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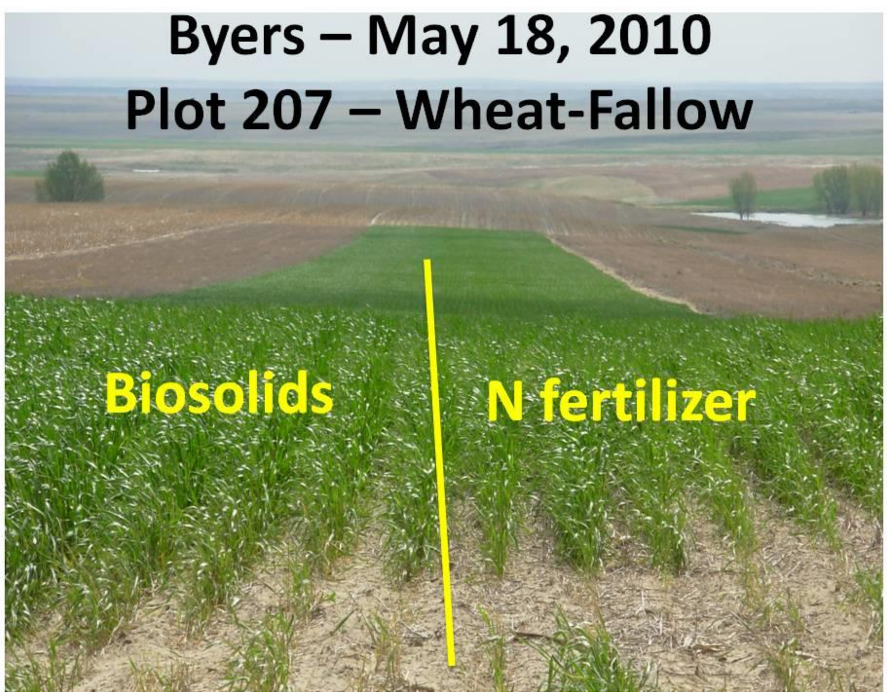
Regression Modeling Weather and Biosolids Effects on Dryland Wheat Yields in Eastern Colorado, 2001-2012



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Regression Modeling Weather and Biosolids Effects on Dryland Wheat Yields in Eastern Colorado

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ABSTRACT

In the western Great Plains, climate dictates dryland wheat (*Triticum aestivum*, L) productivity. Producers use inorganic N fertilizers to improve crop yields in this region, while municipalities recycle sewage biosolids in the area. Will biosolids (from the Littleton/Englewood, CO Wastewater Treatment Plant) applications to western Great Plains dryland agroecosystems interact with weather to affect wheat production? To this end, we regressed crop yields on weather variables from 2000 through 2011 at a site about 40 km (approximately 25 miles) east of Byers, CO (Byers). We used SAS (Proc Reg) to develop several multiple regression models to predict crop yields. Our model of choice included four weather parameters for Byers wheat production. Regression variables included September and May precipitation and October and May monthly mean temperatures. Biosolids or nitrogen fertilizer application did not appear in our chosen model. We validated the wheat models using weather data and yields from the Colorado State University (CSU) Crops Testing Program from Akron, Burlington, Lamar, and Yuma, CO. According to t-tests comparing mean observed and predicted yields, the Byers model predicted yields from 2000-2011 at these locations with a +5.3% mean absolute error. A positive result of these analyses is that biosolids produced the same crop yields as commercial N fertilizer from 2001 through 2011.

INTRODUCTION

Extreme heat and drought often plague dryland crop production in the West Central Great Plains. Development of multiple regression models that account for weather variability could provide a predictive tool for dryland wheat and corn producers using wheat-fallow or wheat-corn-fallow rotations. For example, Nielsen et al. (2010) used regression analyses to determine that the critical rainfall period for dryland corn grown at Akron, CO was between 16 July and 26 August. Their model, however, did not include temperature effects. Lauenroth et al. (2000) used mean annual precipitation and temperature to model winter wheat production in northeastern CO and northern KS. They postulated that regions with annual precipitation ≥ 39.5 cm (15.6 inches) rendered wheat-fallow (WF) rotations as inefficient water-management systems. Most of eastern Colorado receives less than 39.5 cm (15.6 inches) of precipitation in any given year, and thus WF may be a useful system for that region.

