Modeling impacts of drought on wheat and barley in Ethiopia

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Abstract

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Author summary

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Introduction

The ability to monitor and predict crop yields in developing countries is critical to the successful adaptation to changes in our climate. Increased temperatures and variability has already been linked to losses in maize and wheat yields (-3.8 and 5.5% respectively)and crop prices globally [1]. Although much effort has been placed on modeling the spatial distribution of these shifts, less effort has been placed on how yields vary across space and time [2]. Advances in remote sensing provide avenues to monitor agricultural crop health at high spatial and temporal resolution. However, our ability to monitor changes in plant productivity is still limited in the more complex environments common to many developing countries [3].

Remote sensing based efforts to characterize the extent, cultivation practices, and productivity of global croplands has a long history. In fact, agricultural monitoring motivated much of the earliest work in remote sensing for example NASA's LACIE and AgRISTARS programs in the 1970s and 1980s and [4]). Since then, substantial progress has been made in mapping cropland extent, crop types, irrigation status, cropping intensity, and productivity from remotely sensed imagery. For example, the MODIS Land Cover Product MCD12Q1 [8] provides operationally produced, global scale maps of agriculture and agricultural-natural mosaics at an annual time step and 500 m spatial resolution from 2001-present. A finer resolution (˜30 m) dataset is available for the conterminous United States which maps the annual extent and type for over 250 crops using primarily Landsat imagery: the Cropland Data Layer [[10]. These are but two prominent examples out of a broad literature documenting a wide variety of efforts to map cropland extent and type from remotely sensed imagery [11]. Remotely sensed imagery has also been employed to map irrigated areas [17], and cropping frequency/intensity [16].

Initial efforts (e.g. LACIE and AgRISTARS) primarily utilized remotely sensed imagery to characterize the spatial extent and growth stage of crops, but relied on models driven chiefly by meteorological information to predict crop yield [21]. However, the biophysical link between canopy spectral reflectance and net primary production has long been established [23]; indicating that satellite measurements could play a role in determining crop yield directly. Indeed, early experimental work confirmed the usefulness of spectral measurements in predicting LAI and intercepted PAR in crops [24], a result that was later extended to satellite measurements of spectral reflectance [27]. Spectral measurements typically explain variability in LAI and intercepted PAR better than crop yields because a variety of factors other than net primary production (e.g. weather during critical crop growth stages) influence yield. Nevertheless, a wide number of studies have documented highly explanatory empirical relationships between satellite measures such as NDVI (in many forms: growing season maximum and mean, seasonally integrated, etc.) and yields for a variety of crops, particularly at regional scales [30]. Because certain crop growth stages are particularly critical for final yield [36], improved results are often seen when remotely sensed data are used to characterize crop phenology [37]. More recently, methods for forecasting yields with remotely sensed variables at the field scale have been explored [38]. In addition to establishing a direct relationship between satellite measurements and crop yield, combining these observations with model output, through formal or ad hoc data assimilation techniques has also been demonstrated [40].

