Spatial aggregation of weather variables and its implication in climate change analysis: The case of U.S. Corn and Soybean

Ji, Yongjie Ph.D. Center for Agricultural & Rural Development
Miao, Ruiqing Ph.D. Department of Agricultural Economics & Rural Sociology

Background

- Weather variables are key bridge variables in climate change studies to quantify future climate impacts, such as impacts on grain yields, e.g. corn and soybean.
- The available weather products are seldomly tailored to various research needs, as such spatial aggregation schemes must be used to prepare weather data inputs, e.g., aggregating to county specific weather variables.
- Several aggregation schemes are widely used in the literature, e.g. distance weighted, area weighted aggregation schemes. However, the impacts of these schemes on research results have not receive enough attention.

Objectives and methodology

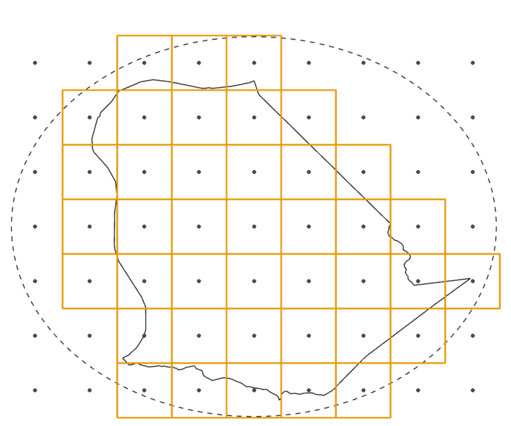
- Study the impacts of three spatial weather variable aggregation schemes on
  - constructed weather variables
  - US corn and soybean yields
  - projected future yields under various climate scenarios.
- Empirical Models
  - [R1]: $y_{it} = \alpha + \overrightarrow{\beta} \sum_{m=3}^{10} \left(pr_{itm} + pr_{itm}^2 + GDD_{itm} + HDD_{itm} + VPD_{itm}\right) + \epsilon_{it}$
  - [R2]: $y_{it} = \alpha + \overrightarrow{\beta} \left(pr_{it} + pr_{it}^2 + GDD_{it} + HDD_{it} + VPD_{it}\right) + \epsilon_{it}$,

dy_{it}: county i's detrended yield in year t
pr_{itm}: daily average precipitation of county i in month m, year t
pr_{itm}^2: daily average precipitation square of county i in month m, year t
GDD_{itm}: daily average growing degree days of county i in month m, year t
HDD_{itm}: daily average extreme heat degree days of county i in month m, year t
VPD_{itm}: daily average vapor pressure deficiency of county i in month m, year t
$\cdot_{it}$: daily average weather variables of county i in year t
State trend dummies are included in the controls.

Estimated empirical models are then used to project yields in more than 20 GCM future climate scenarios.

Spatial Aggregation Schemes

Illustration of three aggregation schemes



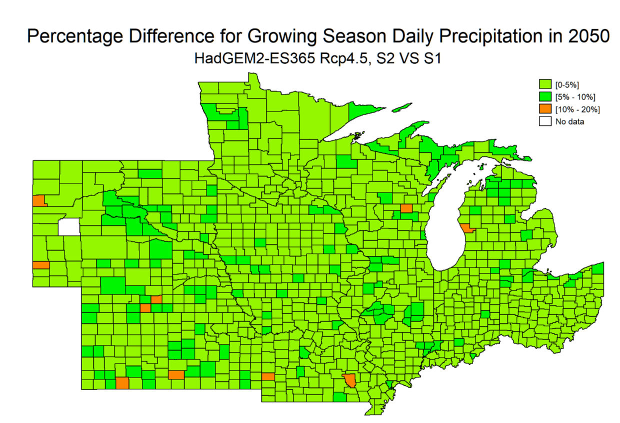
S1: simple average of weather variables within the 100 mile circle from county center on pseudo weather stations (center of raster cells)
S2: simple average of weather variables within in the county boundary on pseudo weather stations (center of raster cells)
S3: area weighted average of weather variables overlapped with the county on raster cells.