Several researchers have developed multiple regression models using weather variables to predict wheat yields (Landau et al., 1998, 2000; Smith and Gooding, 1999; Porter and Gawith, 1999; Lobell and Burke, 2010). All of the referenced models utilized precipitation and temperature data to predict yields with the primary focus on production in the United Kingdom. Landau et al. (2000) developed conservative models based on wheat phenology; anthesis dates were critical in their predictive models. Lobell and Burke (2010) stated: "Results suggest that statistical models, as compared to CERES-maize, represent a useful if imperfect tool for projecting future yield responses, with their usefulness higher at broader spatial scales." CERES-maize is a corn (*Zea mays*, L.) growth and development simulation model.

Because of low leaching or runoff potential of NO_3-N released from biosolids when used as a fertilizer, eastern Colorado is considered an ideal location for biosolids recycling (Lerch et al., 1990). Barbarick et al. (2010, 2012) have conducted long-term studies on the efficacy of biosolids application in dryland wheat-fallow and wheat-corn-fallow rotations. They reported a above county average yield response (above 2 Mg ha^{-1} or 30 bushels/acre) to biosolids or N fertilizer applications when above mean precipitation was received. Below mean annual rainfall usually produced no response to either type of fertilizer. Also, temperature effects on yields seemed common. For example, the highest May mean maximum temperature (24.7^{o}C or 76.5^{o}F) from 1999-2011 was observed in 2006 (Table 1) and a wheat-crop failure was experienced that year. Consequently, we decided to determine what weather parameters, and if biosolids or nitrogen fertilizer applications significantly affected wheat yields from 2001 to 2011. Nielsen and Vigil (2009) discussed the importance of stored soil moisture on wheat production in WF rotations. Basically our study was not originally intended to be a model development project and thus no planting time soil water data were collected.

Our hypotheses were:

1). Wheat yields could be predicted by multiple regression models utilizing weather variables and consideration of biosolids or nitrogen fertilizer application at the Byers research site. We used SAS Institute (2013) Proc Reg to find the most conservative model that had an R^2 of 0.90 or greater, Mallow's Cp less than the number of regression variables in the model, and a Durbin-Watson value near 2.0 ± 0.5.

2). If the model of choice does not contain biosolids addition or N rates as regression variables, then the model's yield predictions will match yields (according to t-tests) from the CSU Crops Testing Program at Akron, Burlington, Lamar, and Yuma, CO.

MATERIALS AND METHODS

The Byers research site in eastern Adams County is located on land owned by the Cities of Littleton and Englewood (L/E). The latitude/longitude for the plot corners are 39.7631921/103.7973089 (southwest), 39.7631773/103.7881839 (southeast), 39.7686818/103.7972862 (northwest), 39.7686588/103.7881651 (northeast). Soils belong to the Adena-Colby association (Adena soil is classified as a fine-loamy, mixed, active mesic Ustic Paleargid and Colby is classified as a fine-silty, mixed, superactive, calcareous, mesic Aridic Ustorthent; Natural Resource Conservation Service, 2013). No-till management was used in conjunction with crop rotations of WF and wheat-corn-fallow (WCF). We installed a Campbell Scientific® weather station at the north edge of the plots in April 2000. Mean weather data are presented in Table 1.

Table 1. Range and mean of weather factors at the Byers research sites, 1999-2011.

Month	Maximum temp.	Mean	Minimum temp.	Mean	Precipitation	Mean
	---------------------------- °C[†]		----------------------------		---------- cm[‡]	----------
January	-0.6 – 11.2	9.5	-11.7 - -4.2	-7.0	0.00 – 0.69	0.20
February	3.3 – 11.3	6.8	-9.4 – -4.1	-7.1	0.00 – 0.64	0.23
March	10.0 – 16.2	12.6	-7.2 – 0.8	-2.6	0.25 – 2.59	1.04
April	15.0 – 19.5	16.9	-1.1 – 3.1	1.2	0.76 – 6.38	3.15
May	18.9 – 24.7	22.1	3.3 – 7.7	6.2	2.03 – 9.52	4.29
June	25.0 – 31.9	28.4	10.6 – 13.8	11.8	0.76 – 12.0	4.93
July	30.6 – 36.3	33.0	13.9 – 16.8	15.8	0.51 – 9.12	3.48
August	28.3 – 32.8	30.8	12.8 – 16.4	14.6	3.81 – 17.4	6.48
September	22.2 – 29.0	26.8	7.2 – 11.1	9.7	0.00 – 3.66	1.60
October	12.2 – 22.4	18.6	-0.6 – 5.1	3.0	0.25 – 3.20	1.32
November	8.9 – 13.8	12.1	-4.4 – -1.0	-2.3	0.00 – 1.96	0.64
December	2.2 – 8.8	6.2	-11.1 – -5.2	-7.2	0.00 – 0.41	0.10
Total					23.9 - 40.4	27.5

