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The Role of Climate Factors in Shaping China's Crop Mix: An Empirical Exploration

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The Role of Climate Factors in Shaping China's Crop Mix: An Empirical Exploration

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Abstract

Climate change (CC) can influence farmers' crop choices and result in changes in the regionally varying crop mixes. Using a data set including sown area shares for each crop at province level over the most recent time period of 2000 through 2013 in China, this study employed a seemingly unrelated regression (SUR) system to investigate the effects of climate variables on regional crop mixes. The influence of economic and land use intensity on crop area shares were also examined. Results show that winter temperature appears to be a more determining factor than growing season temperature for a region's crop mix. Also regions with comparatively high farming values tend to see larger percentages of vegetables and orchards. As temperature rises, grains and soybeans that are linked to traditional food security may encounter compromises in production, whereas tubers, small oil crops, vegetables, and orchards would very likely see increases in area shares. Nonetheless, vegetables and orchards may not necessarily step in under future CC due to cost and land use intensity reasons.

Key Words

Climate Change; Crop Mix; Seeming Unrelated Regression; Multi-Cropping Index

Introduction

Future climate change (CC) can affect crop production patterns spatially. In China in particular, CC has the potential to change crop mix choices that farmers make (Wang et al., 2010), and varying by region, this will have effects on farmers' agricultural income and food security on a larger scale. Studies of the US crop mixes have showed that farmers have responded to CC in the past by altering their crop enterprise choices among other adaptation practices (Rose and McCarl, 2008; Reilly et al., 2001; Attavanich et al., 2013). The changes in crop mix can result in economic consequences locally and inter-regionally. For individual farmers at a given site, staying with existing crop choices may cause their income levels to increase or decline as future CC affects agricultural productivity; on a broader scale, the geographical movements of crop mixes may require upgrades in existing infrastructure or making new investments such as building new storage facilities, shifting toward new transportation modes, and etc., among other options (Attavanich et al., 2013). Simply put, CC can have noteworthy implications for at least the agricultural and logistical sectors at various levels of decision-making. Understanding how climate factors have shaped crop mixes helps predict the future patterns of agricultural production and thus inform the associated decision-making. This study aims to examine how China's crop mixes were influenced by climate factors and thereupon to provide insights for agricultural adaptation in China to future CC.

Literature Review

Studies of China's crop mixes under climate influence or future CC are limited. Using county-level or household-level panel data, a few studies found that the implicit "changes in crop mix" (Mendelson et al., 1994) has the potential to ameliorate negative impacts, or bring out the positive side, of CC on farmers' income, since producers may shift to more heat-tolerant and, typically more profitable, crop

enterprise choices such as vegetables and fruits (Liu et al., 2004; Wang et al., 2009). Later Wang et al. (2010) conducted a cross-section analysis of the climate effects on farmers' crop choices using farm household survey data. They also predicted future changes in farmers' choices for major crops induced by CC. Nevertheless, the limitations of that study are that the spatial cropping pattern was not explicitly modeled, and they considered only locations where meteorological data were available for the surveyed households. Recently, Tian et al. (2015) used the Agricultural Ecological Zone (AEZ) methodology to explore the potential expanding cropping opportunities in China under various future CC scenarios. They found the farming potential would be enlarged as warming shall allow more areas to accommodate double- or triple- cropping. Nevertheless, studies above typically did not examine how the crop mixes, in terms of land use, have responded to climate variables in China. This study aims to fill that gap by explicitly investigating the quantitative relationships between climate factors and crop sown area shares, using aggregate province-level data that include the most recent and comprehensive cropland use information.

Research Methodology

To explore the role of climatic factors on crop mix in China we draw on earlier econometric approaches such as Cho et al. (2014) and use a seemingly unrelated regression (SUR) system to estimate the climate effects on crop mix choices aggregated at province level. We use a rich data set that includes sown areas for all major crops/crop categories, cultivated land, year-round monthly temperature and monthly precipitation, as well as gross output value of farming at province level for the period of 2000 through 2013. Data were obtained from the China Statistical Yearbooks. The SUR modeling system consists of equations for the full set of crop sown area shares, which are the dependent variables. Averaged growing season and winter temperatures, annual precipitation, and per ha farming value are employed

as explanatory variables. One of the significant differences between the US crop mixes and the China ones is the common presence of multi-cropping in China. Our study hence takes the multi-cropping index into consideration when examining the crop mixes. To control for potential endogeneity caused by the same year per ha farming value and multi-cropping index, the lagged terms are used as explanatory variables. In addition to the SUR modeling, an exploratory visual analysis of relationships between dependent and independent variables shall be conducted also.

Data

As mentioned above, the primary data for this study are from the China Statistical Yearbooks (2000 to 2014). Items collected include sown area for all reported major crops or crop categories, cultivated land area, year-round monthly temperature and annual precipitation, and gross output value of farming. The processing procedure is as follows.

The arithmetic average of the monthly March to October temperatures was used for the variable growing season temperature. The monthly average of November to February temperatures was calculated for winter temperature. Multi-cropping index was obtained by dividing total sown area with cultivated land area. The gross output value of farming was divided by the total sown area to obtain the farming value per sown ha. The farming value was also normalized by scaling on the producer price index of the farming sector. The ratios of the sown areas of crops over the total sown area were calculated as well for crops' sown area shares. Definitions for all the variables could be found in Table 1.

Table 2 provides the summary statistics for the processed data used in SUR modeling. For dependent variables, the portion of grains (including rice, maize, and wheat) in total sown area is not surprisingly the largest, with the provincial average being 56% and the range comparatively as narrow as 67 percentage points. Soybeans and small oil-bearing crops however show large spreads across provinces,

with the maximums being above 30% and the minimums being 0%. Cotton plantation exhibits regional concentration, with Xinjiang in Western China having 40% of its sown area being the crop. Similarly, sugars concentrate in the South China, tea plantation mostly in the Southeast, and tobacco primarily grown in Yunnan, Southwest China. The portions of vegetables, tubers, and orchards show disparities in regional patterns as well, however much lesser than the aforementioned concentration crops.

On explanatory variables, winter temperature shows a considerably larger spread than growing season temperature. The former has a mean of 3.7 Celsius degrees and a range of 35 Celsius degrees, while the latter has 19.6 and 16.4 Celsius degrees, respectively. Annual precipitation sees a remarkable variation across different provinces. Its minimum is as low as 7.5 centimeters, while the highest reaches up to 268 centimeters. The multi-cropping index ranges from 100 to 225 percent, moderately spreading around a mean of 129 percent. Farming value per sown ha varies considerably across regions, ranging from 4.3 to 33.7 thousand *yuan* (in 2000 RMB).

Table 3 informs the regional scope of this research, providing a 31-element list of provinces or province-equivalent administrative regions in mainland China for this study. Generally speaking, the crop mix structure varies greatly from place to place in mainland China. The spectrums of natural conditions such as growing season and winter temperatures, as well as annual precipitation, turn out to be quite broad also. So are the farming value per unit of sown area and the multi-cropping index. These cross-sectional differences or contrasts shall provide a reasonably strong basis for parsing out the factor contributions to the correlations and/or causal relationships between the variables.

Exploratory Analysis

Figures 1 and 2 present the scatter plots of crop area shares against the growing season temperature, the data of which cover all regions and years of 2001 through 2013 used for SUR modeling carried out

later in this study. As shown in the figures, vegetables and orchards exhibit unambiguously increasing trends as temperature goes higher. Soybeans, on the other hand, shows downward trends. Grains and tubers exhibit nonlinear trends, with the former showing an inverted U while the latter indicating a slight U shape. For other crops, small oil-bearing crops show an overall downward trend with a slight U shape on the higher end. Sugars show positive correlations with warmer growing temperatures on the high end, implying its regional concentration in the South China.

Figures 3 and 4 illustrate the crop area shares against the winter temperature. Compared with growing season temperature, crop shares show clearer trends against winter temperature with less ambiguity. Vegetables, orchards, and tubers show upward slopes, while grains and soybeans exhibit downward slopes. Small oil-bearing crops exemplify a clear inverted U shape.

The relationships between crop area shares and annual precipitation are depicted in Figures 5 and 6. Vegetables and orchards, again, exhibit recognizable upward slopes. So do sugars. Cotton, soybeans, and small oil-bearing crops however show decreasingly visible downward trends as annual precipitation increases.

