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Noah Miller, Mykel Taylor, Ignacio Ciampitti, and Jesse Tack*

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Recent literature on basis forecasting has attempted to improve upon naïve forecasts by incorporating current marketing year information (in the form of basis deviation from historical levels). Given that basis is determined at each grain elevator location, inclusion of proxies for current, local supply conditions could alternatively improve upon naïve forecasts. Large weather datasets have been effectively utilized in the agronomy literature to predict harvest yields in real time, however they have, to the best of our knowledge, not been incorporated into any previous basis price forecasting research. Here we match 858 weekly elevator-level, winter wheat price observations (spread over eight states and spanning 14 years) to gridded soil moisture readings (at a 0.25º x 0.25º spatial resolution) obtained from the European Space Agency and forecast winter wheat harvest basis from each weekly vantage point within the growing season. Our results indicate that inclusion of soil moisture into basis forecasts can substantially improve harvest basis forecasts for forecasts made in the middle and final part of the growing season; this result is improved upon further by disaggregating the data and forecasting at the sub-state, regional level.

Key words: basis forecasting, climate data.

Introduction

Producers face a significant amount of price risk in marketing their grain at harvest. One way they can limit exposure to volatility in the cash markets is to 'lock in' prices with forward contracts, however, in so doing producers open themselves up to basis risk. Basis (defined as cash price minus futures price) levels have historically been relatively stable, due to similar co-movement patterns between cash and futures markets from year to year. The historic stability of interyear basis has allowed for simple harvest basis forecasts (in which next year's harvest basis is solely a function of this and prior year's basis) to be highly accurate (Hatchett et al. 2010). However, increased price volatility in cash and futures markets over the past fifteen years has been accompanied by a collapse in basis' historic pattern (Adjemian et al. 2013; Taylor et al. 2014). Under these conditions, simple basis forecasts have performed poorly and have produced the need for forecasting models which can better handle the year-to-year oscillation in basis.

To meet this need we match soil moisture observations to historic elevator-level harvest basis to forecast basis using within growing-season weather. Here, soil moisture conditions around a grain elevator serve as a proxy for local supply (i.e. crop yields and production) which harvest basis is a function of. Specifically, we construct a panel model in which harvest basis is a defined as a function of prior harvest basis, elevator fixed-effects, and weekly, additive cubic soil moisture. We then compare the accuracy of our preferred model to baseline models (in which weekly soil moisture readings are omitted) through an out-of-sample forecasting exercise. Our findings indicate that inclusion of weekly soil moisture in harvest basis forecasts made from the fourth week of September onward improves forecast accuracy (by up to 16% from the first week in December, to up to 46% from the first week in May). We find that our preferred model is robust to inclusion of additional weather and price covariates and that inclusion of these covariates does not substantially improve forecasting accuracy further. When we expand the geographic scope of our analysis and try to forecast basis over larger, multi-state regions we find that the forecasting performance of our preferred model decreases, converging to the performance of the baseline model. When we forecast over smaller, sub-state regions within the state of Kansas, the resulting RMSE are lower than those made when forecasting across the entire state (with improvement in RMSE depending on regional location) suggesting that aggregating data across larger geographic scopes minimizes forecasting accuracy.

Research conducted prior to the onset of the recent surge in price volatility found (for a range of row crops) that the best predictor of future harvest basis was the prior year's basis or a historical moving average of prior years' harvest basis (Kastens et al. 1998; Garcia et al. 1986). A more recent study by Taylor et al. (2006) examined the effectiveness of incorporating current market information (in the form of basis deviation from the historical average) in harvest and post-harvest forecasts for Kansas corn, soybean, milo, and wheat – and found that this approach offered improvements, but only for post-harvest forecasts (for harvest forecasts the traditional approach using historical moving averages provided better forecasts). Thompson et al. (2019) similarly found that the accuracy of post-harvest (but not harvest) corn and soybean basis forecasting models for the eastern Corn Belt could be improved by including current basis information. Our research builds on this more recent work of Taylor et al. (2006) and Thompson et. al (2019) by (i) assessing alternative (i.e. weather) sources of within-season information regarding local markets that could potentially improve harvest basis forecasts, (ii) providing harvest basis forecasts for winter wheat for every possible weekly vantage point in the marketing year, and (iii) demonstrating the linkages between the geographic scope of the data and the accuracy of forecasting models.

Data

The data used in this analysis is divided into two types, price and weather data. Daily closing red hard winter wheat cash prices were collected from two sources: Cash Grain Bids (CGB) and Data Transmission Network (DTN) for years 2004 - 2018. The number of grain elevators total 858 and are spread across eight states (Texas, Oklahoma, Kansas, Colorado, Nebraska, Wyoming, South Dakota, and North Dakota) in the Great Plains Region (**Figure 1**). Wheat futures prices for July delivery at the Kansas City Board of Trade (KCBT) were obtained from Bloomberg for the same dates as the cash prices. **Figure 2** shows daily elevator-level basis prices were constructed by differencing futures prices from the corresponding cash prices.

In order to facilitate this analysis, the price data was manipulated in several ways. First, due to gaps in the daily price data, weekly basis prices were constructed by averaging daily prices across each five-day workweek (Monday through Friday) period. Because the number of weeks in any particular month alternated across years, in months that observed five weeks, the fifth week was averaged with the fourth week (resulting in 48 weeks for each year) (in keeping with the approach of Taylor et al. 2006). A growing season comprised of 40 weeks (beginning the 1st week in September and ending the 4th week in June) was then defined and weekly basis prices that fell outside of this window were removed from the analysis. This left a total number of 549,120 total weekly basis price observations in the dataset.[1]

Weather data, was obtained from the European Space Agency (ESA) and the PRISM Climate Group (PRISM). The soil moisture data compiled for this analysis was taken from ESA's Climate Change Initiative Soil Moisture (ESA CCI SM) product, which includes daily soil moisture (as a percentage) at a 27km x 27km resolution spanning the lower 48 states, from November 1st 1978 to December 30th 2018. Daily minimum and maximum temperatures at a 4km x 4km resolution were collected from PRISM, and interpolated following Schlenker and Roberts (2007) to form degree days. Using the degree day data, two degree day variables (i.e. degree days over 10ºC and degree days over 30ºC), were constructed as measures of moderate and extreme heat. Grain elevator addresses were geocoded and daily soil moisture and degree day data was collected for grids in which an elevator was located. The weather data was then manipulated in exactly the same manner as the price data, resulting in weekly average soil moisture and degree day readings for each week in each growing season, 2004-2018. Despite the use of weekly averages, gaps in the soil moisture data remain. The majority of these gaps are due to weather conditions during the winter, including hard freezing of the soil and/or snow cover, which preclude satellite observation of soil moisture conditions. Boxplots of the key weather and price data for Kansas and for the Great Plains region that were used in this analysis are shown in **Figure 3, Figure 4, Figure 5, and Figure 6**.

Methods

We forecast harvest basis for winter wheat using the prior year's harvest basis and within season weekly soil moisture readings from every vantage point (*j = 1, 2, …40*) in the growing season,

(1) $b_{it} = \alpha_i + \beta_0 0.2 \sum_{n=1}^{5} b_{it-n} + \sum_{w=1}^{J} I_j \sum_{k=1}^{3} \gamma_{w.k} sm_{wit}^{k} + \varepsilon_{it}, \quad (I_j = 1 \text{ if } w \leq j \text{ and } 0 \text{ otherwise})$

where b_{it} is harvest basis at elevator *i* in year *t*; α_i are fixed effects that capture variation in basis caused by time invariant, elevator-specific characteristics; and sm_{wit} is the soil moisture reading in week *w* at elevator *i* in year *t*. We incorporate an indicator variable (I_j) into the model such that at any vantage point only the current and prior week's soil moisture readings are admitted additively. Given the likely nonlinear effect of soil moisture on price, we also include both quadratic and cubic functions (k =2,3) of soil moisture.[2]

To evaluate forecasting performance of model (1) (hereafter denoted as the 'preferred' model), an out-of-sample forecasting exercise was conducted in which one year's worth of data was dropped from the dataset at a time and the model was estimated from all forty weekly vantage points with the remaining years' data. The resulting parameters were then used to predict out-of-sample harvest basis and calculate root-mean-squared-error (RMSE). Two baseline models (the first is the same as the preferred model only with average weekly soil moisture omitted; the second omits average weekly soil moisture and replaces a 1-year lagged harvest basis term in place of the 5-year historical average) was similarly estimated and RMSE calculated. This process was repeated $t = T - 5$ times – that is, until every year except the first five years in the dataset had been forecasted. Since the dataset includes 14 (i.e. $t = 9$) years of weekly observations from all forty vantage points, a total of 360 forecasts were produced.[3]

Results

The results are divided into two sections. In the first section, we compare the RMSE resulting from our out-of-sample exercise for the baseline and preferred models for the state of Kansas. We also compare the RMSE that results when our preferred model is altered (through changes in the specification of soil moisture, through inclusion of additional weather and price covariates, and through exclusion of portions of early and mid-season soil moisture readings). In the second section we consider the generalizability of the preferred model when we (i) aggregate our data to include other Great Plains states and forecast basis for larger, multi-state regions, and when we (ii) produce regional-level forecasts for sub-state regions in Kansas.

