Does the Future Look Irrigated? Evaluating the Likelihood of Irrigation Adoption Within Alabama

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HIGHLIGHTS:

- Alabama's growing season precipitation is highly variable. Irrigation can reduce such climate vulnerabilities.
- Using multi-scalar datasets, we derive an irrigation adoption index map for Alabama in the range between 0 and 1.
- The spatial assessment helps to identify areas having a higher or lower likelihood of irrigation use.
- Multi-scale calibration and assessment increase the rigor of index development.

ABSTRACT: *Farmers have time and again adopted new methods or technologies. However, recent increases in global temperatures and occurrences of extreme weather events, call for an urgency to address and reduce the risks associated with climate change. Irrigation is a key adaptation that reduces crop heat stress and enhances agricultural production. Alabama is considered water-rich but lately has experienced increased rainfall variability and temperature extremes. Various state-wide initiatives to increase irrigation have been implemented, but adoption remains limited. Existing studies have explored factors influencing irrigation uptake, but none have engaged in a state-level assessment of its adoption potential. In this study, we provide spatially explicit estimates of the potential to implement irrigation practices across the state. Moreover, we derive an irrigation adoption index map for Alabama to identify areas where implementation is more or less likely based on a multi-criteria analysis. The results highlight a large potential for expansion in areas that have high shares of existing irrigation. Such an analysis can enable targeted mobilization of resources towards areas where uptake is currently low but feasible through increased adaptation efforts. Additionally, these estimates can be further used to evaluate future water demands or conduct other regional analyses.*

KEYWORDS: Southeastern US, Climate change adaptation, Multi-scale, Spatial assessment, Technology adoption

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INTRODUCTION

Farmers constantly change their practices and adopt new technologies based on their needs, perceived risks to farming operations, and other socioeconomic and biophysical contextual conditions, regardless of their beliefs in changing weather and climatic conditions (Arbuckle, Morton and Hobbs 2015). However, recent increases in the frequency and severity of extreme weather events (e.g., droughts, floods) highlight the need to urgently address and reduce the risks associated with climate change (Hatfield et al. 2014, USGCRP 2018). In the last few decades, the average annual temperature over the contiguous United States has increased by 0.7°C and additional increases of about 1.4°C are expected over the next few decades irrespective of future emissions (USGCRP 2018). Agriculture is sensitive to these temperature changes (Kurukulasuriya and Rosenthal 2013) and yield reductions are already being observed globally for major crops like wheat and maize (Zhao et al. 2017, Obembe, Hendricks and Tack 2021). Such reductions are projected to continue (Miller et al. 2019), resulting in significant implications for global food security (Anderson, Bayer and Edwards 2020, Swinnen, Arndt and Vos 2022). Although climate change is a global problem, its impacts are experienced locally, which are further shaped by multiple global, national, and local drivers (e.g., pandemics, international agreements, or environmental policies) and specific socioeconomic, political, and biophysical contexts (Kirby 2021, Baldos et al. 2023), making regional and local adaptations generally more effective (Ramalho, Ferreira and Jóia Santos 2022).

Climate change adaptations within the agricultural sector involve changes in practices, processes, or structures to deal with expected or unexpected climatic changes to reduce vulnerability, sustain productivity, and build and enhance the resilience of food systems (Intergovernmental Panel on Climate Change 2001, Janowiak et al. 2016, Aryal et al. 2020). Potential adaptations include changing planting dates and cropping patterns, using new or improved crop varieties, and practicing better water and soil management regimes, followed by technological or infrastructure-related modifications (Aryal et al. 2020, Weiskopf et al. 2021, Gebre et al. 2023). Irrigation is one such common adaptation that reduces heat stress and consequently, the risks of climate variability and extremes, and helps enhance agricultural production even in regions that receive sufficient rainfall (Tack, Barkley and Hendricks 2017, Bierkens and Wada 2019, Lankford et al. 2023). Even though many hydrological, ecological, and equity-related issues and uncertainties still surround its expansion, irrigation is projected to play a crucial role in achieving global food security (Partridge et al. 2023).

There exists a vast literature from around the world on irrigation use. Some evaluated impacts on crop yields (e.g., Araya and Stroosnijder 2011, Birthal et al. 2021, Troy et al. 2015), land and water resources (e.g., de Graaf et al. 2019, Pulido-Bosch et al. 2018), and regional and global climates (e.g., Douglas et al. 2009, Puma and Cook 2010). Others quantified existing global irrigation patterns (e.g., Siebert et al. 2015, Meier, Zabel and Mauser 2018), or estimated the potential for irrigation expansion for a particular region or country (e.g., You et al. 2011, Xie et al. 2014, Xie, You and Takeshima 2017, Deines et al. 2019). At a more local/farm level, studies usually investigate irrigation adoption decision-making by farmers (e.g., Castillo et al. 2021, Nejadrezaei et al. 2018, Pokhrel et al. 2018, Zhang et al. 2019). While large-scale (global, national, or regional) studies advance our understanding of regional to global patterns of adaptation and mitigation options for impact assessments, subregional or local-scale analyses can help capture climate change-related risks and impacts specific to those locations or systems necessary for policy formulation and implementation (Giorgi, Jones and Asrar 2009).

In Alabama, rain-fed agriculture has been the common practice, particularly for vegetable crop production (Shange et al. 2014), with about 142,001 acres irrigated out of the 8,580,940 acres of farmland (USDA NASS 2017). Despite an average annual precipitation rate of 55 inches and having abundant surface water resources, higher summer temperatures and seasonal droughts are persistent challenges (Carter et al. 2018, National Integrated Drought Information System 2023, NOAA National Centers for Environmental information 2023), with three of the five worst droughts occurring in the last two decades (National Integrated Drought Information System 2023). Receiving an adequate amount of moisture at the right time is crucial for maintaining and safeguarding crop yields, and irrigation can help mitigate such climate vulnerabilities (Rosa et al. 2020). Many existing studies have explored patterns of irrigation adoption and the various factors influencing its implementation in Alabama (e.g., Estes et al. 2022, Price et al. 2022, Sydnor & Molnar 2020), but they either focus on a particular region, a particular technology, or large-scale farms and thus, represent a small sample of farmers. None have engaged in a state-level assessment of irrigation adoption potential. Therefore, in this study, we present a spatially explicit, state-level assessment of potential irrigation expansion while also addressing the spatial heterogeneity of factors related to irrigation adoption decisions within the agricultural regions across Alabama. The main objective of this paper is to derive an irrigation adoption index map for the state in the range between 0 (low likelihood) and 1 (high likelihood) to identify areas where irrigation implementation is more likely based on a multi-criteria analysis. Such an analysis can enable targeted mobilization and distribution of resources towards areas where adoption is low but feasible through increased adaptation interventions and efforts. Additionally, these estimates can be further used to evaluate future water demands, study regional climate impacts, assess land suitability for irrigation, or conduct Food-Energy-Water (FEW) -related regional analyses (e.g., Magliocca 2020).

STUDY AREA

Alabama's agriculture and forestry sectors have a significant impact on its economy. According to the 2020 Alabama State Economic Report, Alabama generated almost $5.8 billion in agricultural cash receipts (Gross 2020). Moreover, the food and agriculture industries in the state accounted for a total of 620,286 jobs as per the latest Feeding the Economy (2023) report. On average, one out of every 4.6 jobs in the state is linked to the agriculture and food production industry (Nichols 2023). Cotton, peanuts, and soybeans are considered the top agricultural cash crops of Alabama. Although the state is commonly known for its cotton production, as per the 2017 Census of Agriculture report, livestock accounts for nearly 80 percent of the total market value of agricultural products sold. The state was also ranked fourth out of the fifty states for both poultry and eggs and aquaculture (USDA NASS 2017).

Alabama is divided into six agricultural regions, or agricultural statistics districts (ASD) by the USDA (U.S. Department of Agriculture), which are defined as groups of counties within each state having similar physical geography (soil type, terrain, and elevation), climate (mean temperature, annual precipitation, and length of growing season), and cropping practices (USDA NASS 2018). These groupings further influence the types of crops produced and the occurrence of irrigation within farms in each region (Price et al. 2022) (Figure 1).