Lagged farming value per sown ha, which indicates farmers' economic well-being, may have significant impacts on crop mix also, as shown in Figures 7 and 8. Vegetables and orchards show significant positive trends as farming value increases. Tea exhibits a slight yet recognizable increasing trend. Soybeans, small oil-bearing crops, and tubers exemplify downward slopes however. Grains and cotton show nonlinear trends, with the former showing a sine wave and the latter an inverted U shape.

Lagged multi-cropping index, which represents land use intensity, may not impose statistically significant influence on crop mix, as suggested by Figures 9 and 10. Nevertheless, small oil-bearing crops exhibit a visible increasing trend against multi-cropping index.

In general, the visual inspection shows that vegetables and orchards are the two major plantations that exhibit significant and positive relationships with growing season and winter temperatures, annual precipitation, and farming value. Soybeans do the opposite. Other crops typically show nonlinear, ambiguous, or unresponsive relationships with climatic and economic variables. Moreover, land use intensity, as indicated by multi-cropping index, may not have significant effects on crop mix.

The positive, negative, and ambiguous correlations between crop shares and climatic and economic conditions discussed here shall be tested in the next section where SUR modeling would be carried out.

Regression Results and Discussion

Two sets of econometric specifications were used for the SUR system modeling. Model 1 is without the square terms of climatic variables, while Model 2 includes those nonlinear terms. The square terms were introduced because of the nonlinear relationships demonstrated in the section above.

Table 4 presents the two sets of SUR results for each crop equation. Overall, the McElroy-R2 value is significantly higher for Model 2 (0.58) than for Model 1 (0.50), suggesting the necessity or at least desirability of incorporating nonlinear climatic variables. For individual equations, soybeans, small oil-bearing crops, sugars, tobacco, vegetables, and orchards all show R2 or adjusted R2 values greater than 0.50 under Model 2. In addition, nearly all equations exhibit noticeable to remarkable increases in R2 value when considering the nonlinear effects of climatic conditions.

As shown in Table 4, winter temperature turns out to impose negative effects on grain crops' shares, significant in both with and without square terms models. This corresponds to the dominant role that Northeast China plays in grains production. Tubers, on the other hand, see its shares increase, nonlinearly, in places with higher winter temperatures. Precipitation appears to have negative effects on

tubers' shares, implying the drought-tolerant characteristic associated with tubers. The lagged multi-cropping index and per ha farming value show negative effects as well, suggesting that tubers plantation tends to occur in areas with relatively lower farming revenues in China.

On Soybeans, higher growing season temperature and lower winter temperature would raise its area shares, albeit the significant square terms with opposite signs suggest offsetting nonlinear effects. Similar to tubers, lagged multi-cropping index and per ha farming value exhibit negative effects on soybeans' area shares. This corresponds to soybeans' consolidated presence in Northeast China. Small oil-bearing crops, however, show relationships with growing season and winter temperatures that are opposite to those for soybeans. The same applies to its responses to temperatures' square terms. As for land use and economic conditions, lagged multi-cropping index exhibit positive effects, whereas lagged per ha farming value shows negative effects. This suggests that it is more likely to see small oil-bearing crops in regions that can accommodate multi-season cropping, and experience higher growing season temperatures as well as relatively lower farming revenues.

For cotton, higher growing season temperature, lower winter temperature, and lower precipitation are estimated to benefit its area shares. This pattern largely reflects the climate patterns in Xinjiang in the West China. Other small fiber crops exhibit similar responses to climatic conditions, and the square terms of temperatures are significant too. Nonetheless, fiber crops, like small oil-bearing crops, are more likely to be grown in regions with a less affluent farming sector.

The above is about staples, oil-bearing crops, and fiber crops. Below the focus would shift to cash crops. As shown in Table 4, winter temperature has positive and nonlinearly increasing effects on sugar crops' area shares. Multi-cropping index and per ha farming value however impose negative effects. This phenomenon again suggests that sugar plantation tends to occur in regions with relatively lower farming revenues. Likewise, tobacco exhibits positive and nonlinearly increasing responses to higher winter

temperatures, and negative signs to per ha farming value. These are more of a reflection of Yunnan's climatic and economic conditions, as the region is home for the majority of tobacco production in China. Vegetables, compared with the many crops visited above, show significantly positive coefficients for the lagged farming value variable, suggesting its popularity among the preferred choices in regions with a more affluent farming sector. Higher winter temperature, has significantly positive and relatively large effects on vegetables' area shares also. Similarly, for tea, higher winter temperature implies nonlinear increases in its area shares, and lagged farming value raises its shares as well. For orchards, annual precipitation turns out to impose significantly negative effects on its area shares, despite of the slightly positive nonlinear effects. Orchards also appear to be more likely present in regions with higher farming revenues. Nevertheless, higher multi-cropping index values, indicating greater land use intensity, would reduce its likelihood.

In general, the regression results suggest that vegetables, tea, and orchards may have much higher economic values than the rest of the crops examined. Grains and cotton stand in the middle, whereas tubers, soybeans, small oil-bearing crops, small fiber crops, and sugars are comparatively less economic competitive. Nonetheless, they may be still among the best choices when considering the regionally varying climatic conditions. As for specific climate variables, the research carried out in this study suggests that, compared with growing season temperature, winter temperature may be a more determining factor for the degree of prevalence of a crop. In addition, precipitation plays a clearer, and meanwhile negative, role in cotton and orchards area shares than for other crops.

Concluding Remarks

The set of the dependent variables included the sown area percentages for grains, oils, fibers, sugars, vegetables, tea, and orchards. Key findings are as below.

- Staples: Higher winter temperature decreases grains' area shares. This corresponds to the concentration of grains production in Northeast China. Tubers, on the other hand, would increase its shares, nonlinearly, as winter temperature rises. So far, the presence of tubers is associated with regions having relatively lower farming revenues, whereas that phenomenon for grains is insignificant.
- Oils: Regions with colder winters and relatively warmer growing seasons see larger soybeans shares. This, again, reflects the center role that Northeast China plays in soybeans production. Other small oil-bearing crops however respond differently to growing season and winter temperatures. Their shares tend to increase as winter gets warmer. Moreover, oil crops so far tend to occur in regions with lower economic competitiveness in farming.
- Cotton and Fibers: Both cotton and non-cotton fiber crops are estimated to benefit from higher growing season temperatures and lower winter temperatures. Cotton also prefers drier climates. This may be more of an indication of Xinjiang's climate conditions, however.
- Vegetables and Orchards: Vegetable growing appears to be a favored enterprise choice for regions with warmer winters and higher farming income levels. Not surprisingly, vegetable production is comparatively more popular in developed regions in China, such as the Yangtze River Delta region. Orchards tend to be present in regions with moderately low levels of precipitation, higher farming revenues, and lesser land use intensity.

Overall speaking, higher winter temperature may have negative impacts on grain crops and soybeans production as well as cotton and non-cotton fiber crops plantation, if no regional reallocations of those crops are to occur. On the other hand, most other crops, including tubers, small oil crops, sugars, tobacco, vegetables, tea, and orchards are estimated to benefit from higher winter temperature, while cotton and fibers would likely increase under warmer growing seasons. In one word, traditional grains and oils would very likely incur compromises while non-staples see increased likelihood of fitting into

warmer climate environment under future scenarios. We also infer that under future CC when larger multi-cropping possibility arises (Tian et al., 2015), small oil and fiber crops are more likely to fit into the alternatives. Vegetables and orchards may not necessarily fit into the multi-cropping expansion despite of their comparatively high value-added features, since multi-season vegetables growing may not be economically desirable for the more affluent regions, and orchards plantation implies taking land away from multi-season crop plantations.

Future Research

Food security is among the largest concerns facing China's various kinds of future scenarios. CC-induced changes in crop productivity can be an issue. For example, Chavas et al. (2009) found the effects of climate variables significant and that all major crops' yields would suffer under future CC in the Eastern China, assuming no CO₂ fertilization effects. Piao et al. (2010) investigated the climate variability in China for the past over 50 years, and they depicted a complicated picture where CC impacts on crop yields were mixed in the Western China, negative in the Northeast, and uncertain in the Southeast. These studies have largely focused on the biophysical aspects of food security under CC. Individual or societal management responses to CC were not considered however. This study investigated the crop mixes at aggregate province-level in China, providing a view that considered the "offsetting" effects via human management. While Tian et al. (2015) found emerging multi-cropping opportunities under future CC, the regression results in our study suggest that staple grains may not necessarily step in on the production side for food security. Similarly, vegetables and orchards may not be among the preferred choices due to economic incentive and cost reasons.

