Supplement Yoon et al. 2025:

Groundwater Cost Curve Geospatial Datasets and Processing:

The cost curve function requires four hydrogeologic attributes (water table depth, aquifer thickness, specific yield, and hydraulic conductivity) and recharge. These parameters are defined for every grid cell in the CONUS using publicly available datasets. Table S1 summarizes the geospatial datasets, including their spatial coverage, resolution, authors, and link to the associated study or dataset. Geospatial attributes for each NLDAS grid cell were organized into a single lookup table indexed by NLDAS ID. The lookup table and the original and processed geospatial datasets are provided in the accompanying data repository (Yoon et al., 2025).

Table S1: Geospatial datasets used for the NLDAS cost curve attribute lookup table.

Parameter	**Spatial coverage**	**Resolution**	**Dataset**	**Link:**
Long term average recharge	CONUS	1 km	Wolock et al., 2003	https://doi.org/10.3133/ofr03311
Long term average recharge	Global	0.5 degree	Döll and Fiedler, 2008	https://doi.org/10.5194/hess-12-863-2008
Permeability	Global	Vector	Gleeson, 2018	https://borealisdata.ca/dataset.xhtml?persistentId=doi:10.5683/SP2/DLGXYO
Porosity	Global	Vector	Gleeson, 2018	https://borealisdata.ca/dataset.xhtml?persistentId=doi:10.5683/SP2/DLGXYO
Aquifer thickness	Global	250 m	De Graaf et al., 2020	https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019WR026004
Water table depth	Global	0.25 degree	Fan et al., 2013	https://www.science.org/doi/10.1126/science.1229881
Depth to bedrock	Global	0.125 degree	Shangguan et al., 2017	https://agupubs.onlinelibrary.wiley.com/doi/full/10.1002/2016MS000686

Water table depth is sourced from Fan et al. (2013), which has been used to parameterize groundwater depth in many large-scale studies (e.g., Gleeson et a 2016; Benz et al., 2024; Niazi et al., 2024). Aquifer thickness was parameterized using a hybrid of De Graaf et al. (2020) and Shangguan et al. (2017), with preference given to De Graaf where available due to it being designed specifically for groundwater modeling. Specific yield is assigned from the GLHYMPS dataset (Gleeson, 2018). We assume that specific yield is equal to porosity, as done in Niazi et al. (2025). Exploratory modeling using hydraulic conductivities derived from GLHYMPS permeability revealed that permeability values are too low over large portions of the CONUS to allow for pumping using our minimum considered pumping rate of 50 gallons per minute, even in regions where large groundwater production for irrigation is known to occur – for example, only half of the 5,000 largest irrigated grid cells had viable groundwater production using GLHYMPS permeabilities (Figure S7). Due to this limitation, we chose to assign a range of plausible hydraulic conductivity values ranging from 0.5 to 50 m/d for each grid cell; the GLHYMPS value was also evaluated, while those results are not used in this study, they are available at Yoon et al. 2025. The results in this paper present an intermediate hydraulic conductivity value of 2.5 m/d. Recharge, sourced from Wolock (2003), is the estimated long-term annual average recharge for the CONUS at 1 km^2 resolution.

The lookup table includes additional fields not used for the cost curve scenarios in the paper. We thought the additional hydrogeological and recharge data could be of interest to other researchers, so they were retained in the lookup table. The additional fields include two other hydraulic conductivity values ("K high" and "K de Graaf)" and an alternative recharge dataset. The K high values reflect the baseline permeability increased by 1 standard deviation using the reported lithological-specific standard deviations of hydraulic conductivity in the GLHYMPS dataset. The de Graaf values are from the de Graff et al. (2020) study that modified the permeabilities for certain lithologies. In all cases, the default K, high K, and de Graaf K were calculated from the permeability values, reported as log(k) using Eq. S1, which converts permeability in units of m^2 to hydraulic conductivity in units of m/s. Note – the Readme for GLHYMPS states k values are reported as log(k) * 100 but the data downloaded from Gleeson (2018) did not have this factor of 100 applied to the log(k) values.