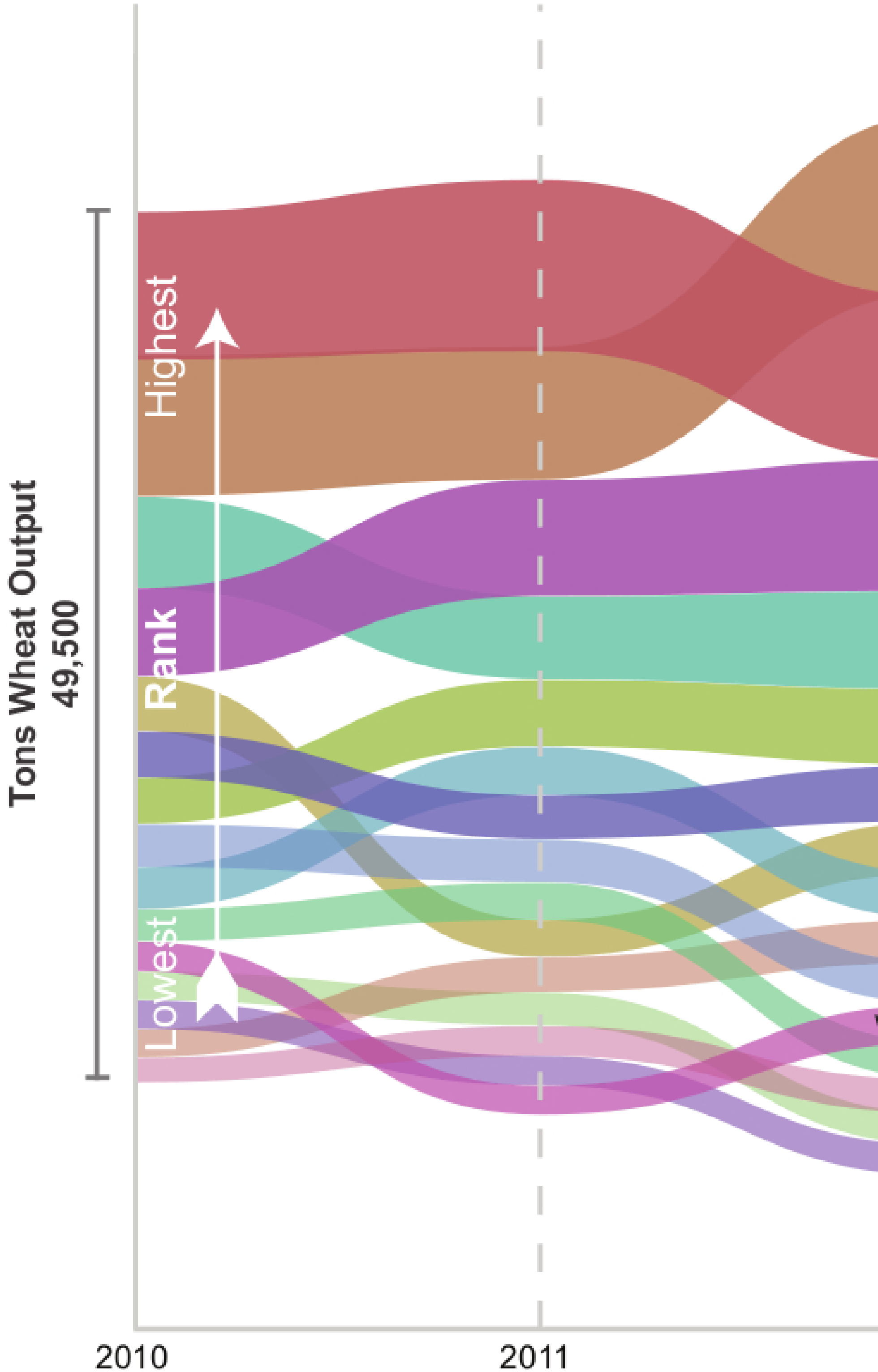
The main objectives of this paper is to ________________. In particular, we will focus on the application of ___________________. We also created and present a suite of algorithms used to extract, summarize, and organize remotely sensed data and prepare it for spatiotemporal analysis.

Drought meets distribution

Spured by a long history of monsoon failures across the Sahel, forecasters and aid teams axiciously watched eastern Africa at the onset of a significant El Nino event in late 2014. Below average rainfalls in 2015-17 across the low lying pastoral communities and South Eastern Ethiopia triggered an international effort to provide food aid to roughly 8.5 million people in the summer of 2017 [43]. The understated response from the Ethiopian government has lead to accusations that the government is downplaying the severity of the drought as early as 2016 [45]. Despite the reality of a severe and crippling drought in food insecure low lying areas, there is little sign of food shortages nationally, with a recent study observing no significant change in grain prices throughout the country ((((**???**)))). The lack of a price response would indicate that while food insecure areas were hit heavily by water shortages largely effecting livestock, leaving the highland areas largely unaffected or triggering only minor losses. Despite international concern, conditions up until the 2016-2017 growing season may have been largely handled by domestic resources and trade flows, therefore requiring shifts in distribution rather than a large-scale interational intervention.