Our research is certainly subject to at least the following limitations. Firstly, water resources that may be a serious constraint for China's agriculture (Tao et al., 2003; Xiong et al., 2010) were not considered. Nor

were the CO₂ fertilization effects that may help increase crop yields under CC (Chavas et al. 2009). Last but not least, conducting analyses using a longer panel plus regional CC projections with greater spatial resolution shall be desirable for future research.

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Table 1 Variable Definition

Variable	Definition
<i>Independent Variables</i>	
GrsAvg.cel	Averaged monthly temperature for growing season (March to October), in Celsius degrees
WinAvg.cel	Averaged monthly temperature for winter (November to February), in Celsius degrees
SowCult.pct	Multi-cropping index, the ratio of total sown area over cultivated land area multiplied by 100
FarmRev.1K_ha	Gross output value of farming per sown ha, in 1K <i>yuan</i> (2000 RMB) per ha
Prep.cm	Annual precipitation, in centimeters
<i>Dependent Variables</i>	
Grains.pct	Sown area shares for grain crops, which include rice, maize, and wheat
Tubers.pct	Sown area shares for tuber crops
Soybeans.pct	Sown area shares for soybeans
Oils.pct	Sown area shares for non-soybeans oil-bearing crops
Cotton.pct	Sown area shares for cotton
Fibers.pct	Sown area shares for non-cotton fiber crops
Sugars.pct	Sown area shares for sugar crops
Tobacco.pct	Sown area shares for tobacco
Vege.pct	Sown area shares for vegetables
Tea.pct	Sown area shares for tea
Orchards.pct	Sown area shares for orchards

Table 2 Regions Used

<i>Province or Province-Equivalent</i>		
Beijing	Anhui	Chongqing
Tianjin	Fujian	Sichuan
Hebei	Jiangxi	Guizhou
Shanxi	Shandong	Yunnan
Inner Mongolia	Henan	Tibet
Liaoning	Hubei	Shaanxi
Jilin	Hunan	Gansu
Heilongjiang	Guangdong	Qinghai
Shanghai	Guangxi	Ningxia
Jiangsu	Hainan	Xinjiang
Zhejiang		

Table 3 Summary Statistics

Variable	Min	Max	Range	Median	Mean	Std. Dev
<i>Explanatory Variables</i>						
GrsAvg.cel	11.013	27.475	16.463	20.513	19.641	3.916
WinAvg.cel	-13.900	21.275	35.175	4.625	3.705	7.918
SowCult.pct	100.000	224.624	124.624	115.371	128.819	30.861
FarmRev.1k_ha	4.281	33.701	29.420	11.687	13.174	6.350
Prep.cm	7.490	267.890	260.400	74.080	86.537	50.217
<i>Dependent Variables</i>						
Grains.pct	27.145	94.229	67.084	56.634	58.037	13.344
Tubers.pct	0.130	21.753	21.623	4.080	6.516	5.807
Soybeans.pct	0.000	39.985	39.985	4.690	6.394	6.262
Oils.pct	0.397	33.963	33.566	7.354	8.492	5.767
Cotton.pct	0.000	42.417	42.417	0.328	2.940	6.436
Fibers.pct	0.000	1.289	1.289	0.021	0.112	0.198
Sugars.pct	0.000	19.139	19.139	0.142	1.229	3.097
Tobacco.pct	0.000	7.878	7.878	0.257	0.746	1.400
Vege.pct	1.518	37.662	36.144	11.538	13.346	7.969
Tea.pct	0.000	9.787	9.787	0.210	1.056	1.849
Orchards.pct	0.286	28.335	28.049	6.393	8.378	7.236

Table 4 Regression Results (To Be Continued)

	Grains		Tubers		Soybeans	
	<i>Model 1</i>	<i>Model 2</i>	<i>Model 1</i>	<i>Model 2</i>	<i>Model 1</i>	<i>Model 2</i>
(Intercept)	54.0277*** (5.791)	15.0714 (18.789)	22.421*** (2.230)	17.659* (7.179)	8.257*** (2.174)	-13.288* (6.452)
GrsAvg.cel	0.115 (0.386)	4.562* (2.073)	-0.297* (0.149)	0.344 (0.792)	0.373* (0.145)	2.338** (0.712)
GrsAvg.sq		-0.128* (0.0603)		-0.0211 (0.0230)		-0.0636** (0.0207)
WinAvg.cel	-0.674*** (0.171)	-0.571** (0.180)	0.507*** (0.0658)	0.546*** (0.0688)	-0.586*** (0.0642)	-0.603*** (0.0619)
WinAvg.sq		0.00349 (0.0137)		0.0108* (0.00522)		0.0366*** (0.00469)
Prep.cm	-0.00620 (0.0201)	0.0402 (0.0546)	-0.00646 (0.00773)	-0.0737*** (0.0209)	0.0434*** (0.00753)	0.0928*** (0.0188)
Prep.sq		-0.000107 (0.000209)		0.000243** (0.0000800)		-0.000312*** (0.0000719)
SowCult.lag	0.0293 (0.0283)	0.0213 (0.0334)	-0.0535*** (0.0109)	-0.0303* (0.0128)	-0.0423*** (0.0106)	-0.0116 (0.0115)
FarmRev.lag	0.0821 (0.118)	0.104 (0.118)	-0.360*** (0.0453)	-0.355*** (0.0453)	-0.427*** (0.0442)	-0.375*** (0.0407)
R-Squared	0.122	0.140	0.312	0.337	0.438	0.540
Adjusted R-Squared	0.111	0.123	0.303	0.324	0.431	0.530

* Standard errors in parentheses. Significance indicated by: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 4 Regression Results (Continued)

	Oils		Cotton		Fibers	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
(Intercept)	24.620*** (2.182)	104.247*** (5.610)	-11.182*** (2.725)	-24.498** (8.829)	-0.176* (0.0824)	-0.795** (0.262)
GrsAvg.cel	-1.430*** (0.145)	-10.317*** (0.619)	0.852*** (0.182)	2.579** (0.974)	0.0125* (0.00549)	0.0745* (0.0289)
GrsAvg.sq		0.267*** (0.0180)		-0.0506. (0.0283)		-0.00196* (0.000841)
WinAvg.cel	0.354*** (0.0644)	0.150** (0.0538)	-0.466*** (0.0804)	-0.387*** (0.0847)	-0.0103*** (0.00243)	-0.00985*** (0.00251)
WinAvg.sq		-0.0562*** (0.00408)		0.00335 (0.00642)		0.000897*** (0.000190)
Prep.cm	0.0181* (0.00756)	0.0511** (0.0163)	-0.0299** (0.00944)	-0.0897*** (0.0257)	0.000631* (0.000285)	0.000854 (0.000761)
Prep.sq		-0.0000935 (0.0000625)		0.000268** (0.0000984)		-0.00000332 (0.00000292)
SowCult.lag	0.0929*** (0.0107)	0.0319** (0.00997)	0.00258 (0.0133)	0.0153 (0.0157)	0.00148*** (0.000402)	0.00239*** (0.000466)
FarmRev.lag	-0.227*** (0.0443)	-0.309*** (0.0354)	0.109. (0.0554)	0.109. (0.0557)	-0.0131*** (0.00167)	-0.0119*** (0.00165)
R-Squared	0.333	0.590	0.164	0.184	0.197	0.245
Adjusted R-Squared	0.324	0.581	0.154	0.167	0.187	0.229

* Standard errors in parentheses. Significance indicated by: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 4 Regression Results (Continued)