Eq. S1) K = 10^(k) * 1e+7 * 86400

In addition to the Wolock (2003) recharge data used in the study, we also processed the global recharge dataset from Döll and Fiedler (2008) as an alternative recharge value. We opted to use the Wolock data because it has much higher spatial resolution and is from a CONUS-specific study rather than the lower resolution, global data provided in Döll and Fiedler (2008).

QGIS was used for most of the geospatial data processing workflow (QGIS, 2025). Python was used in a few instances, as noted below. The workflow involved the following steps:

- Datasets imported into QGIS and transformed into a common coordinate reference system (WGS84).
- Global datasets clipped to the CONUS boundary.
- Convert GLHYMPS log(k) values to K (m/d) using Eq. S1. Calculate K high by adding the log(sigma) to the log(k) value before applying Eq. S1. The alternative values from de Graaf et al. (2020) only applied to certain lithologies. The K de Graaf field was created by duplicating the mean K values and only replacing the K values for the lithological modifications documented in de Graaf et al. (2020). The K de Graaf values were assigned in Python.
- Rasterize the GLHYMPS data. Four separate rasters were created from the vector dataset: mean K (default), high K (+ 1 sigma), K de Graaf, and porosity. Rasters were created with a resolution of 0.025 degree over the extent of the NLDAS grid so the rasterized GLHYMPS data was aligned with the farm grid (but at higher resolution).
- The Döll and Fiedler (2008) recharge data was obtained from the data supplement from Gleeson et al. (2016). This data was mapped to the Hydrosheds vector data for use in their study. The resolution was still at the original 0.5 degree resolution but assigned to smaller watersheds with each 0.5 degree grid cell. We rasterized the Gleeson et al. (2016) Hydroshed-based mapped Döll and Fiedler (2008) data to 1/8th degree resolution.
- The Wolock (2003) data was already rasterized and within the bounds of CONUS and did not require any additional processing.

- The aquifer thickness raster was built in Python by sweeping across all 250m x 250m grid cells in the de Graaf et al. (2020) dataset and filling the value with the Shangguan et al. (2017) if there was no data (-999 value) for de Graaf. The output is a 250 m resolution raster for the CONUS.
- Zonal statistics to calculate the mean value of each parameter within each of the NLDAS grid cells. This generates a new output file with the data structure of the NLDAS grid shapefile but with an added field that is the mean calculated parameter value. This resulted in new output shapefiles whose mean parameter values were aggregated into single attribute table NLDAS_Cost_Curve_Attributes.csv.

Figures S1 through S5 are maps of the final processed groundwater cost curve geospatial datasets used in this study where the parameters values have been processed at the 1/8 degree resolution of the NLDAS grid.