† $°\mathrm{F} = (°\mathrm{C} * 1.8) + 32$

‡ $inches = \frac{cm}{2.54}$

All phases of each rotation were present each year (10 total plots per replication) in a random complete block design in a split-plot arrangement with two replications. Each plot was 30 m (100 feet) wide by approximately 0.80 km (0.5 mile) long. Each 30-m (100 feet) plot was split so that one 15-m (50-foot) section received commercial N fertilizer and the second 15-m (50-foot) section received biosolids (applied by L/E with a rear-discharge manure spreader). The biosolids and N fertilizer treatments were first applied in fall 1999. We estimated that each Mg (metric ton or ton) of dry biosolids would provide 8 kg (16 pounds) available N for each application (Barbarick and Ippolito, 2000, 2007). Biosolids and N fertilizer rates were based on soil test recommendations for each crop. The last biosolids and N fertilizer application was fall of 2004. Because of underestimation of N mineralization from the biosolids and drought-induced crop failures where no N was removed from the soil (Barbarick et al., 2012), NO_3-N accumulated to the extent that N additions were not required in subsequent years based on soil testing and fertilizer recommendations for dryland winter wheat (Davis and Westfall, 2009). Wheat was harvested in July 2000 through 2010, except 2006 when a crop failure was experienced. The grain was harvested from four areas of 1.5 m (5 feet) by approximately 30 m (100 feet) within each subplot. The models were developed using 2000-2011 yield data. We employed our selected model for Byers to estimate the 2012 yields.

We employed SAS Proc Reg (SAS Institute, 2013) to develop multiple regression models using the variables listed in Table 2. We focused on the Maximum R^2 Improvement (MAXR), Minimum R^2 Improvement (MINR), Adjusted R^2 Selection (ADJRSQ), and Mallow's Cp Selection (CP; Mallows, 1973) model selections. We eliminated models which contained nonsensical parameters such as a negative effect of March precipitation on wheat production.

Table 2. Model parameters used in multiple regression analyses for wheat at Byers.

Byers wheat
• Each month's mean maximum temperature
• Each month's mean minimum temperature
• Monthly mean temperature
• Each month's total precipitation
• Each month's total evapotranspiration
• Rotation (1=WF, 2=WCF)
• September through March precipitation (vegetative phase)
• April through June precipitation (reproductive phase)
• Total precipitation (July through June)
• Total evapotranspiration (July through June)
• Growing season precipitation (September through June)
• Type of fertilizer (N fertilizer=1 or biosolids=2)
• Number of fertilizer applications
• Ratio of monthly precipitation to mean maximum temperature
• Interaction between monthly precipitation and mean monthly maximum

When screening the regression results, we used selected models that had an R^2=0.90 or greater, a Mallow's Cp less than the number of regression variables in the model, and a Durbin-Watson (Durbin and Watson, 1950, 1951) value near 2.0 ± 0.5. Also, we utilized an F-test (Graphpad.com, 2013) to compare our models to more complicated models (i.e., with more regressors) to ensure parsimony.

If the models did not include a biosolids/N fertilizer parameter, we used our wheat models to predict yields for similar wheat varieties (Prairie Red or Ripper depending on the year) grown in the CSU Crops Testing Program at Akron, Burlington, Lamar, and Yuma, CO from 2000 to 2012 (Colorado Agricultural Experiment Station, 2013). These locations were selected since they had the same Campbell Scientific® weather station model that we used at the Byers location. The data were available from CoAgMet (CoAgMet, 2013). Not all weather data were available for all sites for all years due to weather station errors or shutdowns. We did not include data for the years where key weather data was missing in our model development. We used a paired-wise t-test to determine if a statistical difference (*P*=0.05) existed between mean observed and mean predicted yields. We also calculated the %mean absolute error for each model and model test.