Looking at the example of wheat production for the top 15 producing zones (Figure: 1), we can see that total output has remained steady or increased in the majority of top performing zones. This can be seen by the increase in total production from 49,500 (?00s quintiles) in 2010 to 64,209 in the 2015 planting season. Additionally, we can see that the total production of each zone (as indicated by the width of each bar) generally increases over time, or remains relatively constant. Moreover we can see that the rank of regions (as indicated by the plot order, bottom being lowest rank, top being highest rank) remains surprisingly steady dispite the exogenous shock of drought begining in the 2015 planing season.

Figure 1: Total Wheat output of top 15 producing zones



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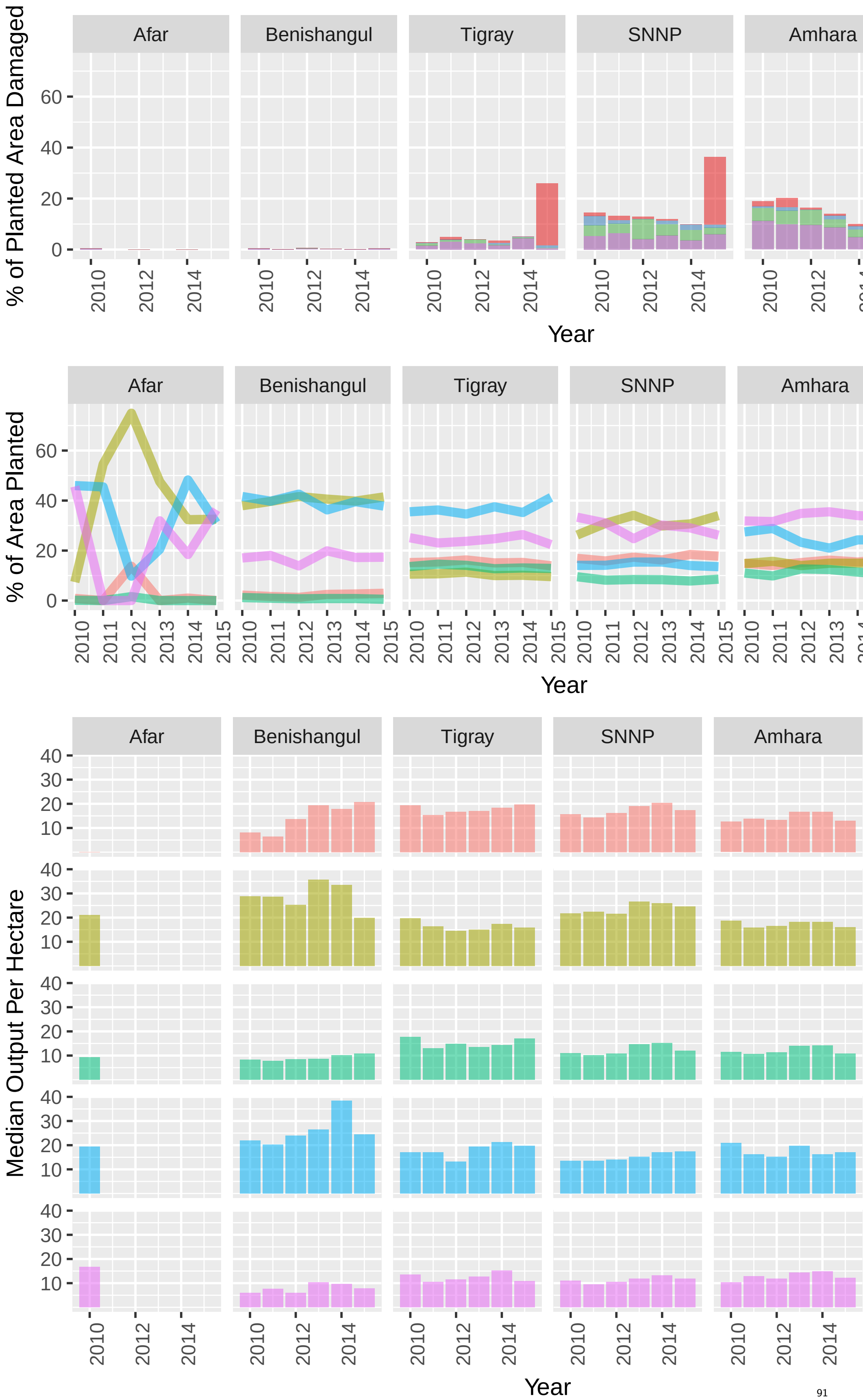
