



Article Climate Change Impacts on Farmland Values in the Southeast United States

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Abstract: This study uses the Ricardian (hedonic) approach to estimate the impact of potential climate change on agricultural farmland values in the Southeast U.S. as a distinct agricultural region. Using the Agricultural Resource Management Survey and seasonal county-level climate and data, we find that regional farmland values increase with spring and fall temperatures and fall precipitation and decrease with winter and summer temperatures. Long-term climate change projections predict aggregate farmland value losses of 2.5–5% with differential state-level impacts, ranging from large losses in Florida to significant gains in Virginia. The results are consistent with recent research and can be helpful in policy design and forecasting land use change.

Keywords: farmland values; climate change; Ricardian analysis; Southeast U.S.

1. Introduction

Weather and climate have a strong impact on agricultural production. The impacts vary by production type (livestock vs. crop) and by crop. Climate change impacts agriculture through both direct (biotic) effects on crop and livestock development and indirect (abiotic) effects arising from changes in pest pressure and performance of ecosystem services, such as pollination, that affect agricultural productivity [1]. Adaptation, defined as adjusting profit maximizing or cost minimizing input-output mix to better suit the changing climatic conditions, is the most feasible strategy for mitigating the impacts of climate change on agriculture [2,3].

Agriculture in the Southeast U.S. (Figure 1), which can be identified as a distinct production region, is quite diversified ranging from row crops to fruits and vegetables, with cotton accounting for almost 22% of the total U.S. production for the 2017/18 growing season [4]. With the increasing world demand for food and rising food prices, the Southeast agriculture is becoming increasingly important [5,6]. At the same time, the region may be relatively more vulnerable to climate change because of low elevation along the long coastline that exposes it to sea level rise and hurricanes [7,8].



Figure 1. The U.S. Southeast.

Climate change data for the U.S. show that, over the past 22 years, average temperatures in the Southeast increased the least in the country, while precipitation has been volatile but and only slightly higher than the past average, which makes the Southeast climate trends rather different from the rest of the continental US [9]. However, existing research notes that this regional trend is not necessarily permanent and that its internal dynamics may change with further changes in sea surface temperatures [5,10]. Regardless of whether the region continues to experience decreases or increases in temperature, adaptation to climate change reflected in location specific farmland values is important. To the best of our knowledge, there has not been a study estimating climate change impacts on farmland values in the Southeastern United States using seasonal weather and farm level data.

This study uses the Ricardian (hedonic) approach to identify the impact of climate, locational and economic variables on agricultural farmland values. Projected future impacts of climate change on those values are made using climate change predictions from the three major Atmospheric Oceanic General Circulation Models. Individual farm data collected by the U.S. Department of Agriculture Agricultural Resource Management Survey (ARMS) are pooled by county to match the weather data.

The paper is structured as follows. Section 2 presents a brief review of the literature. Section 3 describes the analytical framework and the empirical model. Data and estimation procedures are described in Section 4, followed by a discussion of the results in Section 5. The results section focuses on the Ricardian model estimates and the predicted long-term climate change impacts on the farmland values in the region.

2. Literature Review

The potential impacts of climate change on agriculture across different geographical locations have been well researched. There are multiple studies seeking to identify adaptation strategies and long term of climate change on the entire farming sector or individual crops or livestock production [11,12].

The two main approaches used to estimate the impact of climate change on agriculture involve using agronomic and economic models. The agronomic studies focus on the yield of a particular crop as a function of weather inputs, nutrient application and soil conditions. They typically use empirically derived and very detailed crop growth models to simulate the impacts of changes in weather and, thus, climate [13–19]. The economic analysis mainly uses the Ricardian (Hedonic) approach to measure the sensitivity of farm profits or land values to climatic, geographic, economic and demographic factors. The underlying assumption is that producers are profit maximizers and, thus, adjust their input-output mix to the local climatic and geographic conditions. Thus, with enough variation in

the local or regional weather data, the estimates incorporate adaptation. The studies that use the Ricardian approach in estimating the impact of climate change on farmland values include [20–26], among others.

Different researchers have pointed out the strengths and weaknesses of the agronomic and economic analyses and the choice of a particular approach is based on the focus of a particular study. Schlenker and Roberts (2008) note the robustness of the agronomic models that comes from accommodation of the seasonal distributions of weather outcomes as opposed to seasonal averages typically used in regression-based approaches. The weaknesses of this approach include the lack of incorporation of producer adaptation [22], issues related to misspecification and omitted variable bias [27,28], uncertainty about the functional form (physiological process) and model parameterization [18] and an inherent bias leading to over-estimation of the negative impacts of climate change, which is caused by not allowing for substitution (i.e., adaptation) in response to changing climate conditions and, thus, by not permitting a sufficient range of adjustments that leads to overestimation of the damages [20].

Hedonic/Ricardian models, on the other hand, operate with land values and farm profits, which permits analysis of the entire agricultural sector as opposed to a single crop. More importantly, these models explicitly accommodate producer adaptation by using cross-sectional variation in the data in order to reflect climate dependent production practices, crop choices and land allocation instead of directly rationalizing producer behavior in the crop simulation modelling framework [22]. The challenges involve mostly econometric issues that include the limitations of partial equilibrium analysis since, by construction, the approach assumes constant input and output prices [21], the inability to estimate adjustment costs and results not necessarily robust across different weighting schemes [29], as well as issues with the treatment of irrigation. There also are concerns about the omitted variable bias associated with the hedonic model.