Soil Moisture Improves Model Performance for Kansas Elevators from Mid-April Onward

We perform our out-of-sample forecasting exercise for our baseline and preferred models for all elevator locations in Kansas. We also prepare two alternative versions of our preferred model (one which drops the set of all weekly cubic soil moisture variables, and one which drops the set of all quadratic and cubic soil moisture variables) and rerun our out-of-sample-forecasting exercise. Average RMSE for all forty vantage points for the two baseline, preferred, and two alternative soil moisture models are reported in **Figure 7**. Basis forecasts that include soil moisture perform worse relative to our baseline models for the early part of the growing season (i.e. the first three weeks in September). From the fourth week (i.e. the fourth week in September) onward however, RMSE of the models that include soil moisture drops. The magnitude of this drop depends on the polynomial degree of soil moisture – by the 33rd week in the growing season (i.e. the first week in May) the RMSE for the preferred model (that includes linear, quadratic, and cubic soil moisture variables) drops by 46%; compared with a drop in RMSE by 44% and 41% for the alternative model that includes only linear and quadratic soil or only linear soil moisture respectively. However, the reduction in RMSE is such that all models outperform the baseline models at all vantage points from the 4th week in the growing season onward.[4]

Inclusion of Additional Price and Weather Covariates Does Not Improve Model Performance

We examine the degree to which our preferred model can be improved upon through inclusion of additional price and weather covariates. We construct three alternative models. The first alternative model is identical to our preferred model except for an additional price variable that captures the weekly average Kansas City Board of Trade July futures contract for winter wheat. The second alternative model is identical to the preferred model except for two additional degree day variables that capture exposure to temperatures greater than 10ºC and 30ºC. The third alternative model is identical to the preferred model but includes both the futures price variable and the two degree day variables. We rerun our out-of-sample forecast using these three alternative specifications. **Figure 8** shows average RMSE by vantage point for the three alternative models, as well as average RMSE for the baseline and preferred models. The out-of-sample performance of the three alternative models produce virtually identical RMSEs to the preferred model. These results suggest that inclusion of additional weather and price covariates does not improve our preferred model's forecasting ability.

Forecast Performance of Preferred Model for Multi-State Regions Approaches the Baseline

We seek to understand how expanding the geographic scope of our analysis impacts the forecasting performance of our preferred model. We do this by constructing four increasingly large, multi-state elevator-level datasets (i.e. data drawn from: (i) Kansas and Nebraska; (ii) Kansas, Nebraska, and Oklahoma; (iii) Kansas, Nebraska, Oklahoma, and South Dakota; and (iv) all states in the Great Plains – Kansas, Nebraska, Oklahoma, South Dakota, North Dakota, Colorado, Texas, and Wyoming) and rerunning our out-of-sample forecast exercise with our baseline and preferred models. Average RMSE for the baseline model and for the preferred model by region are shown in **Figure 9 and Figure 10**. These results show that as the geographic scope of the data increases, the resulting RMSE produced by forecasting using the preferred model increases and approaches the average baseline RMSE. This result holds across all weekly vantage point except for the earliest week vantage points.

Forecast Performance of Preferred Model Increases in Southern Great Plains States

We also seek to understand how model performance is impacted when applying the preferred model for Kansas to smaller, sub-state-level analyses. We do this by partitioning Kansas into geographic thirds (based on longitude), constructing datasets for these sub-state Kansas regions and rerunning our out-of-sample forecast exercise with our baseline and preferred models. Average RMSE for the baseline model and for the preferred model by region are shown in **Figure 11**, **Figure 12**, and **Figure 13**. Comparing the RMSE associated with forecasting across the entire state of Kansas against the RMSE when forecasting across sub-state regions, we see that forecasts for sub-state regions are more accurate (i.e. lower RMSE scores) than those made using data drawn from the entire state of Kansas. This is true across all regions, though the most substantial improvement in seen with forecasts made in Western Kansas (with, depending on vantage point, added improvements in accuracy of over 55%). This along with the result in the previous section suggests that the geographic scope of the data impacts forecasting accuracy, with improvements in forecasting accuracy occurring with datasets that are of more limited geographic scope.

Conclusion

Recent literature has used time series methods to determine the value of including current market information, typically in the form of basis deviation from historical averages, on the accuracy of harvest basis forecasts. Our analysis seeks to complement this work in two ways: (i) by providing a fixed effects panel regression approach to forecasting basis, and (ii) by demonstrating how inclusion of another indicator of current market conditions (weekly soil moisture at grain elevator locations) impacts the accuracy of our harvest basis forecasts. Our results show that including soil moisture in basis forecasts leads to an improvement in accuracy (as measured by RMSE) relative to a baseline model from the fourth week of the growing season onward. We find the results of our model are robust to different specifications of soil moisture and to inclusion of additional weather and price covariates.

The performance of our preferred model is however sensitive to the geographic extent of our data. We find our preferred model produces more accurate (relative to the baseline) forecasts, in general, when using data from smaller geographic regions, and that aggregating up to multi-state regions produces forecasts that converge to the (5-year historical average) baseline. This is in keeping with the panel forecasting literature (Baltagi 2013) which argues that pooling observations at a large geographic scale can lower forecasting performance and that construction of models (e.g. spatial autoregressive error model) that explicitly account for spatial dependencies can improve performance. For now, we leave the tasks of determining the selection of the geographic scope of our data and comparing our preferred model to an explicitly spatial econometric model for future research.

We hope the results of our analysis can be useful to extension professionals, but we must advise caution in applying our preferred model to elevator-specific forecasts. As mentioned earlier, determination of the set of elevators' price data to include in training the model is critical to its forecasting accuracy. It is also very important to not assume that the preferred model can be used in forecasting basis at some point in the year other than at harvest and that our model can accurately forecast harvest basis for crops other than winter wheat. The implicit assumption underlying our analysis was that a growing season's soil moisture will have the largest impact on local supply, and thus the basis level, at harvest-time when crop production for a year is realized. Therefore, we recommend using our preferred model for middle- and end-of-season harvest basis forecasts and using already established model (a 5-year moving average; Taylor et al. 2006) for the earliest (i.e. forecasts made in the first three weeks of September) season harvest basis forecasts and for all post-harvest basis forecasts.

Footnotes

[1] The growing season differs by geographic location, based on local climate conditions – however for the purposes of comparison, we defined a growing season that begins in the first week of September and ends the fourth week in June, irrespective of elevator location.

[2] Prior to estimation all covariates were demeaned – that is the levels of the covariates were subtracted by their averages over years (i.e. $\tilde{x}_{it} = x_{it} - \bar{x}_i$), such that fixed effects parameters were not directly estimated.

[3] The first five year's harvest basis (2005) could not be forecasted because the preferred model requires the prior year's harvest basis observations.

[4] Inclusion of higher degree soil moisture polynomials beyond cubic terms did not provide any noticeable further reductions in RMSE.

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Table 1. Summary Statistics for Forecasting Data

Variable	State	Mean	Std Dev	Min	Max
# of elevators by year	*Colorado*	28.87	7.05	11	36
	Kansas	361.54	76.11	140	478
	Nebraska	101.16	14.97	11	112
	North Dakota	19.15	7.44	5	35
	Oklahoma	34.80	10.21	6	54
	South Dakota	54.22	11.91	10	70
	Texas	25.73	7.71	4	37
	Wyoming	3.56	1.10	1	5
# of years by elevator	*Colorado*	10.99	2.57	3	14
	Kansas	10.82	2.64	1	14
	Nebraska	10.78	2.31	1	14
	North Dakota	8.34	3.05	1	12
	Oklahoma	9.29	2.92	1	14
	South Dakota	10.66	2.30	2	14
	Texas	9.36	2.38	2	14
	Wyoming	9.47	2.57	5	12
Harvest basis ($)		-0.49	0.38	-2.25	2.18
KBOT July futures – week 1 ($)		6.30	1.59	3.47	8.84
KBOT July futures - week 9 ($)		6.17	1.51	3.38	9.29
KBOT July futures - week 29 ($)		6.19	1.83	3.22	9.95
KBOT July futures - week 37 ($)		6.07	1.50	3.32	9.06
Soil moisture - week 1		0.20	0.05	0.04	0.37
Soil moisture - week 9		2.49	0.06	0.04	0.37
Soil moisture - week 29		0.74	0.06	0.04	0.39
Soil moisture - week 37		0.21	0.05	0.04	0.35
10ºC dday - week 1		193.66	143.99	27.98	1141.26
10ºC dday - week 9		1023.26	771.74	148.81	6375.672
10ºC dday - week 29		1364.40	1052.71	148.81	8765.35
10ºC dday - week 37		2,199.33	1668.41	232.43	12,878.43
30ºC dday - week 1		7.05	9.61	0	103.07
30ºC dday - week 9		16.92	19.61	0	173
30ºC dday - week 29		17.16	20.15	0	173
30ºC dday - week 37		24.70	28.15	0	249.36