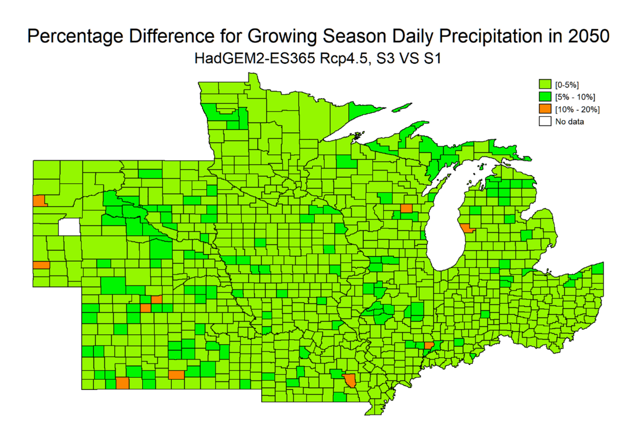
Significant Discrepancy in precipitation

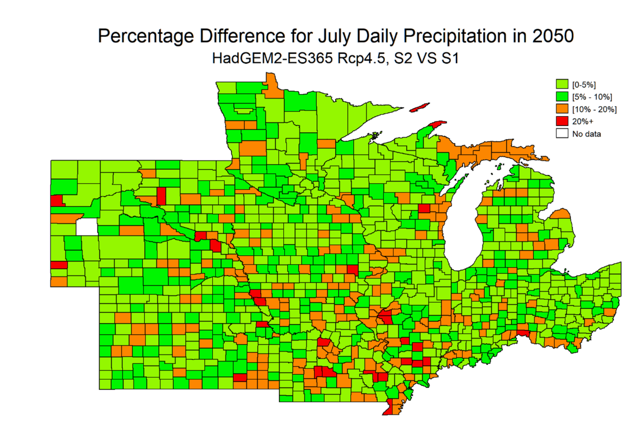
Daily Precipitation (mm)	S1	S2	S3	No. County with % change from S1 larger than			
				S2		S3	
				10%	25%	10%	25%
Annual	2.87	2.87	2.87	10	0	10	0
March	1.90	1.91	1.91	43	15	43	15
April	2.83	2.84	2.84	42	13	42	13
May	3.57	3.57	3.57	44	15	44	15
June	3.68	3.68	3.68	53	22	53	22
July	3.15	3.15	3.15	59	29	59	29
August	2.92	2.93	2.93	59	30	59	30
September	2.66	2.66	2.66	57	28	57	27
October	2.25	2.25	2.25	48	20	48	19

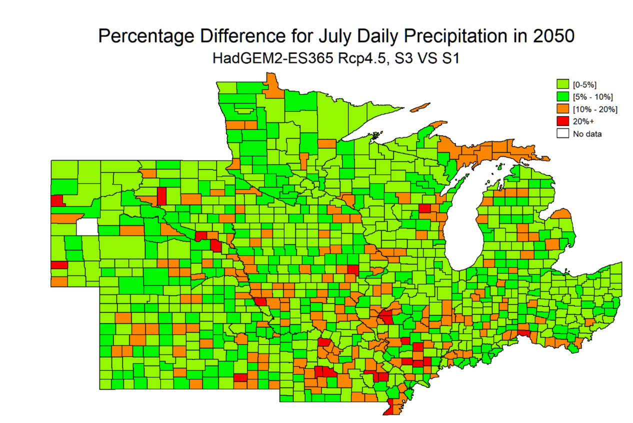
Discrepancy in annual statistics is moderate, while the difference in monthly statistics is substantially larger.

Discrepancy Example in GCM (HadGEM2-ES365 Rcp 4.5)









Observation

- Small changes in annual precipitation, larger differences in monthly statistics
- Similar patterns are found on other variables (not shown).