The estimates of the impacts of climate change on the U.S. agriculture vary significantly. Adams et al. (1995) [30], Easterling et al. (1991) [14] and Kaiser et al. (1993) [31] predicted very large losses in the agricultural sector by the end of the 21st century, whereas Schlenker et al. (2008) [18], Kelly et al. (2005) [32] and Schlenker et al. (2005) [21] project only mild negative impacts of climate change. On the other hand, Deschenes and Greenstone (2007) [25] find that climate change, on aggregate, would be slightly beneficial to the U.S. agriculture. Finally, studies by Schlenker et al. (2006) [22] and Massetti and Mendelsohn (2011) [33] conclude that climate change impacts are region specific ranging from mild gains to large losses. This study follows up on these aspects and uses a similar approach in the analysis of farm level data in the Southeast U.S.

One of the main criticisms of the original Ricardian model by Mendelsohn et al. (1994) [20] is that, instead of implicitly assuming infinite adjustment costs in agronomic studies, the model assumes zero adjustment costs thus yielding a lower-bound estimate of the climate change costs [29]. Since these costs might constitute a significant part of the total cost, research should try to relate them to the rate of temperature change. Other criticisms address the instability of the regression coefficients resulting from the inconsistency with plant physiology and economics of grain production [34] and the weaknesses of the underlying partial equilibrium model that ignores relative price changes and resource constraints, particularly irrigation water [35]. All these issues might lead to underestimating the adverse effects of climate change.

Consequently, subsequent Ricardian analysis attempted to address the shortcomings of the original. Seo et al. (2008) [26] estimated the impact of climate change on South American farms taking into account farmer adaptations and testing several econometric specifications of five different models. Small farms were found more vulnerable to climate change, regardless of irrigation, losing more than half of their income by 2100. Schlenker et al. (2006) [22] studied the relationship between farmland values and climatic, soil and socioeconomic variables for the U.S. counties east of the 100th meridian (in order to avoid the irrigation bias). They found that, due to the non-linear relationship between climatic variables and plant growth, degree days were a better predictor. Using a similar approach but

accounting for irrigation, Schlenker et al. (2005) [21], argued against pooling irrigated and dryland counties in a single regression. Mendelsohn and Dinar (2003) [36] also used a refined Ricardian model to test whether surface water withdrawals help to explain variation of the U.S. farm values finding that irrigated cropland values are not sensitive to precipitation but increase with annual temperature and that drip systems complement higher temperatures.

Similar to the hedonic model, Deschenes and Greenstone (2007) [25] used farm profits instead of land values and justify their approach by better accommodation of farmer adaptation and of the omitted variable bias associated with the production function and the hedonic approaches respectively (similar because the hedonic model itself is derived from a farm profit function). Their estimation of the impacts of temperature and precipitation on agricultural profits also exploited inter-annual and not only cross-sectional, variation of the weather variables. Subsequent simulations showed an average increase of 4% in annual profits as a consequence of climate change, which is different from many previous studies.

Empirical estimates of the adaptation costs and measures are harder to come by but there are some practical steps that have been taken in recent years. For example, first steps towards adaptation to climate change were identified at the 2010 EPA Southeast Climate Change Adaptation Planning workshop as discouraging risky behavior (e.g., building in vulnerable coastal areas) and encouraging retreat from vulnerable/marginal areas. In another study, Bartels et al. (2012) [37] described ongoing interactions and experiential learning among the sector's diverse participants. They showed how participatory events such as workshops facilitate diffusion of knowledge and suggested that stakeholder engagement and its design can be powerful tools in helping to improve decision support and the adaptive capacity within rural communities. Other studies of the issues of adaptation include Cammarano et al. (2012) [38], Royce et al. (2012) [39] and Cabrera et al. (2009) [40].

3. Analytical Framework

The Ricardian approach (Hedonic analysis) that we use follows closely that of Van-Passel, Massetti and Mendelsohn (2016, henceforth PMM) [41] who estimated the climate impact on farmland values in the EU-15 countries. The model assumes that farmland value per acre of producer i in county c is equal to the present value of net returns from farming that are assumed constant for the foreseeable future

$$V_{i,c} = (P_c Q_{i,c} - M_c X_{i,c}(Z_c)) / \varphi$$

where $V_{i,c}$ is the farmland value per acre, P_c is the vector of crop prices, $Q_{i,c}$ is crop outputs, M_c and $X_{i,c}$ are input prices and profit maximizing inputs (except land) that are functions of local (exogenous) variables in Z_c including climate and soil variables and φ is the discount rate. The profit maximizing crop mix, profits and farmland values are thus a function of Z and (implicit) production function parameters and inputs assumed at profit maximizing level.