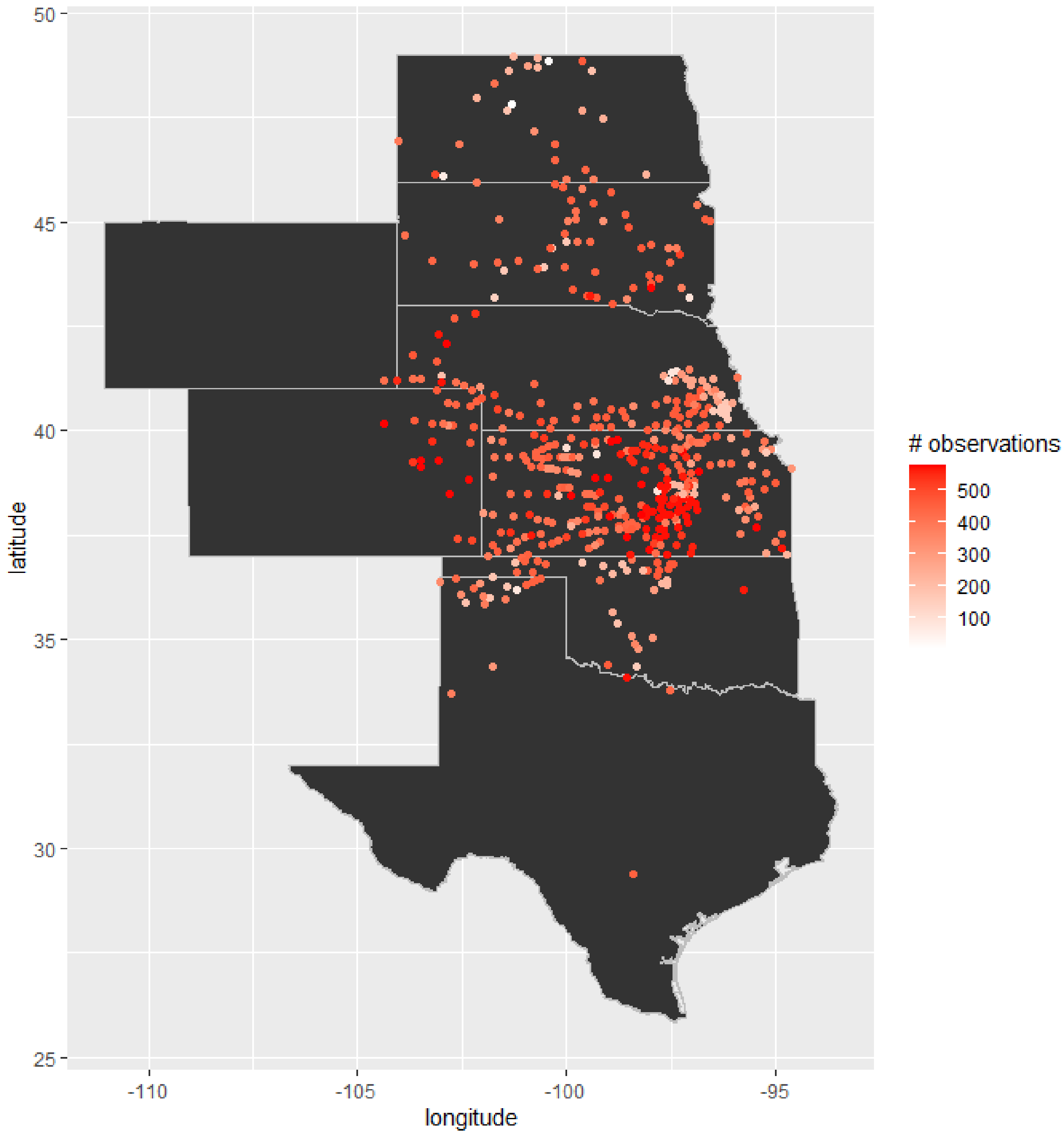

Figure 1. Number of Total Weekly Basis Observations by Elevator Location, Years 2005-2019

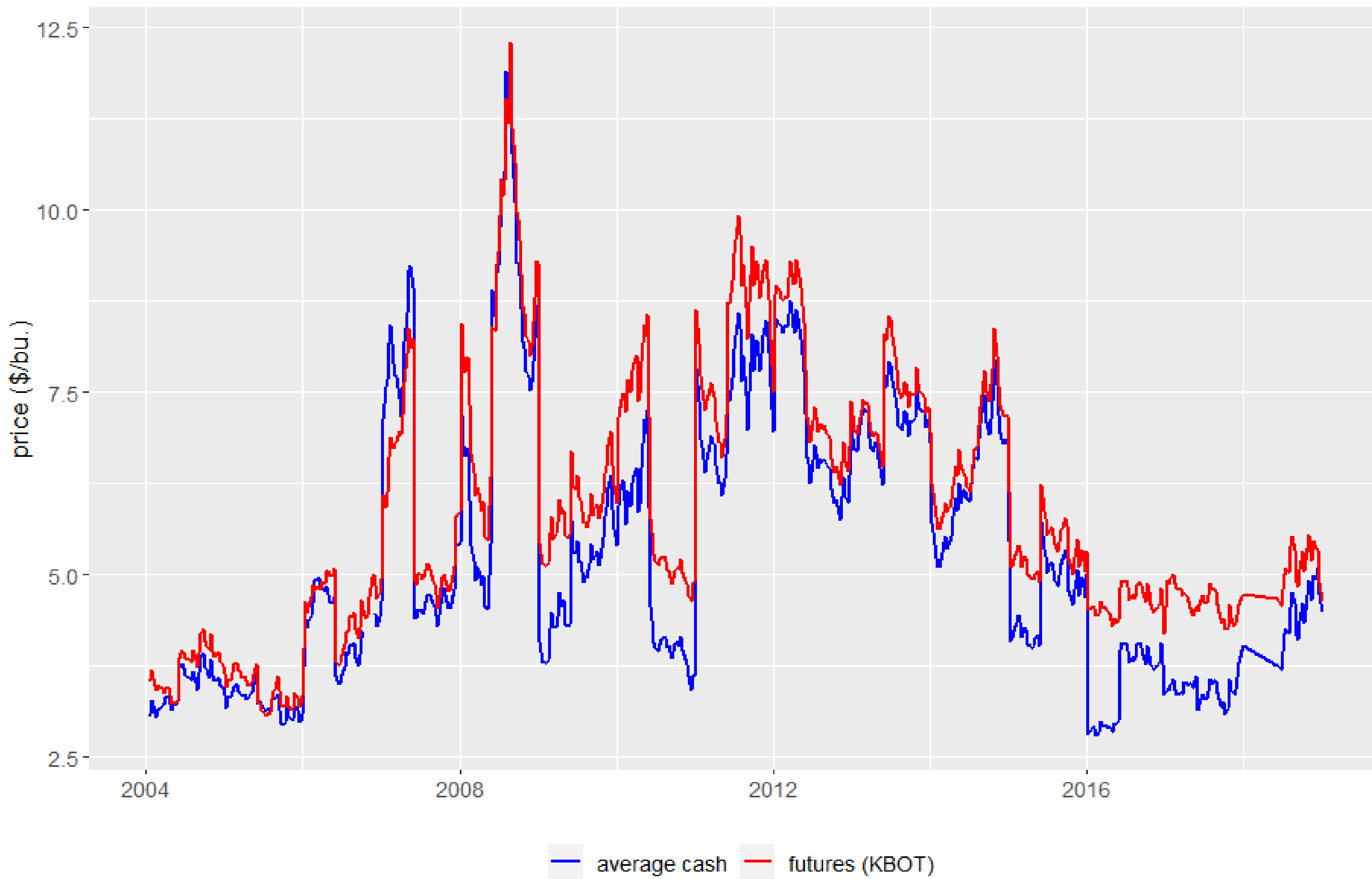

Figure 2. Average Kansas Cash and Kansas City Board of Trade (KBOT) July Futures Hard Red Winter Wheat Contract Prices, 2004-2019.