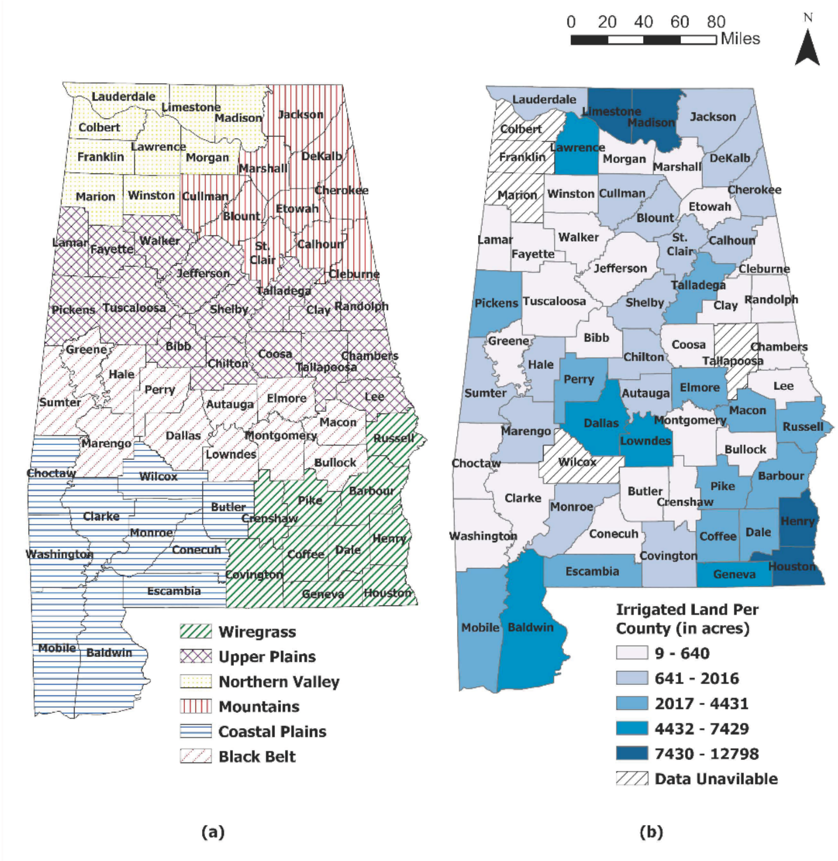

Figure 1. (a) Six agricultural regions within Alabama. (b) Irrigated land in acres per county (USDA 2017).

Alabama's irrigated acreage (76,486 ha) is well behind the neighboring states of Mississippi (667,731 ha) and Georgia (586,794 ha) (Chaney et al. 2020, Shange et al. 2014). Since the state follows the riparian doctrine (i.e., legal rights to owners to use surface water flowing across their property), it creates additional challenges for non-riparian producers, particularly those with limited financial resources, who must either depend on rainfall or invest in retention ponds or wells to access groundwater. Various state-wide initiatives to expand irrigation have been implemented including tax incentives and other federally funded programs (e.g., Alabama Irrigation Project by USDA NRCS (Natural Resources Conservation Service) and Alabama Soil and Water Conservation Committee (ALSWCC); USDA NRCS EQIP funding program), however, adoption is still limited.

MATERIAL AND METHODS

Data Collection

An irrigation adoption index map for Alabama was derived following the methodologies from Prestele et al. (2018) and Zagaria et al. (2023) and the specific steps taken from data collection to the development of index map are summarized in the subsequent sections. Following the index creation, the approach utilized for model calibration and performance assessment has also been outlined in the later sections. The first step was to identify and shortlist the major drivers and/or barriers affecting irrigation uptake by farmers, which were informed through a literature review on irrigation adoption (e.g., Pathak and Magliocca 2022). Next, the spatial datasets representing the identified influential factors and their respective data proxies were compiled (Table 1).

Table 1. Metadata of variables used in this analysis.

Type of Variables	Variable	Proxy	Initial Units	Data Source
Dependent Variables				
Irrigated Acreage	Irrigated Acres (County & HUC8 Watershed level)		Acres	USDA NASS (2017)
	Center pivot irrigation locations		Polygons	Handyside (2016)
Explanatory Variables				
Farm Enterprise	Agricultural Land (Cropland + Pasture)		30m	U.S. Geological Survey (USGS) (2016)
	Land Ownership		% tenants per county	USDA NASS (2017)
	Crop type	Crop Irrigation Dependency: Crop Area in Irrigation (2015)	Acres per county	Dieter et al. (2018)
Demographic	Poverty Rate		% below poverty per county	U.S. Census Bureau (2015)
Social Capital/ Institutional	Access to Markets	Market Access Index	Between 0-1	Verburg et al. (2011)
	Access to Information and Financial Assistance	USDA NRCS EQIP Funding Program (2009-2015)	Counts of contracts per county	Basche et al. (2020)
Biophysical	Access to Water	Well-depth	Depth (ft)	U.S. Geological Survey (USGS) (2020)

Description of the Selected Variables

The factors known to influence farmers' irrigation adoption decision-making are often classified into broad categories (e.g., economic, biophysical, social, and political) that may vary depending on the researchers' preferences and their disciplinary backgrounds (Mwangi and Kariuki 2015). For our analysis, we shortlisted the following variables:

1. Agricultural Land: A prerequisite for deploying irrigation is the availability of agricultural land that includes arable land and land under permanent crops or pastures (Lyuri 2008). We used the U.S. Geological Survey's (USGS) National Land Cover Database (NLCD) for the conterminous U.S. land cover at a 30-meter spatial resolution. This database is classified into sixteen land cover classes; for our study purposes, we only used the 'planted/cultivated' land cover class that includes cropland and pasture/hay to exclude all non-agricultural land from the analysis (U.S. Geological Survey (USGS) 2016).
2. Crop Type: The use of irrigation technology is dependent on the type of crop grown and its sensitivity to heat-related stress (Pokhrel, Paudel and Segarra 2018). As a proxy, we used data related to crop irrigation dependency- total acres irrigated for crops per county in Alabama from the USGS dataset containing water-use estimates for 2015 in the United States (Dieter et al. 2018).
3. Land Ownership: Land ownership has been found to significantly affect agricultural technology adoption decisions in several studies, the rationale being that having land security encourages individuals to sustainably use and manage their land (Séogo and Zahonogo 2019). We calculated the percentage of tenants per county using renter and owner-farm operator rates for the state from the USDA NASS (National Agricultural Statistics Service) Quick Stats database.
4. Poverty Rate: Irrigation implementation may also require large upfront initial investments that might be challenging for those with limited financial resources (Pathak and Magliocca 2022). Thus, the poverty rate variable was used as a direct measurement of average wealth and a proxy for other socioeconomic variables that may influence the likelihood of irrigation adoption.
5. Access to Markets: Investment in irrigation infrastructure is unlikely if the increased revenue from production cannot be realized, and revenues depend on proximity and transportation costs to markets. We used a market access index (between 0-1) developed by Verburg et al. (2011) as a proxy for these economic motivations for increasing production through irrigation investment. This high spatial resolution global gridded data on market accessibility was derived by the authors using the locations of major cities along with travel times and terrain types to account for transportation infrastructure and accessibility to the selected destinations.
6. Access to Information and Financial Assistance: To adopt a certain technology, farmers must be aware of its existence. Having access to information allows farmers to learn the use of technology and its advantages (or disadvantages) and can facilitate its adoption (Mwangi and Kariuki 2015). However, awareness of irrigation technologies alone may be insufficient due to large upfront initial investments, and a lack of credit or capital markets can, therefore, impede its uptake (Feder, Just and Zilberman 1985). Subsidies, external funding, or easy access to loans at low-interest rates have been found to positively affect technology adoption (Ruzzante, Labarta and Bilton 2021). We used the Environmental Quality Incentives Program (EQIP) data as an indicator for this in our study. The EQIP is a financial assistance program offered by the USDA NRCS that helps producers implement certain conservation practices on their farms. Only the records of contracts for practices or physical structures and pieces of equipment related to irrigation (e.g., water pumping plant, irrigation pipelines, water wells, micro irrigation, sprinkler systems, and irrigation water management) were selected for each county between 2009 and 2015 from the database of over 300 EQIP practices.
7. Water availability: Having reliable access to water can significantly influence irrigation uptake (Adeoti 2009). Given the riparian rights restrictions in the state, we used the point locations for agricultural well depths provided by the Geological Survey of Alabama (USGS 2020) as a proxy for water access.

8. Soil quality: Soil quality is a crucial factor in determining the suitability of land for both agriculture and irrigation purposes (Worqlul et al. 2017). Soil suitability data for Alabama developed by the Price et al. (2022) study was used, which in turn followed the methods outlined in the Alabama State Resource Assessment by USDA NRCS, using the fraction of parcel area in favorable agricultural soils (USDA-NRCS 2020).
9. Slope: Topographic features of an area can also influence irrigation use (Worqlul et al. 2017). The terrain ruggedness index developed by Riley, DeGloria and Elliot (1999), which is the amount of elevation difference between adjacent cells of a digital elevation model, was used to represent topographic constraints on agricultural production.
10. Droughts: Drought can have serious consequences for rain-fed agricultural productivity and in turn farm profitability. We used the annual three-month average of the standardized precipitation-evapotranspiration index (SPEI) to represent the onset and magnitude of drought conditions. Using SPEI data from the 4-km daily Gridded Surface Meteorological (GRIDMET) dataset, we quantified drought severity (average SPEI over the growing period) and frequency (total drought events in a period) for the growing season (April to October) in Alabama between 2005-2015 and used both these variables separately in our analysis. For estimating drought frequency, a threshold of ≤ -1 was used to define moderate drought conditions (Wang et al. 2014, 2021).