As previous studies [22,26,33,36] have established, the relationship between farmland values and temperature and precipitation is nonlinear. Very few studies observed the reverse [10]. This study accommodates nonlinearities by inclusion of squared values of temperature and precipitation in a log-linear hedonic model:

$$lnV_{c} = \alpha + \sum_{m} \beta_{T,m} T_{c,m} + \sum_{m} \gamma_{T,m} T_{T,m}^{2} + \sum_{m} \beta_{R,m} R_{c,m} + \sum_{m} \gamma_{R,m} R_{R,m}^{2} + \eta S_{c} + \theta G_{c} + \vartheta H_{c} + ST + \varepsilon_{ic}$$

where V_c represents farmland value in county c, $T_{c,m}$ ($R_{c,m}$) represent average temperature (cumulative precipitation) in county c during season m, G is a vector of geographic variables, H is a vector of farm socioeconomic and demographic variables, S is a vector of soil variables including irrigation and ST represents a State dummy. The model implicitly accommodates adaptation as profit maximizing producers adjust input-output mix according to the market and local climate and topographic conditions which translates into farmland values based on profitability [25]. The log-linear form is

used due to large variation in the land values explained by locational characteristics and productivity. Unlike the PMM study, weights are not assigned to the individual locations due to ambiguities in calculation and PPM noting that the weighting did not alter their results significantly.

The predicted impact of climate change on farmland values by the year 2100 is calculated as the difference between the predicted value of farmland under the new climate and the value of farmland under the current climate. The estimates are aggregated to obtain predicted changes in farmland values at the state and regional levels. The prediction uses three different model scenarios, as in PMM: Hadley CM3, ECHO-G and NCAR PCM.

4. Data

Farm level data for the Southeastern U.S. were obtained from the Agricultural Resource Management Survey (ARMS) database, Phase III and pooled by county and averaged over a 5-year period (2007–2011) as different farmers are surveyed every year. The Bureau of Labor Statistics defines the southeastern United States as eight states and the American Association of Geographers lists 12 states. We chose nine states—Alabama, Georgia, Florida, Kentucky, Mississippi, the Carolinas, Tennessee and Virginia as states with developed agriculture and sufficient climate variability. Climate data were obtained from the Global Historical Climatology Network (GHCND) monthly summaries that include temperature and precipitation from the National Climatic Data Center (NCDC). The climate data are classified by cities, with the city data individually matched with respective counties since the land value model used in this study is at the county level. The Soil Survey Geographic Database (SSURGO 2.2.6) was the most current source of soil data at the time this study. The soil data and the county population and income data collected from the US Census Bureau were merged with the ARMS data using five digit FIPS (Federal Information Processing Standard) county codes. The 5-year pooled-cross sectional ARMS data for the region have a total of 103,560 observations. Averaging over the period produces a total of 647 county level observations across 9 Southeastern states. Table 1 provides a detailed description of the variables and Table 2 shows the summary statistics of the variables used.

Variable	Description	Unit of Measurement	Source	A Priori Sign
Farmland Value	Estimated market value of farmland	Dollar/acre	ARMS	
Acres Operated	Total Size of land under operation	Acre/acre	ARMS	
Land Owned	Acres of farmland owned	Acre/acre	ARMS	
Land Rented	Acres free rented + acres share rented + acres cash rented	Acre/acre	ARMS	
	Average County Specific Climate Varia	bles		
Winter Temp	Winter mean air temperature, 1981–2010	°F	GHCND	+/-
Spring Temp	Spring mean air temperature, 1981–2010	°F	GHCND	+/-
Summer Temp	Summer mean air temperature, 1981–2010	°F	GHCND	+/-
Fall Temp	Fall mean air temperature, 1981–2010	°F	GHCND	+/-
Winter Precip	Winter mean cumulative precipitation, 1981–2010	cm/month	GHCND	+/-
Spring Precip	Spring mean cumulative precipitation, 1981–2010	cm/month	GHCND	+/-
Summer Precip	Summer mean cumulative precipitation, 1981–2010	cm/month	GHCND	+/-
Fall Precip	Fall mean cumulative precipitation, 1981–2010	cm/month	GHCND	+/-
	Average County Specific Soil Character	istics		
T-1-1-C1	Mineral particles 0.05–2.0 mm in equivalent diameter as a	0/ 147 1 1	COLUDICO	
Iotal Sand	weight percentage of the less than $\frac{1}{2}$ mm fraction	% Weight	SSUKGO	—
TE + 1 C'14	Mineral particles 0.002–0.05 mm in equivalent diameter as a	0/ 147 * 1 /		
Iotal Silt	weight percentage of the less than 2 mm fraction	% Weight	SSURGO	—
	Mineral particles <0.002 mm in equivalent diameter as a weight	0/ 147 * 1 /	SSURGO	
Iotal Clay	percentage of the less than 2 mm fraction	% Weight		—
	Weight of decomposed plant and animal residue expressed as a	0/ 147 1 1		
Organic Matter	weight percentage of the less than 2 mm soil material	% Weight	SSUKGO	+
Ph	Soil pH level	-	SSURGO	+/-
Salinity	Soil Electrical Conductivity	-	SSURGO	_
	Susceptibility of soil particles to detachment by water			
Soil Erodibility	(KW factor)	-	SSUKGO	_
	Average County Specific Geographic Var	iables		
Clana Cradiant	Difference in elevation between two points, expressed as a	0/	SCI ID CO	. /
Slope Gradient	percentage of the distance between those points	%	SSUKGO	+/-
NC1	Number of Miles from farm to the nearest town with a			
Miles to town	population of 10,000+	Miles	ARMS	—
Per Capita Income	Average County Per Capita Income	US Dollars	US Census Bureau	+
Mean Elevation	Mean elevation above sea level	km	GHCND	_
T 1	Decimated degrees with northern hemisphere values > 0 and	P	CHOND.	,
Latitude	southern hemisphere values < 0	Degrees	GHCND	+/-
T 1/1	Decimated degrees with western hemisphere values < 0 and	D	CLICNED	,
Longitude		Degrees	GHCND	+/-

Table 1. Data Description.

