Supplementary Appendix

A1 Supplementary Information on Data Processing Procedure for Adoption Identification

This section describes the procedures used to identifying independent irrigation units for our analysis, allowing us to overcome the empirical challenges related to multiple permits and wells.

The original withdrawal data includes 1,003 permits registered between 1983 and 2021, associated with 3,034 wells. After removing permits without spatial information, we are left with 955 permits and 2,828 wells. The discrepancy between the number of permits and wells indicates that some permits are linked to multiple wells. Additionally, permits are not always uniquely identified, as some farmers hold multiple permits in South Carolina. To address this, we first focus on resolving the issue of multi-permit ownership.

The original dataset includes 88 permits owned by 28 multi-permit holders. To address multi-permit cases, we retain only one permit per holder, selecting the one with the largest historical water withdrawals in any given year of operation. This results in the removal of 60 permits (88 - 28). Consequently, our dataset is reduced to 895 permits (955 - 60) and 2,685 wells. This approach ensures that each permit is associated with a single, independent permit holder.

Next, we address permits for multiple wells. Permits with multi-wells use more than a single well for irrigation in the first year of adoption. We aim to identify one of those multi-wells as a representative well of each permit. Of 895 permits, 330 permits operate 1,609 wells, holding an average of 4.9 wells, while the rest (565) rely on single wells throughout their operating years. We focus on these 330 multi-well holders and choose one well among multi-wells. To do so, we first create a cluster containing all wells under the same permit. We then identify the center of this cluster and select the well closest to the center as the representative well, removing the others. If several wells are reported at the same location, we choose the one with the highest reported water volume. If the reported volumes are also identical, we randomly select one of the centrally located wells. This selection process is repeated annually to account for new wells installed each year. As a result, we match each of the 895 permits with one corresponding well. This dataset is then used to define the installed base for each observation.

To study irrigation adoption behavior, we focus on a subset of the data by excluding farmers who had already adopted irrigation before 2004. There are two primary reasons for this approach. First, early data from the permit system, particularly during the first two years, is unreliable for studying adoption behaviors. High adoption rates during these years were largely driven by the introduction of the permit system, rather than voluntary adoption, and likely reflect farmers who had already adopted irrigation before 1983. Second, drought data is only available from 2003 onward. Since we use one year lag drought data, we restrict our analysis to permits with registration dates after 2004. By excluding the 444 permits adopted prior to

2004, our final sample consists of 451 permits. We analyze the adoption behaviors of these 451 permits from 2004 to 2021.

In addition, we assume that the permit site corresponds to the well location used in the first year of irrigation adoption by each permit holder, and this site remains fixed in subsequent years. While this assumption simplifies the analysis, it may be problematic if farmers in South Carolina frequently change well locations. However, our analysis indicates that farmers in South Carolina typically continue using the same well from the first year of irrigation adoption throughout their operation. As summarized in table A1, nearly 90% of permits are associated with the same well initially used for irrigation. Therefore, using the well from the initial irrigation year as a representative well for each permit is a reasonable and appropriate choice.

Table A1: Well Types based on Location

Type	Permit Count	Percentage (%)
Continuous Well Use	350	77.61
Temporary Well Closure	41	9.09
Permanent Well Switch	16	3.55
Permanent Well Closure	44	9.75
Total	451	-

Notes: This table outlines four types of irrigation well operations in South Carolina. "Continuous well use": refers to permits that consistently use the same well from the first year of irrigation. "Temporary well closure": occurs when permits intermittently use the initial well during the operation years. "Permanent well switch": indicates permits that completely stop using the initial well and switch to a different one. "Permanent well closure": refers to permits that permanently stop using irrigation, either by switching to rain-fed agriculture or ceasing farming altogether.