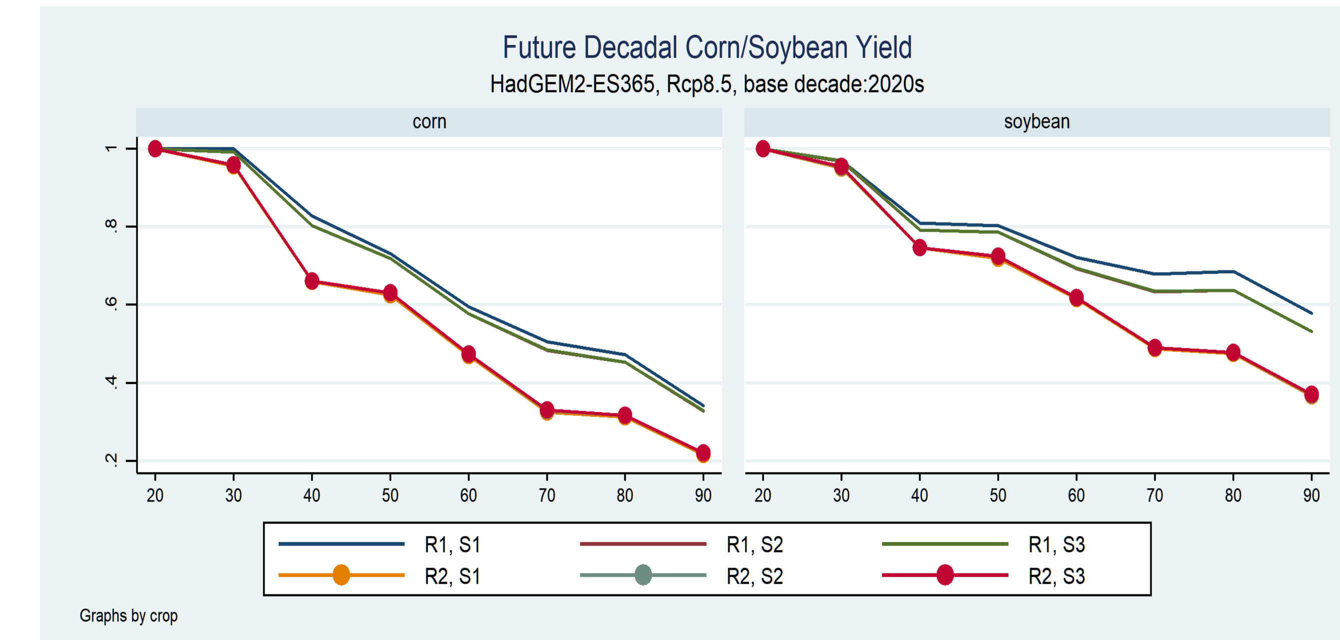
Regression Results

	Variables	S1 Est.	S1 t-value	S2 Est.	S2 t-value	S3 Est.	S3 t-value	S1 Est.	S1 t-value	s2 Est.	s2 t-value	s3 Est.	s3 t-value
precipitation	Annual	0.097	5.27	0.115	7.51	0.115	7.51						
	Mar							0.011	5.817	0.006	3.307	0.006	3.346
	Apr							0.014	7.749	0.010	6.005	0.010	6.035
	May							-0.001	-0.556	0.002	0.916	0.002	0.911
	Jun							0.044	14.116	0.030	12.953	0.030	13.062
	Jul							0.079	28.498	0.063	24.357	0.064	24.485
	Aug							0.006	2.083	0.011	5.341	0.011	5.314
	Sep							-0.008	-3.812	-0.006	-3.450	-0.006	-3.481
	Oct							0.021	10.028	0.020	10.094	0.020	10.094
	Other Variables	Not Reported											
	State Trends	Yes		Yes		Yes		Yes		Yes		Yes	
	Adj. R2	**0.716**		**0.72**		**0.72**		**0.764**		**0.766**		**0.766**	