Variable	Mean	Std. Dev.	Minimum	Maximum
	County Level Fa	ırm variables		
Land Value (mil \$)	258,805	3,499,199	6322	43,700,000
Land Value/acre (\$/ac)	3791	6104	500	105,888.
Acres Operated (,000)	68,262	95,600	200	1,372,887.
Acres Owned (,000)	36,791	73,833	0	1,346,770
Acres Rented (,000)	32,962	44,011	0	481,492
A	verage County Specif	ic Climate Variables	6	
Winter Temp (°F)	45.64	7.84	29.78	69.76
Spring Temp (°F)	61.68	5.35	44.24	76.33
Summer Temp (°F)	78.06	3.05	64.51	93.77
Fall Temp (°F)	63.39	5.71	42.98	79.13
Winter Precip (10 mm)	27.46	7.23	10.65	64.80
Spring Precip (10 mm)	30.11	5.82	0	51.47
Summer Precip (10 mm)	36.68	9.92	14.13	84.90
Fall Precip (10 mm)	27.23	3.94	5.79	44.21
A	verage County Specifi	c Soil Characteristic	S	
Total Sand (% wgt)	55.30	20.99	4.60	90.67
Total Silt (% wgt)	28.98	17.65	0.81	76.97
Total Clay (% wgt)	13.88	6.16	1.63	37.88
Organic Matter (% wgt)	3.55	3.40	0.68	29.14
Ph	5.35	0.38	4.68	7.57
Salinity	0.16	0.80	0.00	18.41
Soil Erodibility	0.23	0.09	0.02	0.47
Ave	erage County Specific	Geographic Variabl	es	
Slope Gradient (%)	8.71	7.04	0.61	42.88
Miles to town (mi)	10.56	8.11	0	120.00
Income Per Capita (\$)	22,813	4983.15	10,925.00	490,001.00
Mean Elevation (m)	106.50	112.34	1.22	670.21
Latitude ($^{\circ}$)	33.91	2.98	25.00	39.14
Longitude (°)	-82.77	3.58	-91.36	-75.7230

Table 2. Summary Statistics.

Table 2 shows a sizeable range in the estimated land values per acre with the highest values in North Carolina and Virginia and the lowest in Mississippi and Alabama. It also shows the regional county per capita average income of \$22,814, which is slightly below the average of about \$24,580 that includes cities.

5. Results

Table 3 presents regression results of the log-linear Ricardian model with all the variables (column 1) and without the state dummies (column 2). Column 3 shows results of regressing the land values on the temperature and precipitation only. Most of the variables are statistically significant and the R² is 0.79 for the full regression, which corroborates the hypothesis that farmland values depend on the location specific climatic, soil and economic attributes. All the state dummies with the exception of Mississippi and Virginia are significant at the 1% level.

lnLandValue	All Variables	Without State Dummies	Only Climate Variables
wintertemp	0.3695 ***	0.3600 ***	0.2139 ***
	(0.0290)	(0.0275)	(0.0349)
wintertempsq	-0.0044 ***	-0.0044 ***	-0.0014 ***
	(0.0003)	(0.0003)	(0.0004)
springtemp	-0.5627 ***	-0.5018 ***	-0.2631 ***
	(0.0726)	(0.0708)	(0.0933)
springtempsq	0.0048 ***	0.0043 ***	0.0026 ***
	(0.0006)	(0.0006)	(0.0008)
summertemp	1.4213 ***	1.6966 ***	1.0734 ***
	(0.1044)	(0.1050)	(0.1315)
summertempsq	-0.0097 ***	-0.0115 ***	-0.0084 ***
	(0.0007)	(0.0007)	(0.0009)
falltemp	-0.0861 * (0.0744)	-0.1436 * (0.0760)	0.0824 (0.1024)
falltempsq	0.0008 *	0.0014 ***	-0.0009
	(0.0006)	(0.0006)	(0.0008)
winterpreci	-0.1352 ***	-0.0732 ***	-0.0336 ***
	(0.0056)	(0.0047)	(0.0061)
winterprecisq	0.0021 ***	0.0010 ***	0.0000
	(0.0001)	(0.0001)	(0.0001)
springpreci	0.0148 *	0.0117	0.0532 ***
	(0.0077)	(0.0076)	(0.0102)
springprecisq	-0.0003 **	-0.0003 **	-0.0010 ***
	(0.0001)	(0.0001)	(0.0002)
summerpreci	-0.0630 ***	-0.0695 ***	-0.1481 ***
	(0.0040)	(0.0038)	(0.0043)
summerprecisq	0.0008 ***	0.0009 ***	0.0017 ***
	(0.0000)	(0.0000)	(0.0001)
fallpreci	-0.0342 ***	0.0035	-0.0931 ***
	(0.0075)	(0.0076)	(0.0101)
fallprecisq	0.0008 ***	0.0001	0.0022 ***
	(0.0001)	(0.0001)	(0.0002)
percapitaincome	0.0489 *** (0.0007)	0.0494 *** (0.0007)	
elevationmean	0.0024 *** (0.0001)	0.0028 *** (0.0001)	
latitudemean	-0.0387 (0.0090)	-0.0800 (0.0080)	
longitudemean	0.0199 (0.0038)	0.0270 ** (0.0030)	
slopegradient	-0.0074 (0.0010)	-0.0074 * (0.0010)	
soilerodibilityfactor_kw	-1.7767 *** (0.1157)	-1.8599 *** (0.1154)	
organicmatter	0.0114 *** (0.0018)	0.0088 *** (0.0018)	
totalsand	-0.0318 *** (0.0015)	-0.0328 *** (0.0016)	
totalsilt	-0.0211 *** (0.0016)	-0.0230 *** (0.0017)	
totalclay	-0.0220 *** (0.0019)	-0.0300 *** (0.0019)	
ph	-0.0946 *** (0.0156)	-0.0270 * (0.0151)	

