Utilizing Topographic and Soil Features to Improve Rating for Farm-Level Insurance Products

Francis Tsiboe and Jesse Tack

Previous studies have shown a strong correlation between topographic/soil features and agricultural production; however, linkages between these features and agricultural insurance products are scarce. Agricultural insurance is an ever-growing means of governmental support for producers globally. However, failure to set insurance premiums that accurately reflect risk exposure can lead to low participation rates and/or adverse selection. The U.S. federal crop insurance program partly guards against this at the farm level by inducing pricing heterogeneity via a rate multiplier curve, which does not consider topographic/soil information. We develop a method for econometrically incorporating this information into existing rating procedures used by the Risk Management Agency (RMA). The empirical application leverages 149,267 farm-level observations of Kansas producers across four dryland crops (corn, soybean, sorghum, and wheat), spanning forty-six years, and matched to fine-scale topographic/soil features. The results suggest that incorporating these features does improve the prediction accuracy of yield losses and can, in general, improve rating performance. However, these improvements are specific to farms with limited yield histories, as there are no improvements for farms with the commonly used yield history of ten years. This suggests substantial rating improvements for new farms or those with limited histories for a particular crop, but more general improvements for the program are not likely to occur given a large number of current participants with a full ten-year yield history.

Key words: crop insurance, premium rate, rate multiplier curve, soil, yield history.

JEL codes: G22, Q14, Q18.

Previous research has established linkages between topographic and soil features with general agricultural production outcomes (Corwin et al. 2003; Cox et al. 2003; Juhos, Szabó, and Ladányi 2016; Li et al. 2019); however, specific links to large negative production shocks and/or agricultural insurance products are scarce. Initiated in Europe over two centuries ago, agricultural insurance is a large and rapidly expanding component of producer oriented governmental support programs in both developed and developing countries (Mahul and Stutley 2010; Smith and Glauber 2012). Although a bit dated, a 2008 World Bank survey found that the global agricultural insurance market provided indemnity and index-based crop insurance products that generated $15 billion in premiums across sixty-five countries (Mahul and Stutley 2010).

A wide range of topographic and soil features have been linked to production, including soil texture/structure (Sene et al. 1985; Cox et al. 2003; Nyiraneza et al. 2012), available water (Campbell et al. 1993), pH (Martín, Bollero, and Bullock 2005; Anthony et al. 2012), bulk density (Corwin et al. 2003), organic matter (Martín, Bollero, and Bullock 2005), nutrients (Cox et al. 2003; Di Virgilio, Monti, and Venturi 2007), and slope (Kravchenko and Bullock 2000). However, these studies typically focus on the cross-sectional (spatial) effects on mean yield across

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Amer. J. Agr. Econ. 104(1): 52–69; doi:10.1111/ajae.12218
Published online April 15, 2021

locations and do not investigate implications for temporal (interannual) risk at a fixed location. Given the strong linkages to cross-sectional yield variation, one might also expect that topographic/soil features affect yield risk at a specific location as well. Furthermore, if this is the case, then it suggests that components of agricultural insurance programs such as premium rates should also be affected by them. To the best of this study's knowledge, Woodard and Verteramo-Chiu (2017) is the only previous study linking a topographic/soil feature to crop insurance using observational data.

We focus on the U.S. federal crop insurance program (FCIP), which began in the 1930s and is currently a public–private partnership where the Risk Management Agency (RMA) is mandated by the Federal Crop Insurance Corporation (FCIC) to oversee the FCIP and provides subsidized, multiple-peril individual and area-wide insurance policies covering both yield and revenue support for over 100 crops planted on a majority of U.S. cropland (RMA 2020). Major concerns for the FCIP include low participation, either caused by or in conjunction with adverse selection, and it deals with these concerns by inducing pricing heterogeneity across farms based on their presumed risk in addition to subsidizing purchases. Cost savings from reducing subsidies is a perennial topic surrounding the program (United States Government Accountability Office [GAO] 2014; Congressional Research Service [CRS] 2015; Congressional Budget Office [CBO] 2017; Lusk 2017), but such a reduction would likely reduce producer participation (Congressional Budget Office [CBO] 2017). Importantly, subsidy reduction would place more importance on RMA's ability to price risk accurately across farms to guard against low participation and/or adverse selection.

There are many determinants of heterogeneous risk across farms, but few are easily observed from the rate-setter's perspective. One is to measure average yield/revenue on-farm and then presume that risk co-varies with that average, and indeed this approach is currently employed by the RMA (Coble et al. 2010). Another dimension that has received less attention is the incorporation of publicly available geo-referenced measures such as topographic and soil features as in Woodard and Verteramo-Chiu (2017), which found that conditioning yield histories on soil feature improved rating performance. We extend the literature by pursuing two related questions: (*a*) whether soil and topography conditioned rates lead to significant predictive and economic gains and, if so, (*b*) whether these gains depend on the number of historical yield observations available to rate setters. Intuition for the second question comes from the potential ability of repeated sampling to naturally "capture" the time-invariant linkage between location and risk.

We also propose a new method of incorporating soil information into crop insurance rates by recalibrating RMA's rate multiplier curve rather than adjusting historically reported yield series like Woodard and Verteramo-Chiu (2017). The method is applied to a sample of 149,267 observations across 5,428 farms and four dryland crops (corn, soybean, sorghum, and wheat) in Kansas (KS) spanning forty-six years (1973-2018). The analysis initially focuses on soil texture features that were considered "optimal" based on machine learning algorithms, but the main results are later shown to hold across a wide range of topographical and soil features including root zone depth, available water storage, slope, exchangeable cations, soil organic carbon, and the National Commodity Crop Productivity Index (NCCPI). Measures for these variables are derived using the nationwide gridded soil data from Soil Survey Geographic (SSURGO).