	Sugars		Tobacco		Vege	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
(Intercept)	1.320 (1.167)	6.774* (3.307)	5.0306*** (0.555)	-17.0379*** (1.326)	-2.557 (1.686)	-4.553 (5.464)
GrsAvg.cel	0.299*** (0.0778)	-0.511 (0.365)	-0.203*** (0.0369)	2.236*** (0.146)	0.159 (0.112)	0.336 (0.603)
GrsAvg.sq		0.0195. (0.0106)		-0.0721*** (0.00426)		-0.00383 (0.0175)
WinAvg.cel	0.121*** (0.0345)	0.0819* (0.0317)	0.158*** (0.0164)	0.207*** (0.0127)	0.321*** (0.0498)	0.313*** (0.0524)
WinAvg.sq		0.0172*** (0.00240)		0.0110*** (0.000964)		-0.00458 (0.00397)
Prep.cm	0.0102* (0.00405)	-0.00558 (0.00961)	-0.0000419 (0.00192)	0.0164*** (0.00385)	-0.00489 (0.00584)	0.0329* (0.0159)
Prep.sq		-0.0000254 (0.0000369)		-0.0000603*** (0.0000148)		-0.000131* (0.0000609)
SowCult.lag	-0.0501*** (0.00571)	-0.0274*** (0.00588)	-0.00242 (0.00271)	0.00495* (0.00236)	0.00473 (0.00824)	-0.00712 (0.00972)
FarmRev.lag	-0.0679** (0.0237)	-0.0529* (0.0208)	-0.0452*** (0.0112)	-0.0243** (0.00836)	0.911*** (0.0343)	0.911*** (0.0344)
R-Squared	0.338	0.505	0.268	0.611	0.791	0.796
Adjusted R-Squared	0.329	0.495	0.259	0.603	0.789	0.792

* Standard errors in parentheses. Significance indicated by: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 4 Regression Results (Continued)

	Tea		Orchards	
	<i>Model 1</i>	<i>Model 2</i>	<i>Model 1</i>	<i>Model 2</i>
(Intercept)	2.226** (0.758)	-11.586*** (2.310)	-8.440*** (2.280)	-4.283 (6.804)
GrsAvg.cel	-0.168*** (0.0505)	1.333*** (0.255)	1.181*** (0.152)	0.944 (0.751)
GrsAvg.sq		-0.0439*** (0.00741)		0.00228 (0.0218)
WinAvg.cel	0.132*** (0.0224)	0.157*** (0.0221)	-0.00250 (0.0673)	0.0461 (0.0652)
WinAvg.sq		0.00537** (0.00168)		0.0163** (0.00495)
Prep.cm	0.00338 (0.00263)	0.0284*** (0.00672)	-0.0191* (0.00790)	-0.167*** (0.0198)
Prep.sq		-0.0000920*** (0.0000258)		0.000533*** (0.0000759)
SowCult.lag	0.00617. (0.00370)	0.00654 (0.00411)	-0.0926*** (0.0111)	-0.0484*** (0.0121)
FarmRev.lag	0.0437** (0.0154)	0.0569*** (0.0146)	0.574*** (0.0463)	0.572*** (0.0429)
R-Squared	0.217	0.323	0.537	0.616
Adjusted R-Squared	0.207	0.310	0.531	0.609
	N	DF	OLS-R2	McElroy-R2
Model 1 system	4433	4367	0.329	0.508
Model 2 system	4433	4334	0.383	0.580

* Standard errors in parentheses. Significance indicated by: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