Table 3. Southeast US Ricardian Regression.

lnLandValue	All Variables	Without State Dummies	Only Climate Variables
salinity	0.0411 ***	0.0225 ***	
	(0.0038)	(0.0039)	
milesfromtown	-0.0058 ***	-0.0088 ***	
	(0.0004)	(0.0004)	
acresowned_acre	1.1494 ***	1.1615 ***	
	(0.0530)	(0.0548)	
acresrented_acre	1.3014 ***	1.2690 ***	
	(0.0553)	(0.0572)	
Florida	0.7221 ***		
	(0.0223)		
Georgia	0.4214 ***		
U	(0.0170)		
Kentucky	-0.0801 ***		
	(0.0286)		
Mississippi	-0.0262		
	(0.0177)		
North Carolina	0.2915 ***		
	(0.0231)		
South Carolina	0.2236 ***		
	(0.0231)		
Tennessee	-0.1082 ***		
	(0.0193)		
Virginia	-0.0014		
	(0.0293)		
Constant	-34.2736 ***	-42.8321 ***	-29.2004 ***
	(2.1465)	(2.1509)	(2.4618)
Observations	647	647	647
R-squared	0.7878	0.7686	0.5491
Adj. R-squared	0.7873	0.7682	0.5487
F test	154.0.0	172.3.0	127.5.0
Prob (F-statistic)	0.000	0.000	0.000

Table 3. Cont.

Robust standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

The seasonal marginal impacts calculated at the mean values and reported in Table 4 show that farmland values decrease with winter and summer temperatures but increase with spring and fall temperatures. This is in accordance with the latest agronomic region-specific experimental findings that report yield reductions from crop stress, shorter ripening and water deficit caused by higher maximum temperatures during late vegetative and early reproductive growth stages [19,42,43]. The discrepancies of seasonal, as opposed to annual, weather impacts can be attributed to the local climate and geography of the Southeast (hot summers and better water retention in colder winters) and seasonal requirements of the crops and vegetables grown in the Southeastern US. The resulting annual impacts are less significant and much smaller as the seasonal impacts largely cancel out.

Precipitation increases farmland values only in the fall but the impacts of precipitation are significantly smaller than those of temperature. This corroborates the empirical crop-specific finding that moisture abundance in the southeastern U.S. diminishes the magnitude of positive precipitation effects on yields and even reverses it if the impacts of flooding are incorporated. Also, the positive impacts of precipitation are more pronounced in areas with sandy soils [19]. The impacts of both temperature and precipitation are declining in magnitude, as evidenced by the coefficients at their squared values.

Temperature	$\Delta V/acre, \%$	dV/dT
Annual	-8.05	-305 *
Winter	-3.21	-121.70 ***
Spring	2.94	111.53 ***
Summer	-9.31	-352.90 ***
Fall	1.53	58.07 *
Precipitation	$\Delta V/acre, \%$	dV/dP
Annual	-1.81	-68.61 **
Winter	-1.99	-75.41 ***
Spring	-0.33	-12.39 *
Summer	-0.43	-16.32 ***
Fall	0.94	35.51 ***

Table 4. Marginal Impacts of Seasonal Temperature and Precipitation at the Mean Values from the Main Regression (all variables), per 1F and 1 Inch of Precipitation.

Robust standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Most of the control variables are significant with the exception of the *longitude, latitude* and *slope gradient* and have plausible signs and magnitudes. Higher sand, silt and clay content reduces, while organic matter increases, farmland values. As expected, soil erodibility and pH levels and distance to nearest town negatively impact farmland values. Higher elevation and soil salinity increase the value of farmland, a finding which contradicts some studies [41]. Possible explanations include exposure to flooding and maybe historical reasons. The state dummies confirm the state level differences in land values.

The results in the second and third columns of Table 3, run as a robustness check, are very similar. Estimation of robust standard errors did not indicate heteroscedasticity. Regressions using mean deviations of temperature and precipitation and a median regression of the same model also show very similar results.

