrastructures. This research also sheds light on the ability to apply the model trained on areas where we have ground-truth data to offer insights on areas of the world where we have few survey data. We compare different methods and protocols of handling the raw data, choosing the right data split and data segmentation, selecting the optimal model, to come up with a standardized data flow that maximizes our chances of making the model generalizable for potentially other areas in the world.

This paper uses a data-driven framework with machine learning techniques to predict the onset of food crises. Combining remote sensing data with household surveys and price data, the models are able to produce the most spatially and temporally granular predictions of food security. With an emphasis on the structure of the prediction error, this paper uses various machine learning techniques to reduce the misclassification of food insecure cluster. The framework developed in this paper has important policy implications for accurately target and aid areas of potential food shortage in data scarce environments.

1. **Data:**

***Food Security measurement***

We predict three measures of food security used by the international humanitarian organizations, including USAID and the World Food Programme (WFP): the reduced coping strategies index (rCSI), the household dietary diversity score (HDDS) and the food consumption score (FCS). The HDDS measures the number of different food categories that a household consumes in past seven days. The FCS gives nutrient-related weighting to the count of food categories to come up with a weighted score of food quality. Higher values of both the FCS and the HDDS indicate higher food security and more diversity of nutrition intake. The rCSI reflects the number of coping strategies a household uses to address possible food shortages with higher values of rCSI, indicating lower food security. The rCSI is believed to capture inadequate quantities of food consumed, which is consistent with acute food insecurity. Governments and international agencies apply cut-offs to categorize food security status rather than use the (Vaitla et al., 2017). This is why this paper focus on the categorical prediction for the given cutoffs instead of the continuous measures of food security in previous works (Lentz et al. (2019) and Jean et al., (2016), among others). The food security category is close to the actual policy scenarios where policymakers are trying to capture all the insecure households in a potential famine year in the currently used IPC system.

***Explanatory data***

The variables used to predict food security are high-frequency data, including precipitation, temperature, market prices, soil quality, and geographic variables. These data are generally collected remotely and are widely available. We handcrafted weather-related variables such as the first day of rain, length of dry spells, growing degree days and heating degree days from the raw precipitation and temperature data during the growing seasons specific for each country. We gather the market price for main food grains for the major markets in each country and align the villages to the prices in their nearest markets. For missing data in the market prices, we construct market thinness measures defined as the number of weeks with price information missing in a given month. Variables regarding wealth status, asset ownership, and household characteristics are created using answers from the LSMS surveys. Although our results rely mainly on these variables from the surveys, we have variables that can serve as proxies for the information from the household surveys. Household roof type is used as a crude proxy of poverty that can be accurately captured from satellite imagery. Cellular phones are access to financial resources, market information, and remittance flow (Eagle et al. 2010, Blumenstock et al. 2016) also serve as significant predictors.

1. **Method**

This section explains the primary approach and techniques used in this paper. In summary, we use readily available data to model the food security status of village clusters in Uganda, Malawi, and Tanzania, with various machine learning related techniques.

***Categorical or continuous measure***

We focus on the categorical prediction for the given cutoffs of each food security measures as it is close to the actual policy scenarios where the policymakers need to locate places with most insecure households. We do care about the overall fit of the prediction on the actual food security measures and we achieve a similar performance of model fit compared to previous studies at around 0.7 R squared. Since this paper focuses on successfully detecting the villages in need of food assistance, we use categorical measures of food security to transform the prediction into a classification problem. In this way, we can utilize data techniques such as choosing the right result metrics, sampling techniques to improve the chance of detecting insecure villages.