RESULTS AND DISCUSSION

Models

Table 3 provides the model that best met the criteria of the fewest regression variables with an R^2 of 0.90 or greater, a Mallow's Cp less than the number of regression variables in the model, and a Durbin-Watson value near 2.0 ± 0.5. September precipitation, October mean temperature, and May precipitation had significant positive impacts on wheat yields.

Table 3. Selected multiple regression model parameters for weather and biosolids or N fertilizer effects on grain yields at Byers research site, 2000-2011.

Variable	Model Coefficient ± std. error	t value	Probability	Partial or Total R^2	Mallow's C_p	Durbin Watson D
September precip., cm	0.59 ± 0.22	2.65	0.016	0.520		
October mean temp., °C	0.21 ± 0.13	1.64	0.119	0.177		
May precip., cm	0.41 ± 0.08	5.36	<0.001	0.181		
May mean temp., °C	-0.20 ± 0.11	-1.81	0.087	0.019		
Total model				***0.897***	***3.76***	***1.68***

$$
\begin{aligned}
&wheat\ yield, \frac{Mg}{ha} = \\
&+0.59(Sep.\,precip., cm) \\
&+0.21(Oct.\,mean\ temp., ^\circ\mathrm{C}) \\
&+0.41(May\ precip., cm) \\
&-0.20(May\ mean\ temp., ^\circ\mathrm{C})
\end{aligned}
$$