Table 5 presents separate regressions for distinct farm types: rainfed, irrigated, crop and livestock. The signs and the magnitudes on the coefficients vary across the sub-groups with some of the variables losing their statistical significance, particularly for livestock farms. As expected, the temperature impact is significantly stronger for non-irrigated farms, as is the impact of fall precipitation. The loss of significance for the crops and particularly livestock only estimates can be explained by smaller sample size.

lnLandValue	Rainfed Only	Irrigated Only	Crops Only	Livestock Only
wintertemp	0.5846 ***	0.1182 ***	-0.0643	0.3982 ***
	(0.1177)	(0.0329)	(0.0516)	(0.0476)
wintertempsq	-0.0068 ***	-0.0011 ***	0.0008	-0.0046 ***
	(0.0014)	(0.0004)	(0.0006)	(0.0006)
springtemp	-1.8903 *** (0.2963)	-0.6550 *** (0.0840)	-0.1084 (0.1294)	-0.9082 *** (0.1184)
springtempsq	0.0154 ***	0.0057 ***	0.0007	0.0078 ***
	(0.0025)	(0.0007)	(0.0011)	(0.0010)
summertemp	3.2890 ***	1.0266 ***	0.9169 ***	1.3095 ***
	(0.4539)	(0.1189)	(0.1800)	(0.1771)
summertempsq	-0.0209 ***	-0.0071 ***	-0.0063 ***	-0.0089 ***
	(0.0029)	(0.0008)	(0.0012)	(0.0011)
falltemp	-1.0979 ***	0.5851 ***	0.4762 ***	-0.1169
	(0.3095)	(0.0844)	(0.1354)	(0.1203)
falltempsq	0.0090 ***	-0.0046 ***	-0.0031 ***	0.0012
	(0.0026)	(0.0007)	(0.0011)	(0.0010)

Table 5. Ricardian Regressions by Rainfed, Irrigated, Crops and Livestock Farms.

InLandValue	Rainfed Only	Irrigated Only	Crops Only	Livestock Only
winterpreci	-0.0732 ***	-0.0906 ***	-0.0473 ***	-0.0990 ***
	(0.0247)	(0.0064)	(0.0109)	(0.0089)
winterprecisq	0.0014 ***	0.0013 ***	0.0009 ***	0.0015 ***
	0.0681 *	0.0600 ***	0.0250 **	0.0020
springpreci	(0.0352)	(0.0088)	(0.0146)	(0.0119)
aprinaprovina	0.0010 **	0.0000 ***	0.0005 **	0.0001
springpreeisq	(0.0005)	(0.0001)	(0.0002)	(0.0002)
summerpreci	-0.0356 *	-0.0910 ***	-0.0865 ***	-0.0555 ***
-	(0.0183)	(0.0045)	(0.0075)	(0.0061)
summerprecisq	0.0005 **	0.0012 ***	0.0011 ***	0.0008 ***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)
fallpreci	-0.1605 ***	-0.0448 ***	-0.0715 ***	-0.0257 **
	(0.0374)	(0.0082)	(0.0137)	(0.0120)
fallprecisq	0.0027 ***	0.0010 ***	0.0012 ***	0.0006 ***
	(0.0007)	(0.0001)	(0.0002)	(0.0002)
percapitaincome	0.0409 ***	0.0565 ***	0.0655 ***	0.0478 ***
	(0.0030)	(0.0008)	(0.0012)	(0.0011)
elevationmean	0.0022 ***	0.0025 ***	0.0027 ***	0.0017 ***
	(0.0004)	(0.0001)	(0.0002)	(0.0001)
latitudemean	-0.0134	-0.0046	-0.0380 **	0.0127
	(0.0380)	(0.0104)	(0.0170)	(0.0139)
longitudemean	-0.0010	0.0380 ***	0.0202 ***	0.0352 ***
	(0.0100)	(0.0044)	0.0121 444	(0.0000)
slopegradient	-0.0192 ***	-0.0083 *** (0.0011)	-0.0121 ***	-0.0039 ***
	(0.0044)	0.10011	(0.0019)	0.55(5 ***
sollerodibilityfactor_kw	-0.7971 (0.5249)	-2.1331 ***	-3.1507 ***	-0.5767 ***
arganismattar	0.0006	0.0202 ***	0.0224 ***	0.0002 **
organicinatier	(0.0085)	(0.0020)	(0.0028)	(0.0036)
totalsand				
totalsarid	(0.0071)	(0.0018)	(0.0025)	(0.0029)
totalsilt	-0.0082	-0.0186 ***	-0.0233 ***	0.0011
totalont	(0.0074)	(0.0019)	(0.0027)	(0.0030)
totalclav	-0.0012	-0.0226 ***	-0.0289 ***	0.0018
	(0.0085)	(0.0022)	(0.0031)	(0.0035)
ph	0.1224 *	-0.0751 ***	-0.0216	-0.0358
1	(0.0642)	(0.0179)	(0.0273)	(0.0254)
salinity	-0.0549	0.0468 ***	-0.0286 ***	0.0627 ***
-	(0.0449)	(0.0043)	(0.0065)	(0.0065)
milesfromtown	-0.0043 ***	-0.0065 ***	-0.0024 ***	-0.0073 ***
	(0.0010)	(0.0005)	(0.0006)	(0.0005)
acresowned_acre	0.6594 ***	1.2764 ***	0.3532 ***	1.1860 ***
	(0.0457)	(0.0604)	(0.0220)	(0.0493)
acresrented_acre	0.6479 ***	1.3006 ***	0.3553 ***	1.3903 ***
	(0.0660)	(0.0625)	(0.0328)	(0.0562)
Florida	0.3549 ***	0.6215 ***	0.7417 ***	0.6034 ***
	(0.0998)	(0.0253)	(0.0446)	(0.0343)
Georgia	0.4080 ***	0.3648 ***	0.3644 ***	0.4050 ***
	(0.0690)	(0.0196)	(0.0363)	(0.0253)
Kentucky	-0.1192	-0.1340 ***	-0.0413	-0.2281 ***
	(0.1134)	(0.0327)	(0.0551)	(0.0435)
Mississippi	-0.1446 ** (0.0689)	0.0760 *** (0.0204)	0.0352	0.0306
	(0.000)	(0.0401)	(0.0000)	(0.04/1)