We find that incorporating soil information does improve the predictive accuracy of losses and is associated with economically meaningful premium rate improvements for the overall sample of farms with varying yield history lengths. [1] Perhaps more interestingly, the economic gains decrease rapidly with yield-history length, as very large gains are associated with histories of less than four years and essentially zero gains associated with yield histories of ten years. We believe that this is the first documented evidence that efficiencies from incorporating soil information into FCIP rate-setting procedures crucially depends on how much historical yield information is provided by producers.

Methods

Crop Insurance Continuous Rating Models

An extensive literature has attempted to estimate farm level rates (Carriquiry, Babcock, and Hart 2008; Ramirez, Carpio, and Rejesus

[1]Revenue insurance dominates the FCIP: however, it includes a yield risk component that is based on that of yield insurance.

2011; Woodard and Verteramo-Chiu 2017) but typically rely on methods based on distributional assumptions of yields. To date, no study has utilized an identification strategy that relies on holding county base and fixed rates constant while adjusting the rate multiplier curve to better fit empirical LCRs from observed farm yield over a large temporal and spatial domain.

RMA sets base insurance rates for county/crop combinations derived from historical loss experiences adjusted for extreme losses (Coble et al. 2010) and then averages them using weather weights as in Rejesus et al. (2015). In a sequential yet separate step, these county-level base rates are adjusted to the individual/unit level based on a presumption of risk relative to others in the same county (Coble et al. 2010). The relative risk adjustment is determined by a rate multiplier curve, which essentially embodies an assumption that risk correlates negatively with mean yield such that relatively productive insureds are lower risk and thus receive lower rates. Section 508 of the Agricultural Adjustment Act of 1938 mandates RMA to modify rating systems to be actuarially sound. Consequently, there is a large and growing literature analyzing RMA insurance rating procedures along the lines of actuarial soundness (Woodard, Sherrick, and Schnitkey 2011), adverse selection (Skees and Reed 1986; Goodwin 1994), technology-induced yield trends (Adhikari, Knight, and Belasco 2012; Seo et al. 2017), and heteroscedastic yields (Harri et al. 2011; Annan et al. 2014).

The main components of FCIP farm-level yield insurance contracts are the rate yield ($\bar{y}_i$), approved yield ($\ddot{y}_i$), yield guarantee ($\tilde{y}_{ig}$), coverage level (C_g), indemnity (I_{ig}), premium rate (R_{ig}), premium (P_{ig}), and subsidy (S_g). Here i denotes farm and g denotes coverage level. The rate yield is the simple average of actual production history (APH) reported by farmers subject to no adjustments. Although the approved yield could in principle be the same as the rate yield, several aspects of the RMA's actuarial process can produce differences as the production history is typically adjusted higher through various mechanisms.[2] The coverage level is selected by the purchaser and is the proportion of the insured unit's approved yield used to set the yield guarantee such that $\tilde{y}_{ig} = \ddot{y}_i \cdot C_g$.[3] Assuming output price is equal to unity without loss of generality, the per-acre indemnity for a given yield outcome, y_{it}, is given by $I_{ig} = max\left\{0, \tilde{y}_{ig} - y_{it}\right\}$.[4]

Insurance policies are supposed to be priced actuarially fairly such that premiums are equal to expected indemnities: $P_{ig} = E[I_{ig}]$. Because I_{ig} is stochastic and not known at the time the policy is written, RMA sets the price as the product of a premium rate, (R_{ig}), determined using a continuous rating formula, and the yield guarantee: $P_{ig} = R_{ig}\,\tilde{y}_{ig}$.[5] The final price paid by the insured is $P_{ig}S_g$, where S_g is a subsidy factor determined by FCIC and is tied to coverage level.[6]

Based on RMA (2000), the specific formula that RMA uses to construct premium rates is given by[7]:

$$(1) \qquad R_{ig} = \alpha_{cg}[\bar{y}_i/\bar{y}_{cr}]^{\beta_c} + \delta_{cg},$$

here the subscript c denotes county, and α_{cg} and δ_{cg} are a base rate and fixed loading factor, both of which vary across coverage levels and are calculated from county-level aggregated loss experience data. The county base rate is scaled up or down for a particular farm based on a rate multiplier $[\bar{y}_i/\bar{y}_{cr}]^{\beta_c}$ that leverages the ratio of the producer's rate yield over the county-level reference yield $\bar{y}_{cr}$ to make this adjustment. RMA defines this reference as an average of county-level yields. For a given ratio, the base rate will be adjusted based on the value of the county-specific rating exponent β_c. Even though equation (1) is a simplified version of RMA's continuous rating formula, it captures all the essential elements for this study.

[2]Common adjustments made to approved yield calculations include yield exclusion, yield substitution, and trend.

[3]Federally approved coverage levels for the 2019 crop year ranged from 55%–85% in 5% increments.

[4]Note that to the extent that approved yield is higher than rate yield, as is often the case, this benefits producers as the yield guarantee will be higher and, thereby, will increase indemnities for a given yield outcome and improves producer welfare (Adhikari, Knight, and Belasco 2013)

[5]In practice, premiums are the product of the premium rate and liability = guarantee × price. However, in the current setup, price = 1, so liability = guarantee.