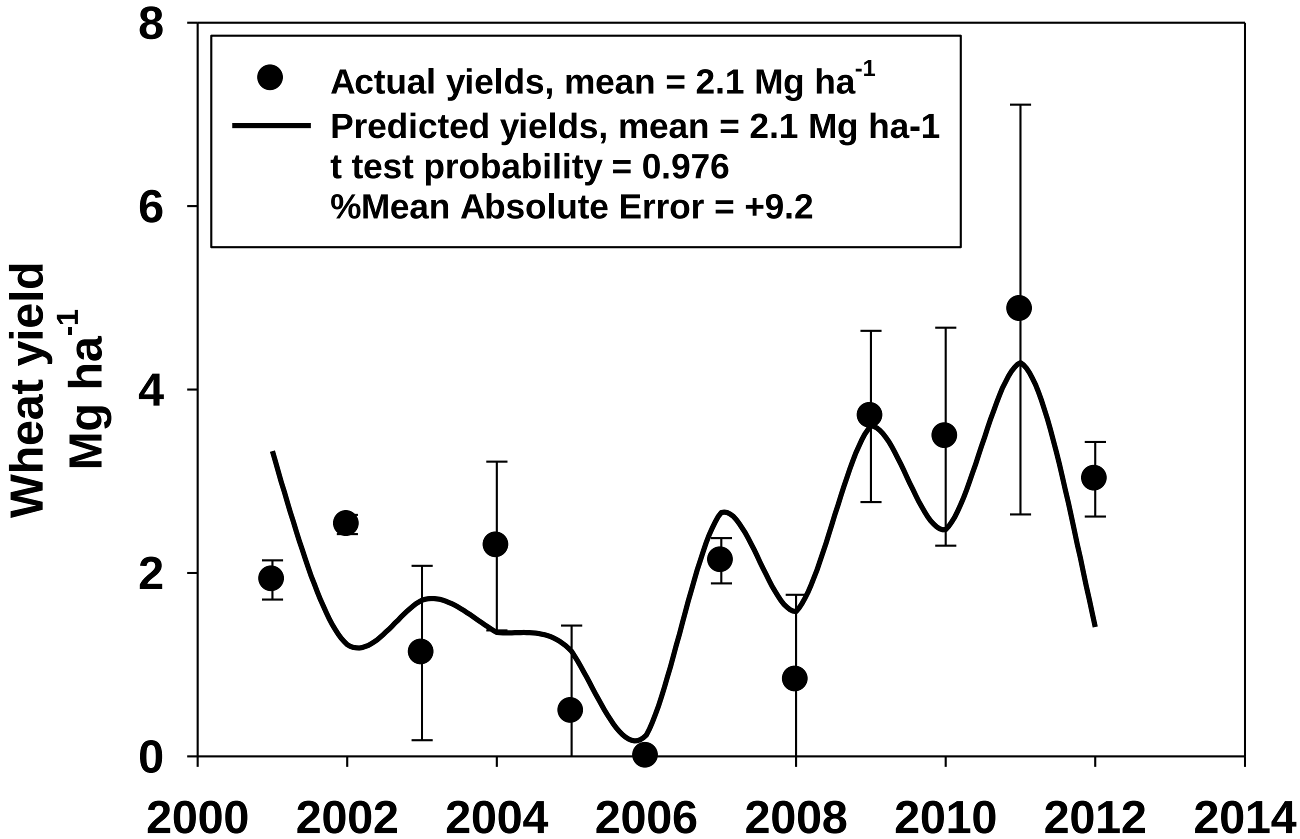
or

$$
\begin{aligned}
&wheat\ yield, \frac{bushels}{acre} = \\
&+19(Sep.\,precip., inches) \\
&+1.8(Oct.\,mean\ temp., ^\circ\mathrm{F}) \\
&+13(May\ precip., inches) \\
&-1.6(May\ mean\ temp., ^\circ\mathrm{F})
\end{aligned}
$$

The September precipitation is important for plant emergence and establishment. Higher October mean temperatures would improve tillering before winter dormancy. May precipitation is critical, since this is the anthesis period for hard-red winter wheat in eastern Colorado. The Byers model also included a negative May mean temperature effect. Higher temperatures in May would be a negative factor because they likely lead to more rapid soil-moisture depletion, leaving less soil water reserve for the critical anthesis period. Wang et al. (1992) used simulation modeling to predict that an increase in mean air temperature of 3^{o}C (5.4^{o}F) during anthesis could decrease wheat biomass by 25 to 60%, depending on the cultivar.

The t-tests showed that predicted were not significantly different than actual yields (Fig. 1). The model did not include type of fertilizer as a regression variable indicating that biosolids had the same effect on yields as N fertilizer. The Byers model accurately predicted the actual yield. The 2012 yield was underestimated (Fig. 1) because the May precipitation was only 0.35 times the average for 2000-2011 (1.5 versus 4.3 cm or 0.6 versus 1.7 inches) and the May mean temperature was 1.11 times greater than the average for 2000-2011 (15.6 versus 14.1^{o}C or 60.1 versus 57.4^{o}F). The % mean absolute error was +9.2.

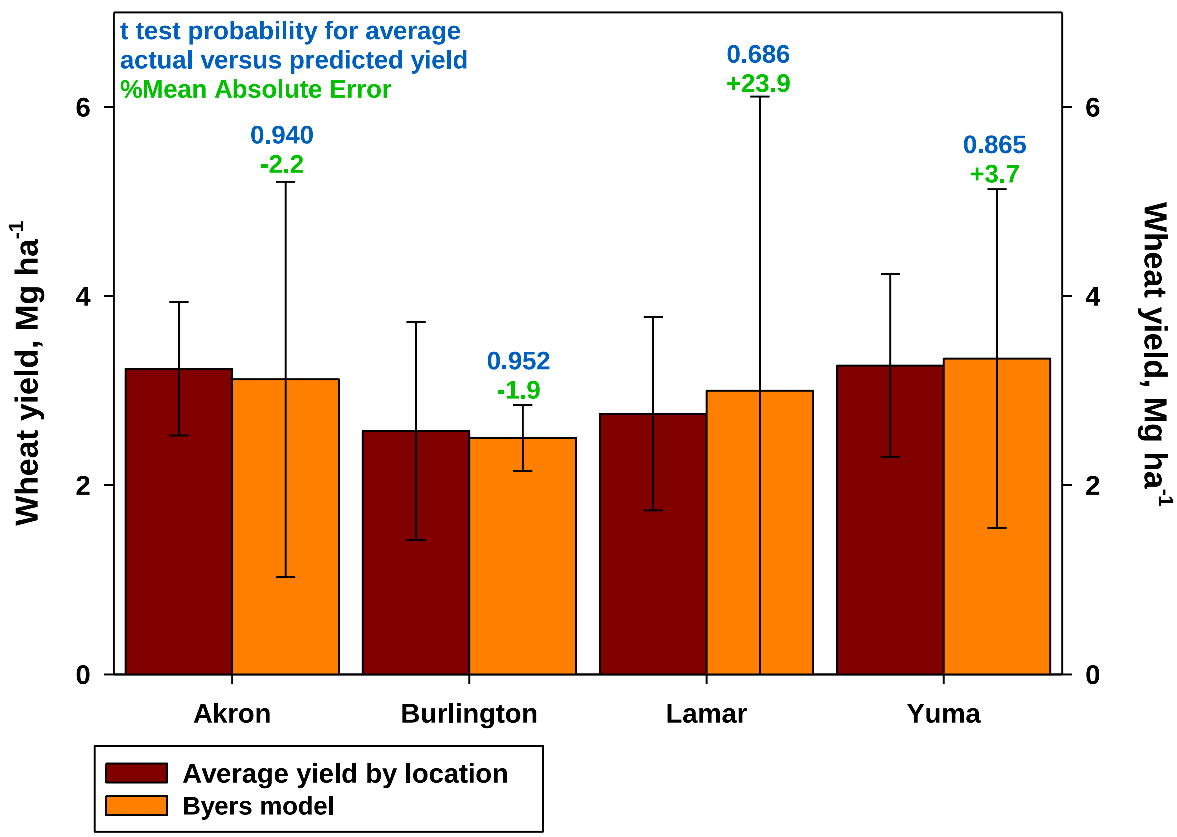
Figure 1. Observed and predicted (model based on 2000-2011 data) wheat yields at the Byers site, 2000-2012. Error bars represent the standard deviation of the observed means. Bushels/acre ≈ 15*Mg ha^{-1}