A2 Supplementary Information on Aquifer

The most important aquifers are primarily located east of the Fall Line. As depicted in the map in figure A1, this area is known as the Coastal Plain and overlays the Atlantic Coastal Plain (ACP) aquifer system (Campbell et al., 2012). The ACP aquifer system consists of multiple layers of confined aquifers with unconfined aquifers on top. The unconfined aquifers, which are composed of permeable sand or carbonate rocks, are separated by confining units of silt, clay, or low-permeability carbonate rock (Campbell et al., 2012). Typically, the aquifers near the Fall Line are shallower and unconfined, due to their greater connectivity with surface water. In contrast, in the southeastern part of South Carolina, aquifers present multiple layers of confined units, separated by low-permeability confining units, as illustrated in figure A2.

Each aquifer has distinct hydrogeological characteristics, with significant differences in recharge rates within the ACP system. The surficial aquifer, the top unconfined layer, receives recharge directly from in-stream areas, leading to vertical recharge throughout the state. In contrast, deeper confined aquifers experience recharge primarily where they converge near the Fall Line, with recharge water flowing laterally along the confined units.

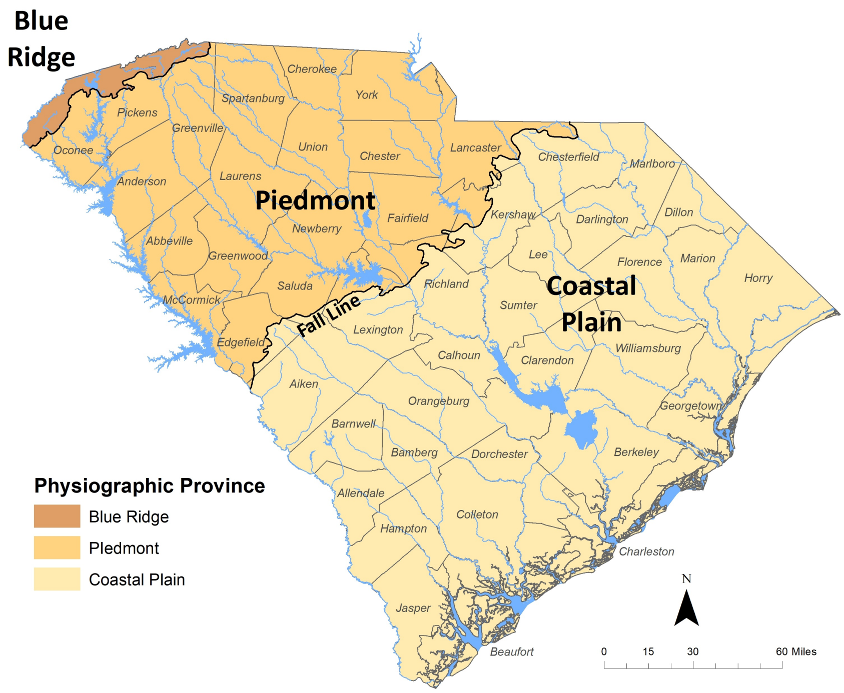

Figure A1: **South Carolina's Available Groundwater Resources for Irrigation.** *Notes:* This figure illustrates the hydrogeological divisions of South Carolina, with aquifers predominantly situated to the east of the Fall Line in the Coastal Plain region. (Source: SCDNR (2025))