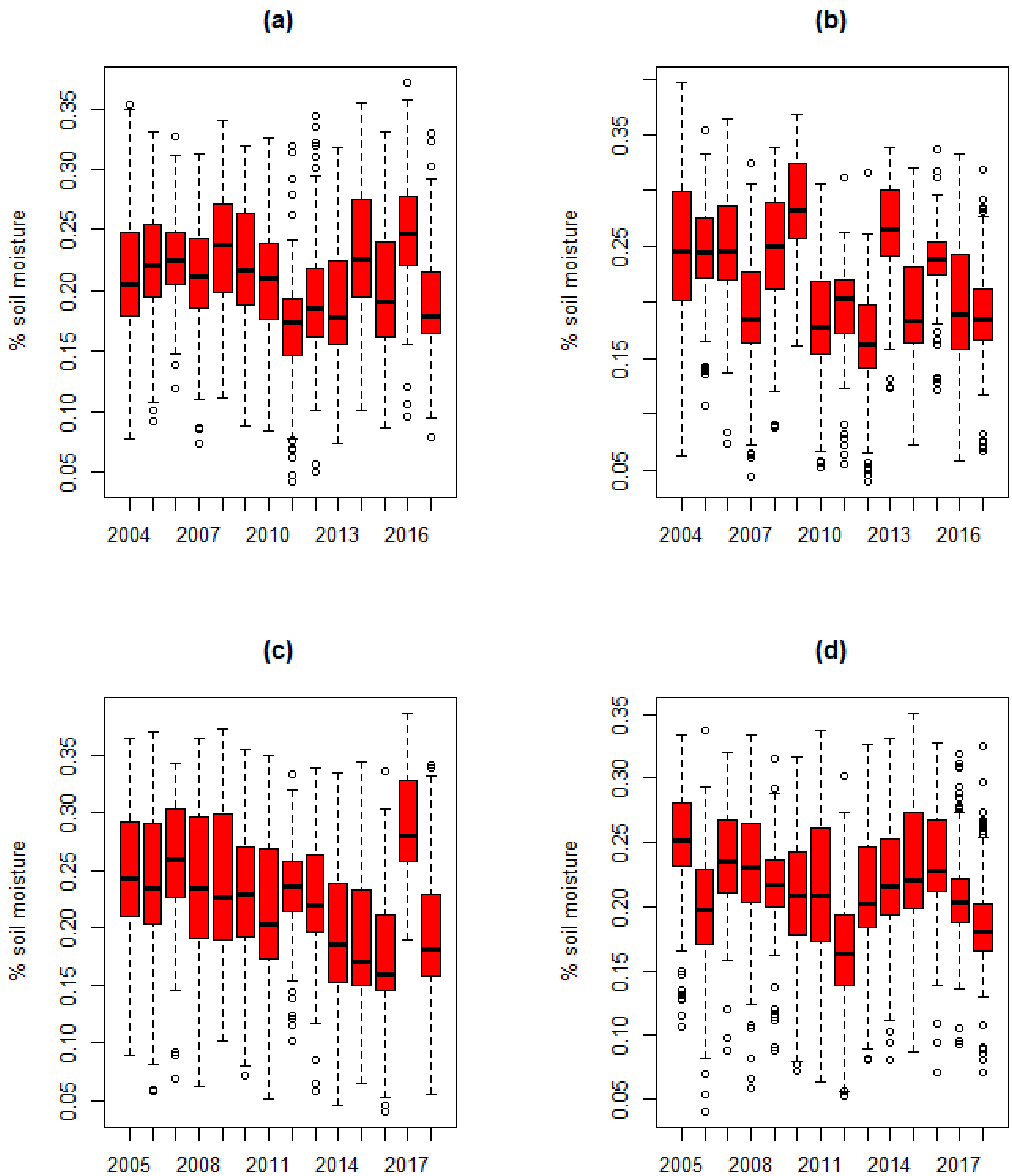

Figure 3. Boxplots of soil moisture at Kansas elevator locations, years 2004-2018, at different points in the marketing year. Figures 3a, 3b, 3c, and 3d show respectively soil moisture readings on the first week in September, November, April, and June.

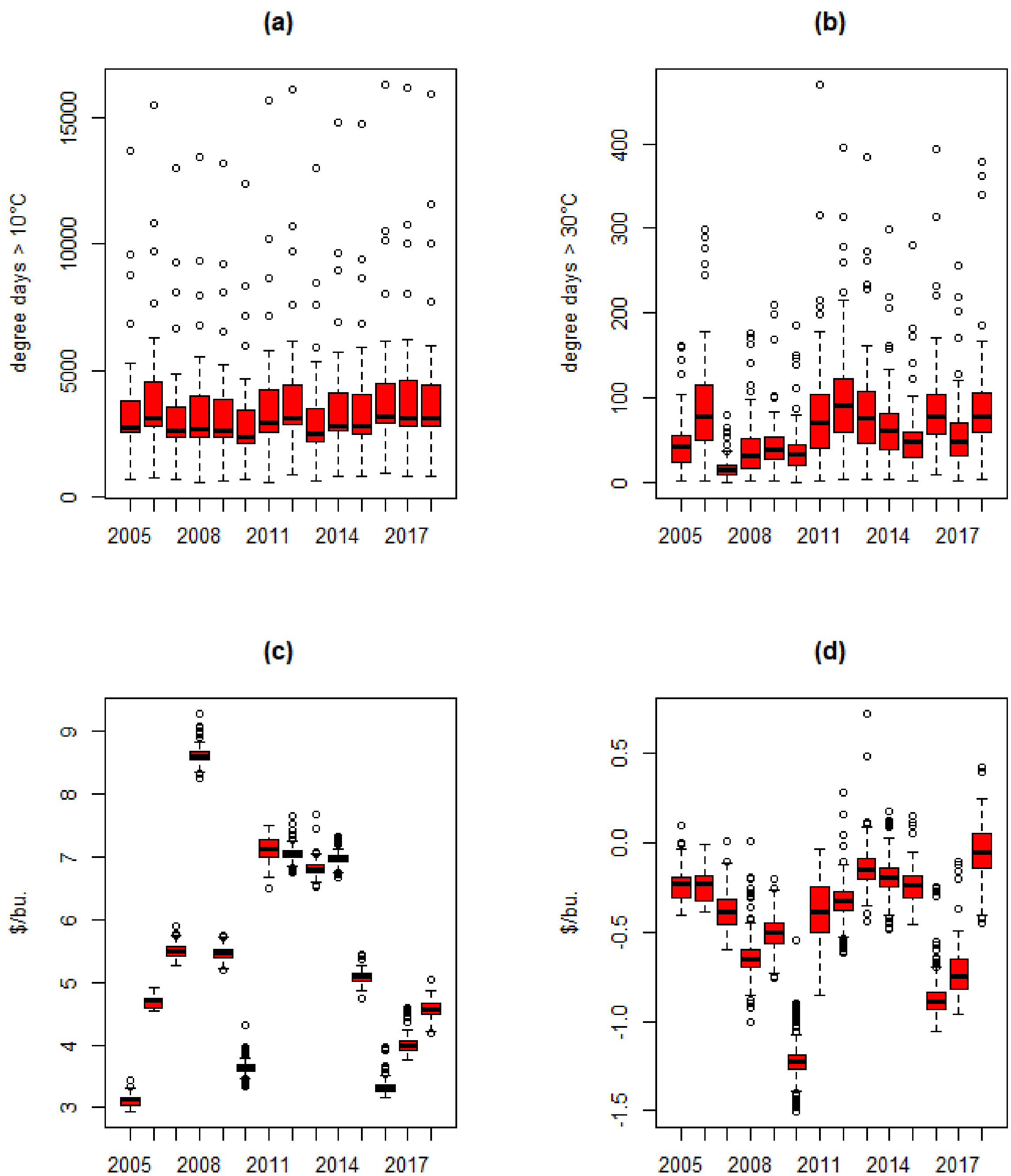

Figure 4. Boxplots of degree days and prices at harvest (the 40th week in the marketing year) at Kansas elevators, years 2005-2018. Figures 4a and 4b show respectively degree days in excess of 10ºC and degree days in excess of 30ºC; figures 4c and 4d show respectively spot prices and basis levels.