[6]For the 2019 crop insurance program, corn, soybeans, sorghum, and wheat policies with coverage levels of 0.55, 0.65, 0.75, and 0.85 had S_g respectively equal to 0.64, 0.59, 0.55, and 0.38. Between 2005–2018, the federal government subsidized on average 61.1% of farmers' premiums (RMA 2019b).

[7]The literature is inconsistent on the difference between rate and approved yield in the FCIP. RMA actuarial documents distinguish between two yields calculated from the farmer's APH: approved yields are used in calculating farmer's guarantee and rate yields are used to calculate premium rates (RMA 2019a).

The adjustment of the county base rate for an individual farm depends on two main pieces of information: (*a*) the farm's relative yield performance to that of its peers and (*b*) the value of the rating exponent. For an average farm with a yield ratio of one, the implied rate multiplier will also take on a value of one regardless of the value of the rating exponent, and the premium rate will be $R_{ig} = \alpha_{cg} + \delta_{cg}$. In practice, farms are either going to be above or below the reference yields, and the county base rate will be adjusted accordingly based on the sign of β_c. If β_c is positive, then the rate multiplier is monotonically increasing in the yield ratio, and relatively more productive farms are considered riskier. Thus, the county base rate is adjusted upward. However, if instead, β_c is negative, then the rate multiplier is monotonically decreasing, and the opposite effect occurs with relatively more productive farms assumed to be less risky. Thus, the county base rate is adjusted downward. According to Milliman and Robertson (2000), the use of a negative β_c by RMA is based on research and is corroborated by (Botts and Boles 1958; Skees and Reed 1986).

The RMA's rating methodology approximates expected losses with rates (Coble et al. 2010). This excludes the cost associated with program delivery because they are provided for in the administrative and operating cost (A&O) agreements. The RMA derives expected losses—referred to as the "loss cost ratio" (LCR)—as expected indemnity divided by liability. Consequently, because LCRs measure loss per unit of exposure, an objective of RMA's method is to derive rates that reflect this. So, what can go wrong with the insurance continuous rating formula presented in Equation (1)? Woodard and Verteramo-Chiu (2017) postulated that biased rate-yields ($\bar{y}_i$) could lead to biased rates (R_{ig}) and showed that conditioning expected yields on soil could mitigate this.

We deviate from Woodard and Verteramo-Chiu (2017) by not adjusting rate yields but rather allowing the key county-level parameter in the rate multiplier, β_c, to be re-estimated to account for topographic and soil features. Based on RMA's approximation of the expected loss component of rates with LCR, Equation (1) can empirically be estimated as

$$(2) \quad LCR_{igt} = \alpha^*_{cg}[\bar{y}_{it}/\bar{y}_{crt}]^{\beta^*_c + f(X_i, CDR_d;\rho)} + \varepsilon_{igt}$$

where the variable LCR_{igt} is an empirical LCR for farm i in year t under coverage level g. Details of its derivation are outlined in the data section. Note that the county level base rate and the exponent in the rate multiplier are being held fixed in this empirical model. These fixed parameters are denoted with an asterisk (*) and take on values based on their 2019 crop year values published in RMA (2019a). The loading factor is omitted from the equation by setting it equal to zero.[8]

The exponent for the rate multiplier curve has been amended to include the fixed value currently used by RMA plus an adjustment: $\beta^*_c + f(.)$, where $f(.)$ is a function of farm-level topographic and soil features (X_i) and crop reporting district-level fixed effects (CDR_d). The main idea is to estimate the ρ parameters while holding both α^*_{cg} and β^*_c fixed, which can then be used to re-estimate current continuous rating exponents to be reflective of empirical LCRs.

Three types of adjustment functions are considered. The first includes only CRD level adjustments that are not based on topographic and soil features but rather ad hoc geographical boundaries: $f(.) = \sum_d^D \rho_d CRD_d$ [i.e., CRD model] where CRD_d is a dummy for crop reporting district d. The second ignores these and instead focuses on topographic and soil features: $f(.) = h(X_i;\rho)$ [SOIL model]. The third considers both types simultaneously: $f(.) = h(X_i;\rho) + \sum_d^D \rho_d CRD_d)$ [CRD-SOIL model]. For comparisons to current rates, a baseline model where the adjustment function $f(.)$ is omitted entirely from the model is also included so that the four models under consideration are:

$$(3) \quad [\text{Baseline}]\ LCR_{igt} = \alpha^*_{cg}[\bar{y}_{it}/\bar{y}_{crt}]^{\beta^*_c}$$

$$(4) \quad [\text{CRD}]\ LCR_{igt} = \alpha^*_{cg}[\bar{y}_{it}/\bar{y}_{crt}]^{\beta^*_c + \sum_d^D \rho_d CRD_d} + \varepsilon_{igt}$$

$$(5) \quad [\text{SOIL}]\ LCR_{igt} = \alpha^*_{cg}[\bar{y}_{it}/\bar{y}_{crt}]^{\beta^*_c + h(X_i;\rho)} + \varepsilon_{igt}$$

$$(6) \quad [\text{CRD}-\text{SOIL}]\ LCR_{igt} = \alpha^*_{cg}[\bar{y}_{it}/\bar{y}_{crt}]^{\beta^*_c + h(X_i;\rho) + \sum_d^D \rho_d CRD_d)} + \varepsilon_{igt}$$

[8]Alternatively, $LCR_{igt} - \delta^*_c$ could have been used as the dependent variable in Equation (2). However, fixing δ at its 2019 crop year value will alter the rate multiplier curve by making it steeper (i.e., a large absolute value for β_c). To demonstrate, suppose the true rate multiplier curve has a continuous rating exponent of −1.5 and the insureds yield ratio is 1.5 with a corresponding $LCR = 1.5^{-1.5} = 0.54$. Subtracting a fixed county rate of 0.02 from the LCR gives an effective continuous rating exponent of $\beta_c = \ln[0.54 - 0.02]/\ln[1.5] = -1.6$.