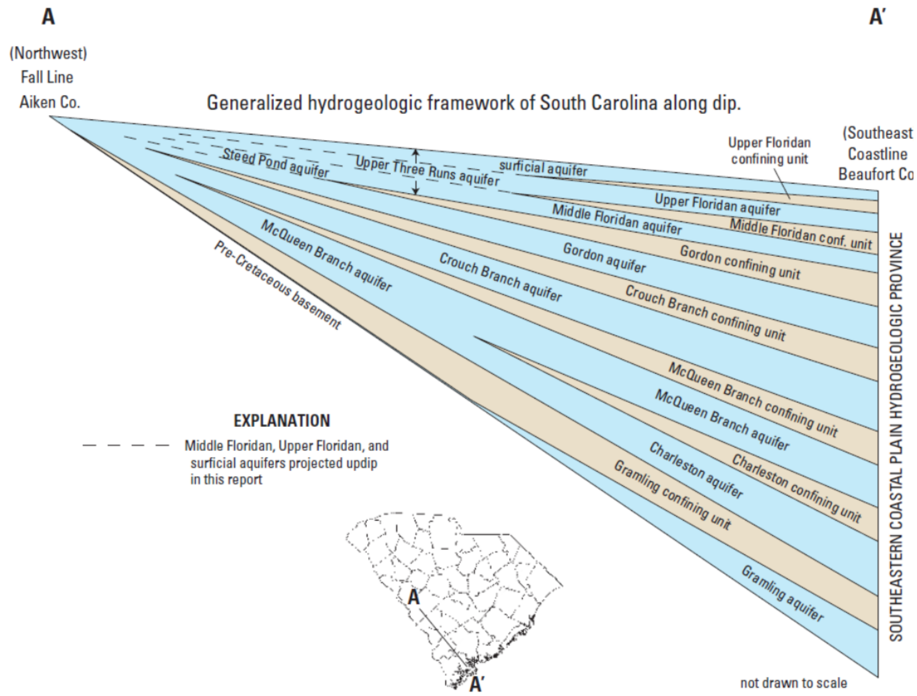

Figure A2: **South Carolina's Cross-sectional Aquifer Framework** *Notes:* This figure presents a cross-sectional aquifer framework in the Coastal Plain region, along a strike from the northwest to the southeast. (Source: Campbell et al. (2012))

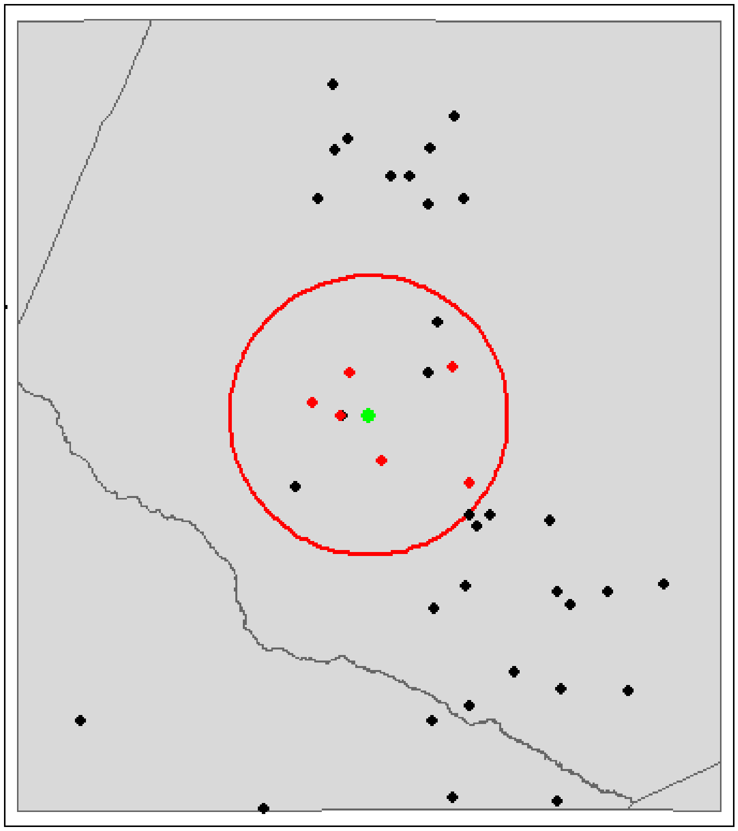

Figure A3: **An illustration of Buffer for Measuring Peer Irrigators (Installed Base).** *Notes:* This figure illustrates the process used to determine the number of peer irrigators for a given farmer i (represented by the green dot) in year t. First, an 8-km buffer is drawn around farmer i. Next, the number of farmers within the buffer who adopted irrigation by year $t-1$ is counted (represented by the red dots). In this example, farmer i has six peer irrigators (i.e., the installed base). This method is applied consistently to calculate the number of peer irrigators for each farmer in the dataset.