Data Analysis

Each of the eleven variables was clipped to the state extent, normalized in the range of 0-1, and mapped individually using ArcGIS Pro software. For four variables- slope, poverty rate, percentage of tenants, and drought severity, the normalized maps were inverted, such that higher values of these variables represent a lower likelihood for irrigation adoption (Prestele et al. 2018). A baseline irrigation adoption index map was created by combining all variables additively with each variable having no weight (i.e., equally weighted) and re-normalized (0-1) to represent the likelihood of irrigation adoption within each grid cell. Adoption index values were then translated into irrigated area estimates by using a range of threshold values above which irrigation was considered likely. For instance, the first estimates were derived using a threshold of 0.5. Next, counts of grid cells above a threshold were obtained for each analytical areal unit (e.g., county, watershed, or agricultural region) and converted to area to obtain predicted irrigated area (in acres) from the model. These predicted irrigated estimates were then compared with observed irrigated acreage data to evaluate model performance and identify influential variables (described in the next section).

Sensitivity Experiments

Two sensitivity experiments were performed with the baseline irrigation adoption index to understand the spatial patterns observed and the influences of each variable on the resulting patterns (Prestele et al. 2018).

1. <u>Exclude-one experiment</u>: eleven alternative maps were created by excluding one variable each time.
2. <u>Double-weight experiment:</u> each variable received double-weight one at a time while all the other variables were kept constant to develop another set of eleven maps.

The irrigation estimates were calculated for each of the twenty-two alternative maps following the methodology outlined in the previous section and were compared with the observed county-level irrigation data to understand the influence of the variables on the model's performance using the root mean squared error (RMSE) metric.

Model Calibration with Irrigated Acreage Data and Center-Pivot Irrigation Locations

Various methods for estimating multi-variate weights for index methods are used in the literature (e.g., analytic hierarchy process, correlation, Delphi method, regression, no or equal weighting) but no consensus exists around a 'best' method and selection often depends on the specific research question and data limitations (Nardo et al. 2005, Greco et al. 2019). To calibrate and evaluate our irrigation adoption index, we used the approach of Principal Component Analysis (PCA) to assign variable weights and generate irrigated acreage estimates with a range of threshold values, which were then compared to observed county- and watershed-level irrigated acreage estimates based on their respective RMSE values. Due to the heterogeneity among agricultural regions, optimal threshold values were estimated for each agricultural region rather than a single value for the state. All statistical analyses were carried out using Python in PyCharm 2022.2.1 (Community Edition) software.

PCA was applied to the mean values of all the predictor variables per county. We used the methodology provided by Abdelaziz et al. (2020) to calculate the absolute weights for all the variables using only the component loadings having eigenvalues greater than one as these components explain more variance in the data (~Kaiser Rule). Each predictor variable was weighted using the computed eigenvalues and component loadings and combined additively and normalized (0-1) to generate a new index map. Irrigated estimates resulting from this map were then compared with observed county, watershed, and agricultural region-level irrigation acreages to identify the adoption index threshold values that produced the lowest RMSE for each unit of analysis.

Further model calibration was performed using locations of center pivots that were installed between 2006 and 2015 across Alabama. This dataset was chosen because it presents information at a finer scale compared to the census data and these polygon locations are identified, mapped, and updated periodically using remote-sensing imagery as part of a project developed by the University of Alabama Huntsville to address the lack of specific irrigation data for the state (Handyside 2016). The calibration was performed by calculating the percentage of center-pivot instances within each agricultural region correctly predicted by various thresholds for adoption index values. If one grid cell above the irrigation adoption index threshold value intersected with a center-pivot polygon, then the instance of center-pivot irrigation was considered correctly predicted. Additionally, thresholds needed for achieving maximum accuracy for center-pivot prediction within each region were determined and compared to the thresholds that produced minimum RMSE estimates of irrigated acreage at the county and watershed levels.

Model Performance Assessment with Farm-level In-Situ Information

Data from the U.S. Agricultural Census was suspected to be biased toward larger farms and large-scale irrigation (Shange et al. 2014, *unpublished field interviews*), and using this data for calibration likely replicated these biases. To assess the calibrated model for potential biases, estimated irrigation adoption index values were compared with *in-situ* information about irrigation practices collected via surveys and personal interviews with small-scale farmers (part of another ongoing study), particularly within the Black Belt region (Figure 1a). Zip code tabulation areas (ZCTAs) (U.S. Census Bureau 2020) were used to map the zip codes of farmers who have implemented or plan to implement micro-irrigation systems on their farms (n=33) as the 'control' group and all the remaining zip codes of the Black Belt region as the 'other' group. Mean adoption index values for each group were compared using a t-test. Moreover, the distribution of discrete center-pivot polygons within the two groups was also examined.

RESULTS

Results from Sensitivity Experiments

The baseline, equal-weighted irrigation adoption index map underestimated irrigation likelihood for some counties where currently high irrigation rates exist, such as the counties of the Northern Valley region (e.g., Lawrence, Limestone, and Madison counties) (Figure 2a). Moreover, the results from the sensitivity analyses revealed that excluding variables like crop type and soil suitability resulted in low RMSE values for the model. Likewise, doubling the weight of well-depth resulted in the lowest RMSE value for the model, while both poverty rate and soil suitability variables resulted in high RMSEs (see supplementary information for all the results from these experiments). Furthermore, excluding the land ownership variable resulted in changing the distribution of irrigation in certain areas. Its exclusion led to an increase in the likelihood of irrigation adoption especially within those counties that the model previously underestimated (e.g., Lawrence County). Hence, considering the distributions observed as part of these sensitivity experiments and having prior knowledge about the existing irrigation patterns within the state, the land tenure variable was removed from further analyses as it produced inaccurate spatial patterns of the occurrence of irrigation in certain areas. Accordingly, a new adoption index map was compiled based on the remaining ten variables.

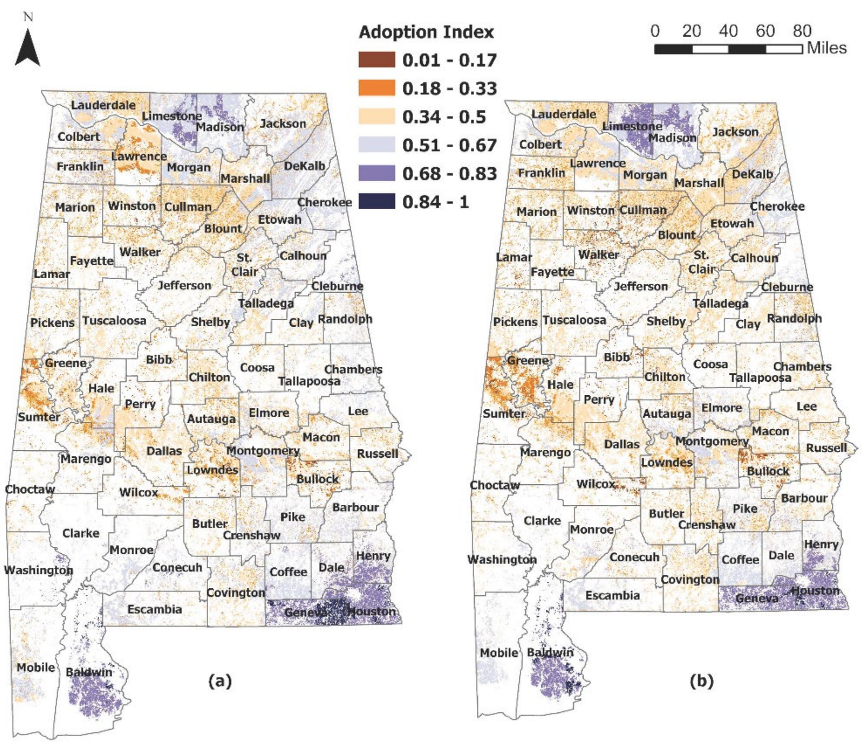

Figure 2. Irrigation Adoption Index maps created: (a) with equal/no weights for all eleven variables, and (b) using PCA-assigned weights and the land tenure variable excluded.

Model Calibration and Validation with Center-Pivot Irrigation Locations

The resulting PCA model explained approximately 78 percent of the variation in the data. Only the first four principal components (PCs) are found to have an eigenvalue greater than one, with PC1, PC2, PC3, and PC4 explaining 28.8 percent, 23.2 percent, 13.9 percent, and 12 percent of the variations respectively. Five variables- crop type, drought frequency, federal funding program, slope, and soil suitability had high correlations with PC1 (i.e., loading values closer to one). PC2 had a large negative correlation with well-depth variable and positive associations with poverty rate and agricultural land variables (Table 2). Additionally, the lowest RMSE values for the state and HUC-8 watershed models were 0.88 and 0.7 respectively, but prediction error was much higher at the watershed level (19,421 acres) than at the state level (3,411 acres) (Table 3). Overall, the model using PCA-generated variable weights resulted in better accuracy and a closer fit to the observed data compared to the baseline model with no- or equal-weights for all variables.