***Result metrics***

Predicting when and where the food security crisis will happen is more important than having an accurate assessment of the food security status of the general population. In technical terms, this study focuses on the recall rate of insecure households, rather than the overall prediction accuracy. Models aiming to maximize the overall accuracy tend to capture characteristics that are rich in the majority of the population and fails to understand the insecure households enough. We do want to maximize the recall rate to try and get all the insecure households, without a too low precision rate so that we do not mistakenly categorize all the secure households as insecure. One of the population measures is the f-1 score serves as a balance between recall and precision, but in this particular application it does not put enough emphasis on the recall rate. Instead, we use a cost-sensitive learning approach to come up with our f-1 score. The cost-sensitive learning approach penalizes misclassifications of the minority class more heavily by having a cost function, which is equal to the inverse of the class proportions. Extra reward for identifying the minority class over the majority class, cost-sensitive learning changes this and uses a function C(p, t) (usually represented as a matrix) that specifies the cost of misclassifying an instance of class t as class p. Penalize misclassifications of the minority class more heavily than we do with misclassifications of the majority class, in hopes that this increases the true positive rate. In this paper, we have the cost equal to the inverse of the proportion of the different categories makes up. This increases the penalization as the class size decreases. The weighted f-1 score, the main result metrics that we use are calculated based on this function.

***Sampling***

Food secure households and villages make up the majority of the data samples. When we feed the prediction algorithms with the training data made up with this proportion, the models naturally pick up the characteristics of the secure households more than the insecure ones. As a result, the models tend to predict villages in the testing dataset to be secure. To force the models to gain as much information as possible regarding the imminent threat of food shortage, we applied the downsampling and oversampling techniques to force the model to learn about the tail of the distribution. Specifically, we downsample the households in the food secure category and oversample the observations that are food insecure to artificially create a dataset where the insecure households make up half of the observations in the training set while the testing set remains intact. These methods are broadly used to imbalanced datasets. We also use a method called SMOTE (Synthetic Minority Oversampling Technique) to creates synthetic new data of the minority class by forming convex combinations of neighboring points, as a way to reduce the overfitting in oversampling.

***Data split***

In the case of spatial and temporal correlations among data, splitting the data set into training and testing is harder than one would think, as the assumption of independence between the training and the testing set is not easily satisfied. The classical assumption of a random split in generating the testing data set may not hold since the points randomly assigned to the testing may have strong spatial and temporal correlations with some of the points in the training set. Because of these correlations, models with high prediction accuracy on the training set would appear to have higher than actual accuracy in the testing set as well. Consequently, the training process would prefer models and parameters that are complex enough to understand every bit of details in the training set. These models would tend to overfit in a truly independent testing set with simulation results shown in Robert et al. (2017). We use three different training, and testing data split methods to feature the importance of having the right split. Yearly split is using one year as a training set to forecast places where the famine may happen in the future. The regional division is used to predict rural or more remote areas given current information in more accessible regions. Random split is used as a demonstration of general prediction or the “best guess” on unknown households based on all the information that we have. Both the regional and random split method would result in some degree of temporal and spatial correlations between the training and testing dataset.

***Data Segmentation***

For data segmentation, we compare the results of models trained on the entire dataset of three countries, with models trained by each country separately and then weight the f-1 score by the number of households in each country. Similarly, we split the data into urban areas to predict urban areas in the testing data and use the models trained on the rural villages to predict rural villages in the testing set. Lastly, we train a shallow tree in each country based on observables to automatically split the data into several subsets. We compare the results of different data segmentation to find the optimal data segmentation strategy in food security prediction.