Equations (4)–(6) are estimated separately for each crop using nonlinear least squares with farm-level data pooled across all counties. Given the estimates of the parameters in ρ, we estimate the adjusted exponent for the three alternative models as $\beta_c^* + \sum_d^D \hat{\rho}_d CRD_d$, $\beta_c^* + h(X_i;\hat{\rho})$, and $\beta_c^* + h(X_i;\hat{\rho}) + \sum_d^D \hat{\rho}_d CRD_d)$, respectively. Note that exponents will be adjusted at the county/CRD level under the CRD model and at the farm level for the SOIL and CRD-SOIL models.

Measuring Predictive Accuracy

Both in- and out-of-sample methods are used to measure the predictive accuracy of the models. In-sample accuracy is measured as the mean squared error, whereas out-of-sample accuracy is based on cross-validation using ten approximately equal-sized subsamples (folds). Both measures are reported relative to the baseline model (Equation (3)), with values below one indicating better performance. The whole process is repeated 1,000 times by bootstrap sampling the farms in the dataset to measure statistical uncertainty.

Measuring Economic Performance

Based on Harri et al. (2011) and Coble, Dismukes, and Glauber (2007), we assume the role of an Agricultural Insurance Provider (AIP) to ascertain whether the models generate premium rate adjustments that are economically different. If the rate prediction from the adjustment model (Equations (4)–(6)) is lower than the baseline (Equation (3)), then the contract is assumed to be overpriced and thus is placed in the retain pool. However, if the rate prediction is instead higher, then the contract is assumed to be underpriced and placed in the ceded pool. By separating all policies into these two pools, one can compare the indemnities that occur based on the observed yield outcomes across pools to quantify economic differences from adopting the adjustment model.[9] We also provide a complete set of results for comparing loss ratios (indemnities over premiums) across pools in the robustness checks section below.

The cede/retain game is operationalized by utilizing an out-of-sample rating simulation approach with sixteen annual iterations from 2003–2018. For each iteration, a training sample of all prior years' data is used to estimate the models and predict premium rates for all farms in that year. For example, data before 2003 would be used to predict rates for all farms in 2003, data before 2004 would be used to predict rates for 2004, and so on. For a given iteration, rates are compared to the baseline rate and farms are separated into cede and retain pools. Indemnities are then calculated based on observed yield outcomes for the farm, summed across all years, and then divided by the total policies in each pool. The aggregate values are then used to form ceded to retained indemnity ratios with values greater than one indicating the economic significance of the predicted rates. The same bootstrap as above is used to measure statistical uncertainty.

Data

The loss experience from RMA Statplan along with accompanying common land unit (CLU) data would be ideal for the current study.[10] However, RMA loss data are not publicly available. Thus, we use data from secondary sources to replicate a mini version of the loss experiences in Kansas. The four main sources of data are: (*a*) 46 years of farm-level Kansas corn, sorghum, soybean, and wheat yields provided by the Kansas Farm Management Association (KFMA); (*b*) actuarial information from RMA's 2019 Actuarial Data Master (ADM) (RMA 2019a); (*c*) gridded topographic and soil features from Soil Survey Geographic (SSURGO) provided by the USDA-NRCS (Soil Survey Staff 2020); and (*d*) gridded crop frequency layer from NASS CropScape (USDA National Agricultural Statistics Service 2019).[11]

Loss Experience Data

We focus entirely on dryland production of corn, sorghum, soybeans, and wheat in Kansas. Observations were dropped from the sample in the following order: (*a*) if the farm

[9]We utilized the cede/retain game because, given the limited geographical coverage of the sample, it will be erroneous to make efficient rating by the RMA the focus of the paper. Additionally, the public–private partnership associated with crop insurance delivery makes the cede/retain game an attractive robust but simple metric.

[10]The Statplan is the standardized database of all policies written by the FCIC since 1948 and is used to support sound actuarial decisions.

[11]All Data and models were processed on Beocat, a High-Performance Computing (HPC) cluster at Kansas State University (https://beocat.ksu.edu/)

cannot be geocoded based on mailing address; (*b*) if the reported yield was 1.5 times the largest recorded contest yield[12]; (*c*) if RMA does not report insurance parameters needed to calculate county base rates and loading factors in that county; and (*d*) any crop/county combination with less than four-years of data from 1999–2002.[13] All notes, tables, figures, and references in the supplementary material have a leading S. Figure S1 shows the spatial representation of the 5,428 sample farms by crop. The 149,267 yield observations spanning 1973–2018 exhibit a great amount of cross-sectional and temporal variation (figure S2, Panel A). The mean [standard deviation] of the yields in kg/ha are 4,833 [2,137], 3,412 [1,484], 1,928 [905], and 2,470 [899] for corn, sorghum, soybeans, and wheat, respectively. Figure S3 shows the representativeness of the KFMA data by comparing sample average yields at the crop-county-year level to yield statistics from NASS.