Model Testing

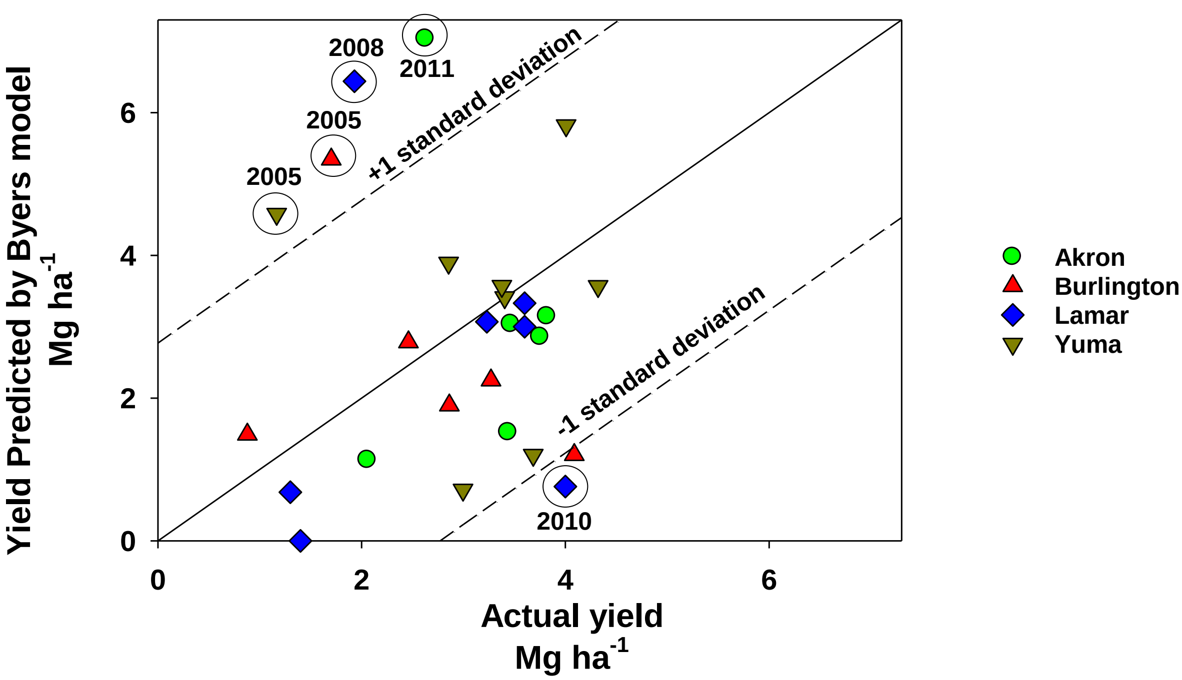
We validated the Byers wheat model (Table 3) with wheat yields from 2000 to 2011 at Akron, Burlington, Lamar, and Yuma, CO (Fig. 2). The Byers model provided a %mean absolute value over all locations of +5.3% and the t-test indicated the probability level for differences between predicted and actual means was 0.861.