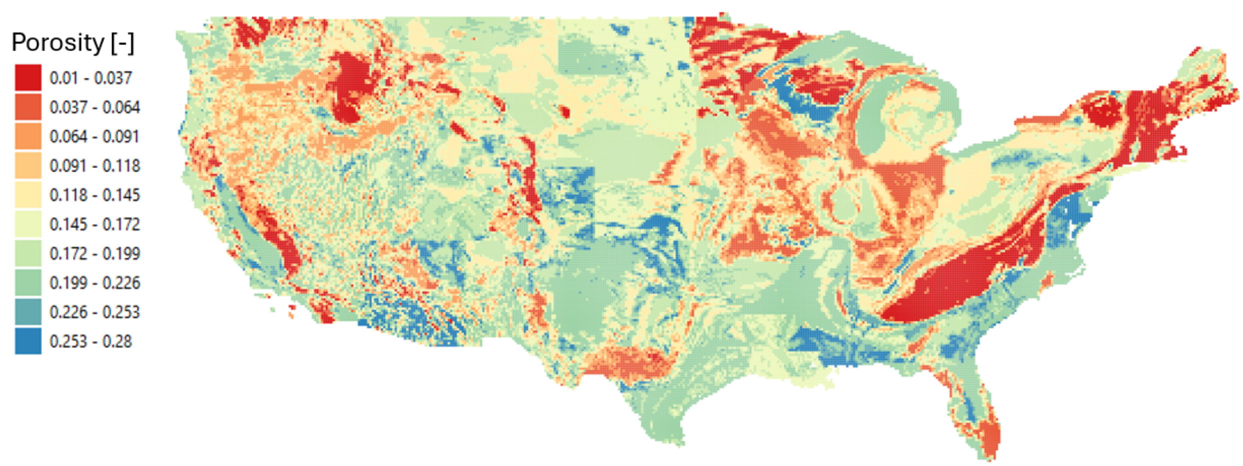

Figure S1: Porosity from Gleeson (2018).

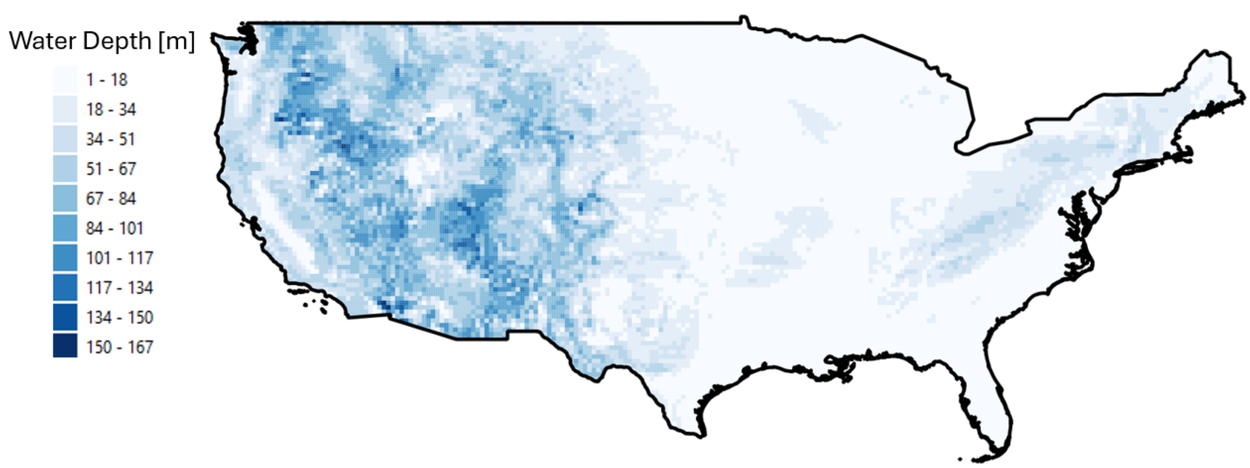

Figure S2: Water depth, meters below ground surface, from Fan et al. (2013).