Table 2. PCA loadings, eigenvalues, and calculated weights for each variable.

		PC 1	PC 2	PC 3	PC 4	
	Eigen Values	2.927196	2.354455	1.411834	1.232903	**Weight**
Variables	Crops Irrigated	0.639036	0.445198	0.333291	-0.23259	0.463779717
	Drought Frequency	0.69567	-0.105	-0.08569	0.521041	0.384407746
	EQIP Funding	0.729364	0.127268	0.168346	-0.21377	0.370392108
	Well-depth	0.401464	-0.78747	-0.13439	-0.16467	0.431720537
	Market Access	-0.09048	0.314809	0.575414	0.649415	0.330430816
	Agricultural Land	0.428412	0.627296	-0.44604	-0.3167	0.47325216
	Poverty Rate	-0.33016	0.74293	0.363702	-0.18934	0.436838984
	Slope	0.822216	-0.28777	0.276608	0.156163	0.46267939
	Soil Suitability	0.602665	0.45006	-0.19114	0.054171	0.398720102
	Drought Severity	-0.04192	0.42309	-0.68675	0.499292	0.341141614

Table 3. Irrigation Adoption Threshold at state and HUC8 watershed levels. RMSE values were calculated in comparison with the 2017 USDA census of agriculture's county-level irrigated acreage data.

	PCA-weighted Variables	
Unit of Analysis	**Threshold**	**RMSE Value**
State-level	0.88	3,411 (acres)
Watershed-level	0.7	19,421 (acres)

Furthermore, the PCA-derived model produced a qualitatively more accurate distribution of irrigation adoption index values compared to the baseline model (see Figure 2b). The highest irrigation potential was found for Limestone and Madison counties in the north and Baldwin, Geneva, Houston, and Henry in the south. High rates were also observed in Dekalb, Cherokee, Cleburne, and Randolph counties in the northeast. Low rates were observed across Upper Plains counties. However, the lowest potential was found in counties of the Black Belt region, with irrigation distribution mainly concentrated in Autauga, Elmore, and Montgomery counties and parts of Marengo and Lowndes counties.

Subsequently, adoption thresholds were determined for each agricultural region based on the threshold values in that region that produced the lowest RMSE estimates of county-level irrigated acreage (Table 4). There were large differences among the regions with the highest thresholds of 0.88 and 0.87 for the Coastal and Wiregrass regions and 0.54 and 0.59 for the Upper Plains and Black Belt regions respectively (refer to Figure 1a for agricultural regions). Additionally, threshold values at which instances of center-pivot irrigation were correctly predicted at the same level of accuracy as the county-level irrigated acreage were calculated for comparison. Despite the known bias in county-level irrigation statistics toward large-scale irrigation, these threshold values were lower for all regions. This suggested that the model was better at predicting regional differences than specific locations of irrigation adoption, such as discrete polygons of center-pivot irrigated fields.

Table 4. Model calibration using discrete center-pivot polygons data.

USDA Agricultural Districts	Threshold with lowest RMSE	Lowest RMSE value (acres)	Proportion of RMSE value to total irrigated acreage	Correctly predicted center pivots at threshold (%)	Threshold needed for pivot calibration accuracy
Black Belt	0.59	2,954	12%	0.6	0.353
Coastal	0.88	1,490	10%	1	0.527
Mountains	0.68	991	11%	0	0.47
Northern Valley	0.72	2,764	9%	26	0.51
Upper Plains	0.54	1,382	12%	0	0.378
Wiregrass	0.87	5,219	11%	3.4	0.538

These regional differences were likely due to their contrasting agricultural systems. Both Coastal and Wiregrass regions have the largest irrigated areas in the state and tend to be dominated by large-scale irrigation techniques, such as center-pivot, that were better represented in the county-level irrigation data. In contrast, agricultural systems in the Upper Plains and Black Belt regions tended to be more heterogeneous with smaller, more diversified operations mixed with a few large-scale and commodity-oriented operations. Thus, higher threshold values were indicative of regions with relatively homogenous, spatially concentrated, commodity-oriented farm operations, while regions with lower threshold values tended to have smaller, diversified operations, and instances of existing irrigation were more spatially dispersed.

Given the inter-regional variation in threshold values, irrigation adoption index values were made more comparable across the state by normalizing each grid cell value relative to its difference with its regional threshold value (Figure 3). Positive values indicated locations with existing irrigation or high potential for irrigation adoption in that region. Increasingly negative values indicated a relatively decreasing potential for irrigation adoption in locations assumed to be less suitable than currently irrigated locations. Following this, the locations of center-pivot polygons were used to determine and compare the thresholds for their adoption prediction within each region (Table 4). These thresholds, when compared with those of the model, exhibited minor differences, indicating that the model is performing well in predicting large-scale irrigation adoption.

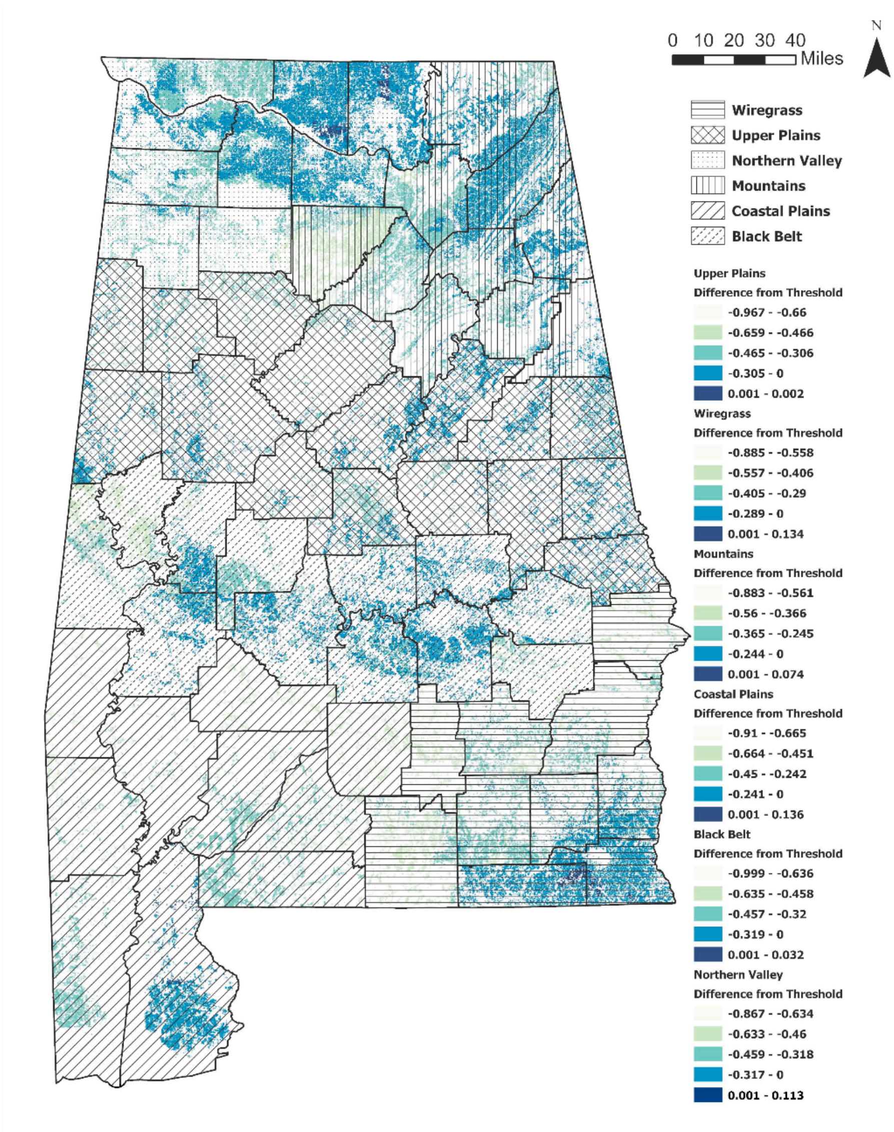

Figure 3. Consistent state-wide categories of irrigation adoption index values based on differences from agricultural regional adoption thresholds. Positive values indicate currently irrigated or high-potential areas and increasingly negative values indicate a declining likelihood for irrigation adoption.

Model Performance Assessment with Farm-level In-Situ Information

The control ZCTA group holds about 25 percent of the total agricultural land between the two groups and only thirty-seven of the total 160 center pivot polygons located in the Black Belt are observed within this group (see Figure 4a) (see supplementary file for more details). This explains the lower mean adoption index values for these control locations as compared to the other areas (Figure 4b). Further, results from the t-test also revealed statistically significant differences between the means of the two zip code groups (Table 5). These results suggest that the adoption model is biased toward large-scale irrigation based on the available data, probably because small-scale irrigated acres might be insignificant/insufficient for a state-level model to accurately capture.