***Classification Algorithms***

For structured data like ours (unlike text or pure image), tree-based methods are popular as they work well with the nonlinearities and a large number of variables in the data. We start with a simple machine learning algorithm known as the Decision Tree. The decision tree splits the training data based on several input variables, such as does the village undergoes a long dry spell in the last year? If so, is the cluster rural or urban? The splits created by the questions divide the training data into different subset of data known as the “leaves.” In this classification problem, each leaf is associated with a probability of falling into the secure or insecure category and the probability is trained using the training dataset. The main hyperparameter of the classification trees is the depth of the trees. Deeper trees tend to capture more complexity of the data in the training set but may suffer from overfitting when applied to the testing set. Shallow trees may suffer from losing essential splits in the data and underfits the training set. As a result, tree-based ensemble learning methods like the Random Forest, and Gradient Boosting help to improve the improve model performances by averaging and sequentially improving the base trees, particularly helpful when there is a large number of variables in our model. Random Forest is a kind of bagging algorithms, short for “Bootstrap aggregating.” The idea of the algorithm is to create many trees based on randomly selected subsamples of the training data with randomly selected variables set at each split of the trees (the bootstrap aspect) and the weighted average of the result from the trees (the aggregating aspect). Boosting differs from the bagging method in that trees are grown sequentially instead of parallelly. Each tree uses error in prediction from the previously grown tree as adjust the weights in each iteration. Errors are corrected by sequentially adding new models to the existing models until no more improvements can be made. The gradient boosting method that we use is a combination of gradient descent and boosting. The Xgboost (Extreme Gradient boosting) algorithm relies on the same principles with gradient boosting but compared to gradient boosting; it is more efficient and faster since it uses sparsity aware algorithms and better processor utilization. We also tried out algorithms of anomaly detection such as clustering methods, One-class SVMs, and Isolation Forests…

***Baseline Model***

We apply a logistic regression as the baseline model, as opposed to the tree-based machine learning algorithms. For the baseline model, we use the year split and by country data segmentation with no downsample or oversample methods. We use the same variable groups used in machine learning including food prices, market thinness, cellphone ownership, floor/roof material, asset index, length of dry spells, average temperature, and rain.

1. **Results**

Table 1: Baseline vs. ML algorithms (year split)

* Higher accuracy for the ML models but similar recall rate
* Results differ greatly between measure on recall, but similar for accuracy

Table 2: Baseline vs ML algorithms with down/oversample technique

* Signification increase in recall rate when ML combined with oversampling

Table 3: Data Split Comparisons

* High accuracy and recall rate on the random split but problematic
* Year split results more reliable since surveys are conducted one or more than one year afterward

Table 4: Data Segmentation Comparisons

* Comparison of one dataset/ by country / urban-rural / automatic segmentation

1. **Discussion**

***Parameter tuning and feature importance analysis***

* Discussion on tree depth, max features and how they impact the results
* Discussion on variables that explains the majority of the variations in data, e.g., cellphone ownership

***Error analysis***

* Urban vs. rural
* By food security measure
* Regional error analysis

***Model deploy and update***

* Model generalization issues: what happens when we directly apply models trained in one country to predict another; what happens when we apply model trained on the three-country as a whole to predict another
* Model update: compare the results of using only one year to predict the third year, with a training set of two years. Thinking of a dynamic process of continually updating the model with new survey data, but the maximum number of years of data we have in each country is 3.

1. **Conclusion**

**Table 1: Baseline vs. ML algorithms: year split**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Country | Food Security Measure | Overall  Accuracy  (baseline) | Overall  Accuracy  (ML) | Recall Rate Insecure category  (baseline) | Recall Rate Insecure category  (ML) |
| Malawi  2010/11, 2013 to predict 2015/16 | FCS | 0.70 | 0.69 | 0.04 / na | 0.00 / na |
| HDDS\* | 0.49 | 0.73 | 0.49 / na | 0.66 / na |
| rCSI | 0.39 | 0.69 | 0.23 / 0.00 | 0.79 / 0.00 |
| Tanzania  2010/11, 2012/13 to predict 2014/15 | FCS | 0.89 | 0.88 | 0.02 / 0.00 | 0.21 / 0.00 |
| HDDS\* | 0.79 | 0.80 | 0.99 / na | 0.95 / na |
| rCSI | 0.63 | 0.63 | 0.37 / 0.00 | 0.38/0.00 |
| Uganda  2010/11 to predict 2012 | FCS | 0.74 | 0.77 | 0.37/0.11 | 0.16 / 0.00 |
| HDDS\* | 0.88 | 0.88 | 1 / 0.00 | 1 / 0.00 |