A3 Alternative Specification with Weather Data

We examine model specification by incorporating additional weather variables—specifically growing degree days and precipitation—alongside drought measures. As noted by Kuwayama et al. (2019), droughts are typically associated with both lower precipitation and higher temperatures. Therefore, it is an empirical question whether including these weather variables provides further explanatory power. To evaluate this in the context of irrigation adoption decisions, we present table A2, which contains two columns. Columns (1) and (2) replicate those in table 2.

The results indicate that the additional weather variables align with prior expectations about weather responses. Specifically, greater growing degree days have a positive impact on irrigation adoption (odds ratio greater than one), although the effect is not statistically significant, while higher precipitation shows a statistically significant negative effect on the odds of adoption. In both models, the estimated marginal peer effects—by number of irrigators and by peer water use—remain statistically significant, consistent with our main results.

Table A2: Estimation Results from Logistic Regression Models with Weather Controls

	(1)	(2)
Peer (# of irrigators)	1.1347**	
	(0.0683)	
Peer squared (# of irrigators)	0.9941	
	(0.0040)	
Peer (Water quantity, Mil.Gal)		1.0006**
		(0.0003)

	(1)	(2)
Peer squared (Water quantity, Mil.Gal)		0.9999
		(0.0000)
Drought D0 (# of weeks)	0.9713	0.9734
	(0.0204)	(0.0201)
Drought D1 (# of weeks)	0.9829	0.9850
	(0.0349)	(0.0347)
Drought D2 (# of weeks)	0.8902***	0.8904***
	(0.0324)	(0.0325)
Drought D3+D4 (# of weeks)	1.0460	1.0497
	(0.0457)	(0.0454)
Soil productivity (NCCPI)	0.9574	1.1673
	(0.5587)	(0.6489)
Soil drought index	1.0536	1.1094
	(0.6285)	(0.6281)
Soil slope	1.0756*	1.0742**
	(0.0414)	(0.0381)
Soil clay content	1.0302**	1.0292**
	(0.0126)	(0.0129)
Drainage category	1.0113	1.0040
	(0.0947)	(0.0929)
CCE (State)	1.1376***	1.1377***
	(0.0418)	(0.0421)
Temperature GDD	1.0009	1.0006
	(0.0016)	(0.0017)
Precipitation Growing Season	0.9985*	0.9985*
	(0.0008)	(0.0008)
Average Marginal Effects		
Peer Effects	0.0038030**	0.0000261**
(p-value)	(0.014)	(0.029)
Year fixed effect	Yes	Yes
County fixed effect	Yes	Yes
N	5526	5526
pseudo R^2	0.261	0.260
Log-pseudolikelihood	-1107.7591	-1109.2454

	(1)	(2)

Notes: Odds ratios reported; standard errors in parentheses. Standard errors clustered by county. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Year and county fixed effects are included in all models. Drought and weather variables are lagged by one year.

A4 Alternative Specification with Crop Data

We re-estimated our preferred model specifications including the Crop Data Layer (CDL) from USDA NASS. The CDL offers annual crop type data at a 30-by-30-meter pixel resolution, identifying specific crops, such as corn and cotton, at each site's location. As this dataset is available starting in 2008, the estimates are based on data from 2008–2021. The results are consistent with those reported in table 2 of the main text, showing that peer effects—both from an additional peer irrigator and from increased water use by peer irrigators—remain statistically significant at the 5% level. Furthermore, the estimated odds for corn highlight its important role in irrigation adoption—growing corn increases the likelihood of adopting irrigation by 65%.

Table A3: Estimation Results from Logistic Regression Models

	(1)	(2)
Peer (# of irrigators)	1.1297**	
	(0.0687)	
Peer squared (# of irrigators)	0.9939	
	(0.0039)	
Peer (Water quantity, Mil.Gal)		1.0004*
		(0.0002)
Peer squared (Water quantity, Mil.Gal)		0.9999
		(0.0000)
Drought D0 (# of weeks)	0.9816	0.9840
	(0.0228)	(0.0223)
Drought D1 (# of weeks)	0.9842	0.9874
	(0.0371)	(0.0369)
Drought D2 (# of weeks)	0.9025***	0.9035***
	(0.0340)	(0.0337)