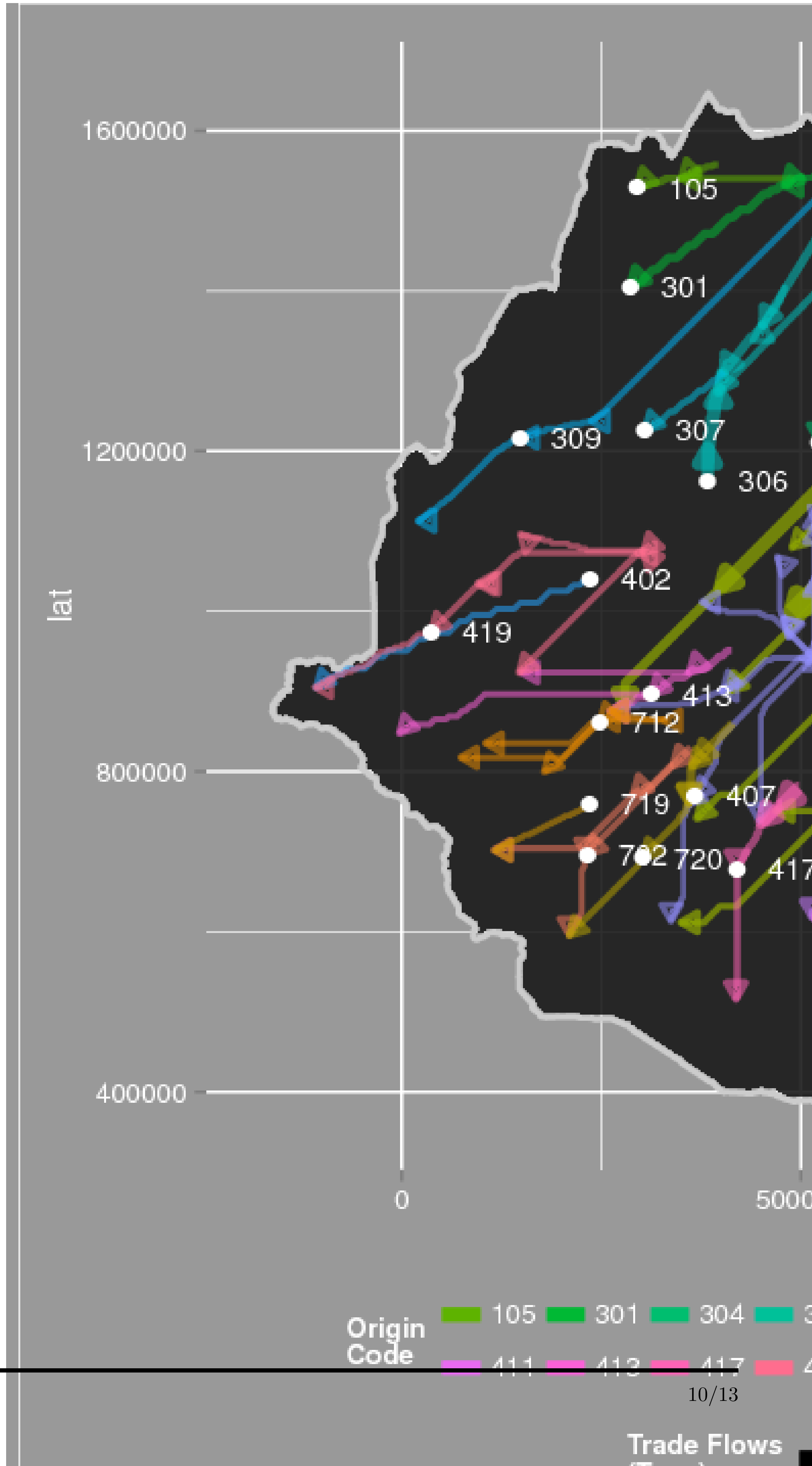
We can see from Figure 2 three time series for the major regions depicting the drought, in the top panel (a) the percentage of planted area damaged by damage type, the middle panel (b) the percentage of area planted in each major crop, in the bottom panel (c) median output per hectare (OPH) in quintiles for each major crop. Although we see a marked spike in reports of drought damage in the 2015 planting season (covering harvest in 2016), we see a few important responses. First, we see that although slight, farmers increased the percentage of area planted in drought tolerant crops such as maize and sorghum. Second, we see that although some regions saw declines in median output per hectare, these losses are largely offset by gains in other crops or by the steady increase in OPH since 2010.