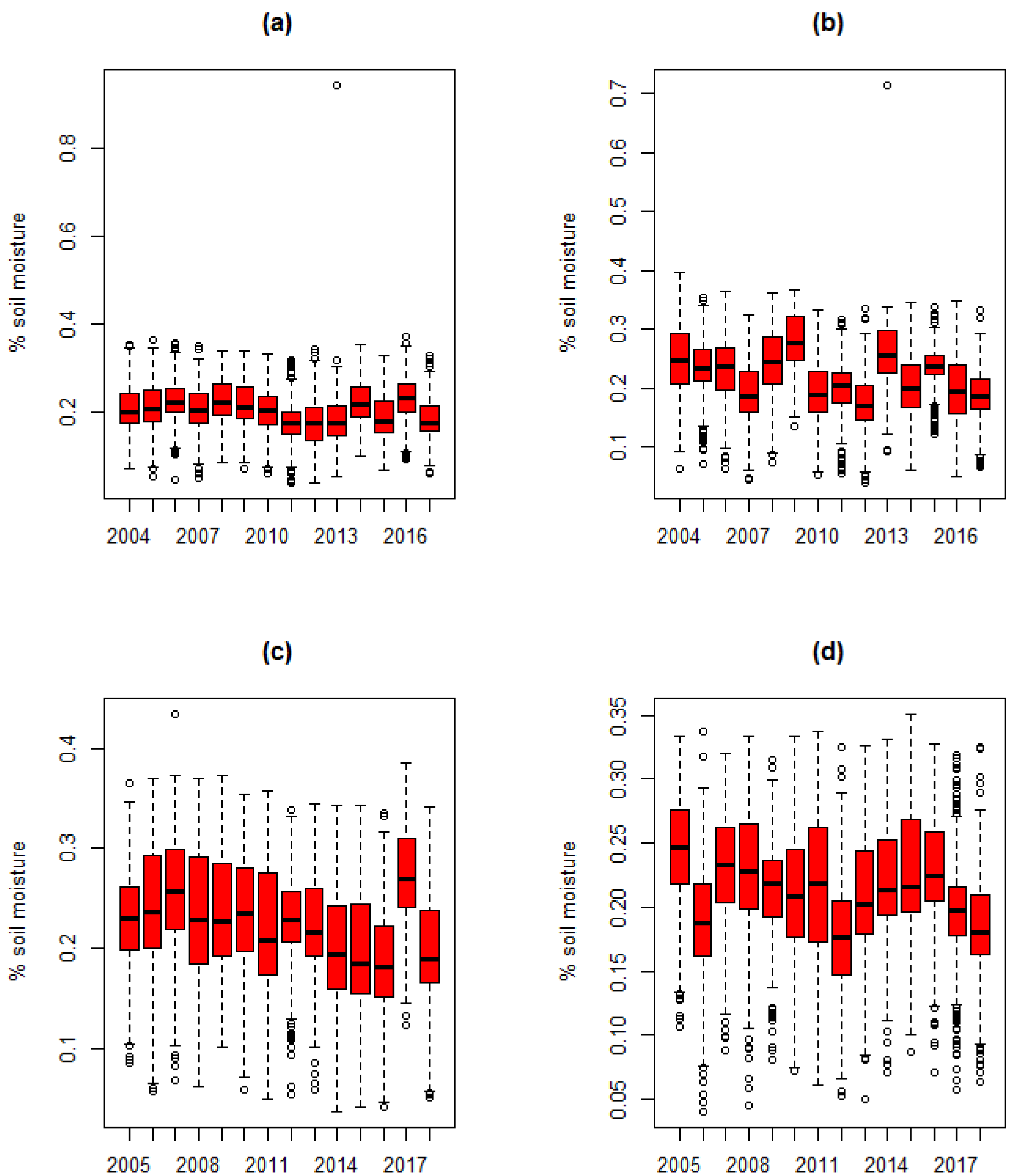

Figure 5. Boxplots of soil moisture at all Great Plains elevator locations, years 2004-2018, at different points in the marketing year. Figures 5a, 5b, 5c, and 5d show respectively soil moisture readings on the first week in September, November, April, and June.

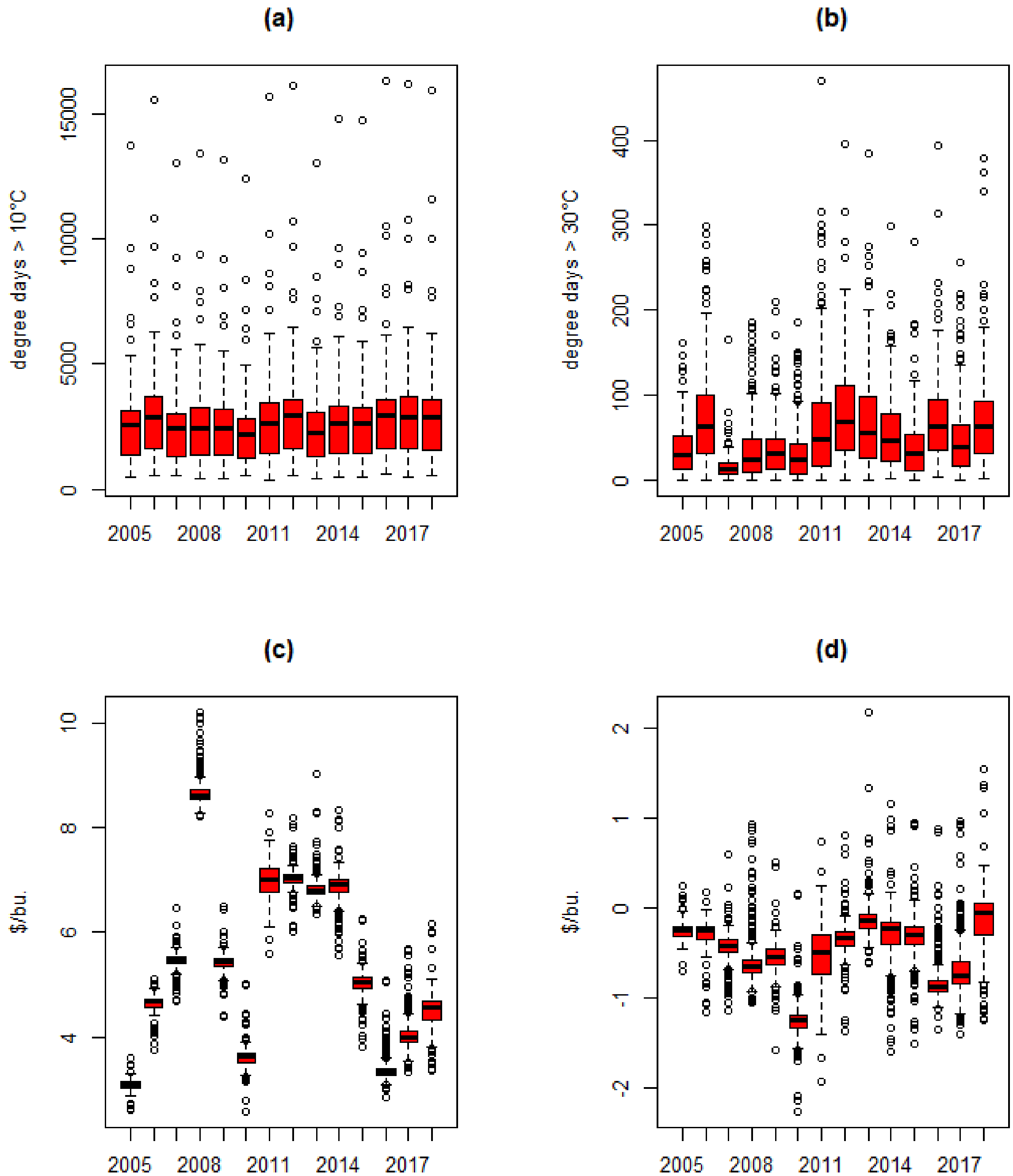

Figure 6. Boxplots of degree days and prices at harvest (the 40th week in the marketing year) at all Great Plains elevator locations, years 2005-2018. Figures 6a and 6b show respectively degree days in excess of 10ºC and degree days in excess of 30ºC; figures 6c and 6d show respectively spot prices and basis levels.