	(1)	(2)
Drought D3+D4 (# of weeks)	1.0338	1.0403
	(0.0412)	(0.0404)
Soil productivity (NCCPI)	0.9849	1.1667
	(0.6483)	(0.7726)
Soil drought index	1.2135	1.2454
	(0.8010)	(0.8001)
Soil slope	1.0828*	1.0812*
	(0.0516)	(0.0477)
Soil clay content	1.0248*	1.0237
	(0.0143)	(0.0148)
Drainage category	0.9997	0.9945
	(0.1015)	(0.1012)
CCE (State)	1.1534***	1.1536***
	(0.0233)	(0.0219)
Corn binary	1.6541***	1.6471***
	(0.3197)	(0.3185)
Cotton binary	1.0519	1.0408
	(0.1861)	(0.1871)
Marginal Effects		
Peer Effects	0.0043654**	0.0000258**
(p-value)	(0.024)	(0.046)
Year fixed effect	Yes	Yes
County fixed effect	Yes	Yes
N	3780	3780
Pseudo R^2	0.242	0.240
Log-pseudolikelihood	-951.751	-953.206

Notes: Odds ratios reported; standard errors in parentheses. Standard errors clustered by county. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Year and county fixed effects are included in all models. Drought variables are lagged by one year.

A5 Supplementary Information on Robustness Checks

To assess the robustness of our primary findings from the non-linear logistic regression model, we conduct a linear regression analysis. The specifications in table A4 mirror those in table 2 of the main text. The linear regression results are broadly consistent with our main findings regarding peer effects. Specifically, the average marginal effects of the number of peer irrigators and peer water use are statistically significant in columns (1) and (2), respectively. This pattern suggests that peer effects are driven both by the number of neighboring irrigators (i.e., peer interactions) and by peers' water use (i.e., social learning).

Table A4: Estimation Results from OLS Regression Models

	(1)	(2)
Peer (# of irrigators)	0.0072	
	(0.0045)	
Peer squared (# of irrigators)	-0.0003	
	(0.0004)	
Peer (Water quantity, Mil.Gal)		0.0000424*
		(0.0000227)
Peer squared (Water quantity, Mil.Gal)		-0.0000
		(0.0000)
Drought D0 (# of weeks)	-0.0020	-0.0020
	(0.0015)	(0.0015)
Drought D1 (# of weeks)	-0.0015	-0.0015
	(0.0023)	(0.0023)
Drought D2 (# of weeks)	-0.0076***	-0.0077***
	(0.0023)	(0.0023)
Drought D3+D4 (# of weeks)	0.0045	0.0045
	(0.0044)	(0.0044)
Soil productivity (NCCPI)	-0.0024	0.0065

	(1)	(2)
	(0.0278)	(0.0275)
Soil drought index	0.0073	0.0114
	(0.0330)	(0.0313)
Soil slope	0.0042*	0.0043**
	(0.0022)	(0.0020)
Soil clay content	0.0016**	0.0016**
	(0.0007)	(0.0007)
Drainage category	-0.0004	-0.0008
	(0.0049)	(0.0048)
CCE (State)	-33.3433***	-33.3644***
	(0.5678)	(0.5647)
Constant	34.3163***	34.3435***
	(0.5713)	(0.5691)
Average Marginal Effects		
Peer Effects	0.0048043**	0.0000376*
(p-value)	(0.019)	(0.059)
Year fixed effect	Yes	Yes
County fixed effect	Yes	Yes
N	5550	5550
R^2	0.240	0.232

Notes: Coefficients are shown with standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Year and county fixed effects are included in all models. Drought variables are lagged by one year.

References

Campbell, B., M. Petkewich, A. Coes, and J. Fine (2012). Ground-water availability in the atlantic coastal plain of north and south carolina.

Kuwayama, Y., A. Thompson, R. Bernknopf, B. Zaitchik, and P. Vail (2019). Estimating the impact of drought on agriculture using the us drought monitor. *American Journal of Agricultural Economics 101*(1), 193–210.

SCDNR (2025). Statewide and coastal plain publications. Accessed: Jan 17 2025.