Figure 2: Drought in one graph


% of Planted Area Damaged
Afar
Benishangul
Tigray
SNNP
Amhara
0
20
40
60
2010
2012
2014
Year
% of Area Planted
2010
2011
2012
2013
2014
2015
Median Output Per Hectare
10
30

91

Figure 3: Aggregate commodity trade flows


lat
1600000
1200000
800000
400000
0
105
301
309
307
306
402
419
413
712
719
407
720
Origin Code
105
301
304
Trade Flows

References

1. Lobell DB, Schlenker W, Costa-Roberts J. Climate trends and global crop production since 1980. Science. American Association for the Advancement of Science; 2011;333: 616–620. doi:10.1126/science.1204531

2. Ray DK, Gerber JS, MacDonald GK, West PC. Climate variation explains a third of global crop yield variability. Nature Communications. The Author(s); 2015;6: 5989. Available: http://dx.doi.org/10.1038/ncomms6989 http://10.1038/ncomms6989 http://www.nature.com/articles/ncomms6989{\#}supplementary-information

3. Mann ML, Warner J. Ethiopian Wheat Yield and Yield Gap Estimation: A Small Area Integrated Data Approach. Addis Ababa, Ethiopia: International Food Policy Research Institute; 2015.

4. MacDonald RB, Hall FG. Global crop forecasting. Science. Washington; 1980;208: 670–679.

5. Hatfield J. Remote sensing estimators of potential and actual crop yield. Remote Sensing of Environment. Elsevier; 1983;13: 301–311.

6. NASA. AgRISTARS: Agriculture and resources inventory surveys through aerospace remote sensing. technical report research report. AgRISTARS: Agriculture and resources inventory surveys through aerospace remote sensing. Technical Report Research Report. NASA; 1984.

7. Pinter Jr PJ, Ritchie JC, Hatfield JL, Hart GF. The agricultural research service's remote sensing program. Photogrammetric Engineering & Remote Sensing. American Society for Photogrammetry; Remote Sensing; 2003;69: 615–618.

8. Friedl MA, McIver DK, Hodges JC, Zhang X, Muchoney D, Strahler AH, et al. Global land cover mapping from modis: Algorithms and early results. Remote Sensing of Environment. Elsevier; 2002;83: 287–302.

9. Friedl MA, Sulla-Menashe D, Tan B, Schneider A, Ramankutty N, Sibley A, et al. MODIS collection 5 global land cover: Algorithm refinements and characterization of new datasets. Remote sensing of Environment. Elsevier; 2010;114: 168–182.

10. NASS U. USDA-national agricultural statistics service, cropland data layer. United States Department of Agriculture, National Agricultural Statistics Service, Marketing and Information Services Office, Washington, DC [Available at http//nassgeodata gmu edu/Crop-Scape, Last accessed September 2012]. 2003;

11. Lobell DB, Asner GP. Cropland distributions from temporal unmixing of modis data. Remote Sensing of Environment. Elsevier; 2004;93: 412–422.