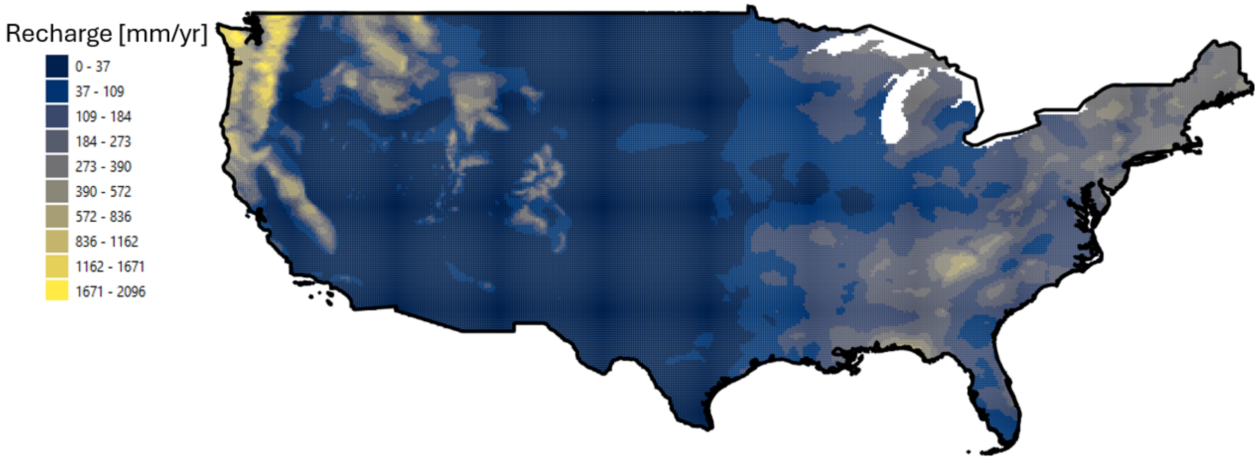

Figure S3: Annual average recharge from Wolock (2003).

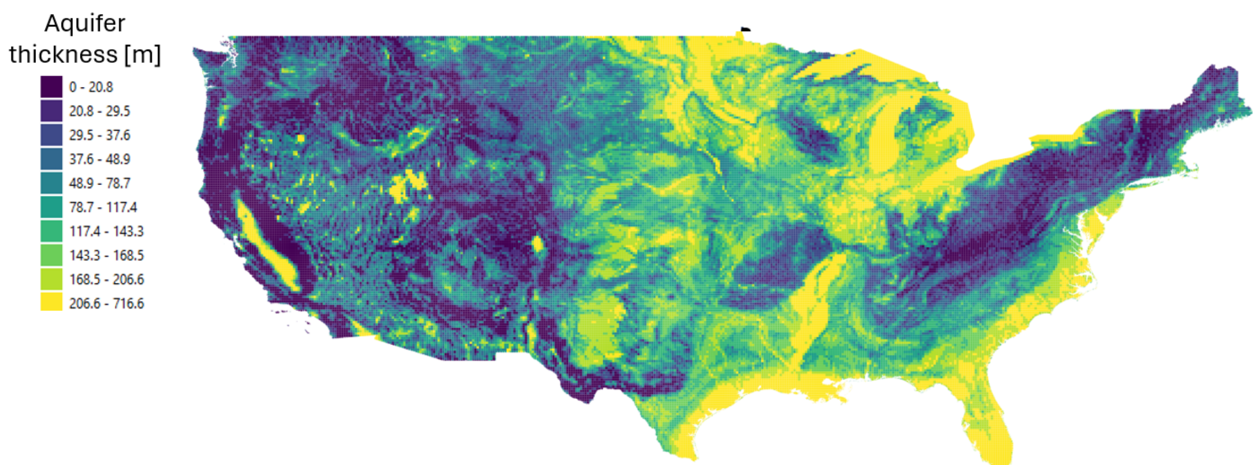

Figure S4: Aquifer thickness generated using a hybrid of de Graaf et al. (2020) and Shangguan et al., 2017.