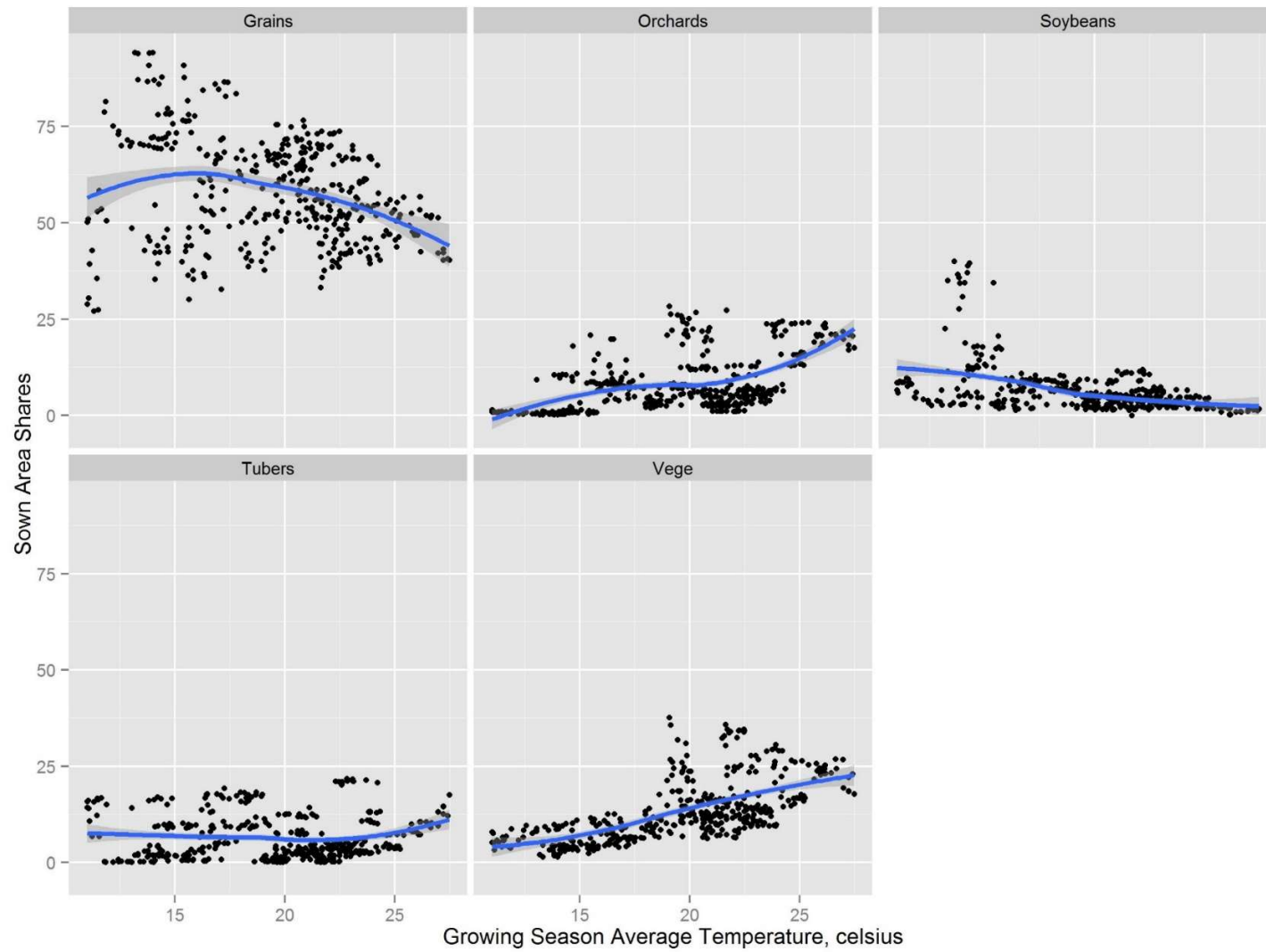


Figure 1 Sown Area Shares vs. Growing Season Average Temperature, Crops 1/2

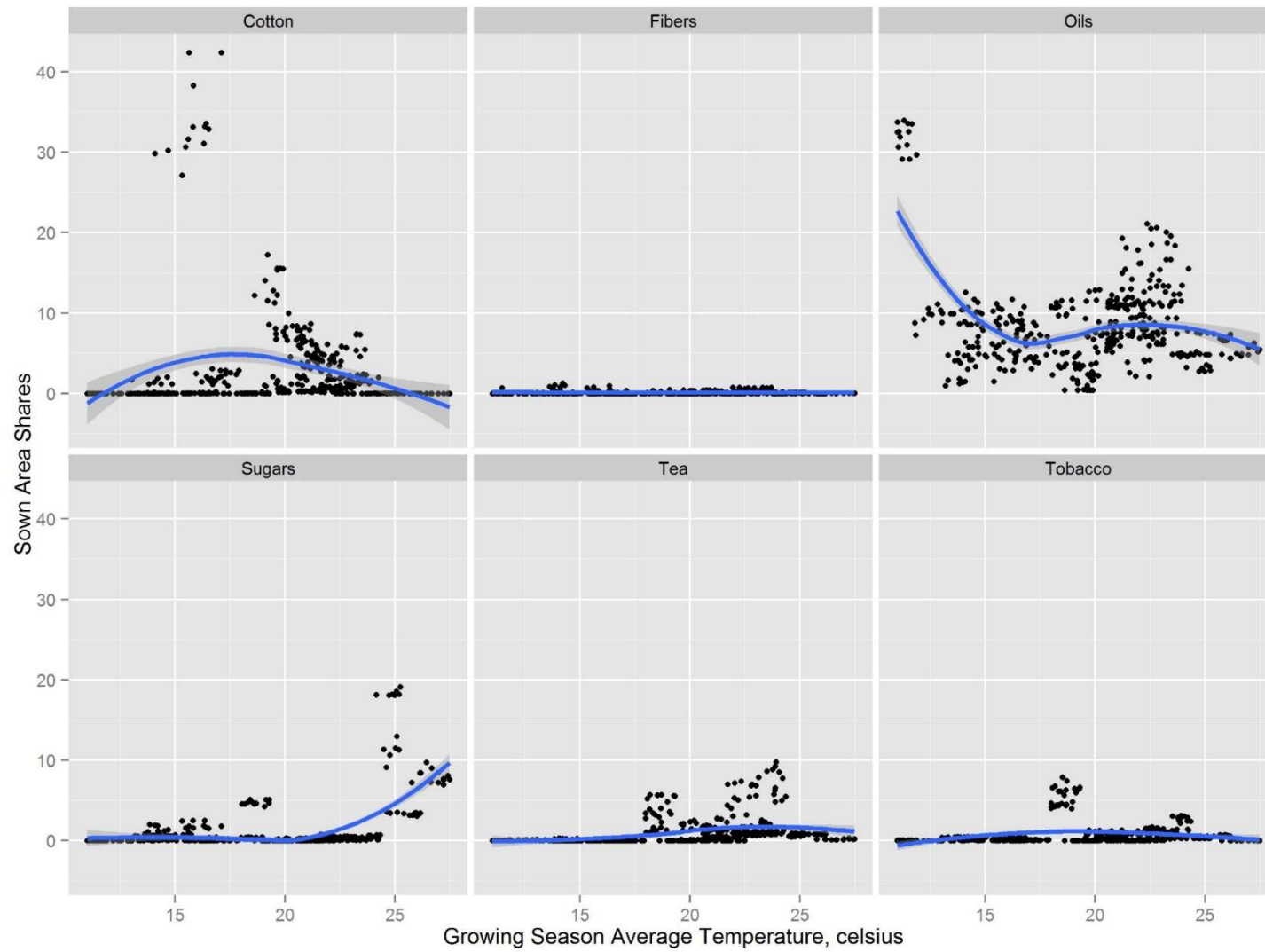


Figure 2 Sown Area Shares vs. Growing Season Average Temperature, Crops 2/2

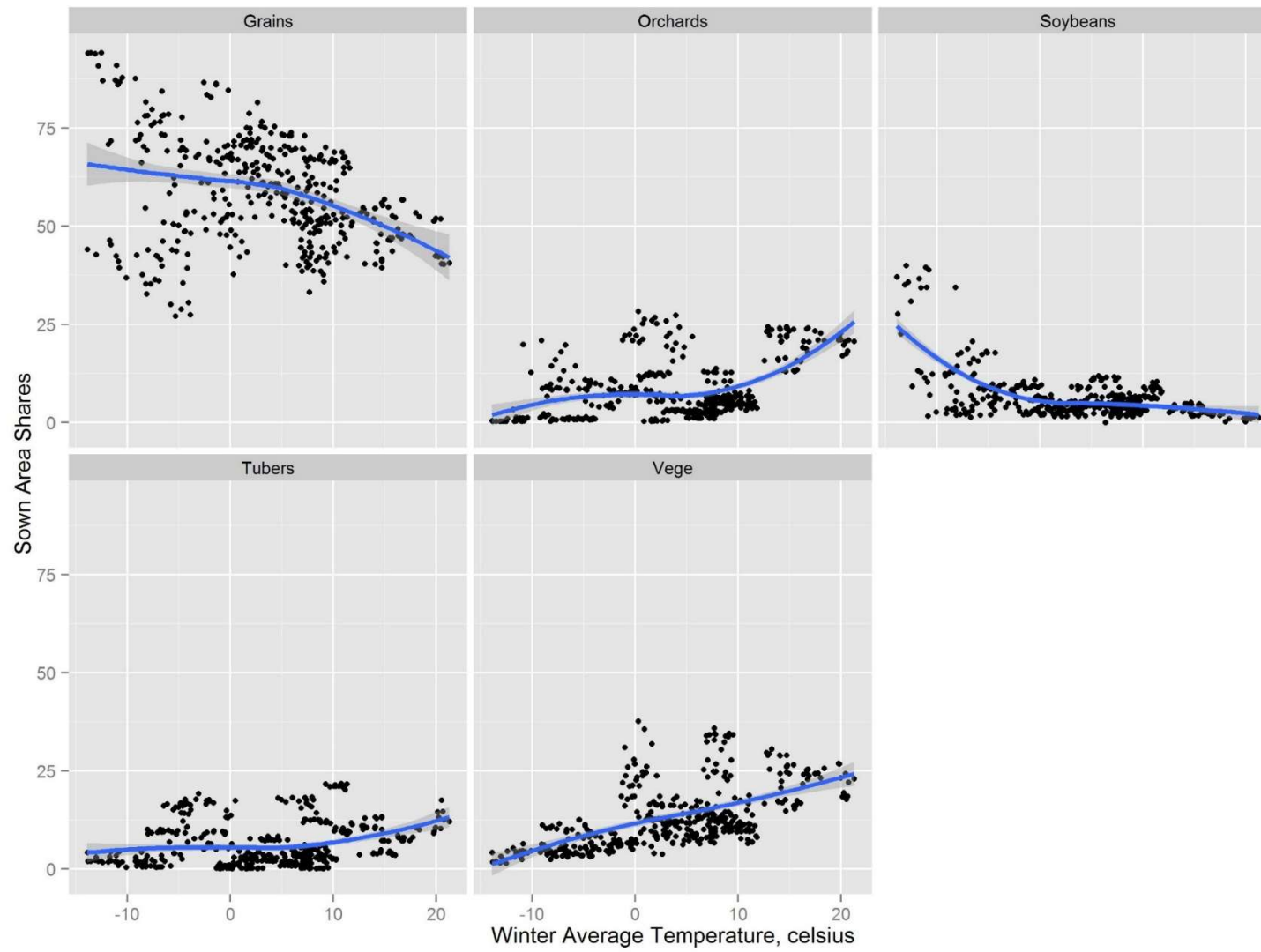