12. Xiao X, Boles S, Frolking S, Li C, Babu JY, Salas W, et al. Mapping paddy rice agriculture in south and southeast asia using multi-temporal modis images. Remote Sensing of Environment. Elsevier; 2006;100: 95–113.

13. Thenkabail P, GangadharaRao P, Biggs T, Krishna M, Turral H. Spectral matching techniques to determine historical land-use/land-cover (lulc) and irrigated areas using time-series 0.1-degree avhrr pathfinder datasets. Photogrammetric Engineering & Remote Sensing. 2007;73: 1029–1040.

14. Ramankutty N, Evan AT, Monfreda C, Foley JA. Farming the planet: 1. geographic distribution of global agricultural lands in the year 2000. Global Biogeochemical Cycles. Wiley Online Library; 2008;22.

15. Wardlow BD, Egbert SL. Large-area crop mapping using time-series modis 250 m ndvi data: An assessment for the us central great plains. Remote sensing of environment. Elsevier; 2008;112: 1096–1116.

16. Biradar CM, Xiao X. Quantifying the area and spatial distribution of double-and triple-cropping croplands in india with multi-temporal modis imagery in 2005. International Journal of Remote Sensing. Taylor & Francis; 2011;32: 367–386.

17. Thenkabail PS, Biradar CM, Noojipady P, Dheeravath V, Li Y, Velpuri M, et al. Global irrigated area map (giam), derived from remote sensing, for the end of the last

millennium. International Journal of Remote Sensing. Taylor & Francis; 2009;30: 3679–3733.

18. Portmann FT, Siebert S, Döll P. MIRCA2000—Global monthly irrigated and rainfed crop areas around the year 2000: A new high-resolution data set for agricultural and hydrological modeling. Global Biogeochemical Cycles. Wiley Online Library; 2010;24.

19. Gray J, Friedl M, Frolking S, Ramankutty N, Nelson A, Gumma MK. Mapping asian cropping intensity with modis. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing. IEEE; 2014;7: 3373–3379.

20. Li L, Friedl MA, Xin Q, Gray J, Pan Y, Frolking S. Mapping crop cycles in china using modis-evi time series. Remote Sensing. Multidisciplinary Digital Publishing Institute; 2014;6: 2473–2493.

21. Idso SB, Jackson RD, Reginato RJ. Remote-sensing of crop yields. Science. American Association for the Advancement of Science; 1977;196: 19–25.

22. Doraiswamy PC, Moulin S, Cook PW, Stern A. Crop yield assessment from remote sensing. Photogrammetric engineering & remote sensing. American Society for Photogrammetry; Remote Sensing; 2003;69: 665–674.

23. Tucker C, Sellers P. Satellite remote sensing of primary production. International journal of remote sensing. Taylor & Francis; 1986;7: 1395–1416.

24. Daughtry C, Gallo K, Bauer ME. Spectral estimates of solar radiation intercepted by corn canopies. Agronomy Journal. American Society of Agronomy; 1983;75: 527–531.

25. Asrar G, Fuchs M, Kanemasu E, Hatfield J. Estimating absorbed photosynthetic radiation and leaf area index from spectral reflectance in wheat. Agronomy journal. American Society of Agronomy; 1984;76: 300–306.

26. Clevers J. A simplified approach for yield prediction of sugar beet based on optical remote sensing data. Remote Sensing of Environment. Elsevier; 1997;61: 221–228.

27. Tucker C, Holben B, Elgin Jr J, McMurtrey III J, others. Relationship of spectral data to grain yield variation. Photogrammetric Engineering and Remote Sensing. 1980;46: 657–666.

28. Groten S. NDVI—crop monitoring and early yield assessment of burkina faso. TitleREMOTE SENSING. Taylor & Francis; 1993;14: 1495–1515.

29. Bartholome E. Radiometric measurements and crop yield forecasting some observations over millet and sorghum experimental plots in mali. International journal of remote sensing. Taylor & Francis; 1988;9: 1539–1552.

