Deep Learning for Crop Yield Prediction in Africa

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Motivation

Though food security is a key global issue, it is especially prevalent in Africa where an estimated 224 million people are undernourished (FAO, 2017). Agricultural monitoring, and specifically monitoring of crop yields, is a vital tool for monitoring the food security in a region. However, collecting high quality data in developing countries can be both expensive and difficult. We propose an alternative approach by using publicly available remote sensing data to predict maize yields in six African countries.

Problem Statement

- We predict crop yields at the **county level.** We predict over each **year** and **growing season.**
- For each labeled year, we have a collection of images. Each image *x* corresponds with a timestep *t* and spectral band *b.*

$$\left\{(x_{b_1}^1 \dots x_{b_1}^t) \dots (x_{b_n}^1 \dots x_{b_n}^t)\right\} \rightarrow y$$

- We restrict the images around the **peak NDVI** of that year. We use 6 months worth of images, with more months towards the growing season (before peak).
- We split our data into train/val/test using two different methods:
  - **Randomized**: randomly split (80/10/10).
  - **Chronological:** data from the most recent year as the test set. We average results predicting over the 5 most recent years, training on preceding years.
- For our main findings, we predict in-country. To test transferability, we also build a **combined** model, which takes in data from **all countries.** This model is tested on the randomized splits.

Data

Yield Data

- Yields provided by the US- AID Famine Early Warning System Network
- Admin 2 (i.e. district) or Admin 1 (i.e. province) level for 6 countries
- Each label corresponds to a harvest season for a specific year
- Measured in metric tons of crop per hectare of land
- Dataset size and yield distribution varies by country

Remote Sensing Data

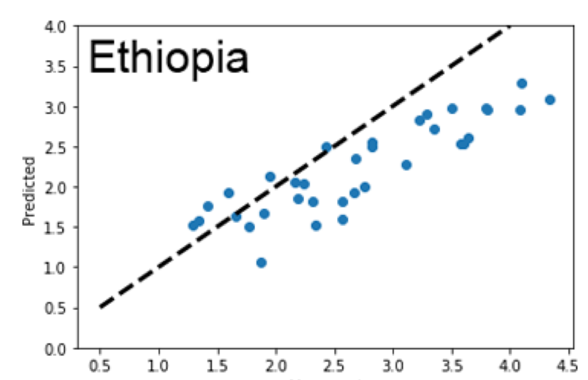
- Satellite Imagery from Google Earth Engine MODIS Collection
  - MOD09A1.006 Surface Reflectance (7 Bands)
  - MOD11A2.006 Land Temperature –Day and Night Temp (2 Bands)

Results

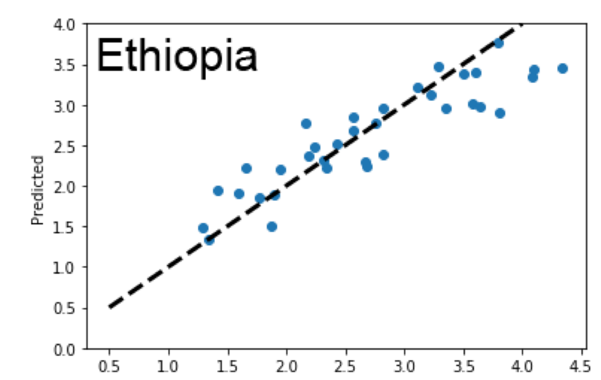
Model Performance On Chronological Splits

	R2				Pearson's r		
Country	Ridge	LSTM	LSTM + GP	Country	Ridge	LSTM	LSTM + GP
Ethiopia	-0.52	-0.35	**0.13**	Ethiopia	0.64	0.74	**0.82**
Kenya	0.40	0.49	**0.56**	Kenya	0.69	**0.82**	**0.82**
Malawi	-0.54	-0.29	**-0.09**	Malawi	0.10	0.25	**0.55**
Nigeria	-3.44	-0.68	**-0.60**	Nigeria	-0.03	0.40	**0.53**
Tanzania	-1.63	0.40	**0.50**	Tanzania	0.11	0.74	**0.80**
Zambia	-0.08	0.39	**0.56**	Zambia	0.55	0.67	**0.77**

- Large amounts of variation depending on model and country
- LSTM + GP model consistently outperforms others
- The models trained on randomized splits consistently performed better than those trained on chronological splits