**Table 2: Baseline vs. ML algorithms with down/oversample technique**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Country | Food Security Measure | Recall Rate Insecure category  (Baseline) | Recall Rate Insecure category  ML + Oversample | Recall Rate Insecure category  ML + SMOTE | Recall Rate Insecure category  ML +   ADASYN |
| Malawi  2010/11, 2013 to predict 2015/16 | FCS | 0.04 / na | 0.93 / na | 0.10 /na | 0.16 /na |
| HDDS\* | 0.49 / na | 0.68 / na | 0.83 / na | 0.71 / na |
| rCSI | 0.23 / 0.00 | 0.80/ 0.00 | 0.16 / 0.00 | 0.13 / na |
| Tanzania  2010/11, 2012/13 to predict 2014/15 | FCS | 0.02 / 0.00 | 0.63/0.00 | 0.49/0.00 | 0.58/0.00 |
| HDDS\* | 0.99 / na | 0.66/na | 0.92/na | 0.85/na |
| rCSI | 0.37 / 0.00 | 0.44/ 0.00 | 0.42 / 0.00 | 0.46 / 0.00 |
| Uganda  2010/11 to predict 2012 | FCS | 0.37/0.11 | 0.24/ 0.00 | 0.44/0.33 | 0.43/0.33 |
| HDDS\* | 1 / 0.00 | 0.89/0.00 | 1 / 0.00 | 1 / 0.00 |

**Table 3: Data Split Comparisons**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Country | Food Security Measure | Year split | | Regional split | | Random split | |
|  |  | Accuracy | Recall | Accuracy | Recall | Accuracy | Recall |
| Malawi | FCS | 0.80 | 0.93 / na | 0.79 | 0.59 / 0.00 | 0.94 | 0.93 / 0.00 |
| HDDS\* | 0.68 | 0.68 / na | 0.90 | 0.89 / na | 0.94 | 0.93/ 0.00 |
| rCSI | 0.71 | 0.80/ 0.00 | 0.80 | 0.64 / na | 0.93 | 0.83 / 0.00 |
| Tanzania | FCS | 0.80 | 0.93 / na | 0.79 | 0.59 / 0.00 | 0.94 | 0.93 / 0.00 |
| HDDS\* | 0.68 | 0.68 / na | 0.90 | 0.89 / na | 0.94 | 0.93/ 0.00 |
| rCSI | 0.71 | 0.80/ 0.00 | 0.80 | 0.64 / na | 0.93 | 0.83 / 0.00 |
| Uganda | FCS | 0.76 | 0.24 / 0.00 | 0.77 | 0.27 / 0.00 | 0.79 | 0.56 / 0.60 |
| HDDS\* | 0.69 | 0.89 / 0.00 | 0.51 | 0.49 / 0.00 | 0.75 | 0.77/ 0.00 |

**Table 4: Data Segmentation Comparisons (keep the same testing set)**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Overall | Food Security Measure | By country  With oversample and ML | One dataset  With oversample and ML | Rural Clusters only  With oversample and ML |
| Malawi  predict 2015/16 | FCS | 0.93 / na | 0.00 / na | 0.01 / na |
| HDDS | 0.68 / na | 0.62 / na | 0.46 / na |
| rCSI | 0.80/ 0.00 | 0.08 / 0.00 | 0.53 / na |
| Tanzania  predict 2014/15 | FCS | 0.63/0.00 | 0.00 / 0.00 | 0.19 / 0.00 |
| HDDS | 0.66/na | 0.96 / na | 0.97 / na |
| rCSI | 0.44/ 0.00 | 0.08 / 0.00 | 0.86 / 0.00 |
| Uganda  predict 2012 | FCS | 0.24/ 0.00 | 0.00 / 0.00 | 0.16 / 0.00 |
| HDDS | 0.89/0.00 | 0.89/ 0.00 | 0.91 / 0.00 |

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**Fig. 1 Map of FCS**

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**Fig. 2 Top tree split**

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