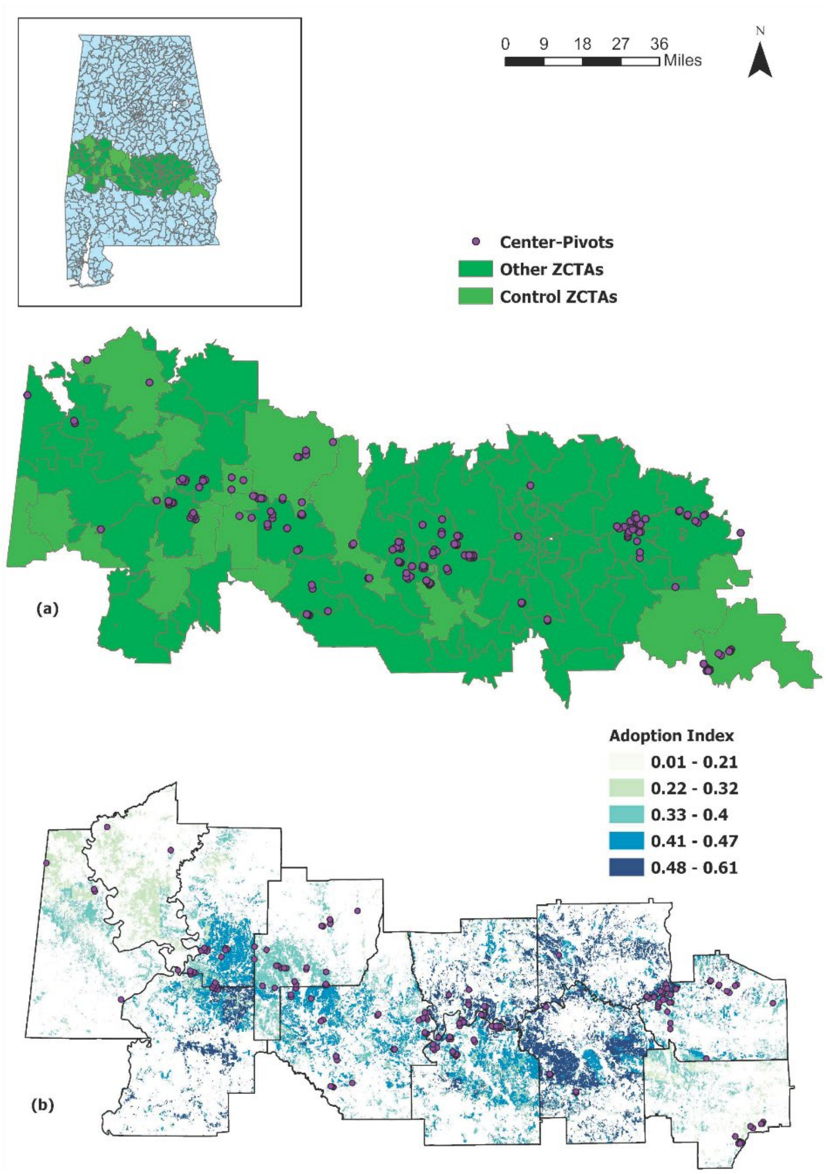

Figure 4. Zip Code Tabulated Areas (ZCTAs) in the Black Belt. (a) Center-pivot locations within the two ZCTA groups. (b) Center-pivot locations aligned with the adoption likelihood model.

DISCUSSION

In this study, we evaluated the irrigation adoption likelihood for the state of Alabama through a spatial analysis of the multiple biophysical and socioeconomic drivers of its adoption. Our analysis showed a large potential for irrigation expansion in counties that already have high shares of irrigation. For instance, counties such as Henry, Geneva, Houston, and Baldwin in the Coastal and Wiregrass regions and Limestone and Madison counties in the Northern Valley region (Figure 1b) currently have some of the largest proportions of irrigated land in the state (USDA 2017) and exhibited more irrigation adoption values near or above their regional threshold values (Figure 2b). One explanation for this could be the prevalence of agriculture within these counties that is facilitating their continued growth and development. All these counties have significant numbers of farm operations and agricultural acreage, with Limestone among the top five counties in the state with the most land in farms (USDA NASS 2017, USDA Farm Service Agency (FSA) 2023). Agricultural economies are agglomeration economies (Garrett et al. 2013), and being in spatial proximity to irrigation users can enable information exchange and support new adoptions and scaling up of technologies (Ward and Pede 2015, Mekonnen et al. 2022). Therefore, the existing focus on agriculture within these counties may have created an enabling environment that is supporting further improvements in agricultural practices and contributing toward their higher irrigation adoption potential. Additionally, research suggests that farmers adopt irrigation technologies to maximize farm production and profits (Pokhrel, Paudel and Segarra 2018), and these counties are among the state's top producers of commodity crops such as cotton, corn, soybeans, and peanuts (USDA NASS 2022).

Our findings suggested relatively lower irrigation adoption potential in certain counties, particularly in Blount, Coffee, Covington, Cullman, Dekalb, Jackson, Lawrence, and Randolph, despite being prominent agricultural counties with existing irrigation. For instance, in the counties of the Mountain Valley region (e.g., Jackson, Dekalb, and Cherokee), slope and soil characteristics might contribute to this reduced potential. Similarly, competing land uses for livestock, forestry, and pastureland in the Upper Plains likely contributed to lower irrigation adoption index values. Moreover, while there is abundant surface water availability in the north, accessibility could be an issue due to riparian doctrine, potentially posing challenges in accessing groundwater and incurring extra costs. Besides, the average agricultural well-depths were relatively lower in the north compared to the southern part (Coastal Plains) of the state based on the well-depth dataset used in this study.

Most of the counties in the Black Belt region showed consistently low irrigation potential, except for a few areas that included parts of Marengo, Autauga, Elmore, Lowndes, and Montgomery counties where large-scale irrigation was found. These findings were anticipated since this region is home to predominately African American communities that have been historically marginalized, socially disadvantaged, and under-resourced. The region has also seen declining farmland, high poverty rates, high unemployment, and inadequate housing, education, food, and healthcare facilities (Gyawu et al. 2015, Zekeri et al. 2016). Moreover, four out of every ten residents in half of these counties have a credit score below 660 due to which they are often denied access to capital and related opportunities to reduce or mitigate poverty (Katsinas et al. 2022a). This region also has less than 50 percent of high-speed internet coverage, which is less than 30 points compared to the rest of the state (Katsinas et al. 2022b), and poorly funded and inadequate water and sanitation infrastructure that raised human rights and environmental justice concerns as well (Winkler and Flowers 2017).

Additionally, our model is biased toward large-scale irrigation as it resulted in relatively higher index values for regions in the Black Belt where center-pivots were located and failed to accurately capture small-scale irrigation. Based on our conversations with farmers through surveys and interviews as part of another ongoing study, factors including starting costs, use and maintenance, electricity, and surface or groundwater access have been cited as influential in considering irrigation adoption. However, with increasing opportunities for and awareness about technical and financial assistance programs designed to address inequities in farming operations, many small and minority producers from this region have adopted or are planning to adopt micro-irrigation systems. Thus, relatively low irrigation adoption index values in this region do not imply that adoption here is impossible or unsuitable. Grounded knowledge of irrigation adoption in this region allows us to critically evaluate this state-wide assessment calibrated to county-level data. By identifying these areas as having "tangible potential" for adaptations (Zagaria et al. 2023), the allocation of resources to fully realize the transition to irrigated agriculture can take place.

This analysis also had several limitations worth noting. First, variable selection was constrained to spatial data that were often proxies for biophysical and socioeconomic drivers of adoption. For instance, data reflecting factors known to affect irrigation adoption decision-making, such as farmers' opinions, preferences, or crop choices, is difficult to obtain in case studies and certainly not available at the spatial extent of our assessment. Second, farm size was excluded as an explanatory variable from our analysis in favor of more resolved socioeconomic variables including poverty rate, land ownership, access to EQIP financial assistance program, and access to markets. Farm size is one of the commonly used determinants for understanding agricultural technology adoption among farmers all around the world. Several studies have used this factor when modeling diffusion and adoption of technology and reported positive correlations between the two variables, with larger farms more likely to adopt a technology than small-scale farms (e.g., Feyisa 2020, Hu et al. 2022). However, farm size can in itself be thought of as a proxy for other influential farm management and socioeconomic variables including economic status or wealth, access to credit, access to information, land tenure, and risk aversion (Andrei 2011). For instance, larger farms have more machinery and equipment or use more technologies because their economies of scale can help mitigate or reduce the risks associated with deploying new agricultural technologies or practices (Brown, Ferguson and Viju-Miljusevic 2020). Finally, due to the above choices and data constraints, our irrigation adoption index was constructed using data at a variety of scales, which can introduce uncertainties through data resampling or rescaling. Given the prevalence of county-level agricultural data, the model was calibrated to that scale, which does not accurately capture the community- or farm-level heterogeneity that is often important for understanding adoption processes (Wardrop et al. 2018).