We use a three-step algorithm to replicate loss experience data for each crop year in the dataset, starting with 1983. The first step uses the yield data from ten successive years to estimate county-level transitional yields (T-yields) and county reference yields ($\bar{y}_{crt}$). For the reference yield, annual county yields were first estimated as the average yield across all the farms in that county. The reference yield was then estimated as the mean of the annual county yields over the ten previous years (Rejesus et al. 2010). Given the county reference yields, the T-yields for each county was calibrated as $\bar{y}_{crt}\vartheta_c$, where ϑ_c is the reference yield to T-yield ratio for county c, calculated from 2019 RMA values.[14]

The second step of the loss experience algorithm estimates rate yield ($\bar{y}_{it}$) and approved yield ($\ddot{y}_{it}$) for each farm/year/crop with their observed yields (y_{it}) in ten successive years serving as the basis for an APH database. In practice, rate and approved yield calculations are complex; however, we shed some of the complexities such as yield exclusion, yield substitution, and trend adjustment to maintain tractability of the analysis.

Based on RMA guidelines (RMA 2018), rate yield is taken as the mean of the actual yields in the APH database; however, if there are no actual yields, the rate yield is taken as the T-yield. For approved yield, the APH database for an insured must have at least four successive yield data points (actual or assigned). If the APH database has actual yields for at least the last four successive years, the approved yield is just the simple average of the actual yields. Where the insured unit has less than four successive years of records, variable T-yields are used as replacements for the years with no records to meet the four-year minimum yield requirement. Particularly, missing yields for insureds with a record of zero, one, two, and three year(s) are taken as 65%, 80%, 90%, and 100% of their counties T-yield, respectively. Finally, the approved yield for an insured is bound between 90% of its value in the previous year (i.e., yield cap) and 70%–80% of the relevant T-yield (i.e., yield floor). The floor is set at 70%, 75%, and 80% if the four-year minimum yield requirement is short by three, two, and one yield(s).

Figure S2, Panels B-E, shows the annual box plots of rate yields, approved yields, T-yields, and reference yields. As expected, all four types of yields are trending up with the rate yields exhibiting a larger amount of cross-sectional variability. The resulting relative yields ($\bar{y}_{it}/\bar{y}_{crt}$) are also presented in figure S4, and unlike the yields, they are stable over the study period as expected. The sample distribution of the loss experience by the number of actual yields used in their rate yield calculation shows that the majority meet the four-year minimum yield requirement (figure S5).

Empirical LCRs based on observed yields y_{it} for each farm/year/crop are calculated as follows. The approved yield ($\ddot{y}_{it}$) from above is used to construct the guaranteed yield by coverage level: $\tilde{y}_{igt} = \ddot{y}_{it} \cdot C_g$, which in turn, is used to measure actual indemnities given by $I_{igt} = max\left\{0, \tilde{y}_{igt} - y_{it}\right\}$. The ratio of these indemnities to the guaranteed yield then defines

[12]Yield contests are annual competitions held at the state and national levels for major grains partly with the goal of; (*a*) recognizing and celebrating the success of high-yielding farmers; (*b*) promoting farming operations and best management practices to improve and sustain yields; and (*c*) sharing data to benchmark production and provide information to increase profitability. In this study, yields well above the highest ever recorded contest yields are deemed unrealistic, thus they are dropped from the analysis.

[13]Crop/county combinations with less than four-years of data from 1999–2002 are drop from the analysis to ensure that all such combinations have the minimum required annual data points used in exponent estimation for the sixteen annual iterations of economic performance from 2003–2018.

[14]The proportional calibration of T-yield based on reference yield was used because the calculation of T-yield is ambiguous in both the RMA and academic literature. Section 502(b) of the Agricultural Adjustment Act of 1938 defines T-yield as the maximum average production per acre or equivalent measure that is assigned to acreage for a crop year. Thus, we alternatively estimate T-yields as the upper value of the 95% confidence interval across all farms in the ten successive years, but the results largely remained the same.

the empirical LCR: $LCR_{igt} = I_{igt}/\tilde{y}_{igt}$. We assume that C_g = 75%, the largest enrolled coverage in terms of acres of corn, soybeans, sorghum, and wheat in KS for 2002–2019 (RMA 2020). The annual averages of the LCRs are shown in figure S6. Overall averages [standard deviation] of the LCRs are 0.076 [0.192], 0.073 [0.185], 0.079 [0.184], and 0.061 [0.171] for corn, sorghum, soybeans, and wheat, respectively.

Preliminary descriptive analysis of the farm level data used in this study in table S1 shows that there is a near one for one inverse relationship between mean relative yield and risk. Thus, the RMA's actuarial methodology assumption is embodied in the raw data. Similar relationships also hold for the case of NASS county-level data (table S2). Table S1 hints that the rating exponent is expected to remain negative even after they are adjusted. Consequently, the negativity restriction of the rating exponent is not directly imposed during estimation but rather evaluated *ex-post*.