Table 5. Cont.

lnLandValue	Rainfed Only	Irrigated Only	Crops Only	Livestock Only
North Carolina	0.8592 ***	0.2348 ***	0.6085 ***	0.1566 ***
	(0.0953)	(0.0267)	(0.0454)	(0.0356)
South Carolina	0.5411 ***	0.2296 ***	0.3509 ***	0.1466 ***
	(0.0906)	(0.0268)	(0.0442)	(0.0363)
Tennessee	0.1084	0.0229	-0.0410	-0.0210
	(0.0755)	(0.0223)	(0.0401)	(0.0290)
Virginia	0.5024 ***	-0.1791 ***	0.2446 ***	-0.3379 ***
	(0.1204)	(0.0336)	(0.0559)	(0.0455)
Constant	-47.4769 ***	-31.5340 ***	-35.9820 ***	-22.2063 ***
	(9.4040)	(2.4507)	(3.6432)	(3.7301)
Observations	647	647	647	647
R-squared	0.5344	0.7545	0.7941	0.6045
Adj. R-squared	0.5264	0.7539	0.7930	0.6029
F test	66.31	1164	738.4	363.7
Prob (F-statistic)	0.000	0.000	0.000	0.000

Table 5. Cont.

Robust standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 6 presents marginal impacts of the annual and seasonal climate variables by state showing significant variation across the Southeast states. A 1F increase in the *annual* temperature increases farmland values by 2.84% on average in Alabama, Georgia, Kentucky, North Carolina, South Carolina, Tennessee and Virginia but decreases them by 1.8% in Florida and Mississippi. A 1 inch increase in annual precipitation decreases land values by about 0.36% everywhere except Alabama, Mississippi and Tennessee, perhaps because of the prevalence of rainfed farming there.

Table 6. Marginal Impacts of Temperature and Precipitation, % of Land Value per 1F and 1 Inch of Precipitation.

State	Annual Temp	Annual Preci	Winter Temp	Spring Temp	Summer Temp	Fall Temp	Winter Preci	Spring Preci	Summer Preci	Fall Preci
Alabama	2.34%	0.19%	-3.80%	4.12%	-11.66%	6.83%	1.85%	-0.69%	-0.98%	1.11%
Florida	-1.28%	-0.04%	-14.4%	10.65%	-15.81%	8.75%	-4.03%	-0.02%	2.19%	1.30%
Georgia	2.27%	-0.31%	-4.90%	4.59%	-11.24%	6.91%	-0.67%	-0.24%	-0.96%	1.36%
Kentucky	3.35%	-0.32%	5.11%	-2.37%	-4.18%	5.21%	-1.90%	-0.60%	-1.59%	1.33%
Mississippi	-2.29%	0.41%	-3.88%	4.74%	-12.71%	6.87%	3.10%	-0.81%	-0.96%	0.92%
North Carolina	2.95%	-0.33%	0.22%	-0.24%	-5.41%	5.81%	-2.61%	-0.26%	-0.75%	1.17%
South Carolina	2.42%	-0.48%	-3.42%	3.45%	-11.29%	6.62%	-2.37%	-0.09%	-0.68%	1.43%
Tennessee	3.10%	0.02%	2.48%	-0.74%	-5.24%	5.56%	0.44%	-0.76%	-1.56%	1.08%
Virginia	3.47%	-0.68%	4.55%	-3.77%	-0.75%	5.01%	-4.15%	-0.23%	-1.64%	1.32%

As in the previous studies, higher summer temperatures depress land values in all the states with the smallest impact in Virginia, which is the northernmost state in the sample. Consistent with the pooled sample estimation, both fall temperature and precipitation are beneficial in all the states and winter, spring and summer precipitation is bad for most.

Finally, Table 7 shows projected changes in land values by the year 2100 based on our estimates and climate change predictions of the three GCM models. Just like the other studies discussed in Section 2, we assume climate change impacts *ceteris paribus*, that is, not accounting for the long-term changes in technology, prices, capital investments, infrastructure, population and so forth. However, producer adaptation is accommodated by the underlying assumption that profit-maximizing producers in different climate areas adjust their input-output mix and practices that best suit local conditions. Predictions based on the Hadley CM3 and the ECHO-G models are of a relatively higher magnitude compared to those based on the NCAR PCM model. The Hadley CM3 model predicts a 4.4 °C increase in temperature and a 27.3 cm decrease in annual precipitation while the ECHO-G model predicts a 4.3 °C increase and a 16.8 cm decrease, respectively. The NCAR PCM model predicts smaller temperature and precipitation changes of a +2.8 °C and -4.2 cm.