Despite this, our analysis presents a useful synthesis of the available, multi-scalar data for understanding the irrigation adoption likelihood in Alabama. The study addresses the need for a state-level assessment of potential irrigation expansion that is at a finer scale than census data and even addresses the spatial heterogeneity within and between the agricultural regions across Alabama. This spatial heterogeneity is difficult to understand from just census or survey data that are often biased toward large-scale irrigation use. Plus, surveys are time-consuming, require extensive funds, and are often challenged to obtain a representative sample of respondents. In our analysis, we considered both large and small-scale irrigation adoption to ensure and maintain the model's accuracy and relevance. Additionally, we presented a way of effectively combining multiple biophysical and socioeconomic variables in a systematic and comparable spatial framework. While there is no consensus on the technique to use for developing such indices, weighing variables using PCA allowed us to better fit the model with the available data. Finally, conducting assessments of model outcomes against three independent data sources, each at different spatial scales, increased the rigor of index development and provided insights into nuanced ways that county-level data can be biased.

CONCLUSION

Irrigation can be a key adaptation strategy to mitigate the risks associated with changing climatic conditions. Even for a state like Alabama that is usually perceived to receive abundant rainfall, irrigation can bolster yields and consequently, farm revenue. Many initiatives have been implemented in the state to increase irrigation adoption, and existing studies have also tried to identify the multiple barriers affecting its uptake. In this study, we evaluated the potential for irrigation adoption and highlighted significant variations within the state. The regions identified as having high potential, namely, Northern Valley, Coastal, and Wiregrass regions, can be further examined to identify the common factors influencing widespread implementation among them. This knowledge can in turn facilitate learning and help in the deployment of resources needed to enhance irrigation uptake in other areas, particularly those with potential but low existing irrigation, such as the counties within the Black Belt, where micro-irrigation practices are becoming increasingly popular. The irrigation adoption index can also help target future data collection efforts on farmer needs and challenges toward areas that are more vulnerable to climate impacts and currently have lower irrigation adoption likelihood. Such targeted data collection can guide interventions designed to support agricultural and community resilience to climate change. Additionally, the irrigation adoption index provides a spatially consistent and extensive data set for investigating regional FEW systems, predicting future water demands, developing land and climate feedback models, and evaluating land suitability for irrigation purposes.

APPENDIX A. SUPPLEMENTARY INFORMATION

Supplementary files can be downloaded from here.

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REFERENCES

Abatzoglou, J.T. 2012. Development of gridded surface meteorological data for ecological applications and modelling. *International Journal of Climatology.* https://doi.org/10.1002/joc.3413.

Abdelaziz, S., Gad, M.I., and El Tahan, A.H.M.H. 2020. Groundwater quality index based on PCA: Wadi El-Natrun, Egypt. *Journal of African Earth Sciences* 172: 103964. https://doi.org/10.1016/j.jafrearsci.2020.103964.

Adeoti, A.I. 2009. Factors Influencing Irrigation Technology Adoption and its Impact on Household Poverty in Ghana. *Journal of Agriculture and Rural Development in the Tropics and Subtropics* 109 (1): 51–63.

Anderson, R., Bayer, P.E., and Edwards, D. 2020. Climate change and the need for agricultural adaptation. *Current Opinion in Plant Biology* 56: 197–202. https://doi.org/10.1016/j.pbi.2019.12.006.

Andrei, P. 2011. Agricultural Technology Adoption: Issues for Consideration When Scaling-Up. *The Cornell Policy Review: Journal of the Cornell Institute for Public Affairs* 1. http://www.cornellpolicyreview.com/wp-content/uploads/2011/06/final-CPR-web.pdf

Araya, A., and Stroosnijder, L. 2011. Assessing drought risk and irrigation need in northern Ethiopia. *Agricultural and Forest Meteorology* 151 (4): 425–436. https://doi.org/10.1016/j.agrformet.2010.11.014.

Arbuckle, J.G., Morton, L.W., and Hobbs, J. 2015. Understanding Farmer Perspectives on Climate Change Adaptation and Mitigation: The Roles of Trust in Sources of Climate Information, Climate Change Beliefs, and Perceived Risk. *Environment and Behavior* 47 (2): 205–234. https://doi.org/10.1177/0013916513503832.

Aryal, J.P. et al. 2020. Climate change and agriculture in South Asia: adaptation options in smallholder production systems. *Environment, Development and Sustainability* 22 (6): 5045–5075. https://doi.org/10.1007/s10668-019-00414-4.

Baldos, U.L.C. et al. 2023. Global-to-local-to-global interactions and climate change. *Environmental Research Letters* 18 (5): 053002. https://doi.org/10.1088/1748-9326/acc95c.

Basche, A. et al. 2020. Environmental Quality Incentives Program (EQIP) U.S. data at state, county and individual practice level for soil and environmental health, 2009-2018. https://doi.org/10.2737/RDS-2020-0076.

Bierkens, M.F.P., and Wada, Y. 2019. Non-renewable groundwater use and groundwater depletion: a review. *Environmental Research Letters* 14 (6): 063002. https://doi.org/10.1088/1748-9326/ab1a5f.

Birthal, P.S., Hazrana, J., Negi, D.S., and Pandey, G. 2021. Benefits of irrigation against heat stress in agriculture: Evidence from wheat crop in India. *Agricultural Water Management* 255: 106950. https://doi.org/10.1016/j.agwat.2021.106950.

Brown, W.M., Ferguson, S.M., and Viju-Miljusevic, C. 2020. Farm Size, Technology Adoption and Agricultural Trade Reform: Evidence from Canada. *Journal of Agricultural Economics* 71 (3): 676–697. https://doi.org/10.1111/1477-9552.12372.

Carter, L.M. et al. 2018. Chapter 19: Southeast. Impacts, Risks, and Adaptation in the United States: The Fourth National Climate Assessment, Volume II. U.S. Global Change Research Program. Retrieved from https://doi.org/10.7930/NCA4.2018.CH19 [Last accessed December 13, 2023].

Castillo, G.M.L., Engler, A., and Wollni, M. 2021. Planned behavior and social capital: Understanding farmers' behavior toward pressurized irrigation technologies. *Agricultural Water Management* 243: 106524. https://doi.org/10.1016/j.agwat.2020.106524.

Chaney, P.L., Roland, J., Moore, M., and Burton, C.G. 2020. Water Use Monitoring for Irrigation in the United States: A Case Study in Alabama and Lessons Learned for Achieving Sustainability. *The Professional Geographer* 72 (3): 433–447. https://doi.org/10.1080/00330124.2020.1730194.

Deines, J.M. et al. 2019. Mapping three decades of annual irrigation across the US High Plains Aquifer using Landsat and Google Earth Engine. *Remote Sensing of Environment* 233: 111400. https://doi.org/10.1016/j.rse.2019.111400.

Dieter, C.A. et al. 2018. Estimated use of water in the United States in 2015. *Circular*. U.S. Geological Survey. https://doi.org/10.3133/cir1441.

Douglas, E.M., Beltrán-Przekurat, A., Niyogi, D., Pielke, R.A., and Vörösmarty, C.J. 2009. The impact of agricultural intensification and irrigation on land–atmosphere interactions and Indian monsoon precipitation — A mesoscale modeling perspective. *Global and Planetary Change* 67 (1–2): 117–128. https://doi.org/10.1016/j.gloplacha.2008.12.007.

Estes, M.G. et al. 2022. Evaluating Ecosystem Services for the Expansion of Irrigation on Agricultural Land. *Land* 11 (12): 2316. https://doi.org/10.3390/land11122316.

Feder, G., Just, R.E., and Zilberman, D. 1985. Adoption of Agricultural Innovations in Developing Countries: A Survey. *Economic Development and Cultural Change* 33 (2): 255–298. https://doi.org/10.1086/451461.

Feeding the Economy. 2023. Feeding the Economy- Alabama Economic Impact. Retrieved from https://feedingtheeconomy.com/ [Last accessed December 13, 2023].

Feyisa, B.W. 2020. Determinants of agricultural technology adoption in Ethiopia: A meta-analysis. edited by Yildiz, F. *Cogent Food & Agriculture* 6 (1): 1855817. https://doi.org/10.1080/23311932.2020.1855817.

Garrett, R.D., Lambin, E.F., and Naylor, R.L. 2013. The new economic geography of land use change: Supply chain configurations and land use in the Brazilian Amazon. *Land Use Policy* 34: 265–275. https://doi.org/10.1016/j.landusepol.2013.03.011.

Gebre, G.G., Amekawa, Y., Fikadu, A.A., and Rahut, D.B. 2023. Farmers′ use of climate change adaptation strategies and their impacts on food security in Kenya. *Climate Risk Management* 40: 100495. https://doi.org/10.1016/j.crm.2023.100495.