30. Rasmussen MS. Assessment of millet yields and production in northern burkina faso using integrated ndvi from the avhrr. International Journal of Remote Sensing. Taylor & Francis; 1992;13: 3431–3442.

31. Benedetti R, Rossini P. On the use of ndvi profiles as a tool for agricultural statistics: The case study of wheat yield estimate and forecast in emilia romagna. Remote Sensing of Environment. Elsevier; 1993;45: 311–326.

32. Funk C, Budde ME. Phenologically-tuned modis ndvi-based production anomaly estimates for zimbabwe. Remote Sensing of Environment. Elsevier; 2009;113: 115–125.

33. Becker-Reshef I, Vermote E, Lindeman M, Justice C. A generalized regression-based model for forecasting winter wheat yields in kansas and ukraine using modis data. Remote Sensing of Environment. Elsevier; 2010;114: 1312–1323.

34. Becker-Reshef I, Justice C, Sullivan M, Vermote E, Tucker C, Anyamba A, et al. Monitoring global croplands with coarse resolution earth observations: The global agriculture monitoring (glam) project. Remote Sensing. Molecular Diversity Preservation International; 2010;2: 1589–1609.

35. Mkhabela M, Bullock P, Raj S, Wang S, Yang Y. Crop yield forecasting on the

canadian prairies using modis ndvi data. Agricultural and Forest Meteorology. Elsevier; 2011;151: 385–393.

36. Butler EE, Huybers P. Variations in the sensitivity of us maize yield to extreme temperatures by region and growth phase. Environmental Research Letters. IOP Publishing; 2015;10: 034009.

37. Bolton DK, Friedl MA. Forecasting crop yield using remotely sensed vegetation indices and crop phenology metrics. Agricultural and Forest Meteorology. Elsevier; 2013;173: 74–84.

38. Lobell DB, Thau D, Seifert C, Engle E, Little B. A scalable satellite-based crop yield mapper. Remote Sensing of Environment. Elsevier; 2015;164: 324–333.

39. Gao F, Anderson MC, Zhang X, Yang Z, Alfieri JG, Kustas WP, et al. Toward mapping crop progress at field scales through fusion of landsat and modis imagery. Remote Sensing of Environment. Elsevier; 2017;188: 9–25.

40. Mo X, Liu S, Lin Z, Xu Y, Xiang Y, McVicar T. Prediction of crop yield, water consumption and water use efficiency with a svat-crop growth model using remotely sensed data on the north china plain. Ecological Modelling. Elsevier; 2005;183: 301–322.

41. Moriondo M, Maselli F, Bindi M. A simple model of regional wheat yield based on ndvi data. European Journal of Agronomy. Elsevier; 2007;26: 266–274.

42. De Wit A de, Van Diepen C. Crop model data assimilation with the ensemble kalman filter for improving regional crop yield forecasts. Agricultural and Forest Meteorology. Elsevier; 2007;146: 38–56.

43. Ethiopia: Drought - 2015-2017 [Internet]. ReliefWeb. Available: `https://reliefweb.int/disaster/dr-2015-000109-eth`

44. Mid-year review, ethiopia humanitarian requirements document, july 2017 [Internet]. ReliefWeb. 2017. Available: `https://reliefweb.int/report/ethiopia/mid-year-review-ethiopia-humanitarian-requirements-document-july-2017`

45. Schemm P. Ethiopia is facing a devastating drought, and food aid may soon run out [Internet]. The Washington Post. WP Company; 2016. Available: `http://www.washingtonpost.com/sf/world/2016/02/22/history-repeats-itself-in-ethiopia/?utm_term=.2b7bb38f3a3e`

46. Schemm P. Ethiopia is facing a killer drought. but it's going almost unnoticed. [Internet]. The Washington Post. WP Company; 2017. Available: `https://www.washingtonpost.com/news/worldviews/wp/2017/05/01/ethiopia-is-facing-a-killer-drought-but-its-going-almost-unnoticed/?utm_term=.ad44d46b0631`