Actuarial Data

The KFMA data are farm level instead of field level; thus, it is a closer approximation to an enterprise unit (EU), thus, actuarial information for EU dryland production of corn, sorghum, soybeans, and wheat for a coverage level of 75% retrieved from the RMA's 2019 ADM is used for the analysis. The specific actuarial parameters retrieved from the ADM are (*a*) county/crop continuous rating exponents; (*b*) county/crop reference rates (R_{cr}); (*c*) county/crop fixed rates (R_{cf}); (*d*) unit residual factors for production unit adjustments (R_p); and (*e*) rate differential factors for coverage level adjustments (R_g). Based on the ADM parameters, the county-level base rate (α_{cg}) and fixed loading factors (δ_{cg}) are calculated as: $\alpha_{cg} = R_p R_g R_{cr}$ and $\delta_{cg} = R_p R_g R_{cf}$. The boxplots of the retrieved and calculated actuarial parameters are shown in figure S7.

Topographic and Soil Features

The exact location of each farmer's field was unknown; however, they were best approximated using their mailing address following the procedure outlined in Note S1. This approach is not ideal with measurement error potentially leading to attenuation bias. However, the approach is somewhat representative of the real-world situation in which RMA historically did not know the exact location of insured fields nor more generally what field the farmer will eventually plant on at enrollment. Additionally, for any given year, the history on which APH is based could have come from other fields. Furthermore, we demonstrate substantial improvements in farmers with low APH history length and no improvements for farms with a high APH history, which suggests that there is a signal in the soil measure used and that the measurement error is likely minimal.

The gSSURGO has over 500 topographic and soil features on which the rating exponent could be conditioned. A viable candidate feature must have significant within-county variation, so all features with a zero standard deviation or a coefficient of variation less than 0.01 were dropped. Next various statistical learning techniques were used to further narrow down the list of features by focusing on those with relatively high LCR predictability. Details of the specific algorithms used by these techniques are in James et al. (2013) and results are shown in figure S8. Based on the selection process, soil texture is chosen as the preferred feature.

The basic elements of soil texture are (*a*) sand: mineral soil particles that have diameters ranging from 2 to 0.02 mm; (*b*) silt: mineral soil particles that range in diameter from 0.02 to 0.002 mm; and (*c*) clay: soil particles that have diameters less than 0.002 mm. The spatial distribution of these is depicted in figure S9 and the farm-level distribution in figure S10. In general, sample farms are located on soils that are abundant in soil particles classified as silt, which is the second-most occurring followed by sand. In addition to soil texture, root zone depth, available water storage, slope, exchangeable cations, soil organic carbon, and NCCPI are also considered as robustness checks.

Results

Continuous Rating Exponent

Equation (3) serves as the baseline model and the county level RMA exponents β_c^* are reported in green in figure 1(a). The alternative models, Equations (4)–(6), are estimated using nonlinear least squares, and the parameter estimates are reported in table 1. Those parameter estimates are used to form adjusted rating exponents for each of the three alternative models, reported alongside the baseline exponents in figure 1(a). In general, the rating exponents remain negative