Figure 3 Sown Area Shares vs. Winter Average Temperature, Crops 1/2

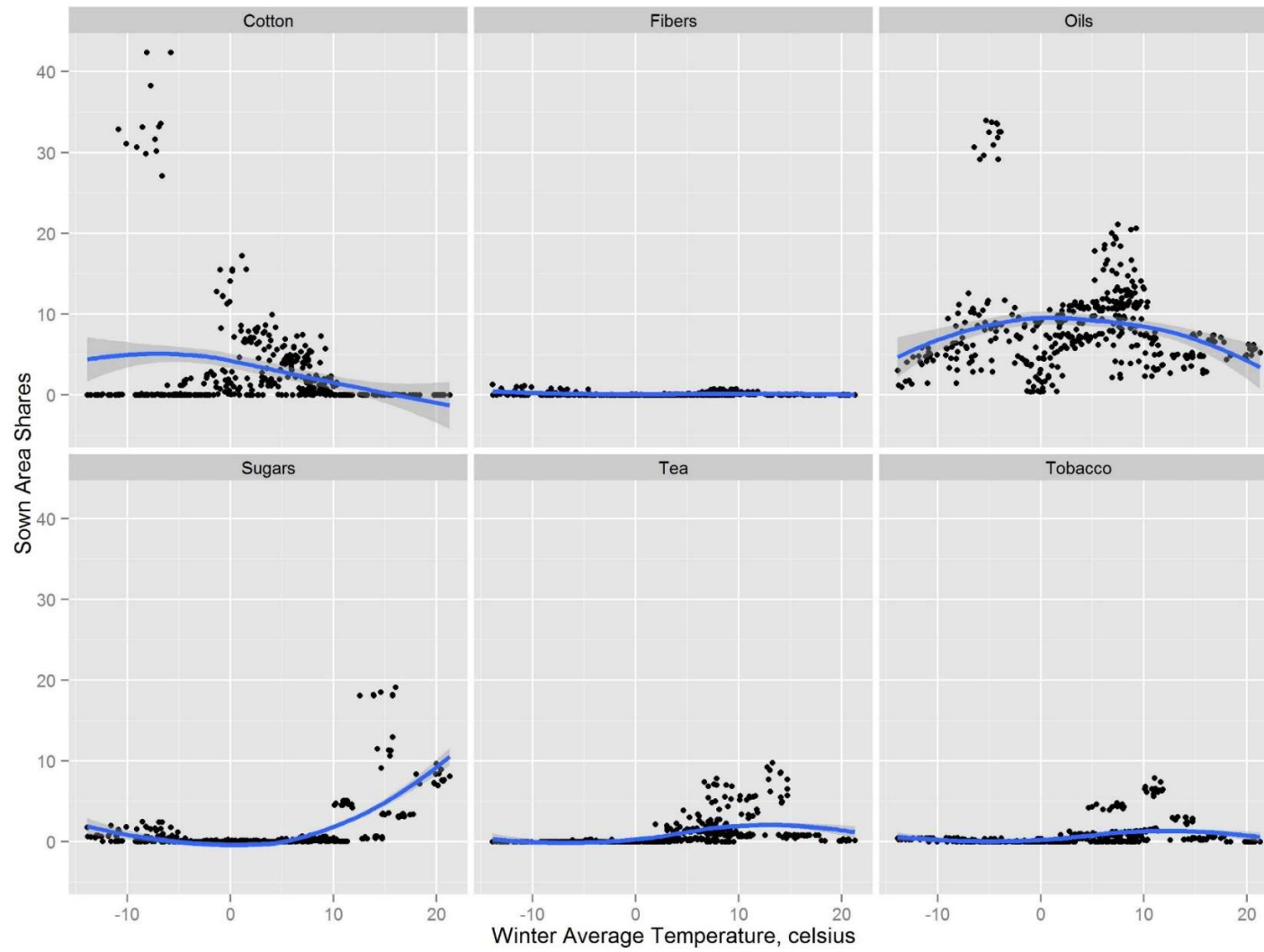


Figure 4 Sown Area Shares vs. Winter Average Temperature, Crops 2/2

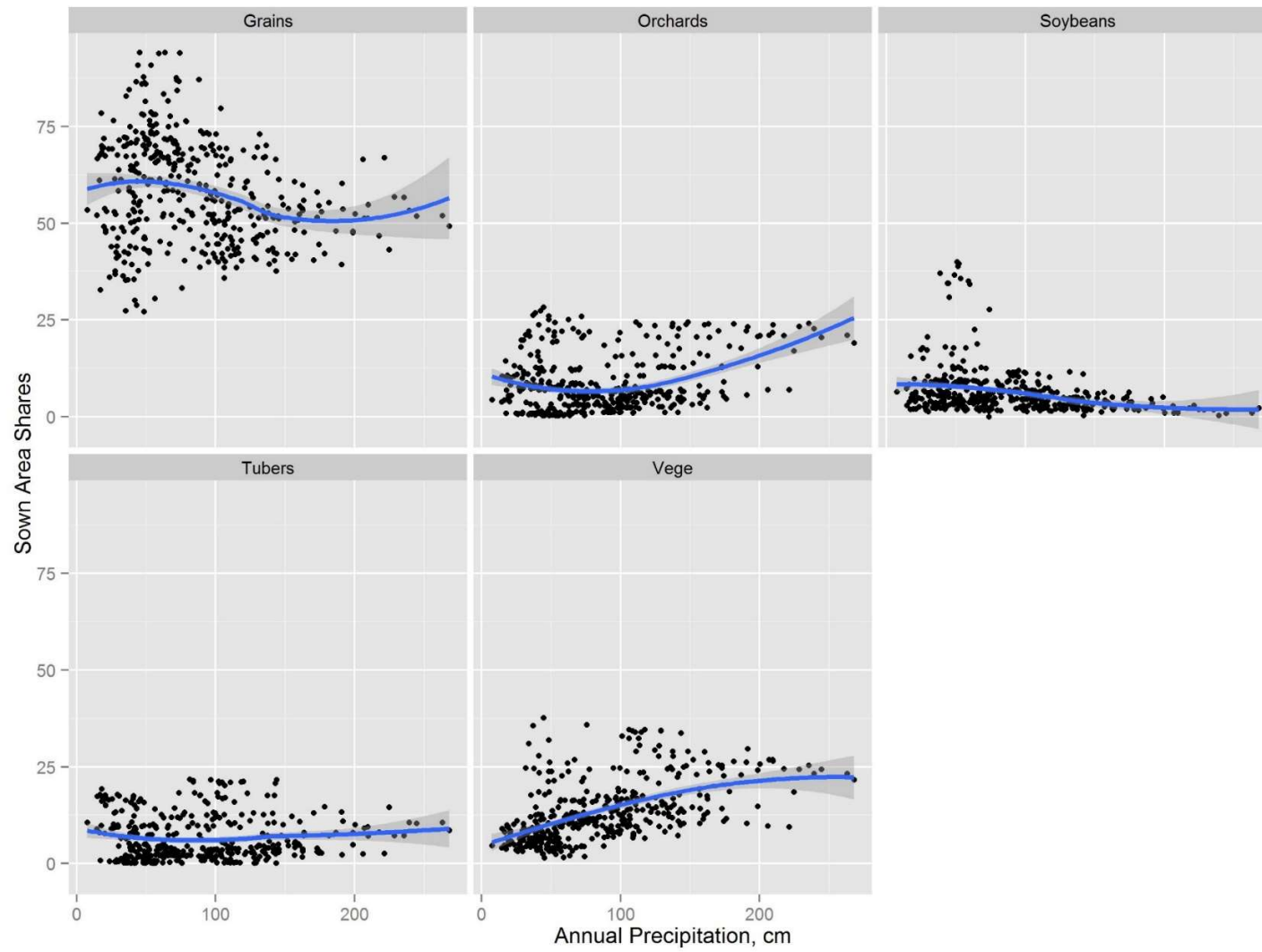


Figure 5 Sown Area Shares vs. Annual Precipitation, Crops 1/2