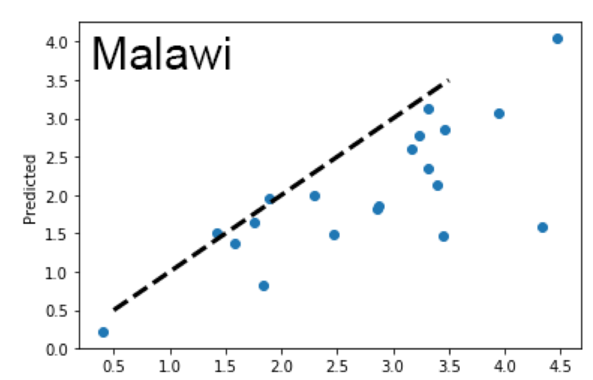


LSTM Model

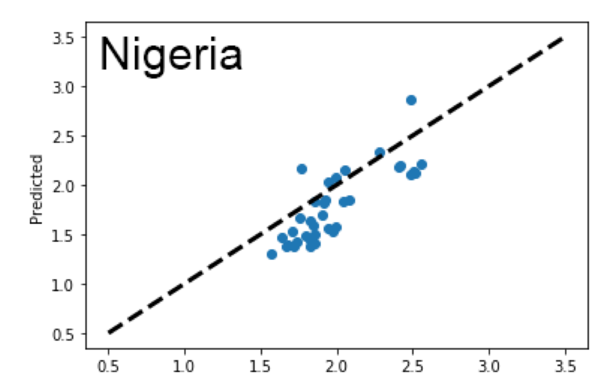


LSTM With GP Model

Chronological error plots for Ethiopia training and testing on random splits. Incorporating the temporal and spatial information through GP improves performance significantly.



Malawi Error Plot



Nigeria Error Plot

The graphs above are error plots for the LSTM Model and chronological splits for Nigeria and Malawi. They indicate how different countries lead to very different errors due to differences in the ground data distribution .

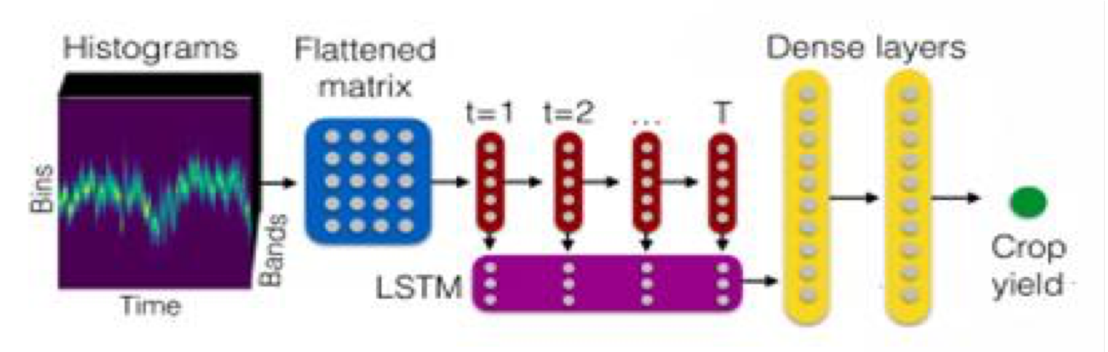
Country	In-Country		Combined	
	R2	Pearson's r	R2	Pearson's r
Ethiopia	0.48	0.76	**0.63**	**0.80**
Kenya	**0.72**	**0.86**	0.68	0.84
Malawi	0.11	0.46	**0.36**	**0.60**
Nigeria	0.34	0.60	**0.58**	**0.77**
Tanzania	**0.24**	**0.61**	-0.96	0.42
Zambia	**0.55**	**0.76**	0.49	0.71

On the right, we show the results of our **transfer learning models.** The models were trained on the LSTM+GP model for all countries, then weights learned on 5 countries were tested on the holdout country. These are on randomized splits.

Methods

Models

- **Baseline:** Ridge Regression on Avg. NDVI and Temp. for each timestep
- **LSTM**:
  - **Inputs**: We use a dimensionality reduction technique to turn raw satellite images into **histograms.** The intuition is that, for crop yield prediction, the **counts of pixel values are more important than the position.**
  - The feature shape for each label in the LSTM model is **[Timestep, #Bands * #Bins]**, where #Bins is a hyperparameter. For our project, we use **#Bins = 32**. We use CE loss and dropout



- **Gaussian Processing (GP):**
  - **Inputs**: coordinates, years.
  - GP is a **non-parametric probabilistic model**.
  - We use a GP that is linear in respect to the weights calculated by the LSTM. We use a **squared exponential kernel**, with the spatio-temporal features as inputs. In this way, we can model the errors made by the LSTM due to variance in spatio-temporal features that may not be captured by remote sensing data.

Discussion and Future Work

- LSTM with Gaussian Processing produces the best results.
- Using randomized splits, all models achieve high levels of accuracy
- Using chronological splits, performance varies
  - possibly due to differences in feature and label distribution and data quality.
- Combined model shows that a collective model performs competitively with in-country models, suggesting that the model can learn important out-of-country features.

Overall our models show that it is possible to predict crop yields using these methods at a relatively high level of accuracy. The results from Gaussian Processing model also emphasizes the importance of incorporating temporal spatial features when predicting crop yields.

For future study, different architectures such as a CNN model run on the histograms or the raw images may also attain significant results.

References

- You, J., Li, X., Low, M., Lobell, D., and Ermon, S. Deep gaussian process for crop yield prediction based on re-mote sensing data. In AAAI , pp. 4559–4566, 2017.
- Wang, A. X., Tran, C., Desai, N., Lobell, D., and Ermon, S. Deep transfer learning for crop yield prediction withremote sensing data. In Proceedings of the 1st ACM SIG- CAS Conference on Computing and Sustainable Societies,pp. 50. ACM, 2018
- FAO. Africa regional overview of food security and nutrition report. 2017.