Appendix B: Farm to Farm – Clustering and Returns to Scale in Agricultural Value Chains

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September 19, 2022

Not for publication, online appendix only

1 Crop suitability measures

In my paper, I use two sources of information regarding agronomic and ecological crop suitabilities. These are the FAO Global Agro-Ecological Zones (GAEZ) dataset (Fischer et al., 2021) as well as the FAO EcoCrop database (Hijmans et al., 2001).

FAO Global Agro-Ecological Zones (GAEZ) dataset

The GAEZ data has been used frequently in economics, such as in Costinot and Donaldson (2012), Costinot et al. (2016), Costinot and Donaldson (2016), Gouel and Laborde (2021), Farrokhi and Pellegrina (2020), Domínguez-Iino (2022), Nunn and Qian (2011), and Sotelo (2020). As of version 4, the Global Agro-Ecological Zones dataset provides productivity information on 29 separate crops at a 5 arc-minute worldwide grid. The GAEZ model takes into account information such soil features, water resources, elevation and slope, as well as climatic variables, which is provided to an agronomic model for each crop in the dataset.

FAO EcoCrop database

In contrast to the more limited scope of the GAEZ database, the FAO EcoCrop database (Hijmans et al., 2001) contains information on 2568 different plants and species, ranging from trees and shrubs to grasses. The EcoCrop database has been used previously by some papers in Economics, such as (Bounadi, 2018), Cruz Martínez (2020), (Daniele et al., 2020), (Gehring et al., 2019), (Moscona and Sastry, ming), and (Sobrino, 2019). For each crop, the EcoCrop database specifies absolute and optimal ranges for variables such as precipitation, pH, or minimum and maximum temperature. In total the EcoCrop database lists temperature ranges, soil textures, salinities, depths, drainages and fertilities, precipitation, latitudes, altitudes, and the amount of light needed for optimal growing conditions (as well as absolute bounds on those conditions). These conditions can then be used to create indices for crop-specific suitabilities, employing these boundary conditions. Although I cannot obtain information for all of the conditions listed by the EcoCrop database, I obtain gridded information regarding precipitation, temperatures, altitude, and certain soil conditions such as soil pH, depth, and salinity.

Information on historical temperature and rainfall comes from Livneh et al. (2015) and is provided at a $1/16^{\circ}$ (≈ 6 km) resolution for Mexico and the continential United States. Information on elevation comes from Global Multi-resolution Terrain Elevation Data 2010 (GMTED2010) provided by the USGS Earth Resources Observation and Science Center (Danielson and Gesch, 2011). The data can be found here. Information on soil salinity comes from Ivushkin et al. (2019) and is provided at a 250 meter grid for 1986, 1992, 2000, 2002, 2005, 2009, and 2016. To match the agricultural census data for Mexico from 2007, I use this data from 2009 in my main analysis. Although measures of salinity are expected to change in the future due to climate change, I could not find projections of salinity change and use measures of 2009 salinity in my future projections. Information on soil depth and pH comes from the SoilGrids 250m dataset provided by Poggio et al. (2021) and Hengl et al. (2017). Absolute depth to bedrock (in cm) predicted using the global compilation of soil ground observations.

To match up this data with information on the growing season of each crop, I rely on information from SIAP to provide me whether a crop is 1) Perennial or grown in the 2) Fall-Winter and/or 3) Spring-Summer. [1] Following INEGI's reference system for crop seasons, perennials are grown from October of the first calendar year to September of the next. Fall-winter crops are grown from October as well to the next calendar year in either February or March. Finally, spring-summer crops are grown from March to August. Of course, some crops have longer or shorter growing periods and planting and harvest times vary both by crop, year, and the particular growing season. However, I assume these features away here and calculate my measures of suitability within one of the three periods above, depending on the type of crop.

Although I rely on the FAO EcoCrop database to expand the range of crops for which I have suitability information for, there are a number of crops that both it and the FAO GAEZ database cover. To understand the potential accuracy of the FAO EcoCrop measures I develop, I regress these measures against each other. In figure 1, I plot the scatterplot between these two measures as well as basic regression statistics. I find that the GAEZ measure explains a little less than 20 percent of the variation in the EcoCrop measure, a moderate correlation, and that the estimated slope of the regression line is upward sloping, as one would expect. In general, EcoCrop suitability measures seem to trend somewhat higher than GAEZ measures, with most of the observations falling above a (hypothetical) 45 degree line.

References

Bounadi, M. (2018). Weather and conflicts in afghanistan. *Working Paper*.

Costinot, A. and D. Donaldson (2012). Ricardo's Theory of Comparative Advantage: Old Idea, New Evidence. *American Economic Review 102*(3), 453–58.

[1] There are other sources of information on growing seasons, such as MIRCA2000 or the Sacks et al. crop calendar dataset, but they are only provided for rather aggregated crop categories. Alternatively, one could use the monthly production data directly from SIAP, but this data has a number of problematic features that make it hard to identify growing seasons at smaller levels of aggregation.