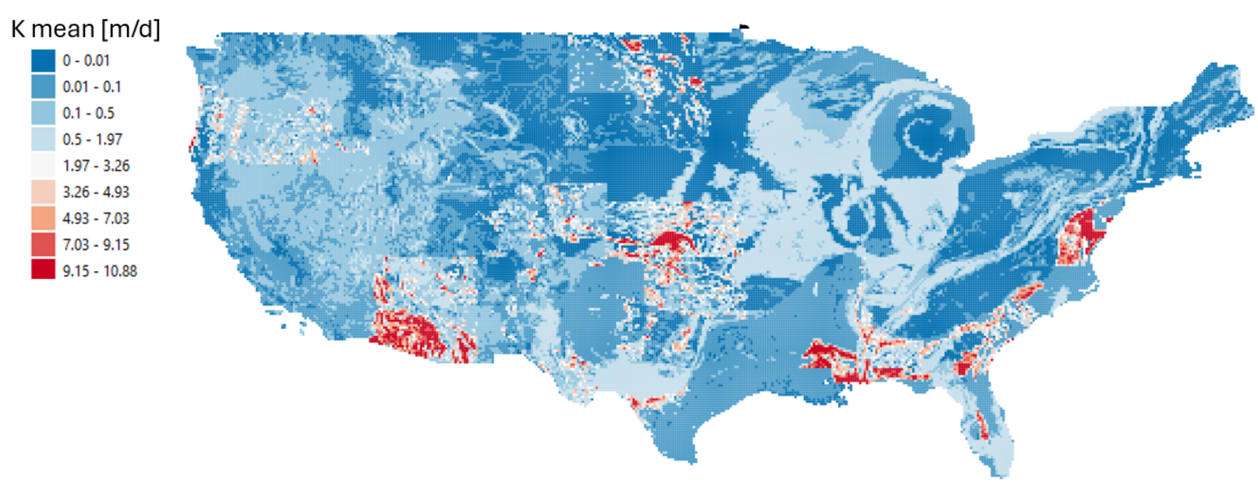

Figure S5: Mean K in meters per day using data from Gleeson (2018).

Cost Curve Implementation:

As cited in the main text, the groundwater cost curve function we use is based on the Superwell code documented in Niazi et al. (2025). The cost curve function is a Python module that is imported into the Farm ABM model, also written in Python. The function has several required positional inputs and a few optional keyword arguments. Required inputs are hydraulic conductivity, specific yield, depth to water, aquifer thickness, irrigation depth, and energy cost. As in Niazi et al. (2025), the cost curve is generated by simulating annual time steps that have 100-day pumping periods followed by 265-day recovery periods. The rationale for this approach is documented in the main text, supplement, and author responses for Niazi et al. (2025). For this study we simulated 100 years of pumping. After each annual period, the storage in the grid cell is updated based on the net depletion that occurs between the volume pumped and the volume of recharge. For grid cells that have a thin saturated thickness, low specific yield, and low recharge, groundwater may be exhausted before 100 years. In these cases, the cost curve script terminates simulated pumping and calculates the cost curve outputs that are passed onto the Farm ABM optimization model. Groundwater becomes exhausted when it is no longer viable to pump, not when saturated thickness is reduced to 0.

Figure S6 shows an example of how aquifer thickness and specific yield influence cost curve attributes, in particular cost evolution and total groundwater availability. Table S2 listed the cost curve settings for the six examples shown in Figure S6. This example uses the same energy unit cost (0.125 $/kWh) as used in this experiment and a simulation length of 100 years.