Figure 2. Average observed and predicted yields (using the Byers regression model) for Akron, Burlington, Lamar, and Yuma, Colorado, 2001-2012. Error bars represent the standard deviation of the observed and predicted means. Bushels/acre ≈ 15*Mg ha^{-1}



The next question we addressed was the applicability of the Byers model in predicting yields for any individual year between 2000 and 2011 at the four test locations. We determined the contribution of each regression parameter to the overall predicted yield (data not shown) at each site-year. The model overestimated (more than one standard deviation above the mean; Fig. 3) the 2005 yield at Burlington and Yuma, the 2008 yields at Lamar and the 2011 yield at Akron and underestimated the 2010 yield at Lamar. For the yield overestimation at Burlington and Yuma in 2005, the yield contribution from September precipitation was 2.44 and 1.67 Mg ha^{-1} (36 and 25 bushels/acre), respectively, greater than the average (2000 to 2011)

Figure 3. Average observed versus predicted yields (using the Byers regression model) for Akron, Burlington, Lamar, Yuma, and North Bennett, Colorado, 2001-2012. Bushels/acre ≈ 15*Mg ha^{-1}



contribution. Overestimation of the May precipitation impact on projected yields led to the 2008 overestimation at Lamar and the 2011 overestimation at Akron (2.82 and 4.21 Mg ha^{-1} or 42 and 63 bushels/acre greater than the average contribution for the May precipitation parameter, respectively). The underestimation of the impact of September and May precipitation (1.85 Mg ha^{-1} or 28 bushels/acre less than the average contribution for the September plus May precipitation parameters) produced the underestimated 2010 predicted yields at Lamar. Other considerations would be the negative impacts of insect or disease infestation.

Our evaluation of the weather parameters in the Byers model is that the yield variations between observed and projected yields were influenced more by the precipitation variables than by the temperature variables. The contribution to the model R^2 for September and May precipitation exceed the R^2 values for October and May mean temperatures (Table 3). These results indicate that the Byers model could not reliably predict yields in a particular year; however, it may be used to look at the overall trend for the four test sites from 2000 to 2011. This supports the findings of Lobeell and Burke (2010) who essentially stated that statistical-model results for predicting yield responses are useful at broader spatial scales.

CONCLUSIONS

We did accept hypothesis 1 since the Byers model met all criteria for "best fit". Neither biosolids nor N fertilizer application appeared in the "best fit" model (had an R^2 of at least 0.90, a Mallow's Cp less than the number of regressors, and a Durbin-Watson value of 2 ± 0.5) for wheat production from 2000-2011 at Byers. These findings indicate wheat yields produced with biosolids at the Byers research site did not significantly differ from wheat yields produced with N fertilizer over the test period and biosolids application did not have any adverse production effects. The largest contribution to the Byers model R^2 came from September and May precipitation. September precipitation helps establish the wheat crop before winter dormancy and May precipitation directly affects anthesis.

Validating the Byers model with weather and yield data from Akron, Burlington, Lamar, and Yuma produced non-significant differences between actual and predicted means and %mean absolute errors ranging from -2.2 to +23.9. Thus, we accepted hypothesis 2 that the Byers model could reasonably predict average yields from 2000-2011 at the four test locations. The scatter in the mean absolute error in any particular year, however, indicated the Byers model could not predict realistic annual yields.

LIST OF REFERENCES

Barbarick, K.A., and J.A. Ippolito. 2000. Nitrogen fertilizer equivalency of sewage biosolids applied to dryland winter wheat. J. Environ. Qual. 29:1345-1351.

Barbarick, K.A., and J.A. Ippolito. 2007. Nutrient assessment of a dryland wheat agroecosystem after 12 yr of biosolids applications. Agron. J. 99:715-722.