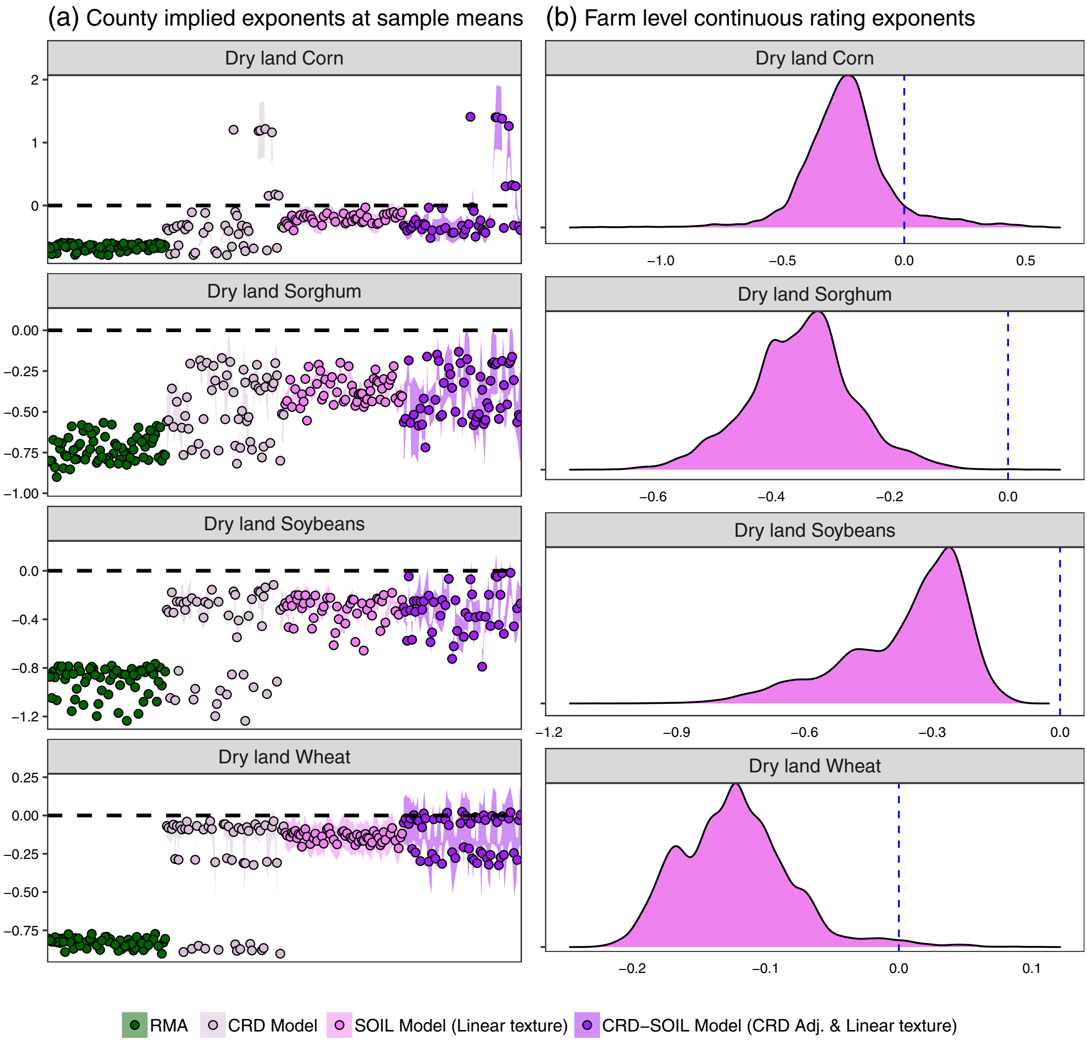

Figure 1. Plots of continuous rating exponents from alternative models in Kansas

Notes: Each panel of graph A shows the plots (circles) of county-level crop insurance continuous rating exponents provided by USDA Risk Management Agency (RMA) for 2019 (green) and from our models (CRD Model–Crop reporting district [CRD] conditioned exponents, SOIL Model–Linear soil texture conditioned exponents, and CRD-SOIL Model–CRD and Linear soil texture conditioned exponents). For SOIL and CRD-SOIL, the soil texture elements (clay, silt, and sand) for each county were taken as the mean of all the farms in that county. The shaded region represents the bootstrap (1,000) 95% confidence interval (CI) for the estimates, and the dashed black line marks the reference for zero. Estimates with their 95% CI overlapping with the zero lines are not statistically significant. Farm-level data were provided by the Kansas Farm Management Association (KFMA).

after adjustment and are lower in magnitude relative to RMAs. This suggests that adjustments are inducing a flatter rate multiplier curve thereby leading to smaller adjustments above and below the reference yield and more homogeneous rates across farms within the county. The latter is a particularly interesting aspect of the results as one might expect that models that include additional farm-level information would naturally lead to more heterogeneous rates across farms. However, as it will be shown below the soil information and yield-history length can be thought of as substitutes in that information only improve rating when sample length is small. Although not empirically verified in this study, we suspect that the soil adjusted exponent is likely counteracting (reducing) the effects of a noisy mean yield estimate.

In figure 1(a), it can be observed that the cross-county variation in exponents from the CRD adjusted models (i.e., models CRD and CRD-SOIL) is relatively higher than RMA's 2019 values. On the contrary, the cross-county

Table 1. Regression Results

	(1) CRD model	(2) SOIL model	(3) CRD-SOIL model
Soil texture			
Silt	-	0.878** (0.488)	0.030 (0.854)
Clay	-	−0.798 (0.621)	1.216 (1.367)
Sand	-	2.023** (1.006)	−0.508 (0.927)
CRD			
NW	0.768*** (0.086)	-	0.563** (0.243)
SW	-	-	-
SC	1.845*** (0.331)	-	1.647*** (0.357)
NE	-	-	-
SE	0.285** (0.105)	-	−0.072 (0.143)
NC	0.531*** (0.151)	-	0.248 (0.197)
Dryland sorghum			
Soil texture			
Silt	-	0.382 (0.265)	0.206 (0.510)
Clay	-	0.415 (0.575)	0.565 (1.116)
Sand	-	0.149 (0.176)	−0.192 (0.205)
CRD			
NW	0.384*** (0.106)	-	0.163 (0.157)
SW	0.397*** (0.088)	-	0.154 (0.101)
SC	0.315*** (0.062)	-	0.214 (0.113)
NE	0.505*** (0.154)	-	0.224 (0.180)
SE	0.249* (0.117)	-	−0.007 (0.178)
NC	-	-	-
Dryland soybeans			
Soil texture			
Silt	-	0.572 (0.501)	0.402 (0.694)
Clay	-	0.637 (0.848)	0.764 (1.170)
Sand	-	0.505** (0.253)	0.068 (0.340)
CRD			
NW	-	-	-
SW	-	-	-
SC	0.649*** (0.093)	-	0.275** (0.135)
NE	-	-	-
SE	0.533*** (0.079)	-	0.055 (0.118)
NC	0.623*** (0.127)	-	0.163 (0.177)
Dryland wheat			
Soil texture			
Silt	-	0.681* (0.350)	0.826** (0.397)
Clay	-	0.659 (0.571)	0.037 (0.888)
Sand	-	0.784*** (0.239)	0.580* (0.362)
CRD			
NW	-	-	-
SW	-	-	-
SC	0.736*** (0.066)	-	0.199 (0.148)
NE	0.544*** (0.152)	-	0.017 (0.212)
SE	0.735*** (0.057)	-	0.214 (0.149)
NC	-	-	-

Significance levels: $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$.
Notes: The table shows the nonlinear least-squares regression results for the adjustment parameters in Equations (4)–(6). A pooled model that included pooled data from all counties was estimated. RMA's rating parameters are county-specific and are included in each model as fixed parameters. Three different regression models were considered, each based on a separate type of adjustment. The first includes only CRD level adjustments (CRD model), which are based on dummy variables at the CRD level and the parameter estimates are reported in column 1. The second focuses on topographic and/or soil features (SOIL model) measured at the farm level and the parameter estimates are reported in column 2. The third includes both types of adjustments simultaneously (CRD-SOIL model). Standard errors are calculated by bootstrap sampling the farms in the dataset.

variation from the SOIL model is comparable to the RMA 2019 values. Figures 1(b) and 2 show within farm and county variation of the continuous rating exponents, respectively.