Giorgi, F., Jones, C., and Asrar, G.R. 2009. Addressing climate information needs at the regional level: the CORDEX framework. World Meteorological Organization (WMO). Retrieved from https://public-old.wmo.int/en/bulletin/addressing-climate-information-needs-regional-level-cordex-framework [Last accessed December 13, 2023].

de Graaf, I.E.M., Gleeson, T., (Rens) van Beek, L.P.H., Sutanudjaja, E.H., and Bierkens, M.F.P. 2019. Environmental flow limits to global groundwater pumping. *Nature* 574 (7776): 90–94. https://doi.org/10.1038/s41586-019-1594-4.

Greco, S., Ishizaka, A., Tasiou, M., and Torrisi, G. 2019. On the Methodological Framework of Composite Indices: A Review of the Issues of Weighting, Aggregation, and Robustness. *Social Indicators Research* 141 (1): 61–94. https://doi.org/10.1007/s11205-017-1832-9.

Gross, J. 2020. 2020 Alabama State Economic Report. Alabama 36849: Auburn University. Retrieved from https://www.auburn.edu/outreach/gedi/documents/2020_AlabamaStateEconomicReport_v2.pdf [Last accessed December 13, 2023].

Gyawu, R., Quansah, J.E., Fall, S., Gichuhi, P.N., and Bovell-Benjamin, A.C. 2015. Community food environment measures in the Alabama Black Belt: Implications for cancer risk reduction. *Preventive Medicine Reports* 2: 689–698. https://doi.org/10.1016/j.pmedr.2015.08.015.

Handyside, C.T. 2016. Development of Agricultural and Irrigation Water Demand. Report No. ADECA_745696_2A146, Alabama Department of Economic and Community Affairs, Montgomery, AL.

Hatfield, J. et al. 2014. Ch. 6: Agriculture. Climate Change Impacts in the United States: The Third National Climate Assessment. U.S. Global Change Research Program. Retrieved from https://doi.org/10.7930/J02Z13FR [Last accessed December 13, 2023].

Hu, Y., Li, B., Zhang, Z., and Wang, J. 2022. Farm size and agricultural technology progress: Evidence from China. *Journal of Rural Studies* 93: 417–429. https://doi.org/10.1016/j.jrurstud.2019.01.009.

Intergovernmental Panel on Climate Change, ed. 2001. *Climate change 2001: impacts, adaptation, and vulnerability: contribution of Working Group II to the third assessment report of the Intergovernmental Panel on Climate Change*. Cambridge, UK; New York: Cambridge University Press.

Janowiak, M.K. et al. 2016. Adaptation Resources for Agriculture. USDA. Retrieved from https://www.climatehubs.usda.gov/sites/default/files/AdaptationResourcesForAgriculture.pdf [Last accessed December 13, 2023].

Katsinas, S.G. et al. 2022a. Poverty, Housing, & GDP in Alabama's Black Belt. Retrieved from https://edpolicy.ua.edu/black-belt.html [Last accessed December 13, 2023].

Katsinas, S.G., Corley, E.G., Till, G., O'Brien, S., and Bray, N.J. 2022b. Infrastructure in Alabama's Black Belt. Retrieved from https://edpolicy.ua.edu/black-belt.html [Last accessed December 13, 2023].

Kirby, A. 2021. Analyzing climate change adaptation policies in the context of the local state. *Environmental Science & Policy* 123: 160–168. https://doi.org/10.1016/j.envsci.2021.05.013.

Kurukulasuriya, P., and Rosenthal, S. 2013. Climate Change and Agriculture: A Review of Impacts and Adaptations. Climate change series Washington, D.C.: World Bank Group. Retrieved from http://documents.worldbank.org/curated/en/757601468332407727/Climate-change-and-agriculture-a-review-of-impacts-and-adaptations [Last accessed December 13, 2023].

Lankford, B. et al. 2023. Irrigation area, efficiency and water storage mediate the drought resilience of irrigated agriculture in a semi-arid catchment. *Science of The Total Environment* 859: 160263. https://doi.org/10.1016/j.scitotenv.2022.160263.

Lyuri, D. 2008. Agriculture. In *Encyclopedia of Ecology*, edited by Jørgensen, S.E., and B.D. Fath, 76–84. Oxford: Academic Press. https://doi.org/10.1016/B978-008045405-4.00838-7.

Magliocca, N.R. 2020. Agent-Based Modeling for Integrating Human Behavior into the Food–Energy–Water Nexus. *Land* 9 (12): 519. https://doi.org/10.3390/land9120519.

Meier, J., Zabel, F., and Mauser, W. 2018. A global approach to estimate irrigated areas – a comparison between different data and statistics. *Hydrology and Earth System Sciences* 22 (2): 1119–1133. https://doi.org/10.5194/hess-22-1119-2018.

Mekonnen, D.K., Yimam, S., Arega, T., Matheswaran, K., and Schmitter, P.M.V. 2022. Relatives, neighbors, or friends: Information exchanges among irrigators on new on-farm water management tools. *Agricultural Systems* 203: 103492. https://doi.org/10.1016/j.agsy.2022.103492.

Miller, O., Helman, D., Svoray, T., Morin, E., and Bonfil, D.J. 2019. Explicit wheat production model adjusted for semi-arid environments. *Field Crops Research* 231: 93–104. https://doi.org/10.1016/j.fcr.2018.11.011.

Mwangi, M., and Kariuki, S. 2015. Factors Determining Adoption of New Agricultural Technology by Smallholder Farmers in Developing Countries. *Journal of Economics and Sustainable Development* 6 (5).

Nardo, M., Saisana, M., Saltelli, A., and Tarantola, S. 2005. Tools for Composite Indicators Building. JRC Publications Repository. Retrieved from https://publications.jrc.ec.europa.eu/repository/handle/JRC31473 [Last accessed December 13, 2023].

National Integrated Drought Information System. 2023. Drought in Alabama. Retrieved from https://www.drought.gov/states/alabama [Last accessed December 13, 2023].

Nejadrezaei, N., Allahyari, M.S., Sadeghzadeh, M., Michailidis, A., and El Bilali, H. 2018. Factors affecting adoption of pressurized irrigation technology among olive farmers in Northern Iran. *Applied Water Science* 8 (6): 190. https://doi.org/10.1007/s13201-018-0819-2.

Nichols, K. 2023. *Farm Bill has Multifaceted Effects on Alabamians*. Alabama Cooperative Extension System, 2023. Retrieved from https://www.aces.edu/blog/topics/farming/farm-bill-has-multifaceted-effects-on-alabamians/ [Last accessed December 13, 2023].

NOAA National Centers for Environmental information. 2023. Statewide Time Series | Climate at a Glance | National Centers for Environmental Information (NCEI). Climate at a Glance Statewide Time Series. Retrieved from https://www.ncei.noaa.gov/access/monitoring/climate-at-a-glance/statewide/time-series [Last accessed December 13, 2023].

Obembe, O.S., Hendricks, N.P., and Tack, J. 2021. Decreased wheat production in the USA from climate change driven by yield losses rather than crop abandonment. *PLOS ONE* 16 (6): e0252067. https://doi.org/10.1371/journal.pone.0252067.

Partridge, T. et al. 2023. Irrigation benefits outweigh costs in more US croplands by mid-century. *Communications Earth & Environment* 4 (1): 1–15. https://doi.org/10.1038/s43247-023-00889-0.

Pathak, R., and Magliocca, N.R. 2022. Assessing the Representativeness of Irrigation Adoption Studies: A Meta-Study of Global Research. *Agriculture* 12 (12): 2105. https://doi.org/10.3390/agriculture12122105.

Pokhrel, B.K., Paudel, K.P., and Segarra, E. 2018. Factors Affecting the Choice, Intensity, and Allocation of Irrigation Technologies by U.S. Cotton Farmers. *Water* 10 (6): 706. https://doi.org/10.3390/w10060706.

Prestele, R., Hirsch, A.L., Davin, E.L., Seneviratne, S.I., and Verburg, P.H. 2018. A spatially explicit representation of conservation agriculture for application in global change studies. *Global Change Biology* 24 (9): 4038–4053. https://doi.org/10.1111/gcb.14307.

Price, A.N. et al. 2022. Multi-Level Influences on Center-Pivot Irrigation Adoption in Alabama. *Frontiers in Sustainable Food Systems* 6.

Pulido-Bosch, A. et al. 2018. Impacts of agricultural irrigation on groundwater salinity. *Environmental Earth Sciences* 77 (5): 197. https://doi.org/10.1007/s12665-018-7386-6.

Puma, M.J., and Cook, B.I. 2010. Effects of irrigation on global climate during the 20th century. *Journal of Geophysical Research: Atmospheres* 115 (D16): 2010JD014122. https://doi.org/10.1029/2010JD014122.

Ramalho, M., Ferreira, J.C., and Jóia Santos, C. 2022. Climate Change Adaptation Strategies at a Local Scale: The Portuguese Case Study. *International Journal of Environmental Research and Public Health* 19 (24): 16687. https://doi.org/10.3390/ijerph192416687.