	Present		esent Hadley CM3 (by 2100)		ECHO-G (l	ECHO-G (by 2100)		NCAR PCM (by 2100)	
	Land Value/acre	Total Operated Acres, 000s	Impact/acre, \$	Total Impact (mil \$)	Impact/acre, \$	Total Impact (mil \$)	Impact/acre, \$	Total Impact (mil \$)	
AL	\$2003	5863	-113.29	-664.15	-111.52	-653.82	-68.10	-399.21	
FL	\$8698	6205	-3656.08	-22,685.77	-3551.5	-22,036.7	-2118.8	-13,146.9	
GA	\$3125	7103	-265.21	-1883.75	-248.84	-1767.48	-139.15	-988.35	
KY	\$2080	11,069	583.17	6455.12	574.48	6358.93	351.20	3887.44	
MS	\$1467	7335	-104.75	-768.34	-105.24	-771.89	-66.47	-487.56	
NC	\$3247	7184	469.63	3373.96	467.80	3360.83	291.39	2093.44	
SC	\$2422	3356	-89.48	-300.33	-76.76	-257.64	-35.02	-117.55	
TN	\$2459	9082	494.63	4492.30	483.22	4388.63	291.18	2644.55	
VA	\$3261	6994	1041.24	7282.31	1032.82	7223.45	638.82	4467.85	
SeUS	\$3791	64,191	-182.24	-1169798	-170.61	-109519	_94 99	-609737	

Table 7. Farmland Value Changes per Acre and Totals in Southeast U.S.

For the entire southeast US, farmland values per acre decrease by \$182, \$171 and \$95 according to the Hadley CM3, ECHO-G and NCAR PCM model predictions, respectively. This translates to aggregate losses of \$11.7, \$11 and \$6.1 billion representing about 4.81%, 4.49% and 2.51% of the total farmland value in the Southeast. These projections compare favorably to much larger losses estimated for other countries and sub-regions in earlier studies [30,31] and are consistent with more recent projections [21,25,26,44].

The most interesting result is that the farmland value impacts of the climate change projections vary greatly by the state suggesting redistribution of wealth. According to our results, Alabama, Florida, Georgia, Mississippi and South Carolina are likely to lose farmland values in the long term (by 2099), with Florida losing about 40% of its farmland value. Kentucky, North Carolina, Tennessee and Virginia are likely to experience increases in farmland values due to the predicted changes in climate conditions by 2100, with Virginia gaining about 30%. To the best of our knowledge, such heterogeneity has been observed only by Deschenes and Greenstone (2005) in their comprehensive estimation of climate change impacts on agricultural profits. Their projections of long term climate change impacts on agricultural profits according to the Hadley 2 scenario by state differ in the nationwide ranking but our estimates for Florida, Alabama, Mississippi and Kentucky are quite close. Annual profit decreases of \$450 mil in Florida, \$21 mil in Alabama and \$16 mil in Mississippi and a gain of \$21 mil in Kentucky estimated by Deschenes and Greenstone imply farmland value losses of \$13, \$40.6 and \$0.45 billion and a gain of \$0.6 billion in the four states using the 2005–2014 constant maturity rate average of 3.45. These values are well within the range of our estimates. The aggregate nationwide impact of about \$0.2 billion is different from our regional estimate of -\$11.7 billion but could be explained by the southern location of our sample. This comparison raises the question of the desired level of aggregation in the analysis of predicted climate change impacts on agriculture, particularly of the common assumption of uniform climate change predictions for all states. It also highlights the consistency of different estimation approaches, although the profitability analysis has been criticized for absorbing inter-annual weather variability by the state-by-year fixed effects and assuming uniform future climate change within each state [45].

6. Conclusions

This study employs the Ricardian (Hedonic) approach in analyzing the impact of seasonal climate and, subsequently, several climate change projections on agricultural farmland values in nine states in the Southeastern US. The results show that farmland values decrease with average winter and summer temperatures and increase with spring and fall temperatures, which confirms recent findings of the experimental agronomic research on the region. Fall precipitation has a positive impact on the farmland values and a small negative impact during the rest of the year. The magnitude of all significant impacts is declining with both temperature and precipitation. Projections based on our estimates and the three climate change models show that the per acre farmland values in the entire southeastern region of the US are likely to decrease by \$182, \$171 and \$95 according to the Hadley CM3, ECHO-G and NCAR PCM model predictions, respectively. This translates into aggregate losses of \$11.7, \$11 and \$6.1 billion representing about 4.81%, 4.49% and 2.51% of the total farmland value in the Southeast.

State level estimates show that annual, as well as seasonal, temperature and precipitation have differential impacts across the states that are consistent with their geography. In particular, our estimates compare favorably in both signs and magnitudes with the results of one of the few comprehensive studies of climate change impacts on agricultural profitability in the US [25]. The differences between the regional and state level effects highlight the complexity of the economic impacts of climate change and the importance of analyses done on a larger scale as the aggregate studies mask local differences.

As pointed out earlier, although the Ricardian approach implicitly accommodates producer adaptation (to climatic conditions) given current technology and market conditions, by construction it does not take into account the likely long-term adaptive changes in technology, particularly the potential of drought, flood and salt tolerant seed varieties, changes in demand affecting prices, as well as investments in infrastructure and other determinants of agricultural profitability and land values. Another caveat of this approach is that it cannot analyze the specific farmer behavior and, thus, should be combined with qualitative field research obtaining producers' feedback, which will help understand their attitudes and adaptive behaviors in a more realistic setting. Also, a potential extension of this model would be to explicitly accommodate county/state farmland area responses to changes in climate variables.

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