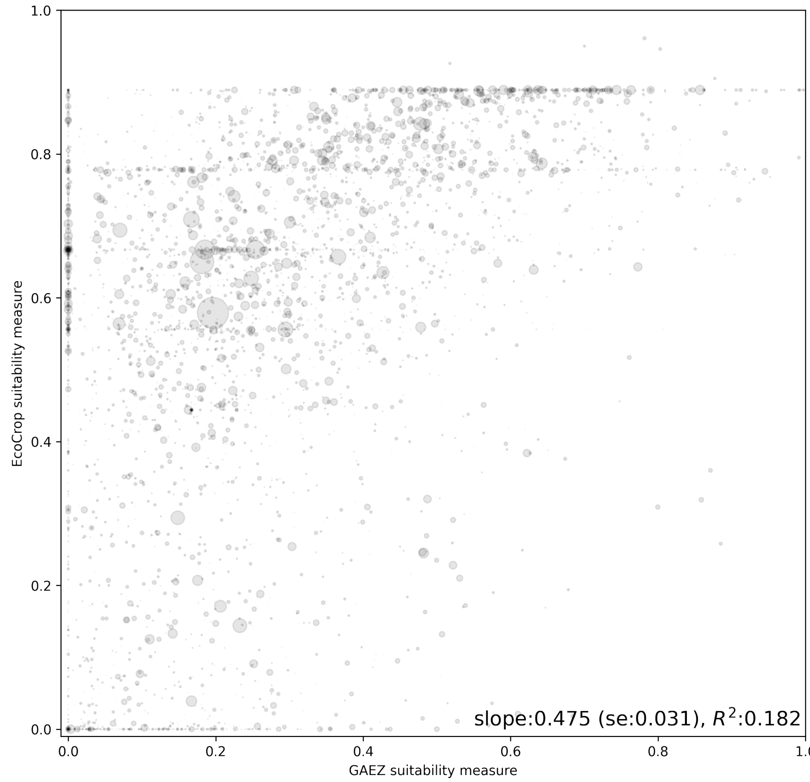

Figure 1: Regression between overlapping GAEZ and EcoCrop suitability measures

Costinot, A. and D. Donaldson (2016). How large are the gains from economic integration? theory and evidence from us agriculture.

Costinot, A., D. Donaldson, and C. Smith (2016). Evolving comparative advantage and the impact of climate change in agricultural markets: Evidence from 1.7 million fields around the world. *Journal of Political Economy 124*(1), 205–248.

Cruz Martínez, K. (2020). El mercado ilegal de la heroína en la violencia y la actividad económica en méxico. *Masters' thesis*.

Daniele, G., M. Le Moglie, and F. Masera (2020). Pains, guns and moves: The effect of the us opioid epidemic on mexican migration. *Working Paper*.

Danielson, J. J. and D. B. Gesch (2011). Global multi-resolution terrain elevation data 2010 (gmted2010).

Domínguez-Iino, T. (2022). Efficiency and Redistribution in Environmental Policy: An Equilibrium Analysis of Agricultural Supply Chains. *Job Market Paper*.

Farrokhi, F. and H. S. Pellegrina (2020). Global Trade and Margins of Productivity in Agriculture. *NBER Working Paper No. 27350*.

Fischer, G., F. O. Nachtergaele, H. van Velthuizen, F. Chiozza, G. Francheschini, M. Henry, D. Muchoney, and S. Tramberend (2021). Global Agro-ecological Zones (GAEZ v4)-Model Documentation.

Gehring, K., S. Langlotz, and K. Stefan (2019). Stimulant or depressant? resource-related income shocks and conflict. *CESifo Working Paper*.

Gouel, C. and D. Laborde (2021). The crucial role of domestic and international market-mediated adaptation to climate change. *Journal of Environmental Economics and Management 106*, 102408.

Hengl, T., J. Mendes de Jesus, G. B. M. Heuvelink, M. Ruiperez Gonzalez, M. Kilibarda, A. BlagotiÄ, W. Shangguan, M. N. Wright, X. Geng, B. Bauer-Marschallinger, M. A. Guevara, R. Vargas, R. A. MacMillan, N. H. Batjes, J. G. B. Leenaars, E. Ribeiro, I. Wheeler, S. Mantel, and B. Kempen (2017, 02). Soilgrids250m: Global gridded soil information based on machine learning. *PLOS ONE 12*(2), 1–40.

Hijmans, R. J., L. Guarino, M. Cruz, and E. Rojas (2001). Computer tools for spatial analysis of plant genetic resources data: 1. diva-gis. *Plant genetic resources newsletter*, 15–19.

Ivushkin, K., H. Bartholomeus, A. K. Bregt, A. Pulatov, B. Kempen, and L. de Sousa (2019). Global mapping of soil salinity change. *Remote Sensing of Environment 231*, 111260.

Livneh, B., T. J. Bohn, D. W. Pierce, F. Munoz-Arriola, B. Nijssen, R. Vose, D. R. Cayan, and L. Brekke (2015). A spatially comprehensive, hydrometeorological data set for mexico, the us, and southern canada 1950–2013. *Scientific data 2*(1), 1–12.

Moscona, J. and K. Sastry (Forthcoming). Does directed innovation mitigate climate damage? evidence from us agriculture. *Quarterly Journal of Economics*.

Nunn, N. and N. Qian (2011). The potato's contribution to population and urbanization: evidence from a historical experiment. *The quarterly journal of economics 126*(2), 593–650.

Poggio, L., L. M. de Sousa, N. H. Batjes, G. B. M. Heuvelink, B. Kempen, E. Ribeiro, and D. Rossiter (2021). Soilgrids 2.0: producing soil information for the globe with quantified spatial uncertainty. *SOIL 7*(1), 217–240.

Sobrino, F. (2019). Mexican cartel wars: Fighting for the us opioid market. *Working Paper*.

Sotelo, S. (2020). Domestic trade frictions and agriculture. *Journal of Political Economy 128*(7), 2690–2738.