Riley, S.J., DeGloria, S.D., and Elliot, R. 1999. Index that quantifies topographic heterogeneity. *Intermountain Journal of Sciences* 5 (1–4): 23–27.

Rosa, L. et al. 2020. Potential for sustainable irrigation expansion in a 3 °C warmer climate. *Proceedings of the National Academy of Sciences* 117 (47): 29526–29534. https://doi.org/10.1073/pnas.2017796117.

Ruzzante, S., Labarta, R., and Bilton, A. 2021. Adoption of agricultural technology in the developing world: A meta-analysis of the empirical literature. *World Development* 146: 105599. https://doi.org/10.1016/j.worlddev.2021.105599.

Séogo, W., and Zahonogo, P. 2019. Land tenure system innovation and agricultural technology adoption in Burkina Faso: Comparing empirical evidence to the worsening situation of both rural people vulnerability and vulnerable groups' access to land. *African Journal of Science, Technology, Innovation and Development* 11 (7): 833–842. https://doi.org/10.1080/20421338.2019.1587257.

Shange, R., Martin, R., Khan, V., Daniels, K., and Hunter, G.X. 2014. Extending Sustainable Irrigation Opportunities to Socially and Historically Disadvantaged Farmers in the Alabama Black Belt to Support Commercial-Level Production. *Professional Agricultural Workers Journal* 1 (2). https://tuspubs.tuskegee.edu/pawj/vol1/iss2/3/

Siebert, S. et al. 2015. Historical Irrigation Dataset (HID). MyGeoHUB. https://doi.org/10.13019/M20599 [Last accessed December 13, 2023].

Swinnen, J., Arndt, C., and Vos, R. 2022. Climate change and food systems: Transforming food systems for adaptation, mitigation, and resilience. Global food policy report: Climate change and food systems. International Food Policy Research Institute, Washington, DC. Retrieved from https://gfpr.ifpri.info/2022/05/11/climate-change-and-food-systems-transforming-food-systems-for-adaptation-mitigation-and-resilience/ [Last accessed December 13, 2023].

Sydnor, E.T., and Molnar, J.J. 2020. Using and Improving Irrigation Systems: Producer Perceptions and Possibilities.

Tack, J., Barkley, A., and Hendricks, N. 2017. Irrigation offsets wheat yield reductions from warming temperatures. *Environmental Research Letters* 12 (11): 114027. https://doi.org/10.1088/1748-9326/aa8d27.

Troy, T.J., Kipgen, C., and Pal, I. 2015. The impact of climate extremes and irrigation on US crop yields. *Environmental Research Letters* 10 (5): 054013. https://doi.org/10.1088/1748-9326/10/5/054013.

Habib, E. et al. 2015. Hydroviz Energy-Water Nexus. University of Louisiana at Lafayette. https://hydroviz.org/Lessons/Index/National/Nexus?sectionID=Intro [Last accessed December 13, 2023].

U.S. Census Bureau. 2015. SAIPE State and County Estimates. Retrieved from https://www.census.gov/data/datasets/2015/demo/saipe/2015-state-and-county.html [Last accessed December 13, 2023].

U.S. Census Bureau. 2020. ZIP Code Tabulation Areas (ZCTAs). Retrieved from https://www.census.gov/programs-surveys/geography/guidance/geo-areas/zctas.html [Last accessed December 13, 2023].

U.S. Geological Survey (USGS). 2016. NLCD Land Cover (CONUS). Retrieved from https://www.mrlc.gov/data/nlcd-2016-land-cover-conus [Last accessed December 13, 2023].

U.S. Geological Survey (USGS). 2020. USGS National Hydrography Dataset Plus High Resolution. Retrieved from https://www.usgs.gov/national-hydrography/access-national-hydrography-products [Last accessed December 13, 2023].

USDA Farm Service Agency (FSA). 2023. ARC/PLC Program Data. Retrieved from https://fsa.usda.gov/programs-and-services/arcplc_program/arcplc-program-data/index [Last accessed December 13, 2023].

USDA NASS. 2017. Census of Agriculture. 2017 Census by State - Alabama. Retrieved from https://www.nass.usda.gov/Publications/AgCensus/2017/Full_Report/Census_by_State/Alabama/index.php [Last accessed December 13, 2023].

USDA NASS. 2018. County Data FAQs. Retrieved from https://www.nass.usda.gov/Data_and_Statistics/County_Data_Files/Frequently_Asked_Questions/index.php# [Last accessed December 13, 2023].

USDA NASS. 2022. USDA's National Agricultural Statistics Service Alabama Field Office- County Estimates. Retrieved from https://www.nass.usda.gov/Statistics_by_State/Alabama/Publications/County_Estimates/ [Last accessed December 13, 2023].

USDA NRCS. 2020. Gridded Soil Survey Geographic (gSSURGO) Database. Retrieved from https://www.nrcs.usda.gov/resources/data-and-reports/gridded-soil-survey-geographic-gssurgo-database [Last accessed December 13, 2023].

USGCRP. 2018. Fourth National Climate Assessment. U.S. Global Change Research Program, Washington, DC. Retrieved from https://nca2018.globalchange.gov/ [Last accessed December 13, 2023].

Verburg, P.H., Ellis, E.C., and Letourneau, A. 2011. A global assessment of market accessibility and market influence for global environmental change studies. *Environmental Research Letters* 6 (3): 034019. https://doi.org/10.1088/1748-9326/6/3/034019.

Wang, Q. et al. 2014. Temporal-spatial characteristics of severe drought events and their impact on agriculture on a global scale. *Quaternary International* 349: 10–21. https://doi.org/10.1016/j.quaint.2014.06.021.

Wang, Q. et al. 2021. A multi-scale daily SPEI dataset for drought characterization at observation stations over mainland China from 1961 to 2018. *Earth System Science Data* 13 (2): 331–341. https://doi.org/10.5194/essd-13-331-2021.

Ward, P.S., and Pede, V.O. 2015. Capturing social network effects in technology adoption: the spatial diffusion of hybrid rice in Bangladesh. *Australian Journal of Agricultural and Resource Economics* 59 (2): 225–241. https://doi.org/10.1111/1467-8489.12058.

Wardrop, N.A. et al. 2018. Spatially disaggregated population estimates in the absence of national population and housing census data. *Proceedings of the National Academy of Sciences* 115 (14): 3529–3537. https://doi.org/10.1073/pnas.1715305115.

Weiskopf, S., Cushing, J., Morelli, T.L., and Myers, B. 2021. Climate change risks and adaptation options for Madagascar. *Ecology and Society* 26 (4). https://doi.org/10.5751/ES-12816-260436.

Winkler, I.T., and Flowers, C.C. 2017. America's Dirty Secret: The Human Right to Sanitation in Alabama's Black Belt. *Columbia Human Rights Law Review* 49: 181.

Worqlul, A.W. et al. 2017. Assessing potential land suitable for surface irrigation using groundwater in Ethiopia. *Applied Geography* 85: 1–13. https://doi.org/10.1016/j.apgeog.2017.05.010.

Xie, H., You, L., and Takeshima, H. 2017. Invest in small-scale irrigated agriculture: A national assessment on potential to expand small-scale irrigation in Nigeria. *Agricultural Water Management* 193: 251–264. https://doi.org/10.1016/j.agwat.2017.08.020.

Xie, H., You, L., Wielgosz, B., and Ringler, C. 2014. Estimating the potential for expanding smallholder irrigation in Sub-Saharan Africa. *Agricultural Water Management* 131: 183–193. https://doi.org/10.1016/j.agwat.2013.08.011.

You, L. et al. 2011. What is the irrigation potential for Africa? A combined biophysical and socioeconomic approach. *Food Policy* 36 (6): 770–782. https://doi.org/10.1016/j.foodpol.2011.09.001.

Zagaria, C., Schulp, C.J.E., Malek, Ž., and Verburg, P.H. 2023. Potential for land and water management adaptations in Mediterranean croplands under climate change. *Agricultural Systems* 205: 103586. https://doi.org/10.1016/j.agsy.2022.103586.

Zekeri, A.A., Nnedu, C.C., Popoola, S., and Diabate, Y. 2016. Household Food Insecurity and Health among African American Women in Black Belt Counties of Alabama: Evidence from Mixed-Methods Research. *Journal of Community & Public Health Nursing* 02 (04). https://doi.org/10.4172/2471-9846.1000138.

Zhang, B., Fu, Z., Wang, J., and Zhang, L. 2019. Farmers' adoption of water-saving irrigation technology alleviates water scarcity in metropolis suburbs: A case study of Beijing, China. *Agricultural Water Management* 212: 349–357. https://doi.org/10.1016/j.agwat.2018.09.021.

Zhao, C. et al. 2017. Temperature increase reduces global yields of major crops in four independent estimates. *Proceedings of the National Academy of Sciences* 114 (35): 9326–9331. https://doi.org/10.1073/pnas.1701762114.

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