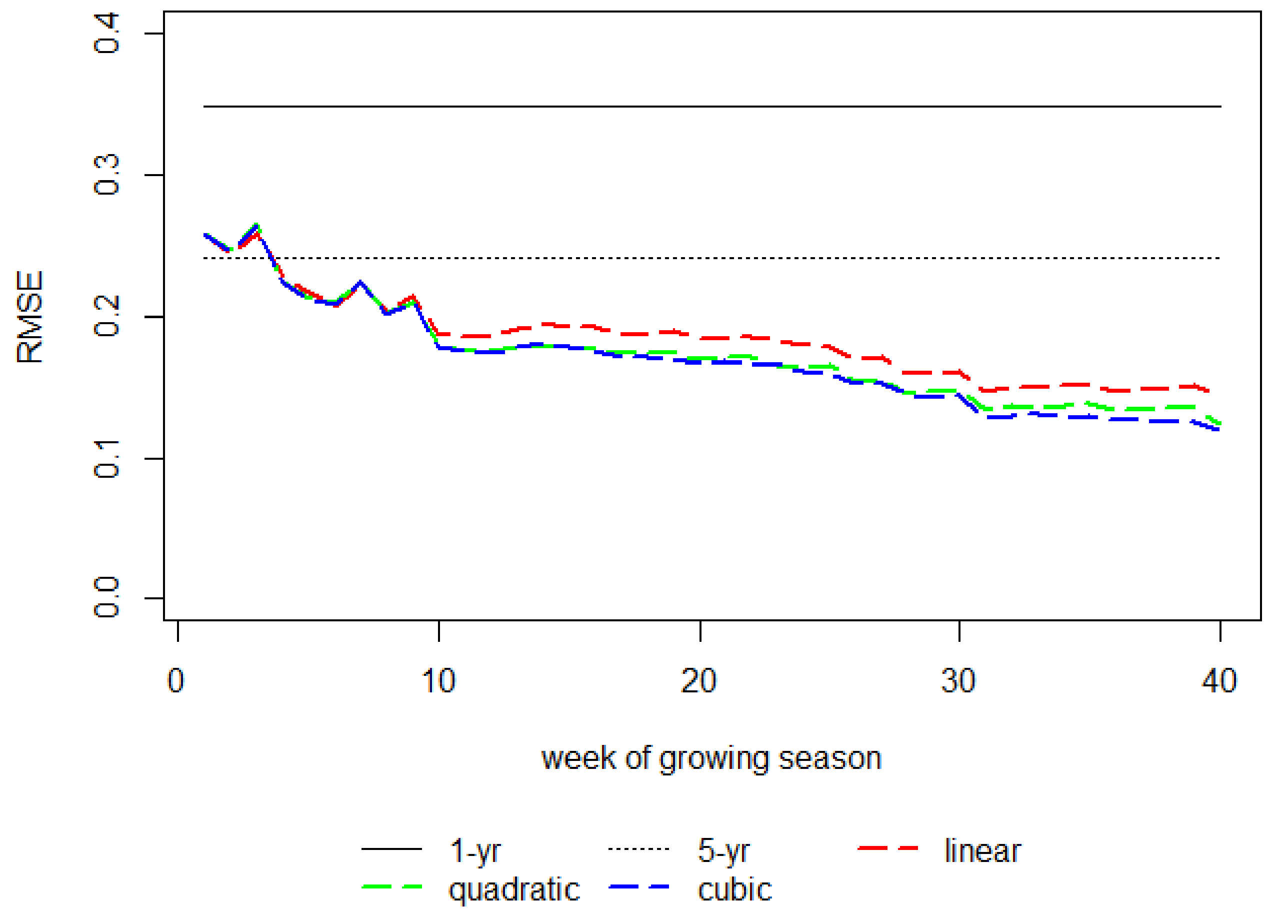

Figure 7. Out-of-sample performance (measured as RMSE) of the baseline models (the gray dotted and solid horizontal lines) and models that include weekly soil moisture (the dashed lines) using Kansas elevator data. The dashed red and green lines are the out-of-sample performance of models that add (respectively) linear and quadratic weekly soil moisture terms. The dashed blue line is the out-of-sample performance of a model that adds cubic soil moisture terms (i.e. the 'preferred' model).

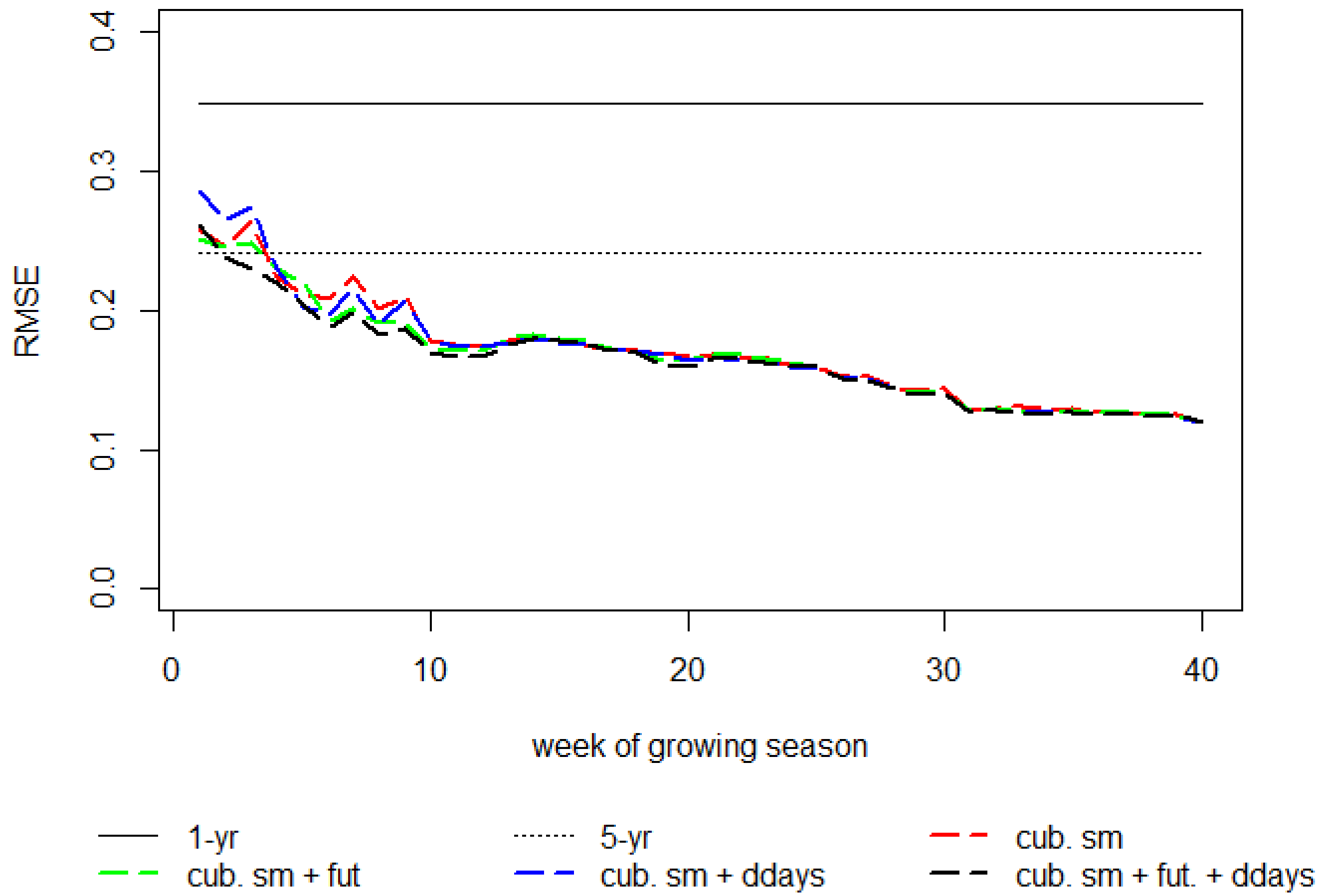

Figure 8. Out-of-sample performance (measured as RMSE) of the baseline model (the gray dotted and solid horizontal lines), the 'preferred' model (the dashed red line), and alternative models (the other dashed lines) which admit additional weather and price covariates using Kansas elevator data. The model associated with the dashed green line adds current KBOT July futures winter wheat price, the model associated with the dashed blue line adds two degree day variables (one measuring degree days greater than 10ºC and one measuring degree days greater than 30ºC), and the model associated with the dashed black line adds both the current KBOT July futures winter wheat price and the two degree day variables.