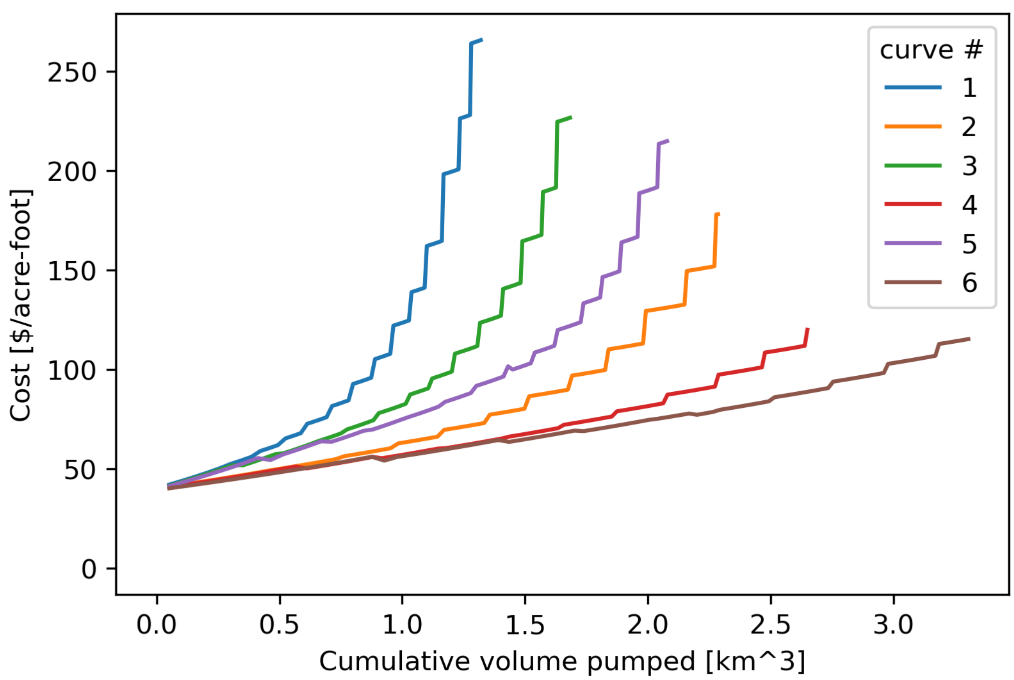

Figure S6: Six cost curves for a hypothetical grid cell. Water level, K, recharge, and irrigation depth are held constant while specific yield and aquifer thickness are varied.

Table S2: Cost curve inputs for figure S6.

Curve	Recharge (m/yr)	Water depth (m)	K (m/d)	Irr Depth (m/yr)	Aquifer thickness (m)	Specific Yield [-]
1	0	10	2.5	0.3	80	0.15
2	0	10	2.5	0.3	80	0.30
3	0	10	2.5	0.3	100	0.15
4	0	10	2.5	0.3	100	0.30
5	0	10	2.5	0.3	120	0.15
6	0	10	2.5	0.3	120	0.30

If an aquifer is too thin and/or has low K, the transmissivity may be too low to support pumping as the cone of depression would entirely dewater the well at our lowest allowed pumping rate of 50 gallons/minute, a rate that below which adequate irrigation application rates would be limited to very small irrigated areas (Figure 3 - Foster et al., 2014). No cost curve is produced in these cases. Figure S7 shows how prevalent the issue of non-viable cost curves was for the largest 5,000 irrigated farm cells using the mean K values from GLHYMPS, which is why this study used an intermediate K of 2.5 m/day.

a)

K scenario	-1σ	-0.5σ	mean	+0.5σ	+1σ
Successful Count	474	1178	2589	3567	4369

b)

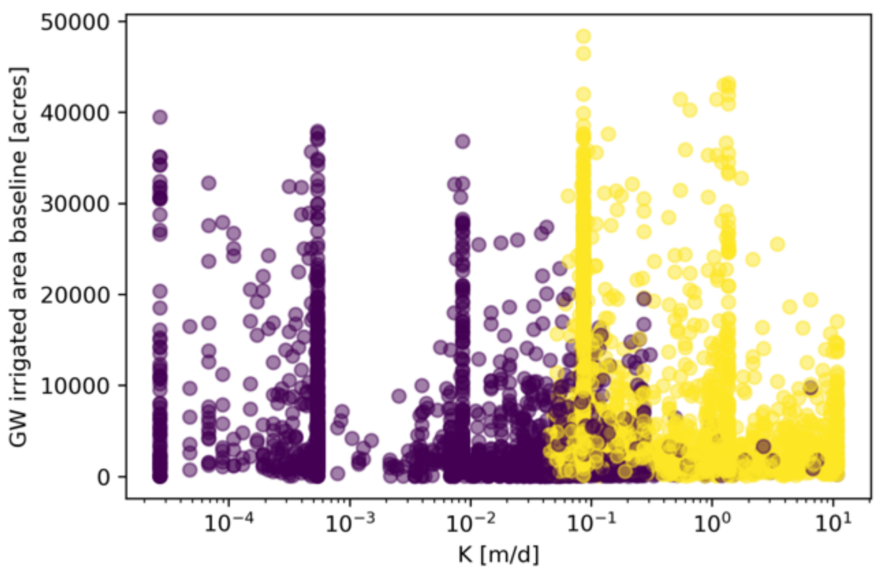

Figure S7: Summary table of cost curves produced for each GLHYMPS K scenario for the 5,000 largest farm cells in the CONUS a) and scatter plot of irrigated area versus mean K for the largest 5,000 farms with yellow indicating a cost curve and purple no cost curve.