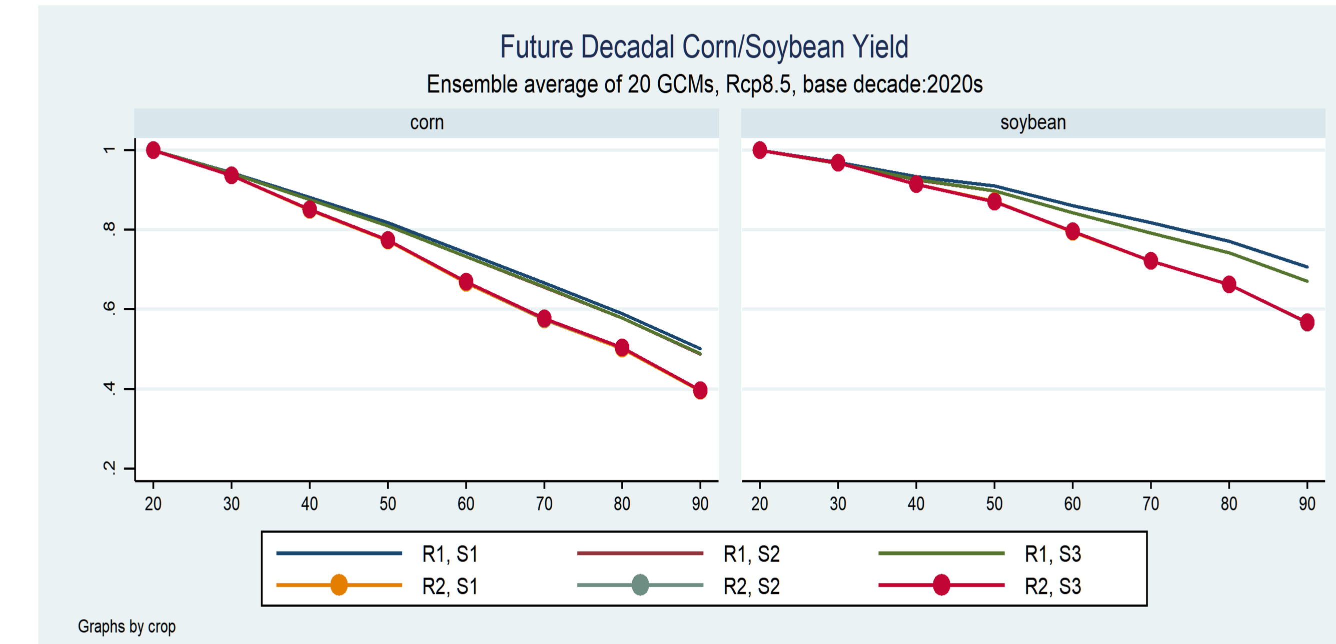
Log(corn yield) is the dependent variable

Observation
- Negligible difference between models with S2 and S3 spatial aggregated data.
- Slightly larger difference from spatial aggregation methods (S1).
- Estimation results for soybean yields show a similar pattern (not shown here).

Similar Future Yield Projection cross Schemes



Ensemble Average among 20 GCMs



Observation:
- Within R1 and R2, similar climate impacts on corn and soybean yields with slightly larger impacts on soybean yields.
- Between R1 and R2, R2 based on annual weather statistics produces roughly 10% more negative climate impacts.
- Between GCM models, the impacts are different since each GCM is describing quite a different climate future (HadGEM2-ES365 vs Ensemble Average)

Conclusions and discussions

- Spatial aggregation schemes do produce substantial discrepancies in several weather variables.
- Under the same temporal setting, these discrepancies do not produce the same level of discrepancies as weather inputs in yield estimation and future yield projection under various climate scenarios.
- However, between temporal settings, yield projections based on annual statistics are substantially lower in all future climate scenarios than those on monthly statistics.
- Findings may be confined to specific empirical settings we used, however, the dramatic difference between monthly (R1) and yearly (R2) models deserves more attention.