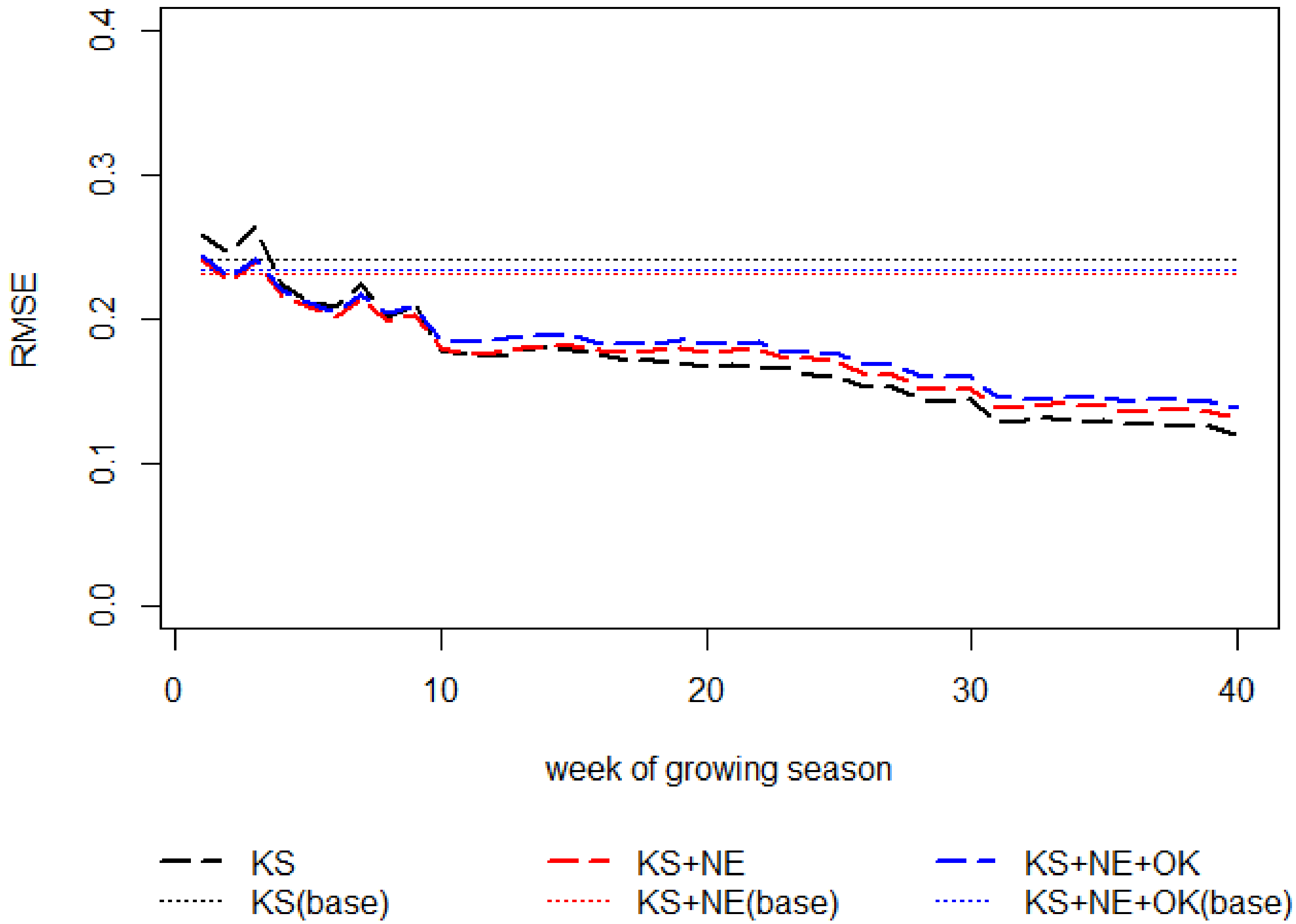

Figure 9. Out-of-sample performance (measured as RMSE) of the baseline model (the dotted horizontal lines) and the preferred model (the dashed lines) when forecasting at three different geographic scales: Kansas (black lines), Kansas and Nebraska (red lines), and Kansas, Nebraska, and Oklahoma (blue lines).

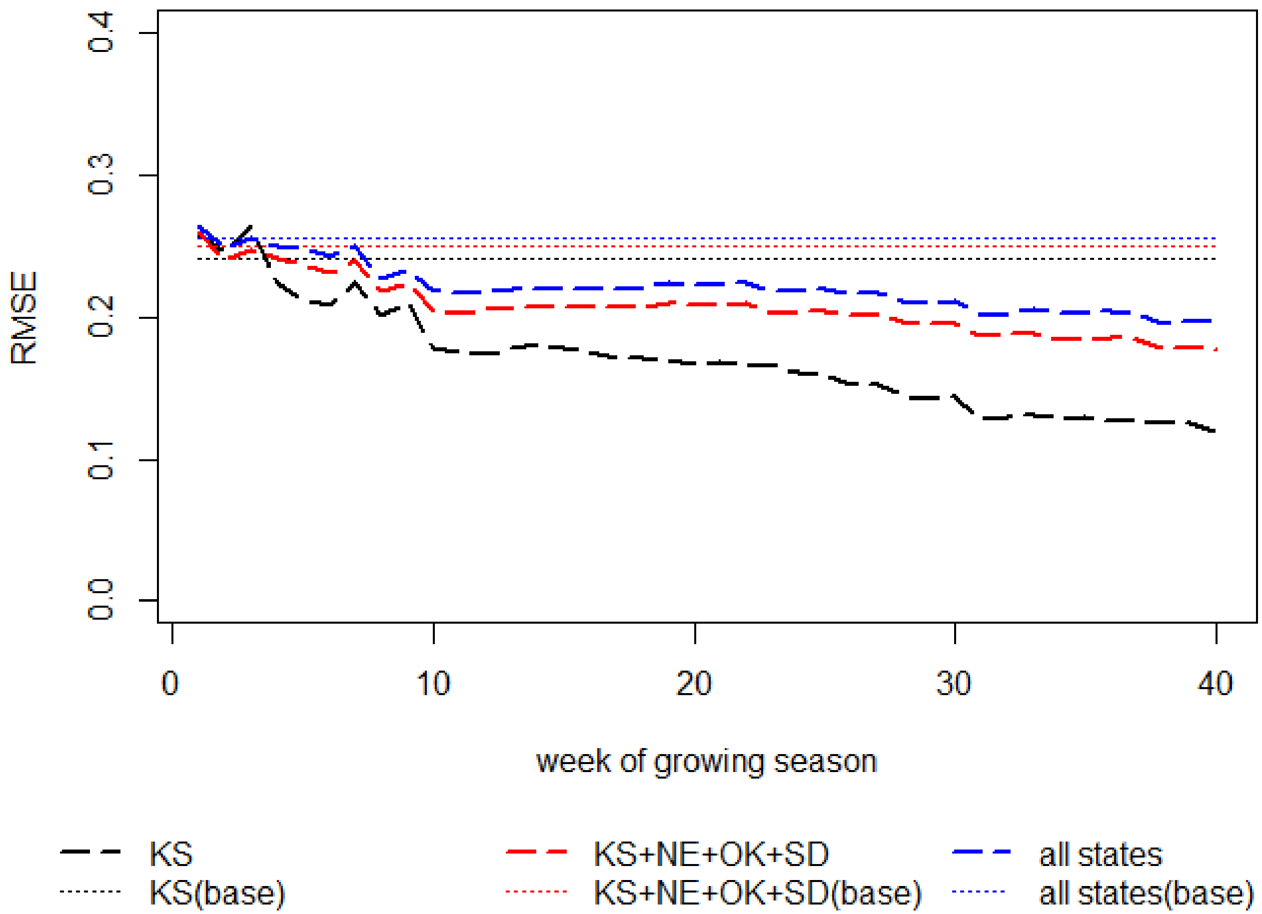

Figure 10. Out-of-sample performance (measured as RMSE) of the baseline model (the dotted horizontal lines) and the preferred model (the dashed lines) when forecasting at three different geographic scales: Kansas (black lines), Kansas, Nebraska, Oklahoma, and South Dakota (red lines), and all states in the study region (blue lines).

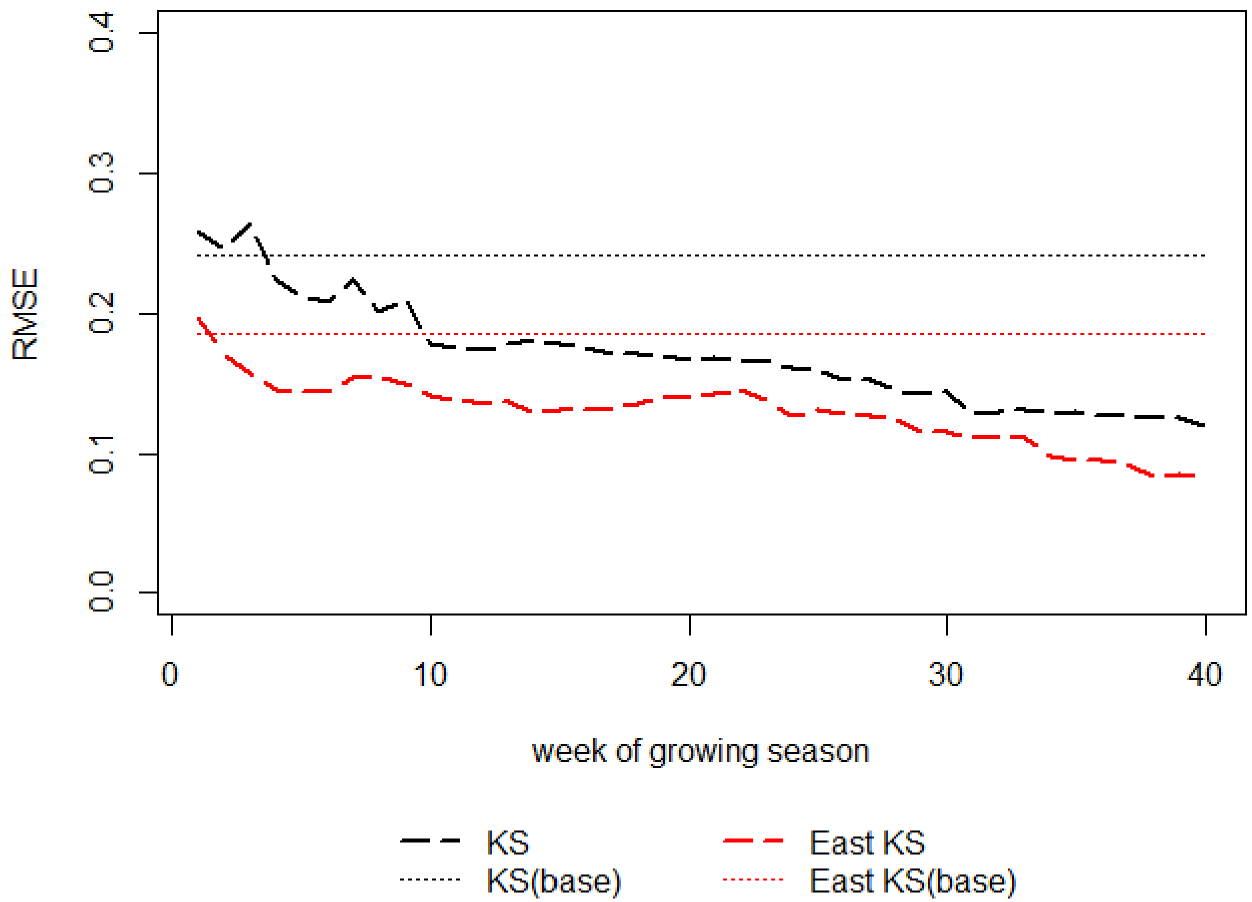

Figure 11. Out-of-sample performance (measured as RMSE) of the baseline model (the dotted horizontal lines) and the preferred model (the dashed lines) when forecasting across the entire state of Kansas (black lines) and across Eastern Kansas (red lines).