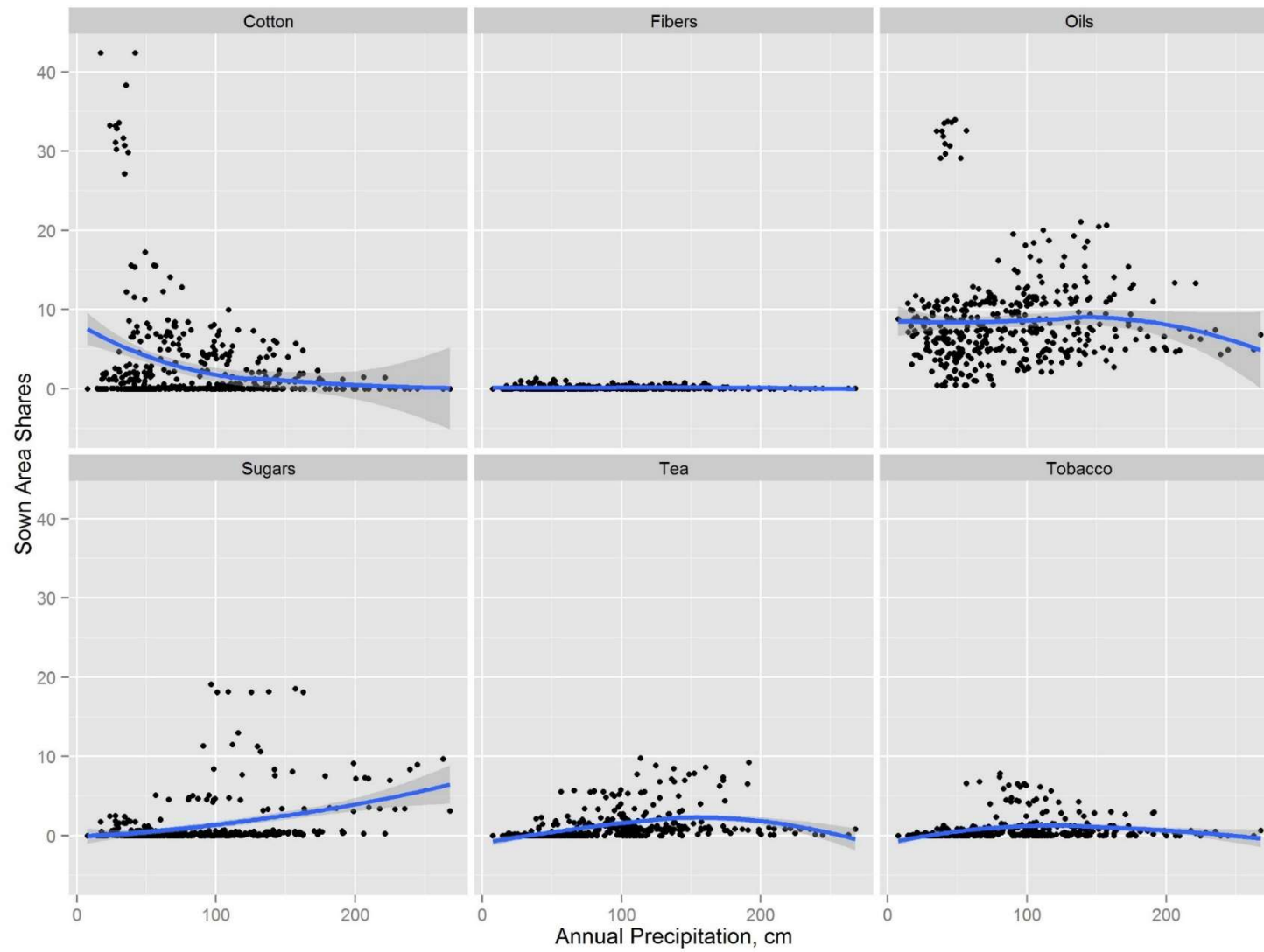


Figure 6 Sown Area Shares vs. Annual Precipitation, Crops 2/2

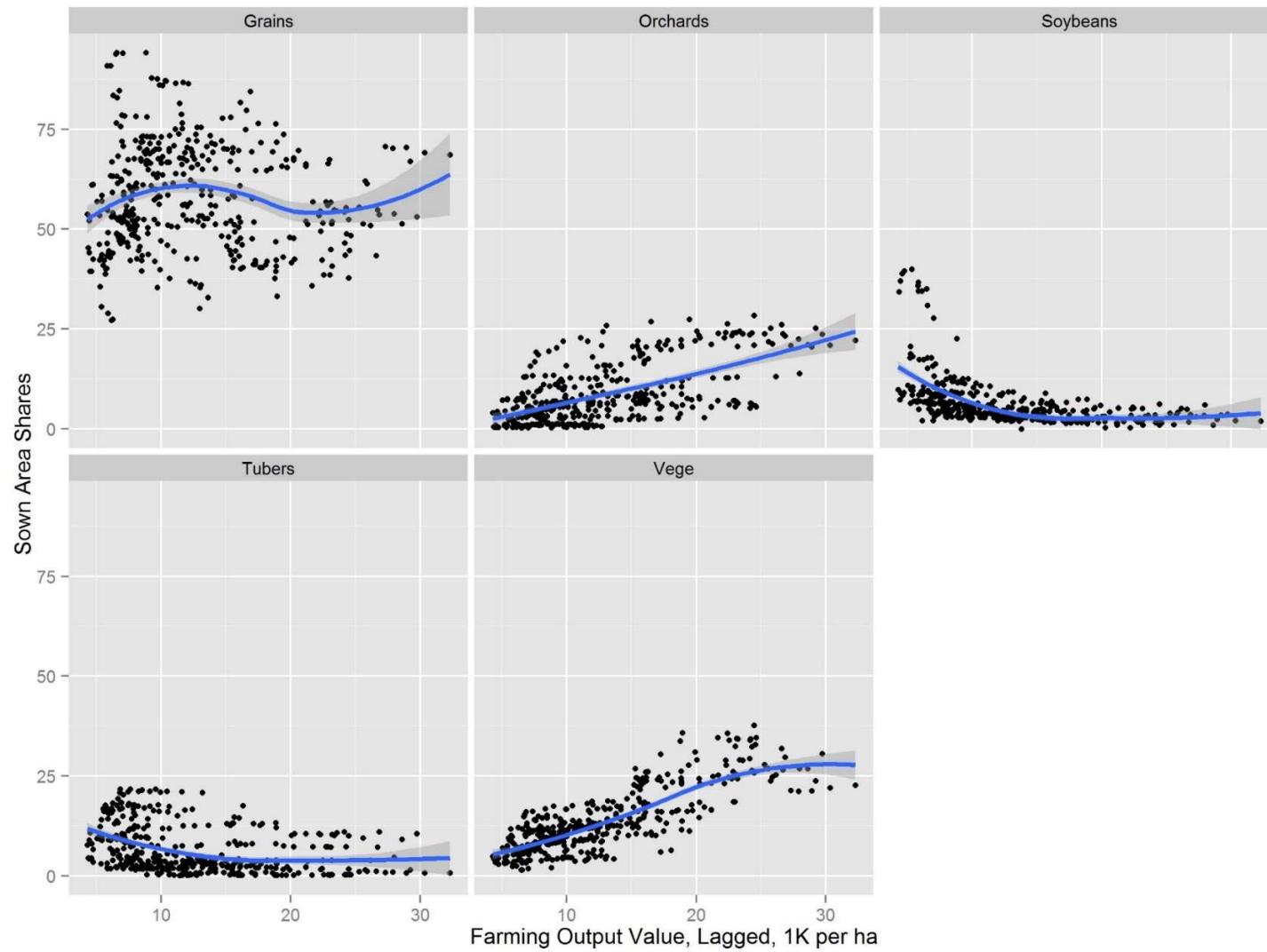


Figure 7 Sown Area Shares vs. Farming Value, Crops 1/2

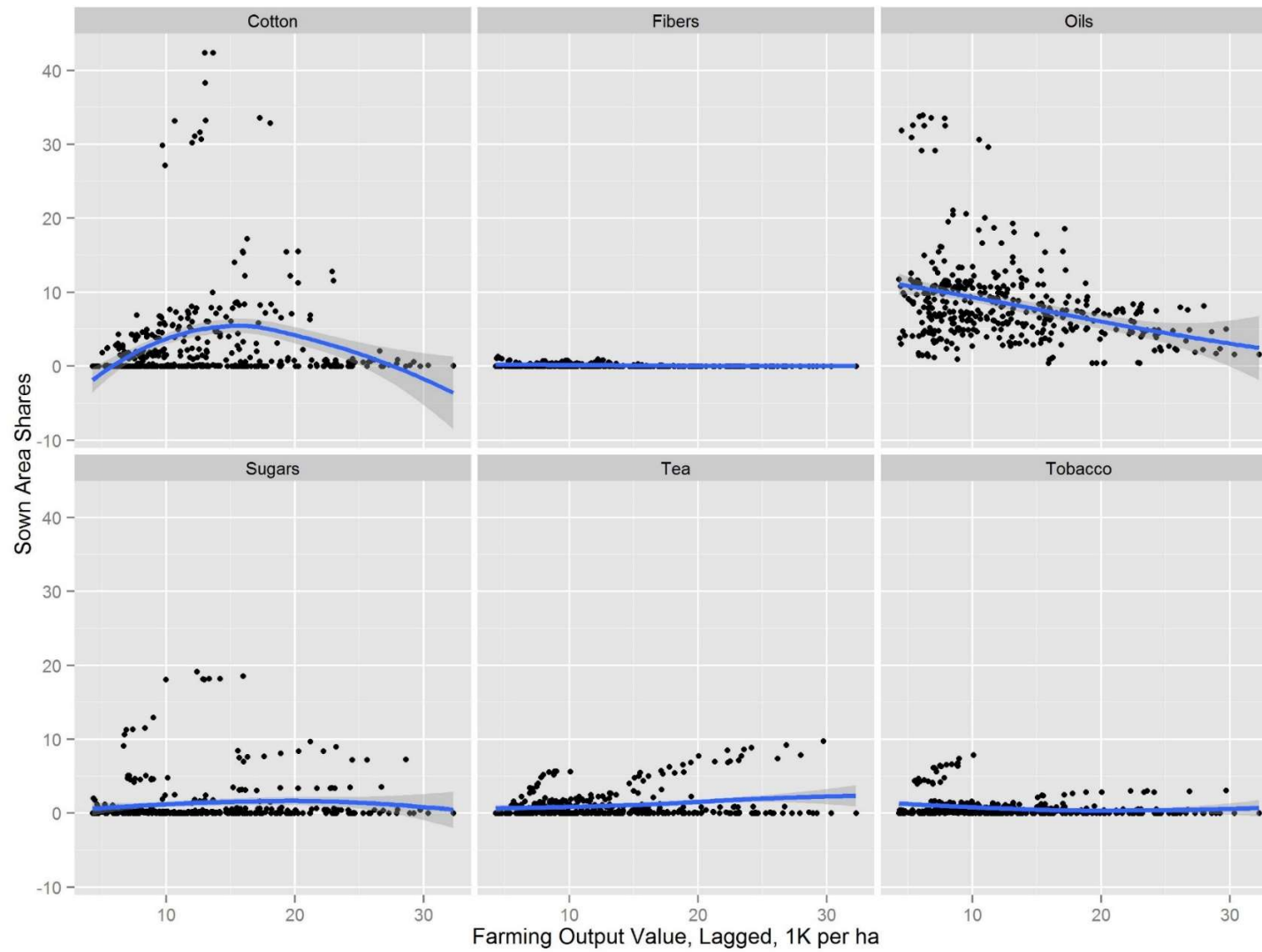