Barbarick, K.A., J.A. Ippolito, and J. McDaniel. 2010. Fifteen years of wheat yield, N-uptake, and soil nitrate-N dynamics in a biosolids-amended agroecosystem. Agricult. Ecosys. Environ 132: 116-120.

Barbarick, K.A., J.A. Ippolito, J. McDaniel, N.C. Hansen, and G.A. Peterson. 2012. Biosolids application to no-till dryland agroecosystems. Agic. Ecosys. Environ. 150:72-81.

CoAgMet. 2013. http://coagmet.com/. Accessed 29 March 2013.

Colorado Agricultural Experiment Station. 2013. http://www.colostate.edu/Depts/AES/pubs_list.html. Accessed 29 March 2013.

Davis, J.G. and Westfall, D.G. 2009. Fertilizing winter wheat. Colorado State University Extension Fact Sheet no.0544. Available at: http://www.ext.colostate.edu/pubs/crops/00544.html. Accessed 29 March 2013.

Durbin, J., and Watson, G. S. 1950. Testing for Serial Correlation in Least Squares Regression, I. Biometrika 37:409–428.

Durbin, J., and Watson, G. S. 1951. Testing for Serial Correlation in Least Squares Regression, II. Biometrika 38:159–179.

Graphpad.com. 2013. Principles of curve fitting. http://graphpad.com/guides/prism/6/curve-fitting/. Accessed 29 March 2013.

Landau, S., R.A.C. Mitchell, V. Barnett, J.J. Colls, J. Craigon, K.I. Moore, and R.W. Payne. 1998. Testing winter wheat simulation models' predictions against observed UK grain yields. Agr. Forest Meteorol. 89: 85-99.

Landau, S., R.A.C. Mitchell, V. Barnett, J.J. Colls, J. Craigon, and R.W. Payne. 2000. A parsimonious, multiple-regression model of wheat yield response to environment. Agr. Forest Meteorol. 101:151-166.

Lauenroth, W.K., I.C. Burke, and J.M. Paruelo. 2000. Patterns of production and precipitation-use efficiency of winter wheat and native grasslands in the central great plains of the United States. Ecosystems 3:344-351.

Lerch, R. N., K. A. Barbarick, D. G. Westfall, R. H. Follett, T. M. McBride, and W. F. Owen. 1990. Sustainable rates of sewage sludge for dryland wheat production. II. Production and income. J. Prod. Agric. 3:66-71.

Lobell, D.B, and M.B. Burke. 2010. On the use of statistical models to predict crop yield responses to climate change. Agr. Forest Meteorol. 150: 1443-1452.

Mallows, C. L. 1973. Some Comments on C_P. Technometrics 15:661–675.

Movable Type Scripts. 2013. Calculate distance, bearing and more between Latitude/Longitude points. http://www.movable-type.co.uk/scripts/latlong.html. Accessed 29 March 2013.

Natural Resource Conservation Service. 2013. Web soil survey. http://websoilsurvey.nrcs.usda.gov/app/WebSoilSurvey.aspx. Accessed 29 March 2013.

Nielsen, D.C., and M.F. Vigil. 2009. Precipitation storage efficiency during fallow in wheat-fallow systems. Agron. J. 102:537-543

Nielsen, D.C., A.D. Halvorson, and M.F. Vigil. 2010. Critical precipitation period for dryland maize production. Field Crop Res. 118:259263.

Porter, J.R., and M. Gawith. 1999. Temperatures and the growth and development: A review. Eur. J. Agron. 10:23-36.

SAS Institute. 2013. SAS/STAT User's Guide. Version 9.2. http://support.sas.com/documentation/cdl/en/statug/63033/HTML/default/viewer.htm#titlepage.htm. Accessed on 29 March 2013.

Smith, G.P., and M.J. Gooding. 1999. Models of wheat grain quality considering climate, cultivar and nitrogen effects. Agr. Forest Meteorol. 94:159-170.

Wang, Y.P., Jr Handoko, and G.M. Rimmington. 1992. Sensitivity of wheat growth to increased air temperature for different scenarios of ambient CO_2 concentration and rainfall in Victoria, Australia – a simulation study. Clim. Res. 2:131-149. Accessed 25 June 2013. http://www.int-res.com/articles/cr/2/c002p131.pdf