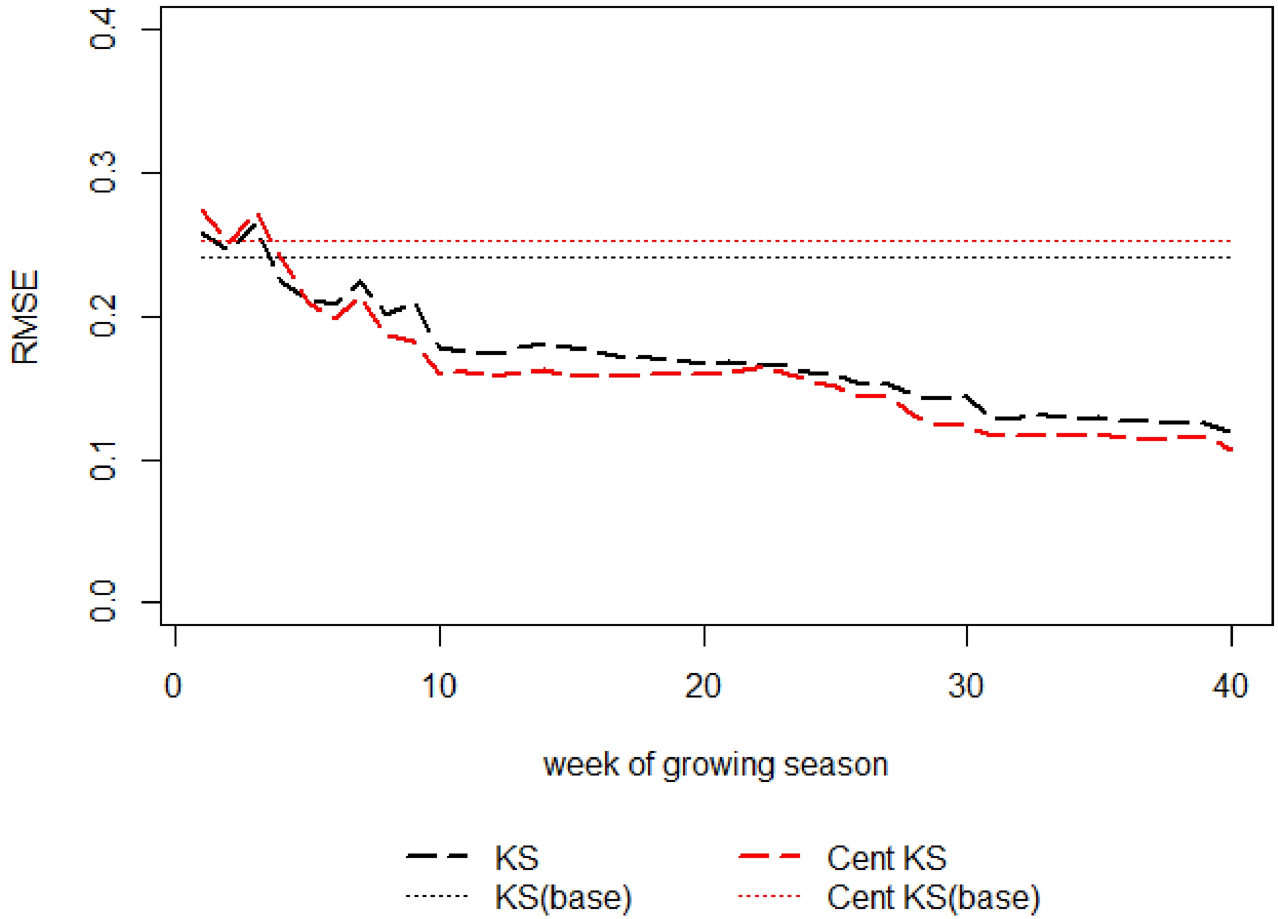

Figure 12. Out-of-sample performance (measured as RMSE) of the baseline model (the dotted horizontal lines) and the preferred model (the dashed lines) when forecasting across the entire state of Kansas (black lines) and across Central Kansas (red lines).

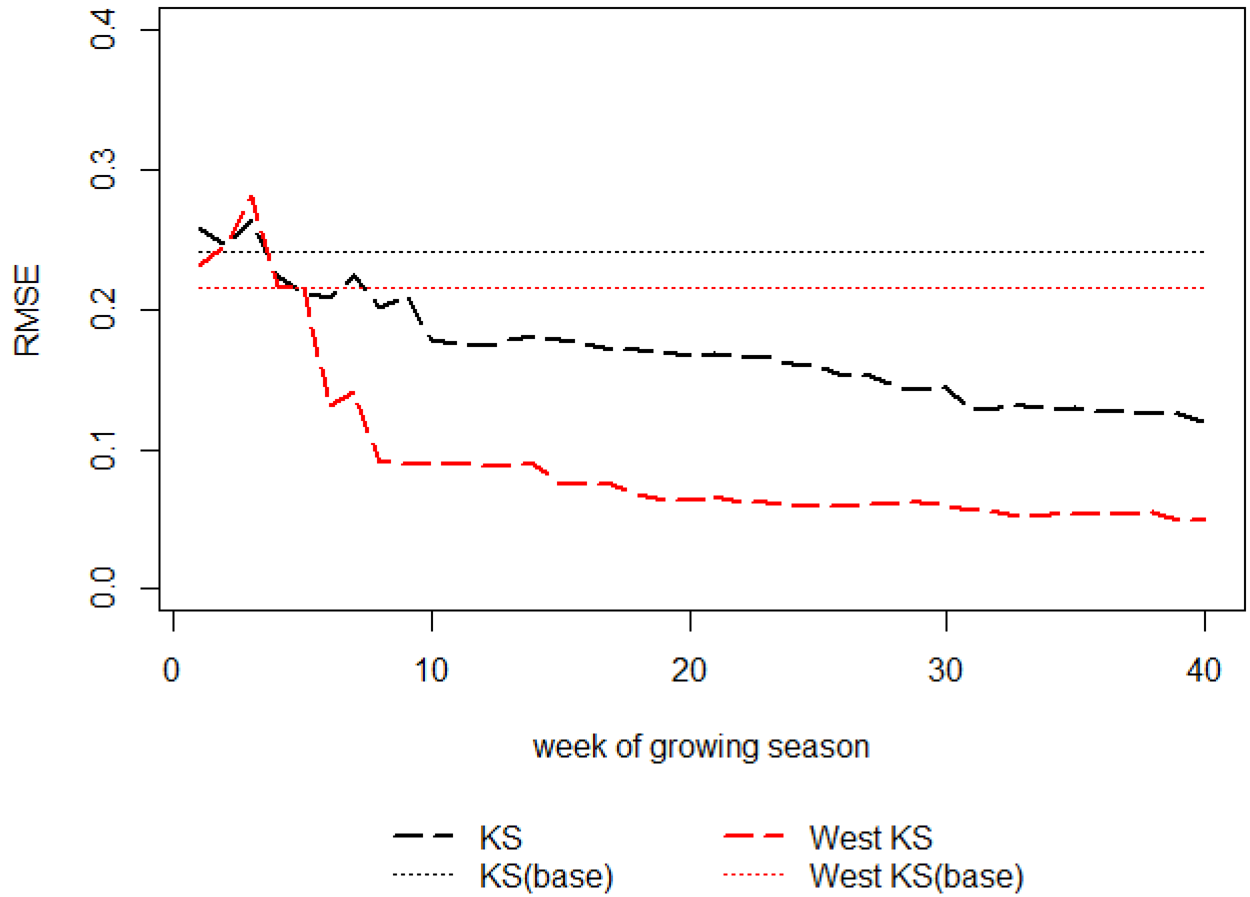

Figure 13. Out-of-sample performance (measured as RMSE) of the baseline model (the dotted horizontal lines) and the preferred model (the dashed lines) when forecasting across the entire state of Kansas (black lines) and across Western Kansas (red lines).