Figure S8 shows six cost curves with the same aquifer properties but with different K values ranging from 2.5 m/d (curve 1) up to 40 m/d (curve 6). This example demonstrates that using a K value of 2.5 m/d does not severely alter the groundwater cost evolution (Figure S8 – which has been normalized to show increase in unit cost against depletion %), in particular for depletion percentages below 50%, and most grid cells do not experience depletion >50% over the 100 year period as shown in the main text.

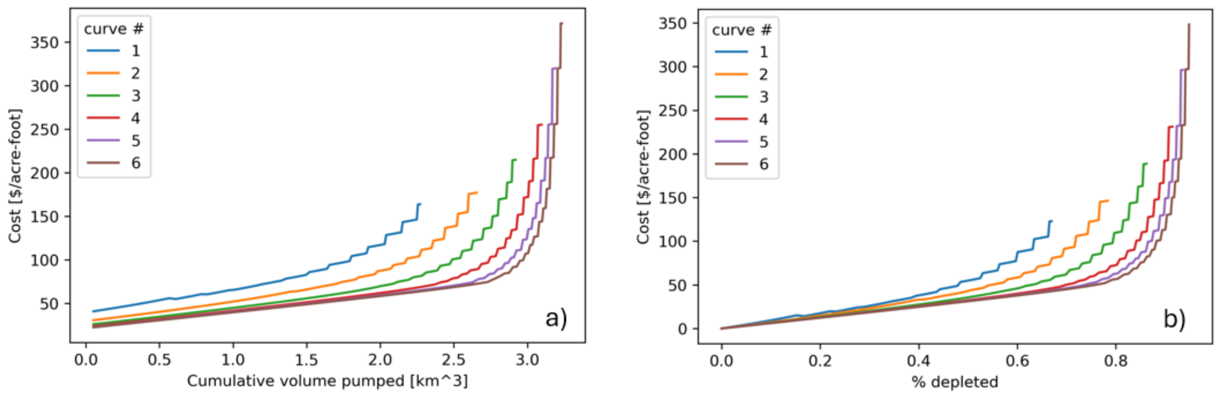

Figure S8: Cost curves showing the effect of different K values on unit cost for a hypothetical grid cell with a initial water depth of 10 m, aquifer thickness of 110 m (saturated thickness 100 m), specific yield of 0.2, recharge of 0 m/year, irrigation depth of 0.3 m/year, and energy cost of 0.125 $/kWh. Raw unit costs shown in a) and normalized unit costs (by subtracting initial unit cost from cost curves) showing unit cost increase b), which is how added groundwater cost is implemented in the farm AMB – cost curve workflow.

Integrated Farm ABM – Groundwater Cost Curve Scenario Workflow:

Pseudo code for the simulation workflow executed for each cell.

1. Select NLDAS grid cell
2. Assign grid cell specific ABM inputs: prices, costs, constraints, and PMP calibration parameters.
3. Define scenario specific econ and hydro factors.
    a. Percent increment hydro = (hydro ratio – 1) / (hydro ratio + 1)
        i. Numerator hydro = 1 + percent increment hydro
        ii. Denominator hydro = 1 - percent increment hydro
    b. Percent increment econ = (econ ratio – 1) / (econ ratio + 1)
        i. Numerator econ = 1 + percent increment econ
        ii. Denominator econ = 1 - percent increment econ
4. Generate cost curve using Superwell_for_ABM_on_the_fly.py
    a. Import grid cell specific hydrogeological parameters
    b. Hydro factor modifies groundwater recharge
    c. Calculate annual irrigation depth for groundwater irrigated crops
        i. Irrigation depth = 1.25 * annual_gw_volume/farm_gw_area