Figure 8 Sown Area Shares vs. Farming Value, Crops 2/2

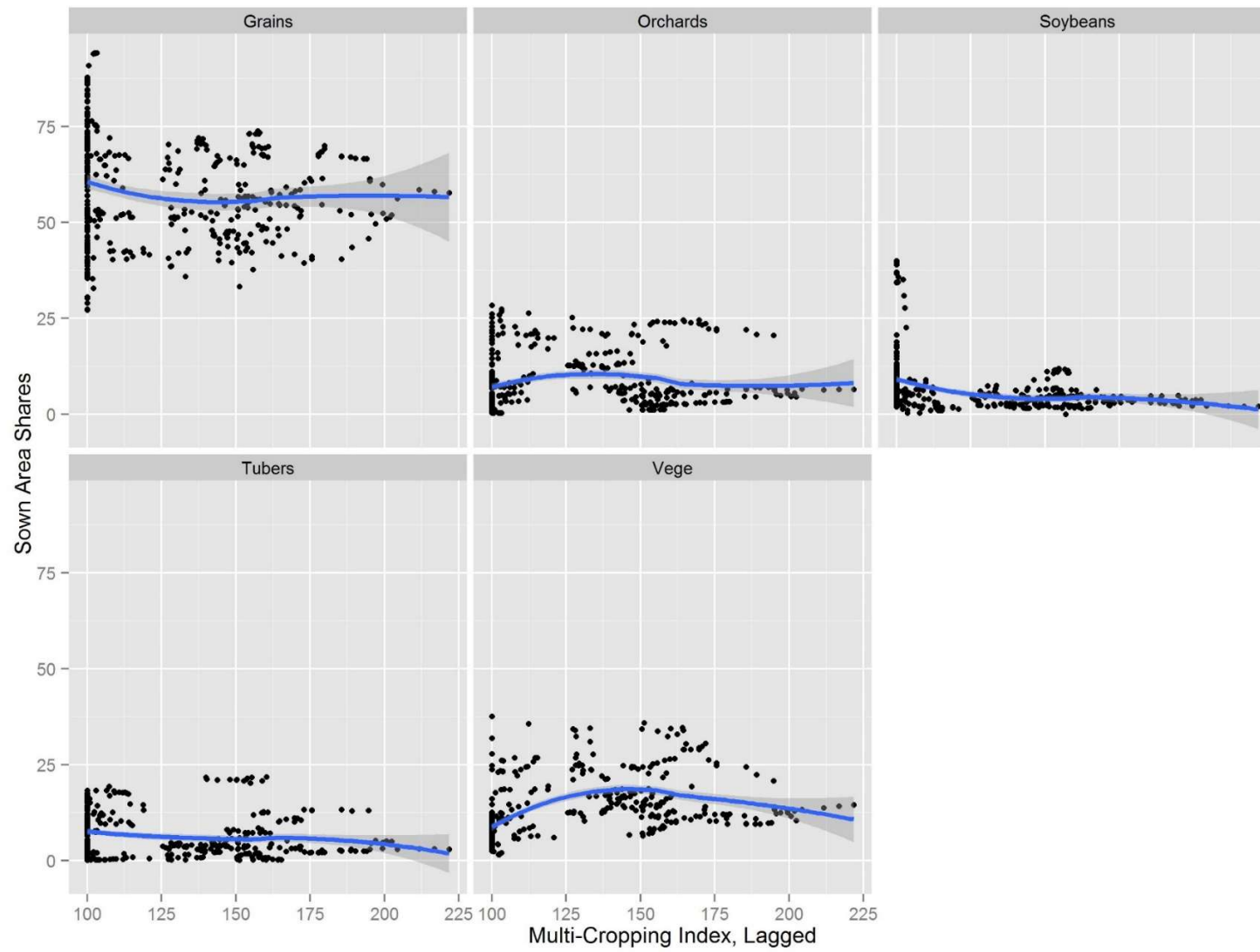


Figure 9 Sown Area Shares vs. Multi-Cropping Index, Crops 1/2

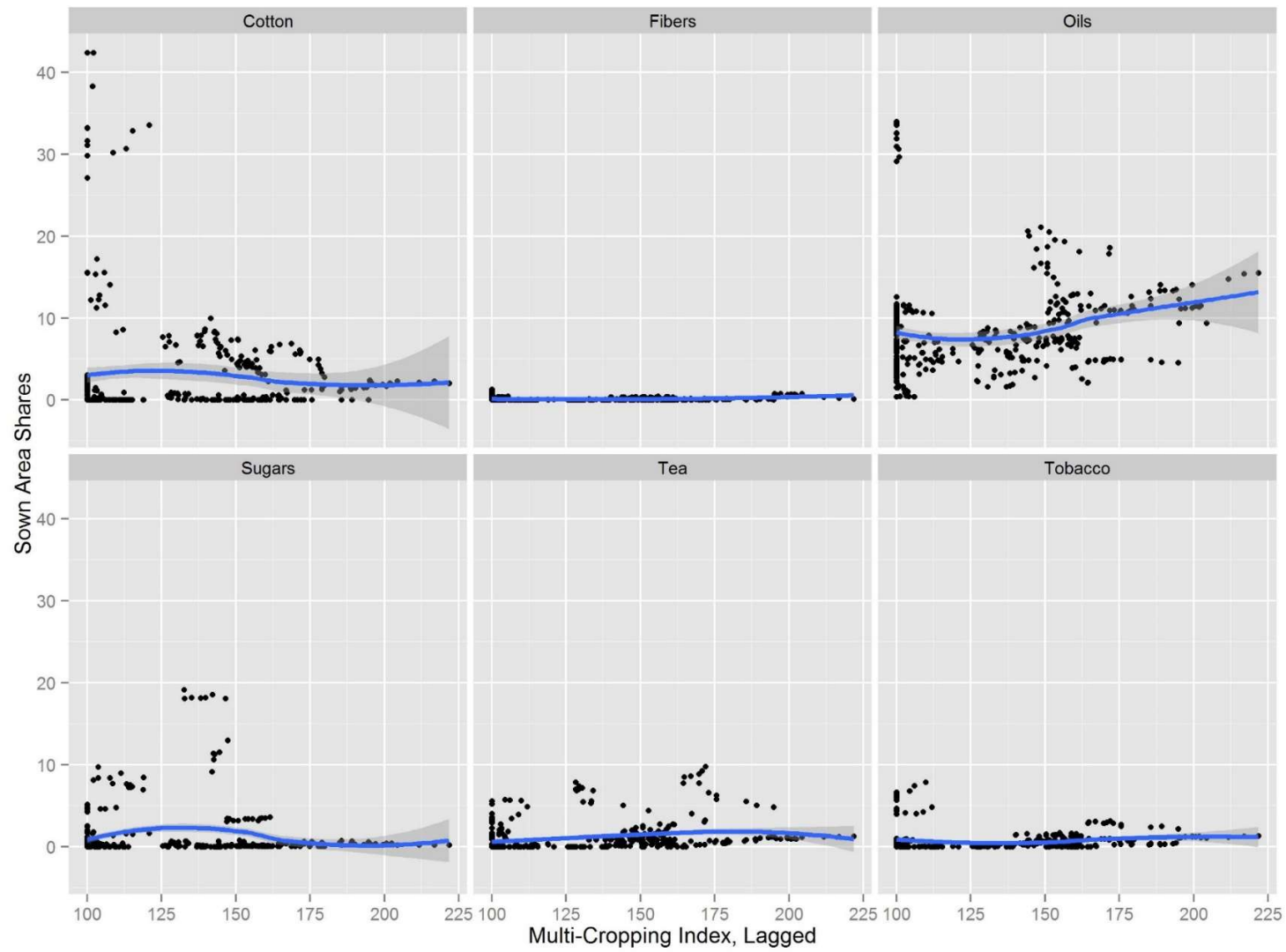


Figure 10 Sown Area Shares vs. Multi-Cropping Index, Crops 2/2