    d. Recharge adjustment if recharge > annual irrigation depth. If true, set recharge to annual irrigation depth so groundwater levels don’t rise in cost curve simulation.
    e. Check if water table depth is below aquifer thickness. If so, adjust aquifer thickness to be 50.999 meters deeper so saturated thickness = 50.999.
    f. Generate cost curve that provides unit cost as a function of cumulative groundwater produced.
        i. If saturated thickness is low, there may be no viable cost curve generated. In these rare cases, the flag “cost_curve” is set to False, and the max_gw_capacity is set to 0.
5. Apply scenario multipliers to ABM inputs
    a. Adjust annual irrigation requirement by hydro factor denominator
    b. Adjust annual surface water availability by hydro factor numerator
    c. Adjust net land prices by econ factor numerator
    d. Adjust groundwater costs by econ factor denominator
    e. If crop-specific gamma value is 0, set net land price for that crop to -9999999999 so PMP won't produce crops because zero gamma value indicates no observed land use for a crop.
6. Initialize flags and variable trackers before executing ABM simulation
    a. Cumulative groundwater pumped = 0
    b. Groundwater cost added = 0
    c. Groundwater availability multiplier = 1
    d. Impose $100/acre profit constraint IF baseline data profit/per acre > 100 $/acre.
    e. Allow groundwater availability expansion (acre-feet/year) as long as surface water is not more expensive than groundwater and surface water area isn’t >10% of crop area in baseline.
7. ABM simulation loop. Execute annual time steps for 100 years.
    a. Instantiate Pyomo model. A new Concrete model is instantiated for each annual time step.
    b. Initialize parameter values
    c. For the first year, groundwater unit cost ($/acre-foot) = adjusted groundwater cost ($/acre)/adjusted annual irrigation requirement (acre-feet/acre). For subsequent years, groundwater unit cost increases based on cost curve progression.
    d. If groundwater expansion = True, groundwater constraint (acre-feet/year) is increased by either 500 acre-feet or 10% of baseline capacity. Groundwater capacity is allowed to increase each annual time step representing expansion of groundwater irrigation infrastructure. The groundwater constraint is not allowed to exceed the baseline irrigation depth * max land constraint, which would represent all of the available land in a grid cell being irrigated by groundwater. This is limited by switching the groundwater expansion flag to False. The groundwater constraint can be reduced by the groundwater availability multiplier that is an output of the cost curve module.
    e. Total crop area, surface water crop area, and groundwater crop area Variables are initialized at 0. The value of these variables are determined during the optimization based on the profit maximization objective function, subject to

constraints on available land, surface water availability, groundwater availability, and the profit per area constraint (if profit constraint = True, Step 6d).

f. Set constraints and define objective function.
g. Pass Pyomo model to IPOPT non-linear solver.
h. Export Variable outputs: surface water, groundwater, and total acreage for each of the 10 crop types.
i. Calculate groundwater volume used during annual time step. Groundwater area * net irrigation requirement * denominator hydro factor.
j. If first annual time step, create DataFrame to store outputs. Output for subsequent years is appended.
k. Calculate cumulative groundwater volume pumped over this and all preceding time steps. Then use cost curve output array to determine unit groundwater cost. Values are interpolated between cost and cumulative volume bins. The additional groundwater cost is calculated by differencing initial groundwater cost at cumulative pumped volume = 0 and the cost at the cumulative pumped volume. The added cost is used to update the unit cost in Step 7c. As part of this process, the water level at the end of the current time step is calculated from the water level field in the cost curve output array. The water level is interpolated using the water level and pumped volume series data from the cost curve.
l. If cumulative pumped volume exceeds cost curve maximum, groundwater cost added is set to 9999 and groundwater availability is multiplied by 0.00001 to make groundwater unavailable for remaining simulation years.

8. Add “profit” field to output DataFrame and calculate profit for each crop for each year by passing the optimized crop areas (surface water and groundwater tracked separately) to the objective function profit equation.
9. Append the 100-year simulation results to output array.
10. After all scenarios for grid cell are run, export results as a single CSV for that particular grid cell. Each CSV contains summary data for 625, 100-year simulations.

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