Predictive Performance

Results for in- and out-of-sample prediction in figure 3(a) and (b) indicate that the adjustment

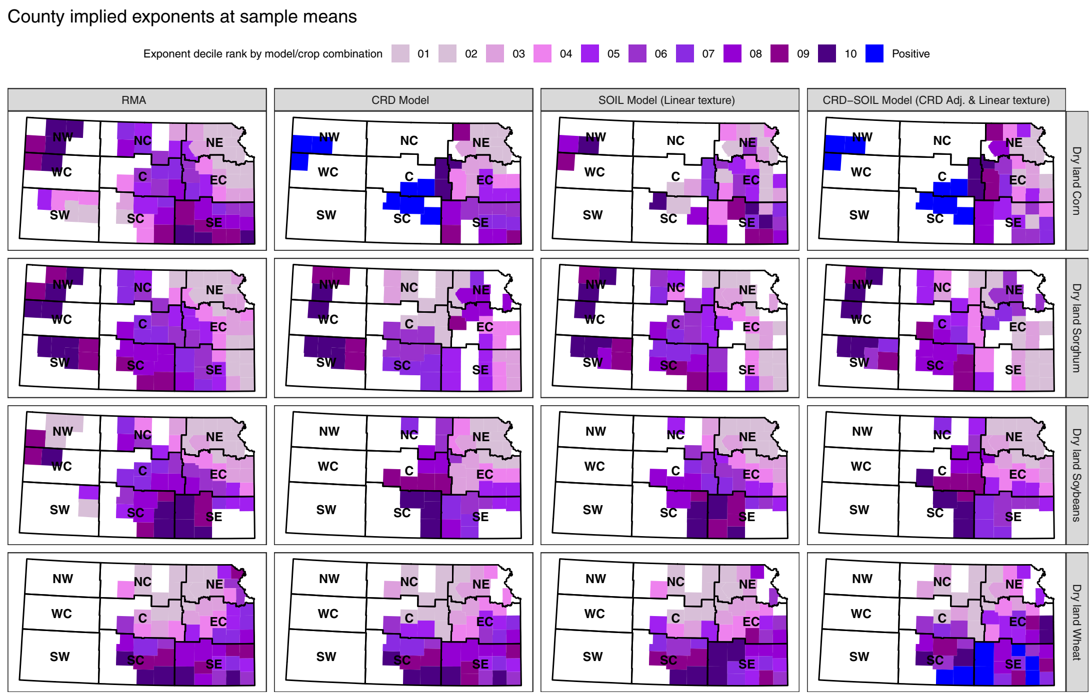

Figure 2. Spatial pattern in county-level continuous rating exponents for alternative models in Kansas

Notes: Each reference map shows the spatial pattern of the decile rank of crop insurance continuous rating exponents by model/crop combination. Counties with positive exponents are excluded from the ranking and displayed as blue. The model designation represents exponents provided by USDA Risk Management Agency (RMA) for 2019 and those from our models (CRD Model–Crop reporting district [CRD] conditioned exponents, SOIL Model–Linear soil texture conditioned exponents, and CRD-SOIL Model–CRD and Linear soil texture conditioned exponents). For SOIL and CRD-SOIL, the soil texture elements (clay, silt, and sand) for each county were taken as the mean of all the farms in that county. Farm-level data were provided by the Kansas Farm Management Association (KFMA).

models reduce LCR prediction error. It is interesting to note that errors are lowest for the models that utilize soil texture to adjust rates. Particularly, figure 3(a) shows that out-of-sample errors from the models that include soil texture (SOIL and CRD-SOIL) are about 3% lower than that of the status quo. This suggests that there is signal in the soil measure used and that the measurement error could be minimal.

Figure 4 presents the mean relative rates (to that of the RMA) from 2003–2018 for each observation using the adjustment from the SOIL model and paints a vivid picture of the resulting flatter rate multiplier curve as rates for yield ratios below one is adjusted lower, whereas rates for ratios above one is adjusted higher. Overall rate adjustments are upward on average suggesting higher out-of-pocket insurance costs for producers, but there is substantial variation across farms from about −19% to 13%.

To provide a measure of program level differences between these rates, we utilized RMA projected price for 2019 for valuation. For the case of the SOIL model, the mean total premium, subsidy, producer paid premium, and AIPs A&O were \$57.13 M, \$43.99 M, \$13.14 M, and \$12.51 M, respectively. For the RMA 2019 exponents, similar values were \$56.05 M, \$43.16 M, \$12.89 M, and \$12.28 M, respectively. Overall, the values when soil information is included in rate setting were only about 2% higher than those from the RMA.

Economic Performance

Results for the ceded to retained indemnity ratios across all policies shown in figure 3(C) indicate that the SOIL model consistently produces rates that are economically different. For all crops together, the ratio was approximately 1.40 indicating that indemnities were 40% larger among the ceded policies relative to the retained.

All crops had ratios above one with soybeans being the largest at ~1.5 and sorghum/wheat being relatively smaller at ~1.2. The difference could be attributed to wheat being a longer season crop spanning fall, winter, and spring months; whereby a large amount of weather

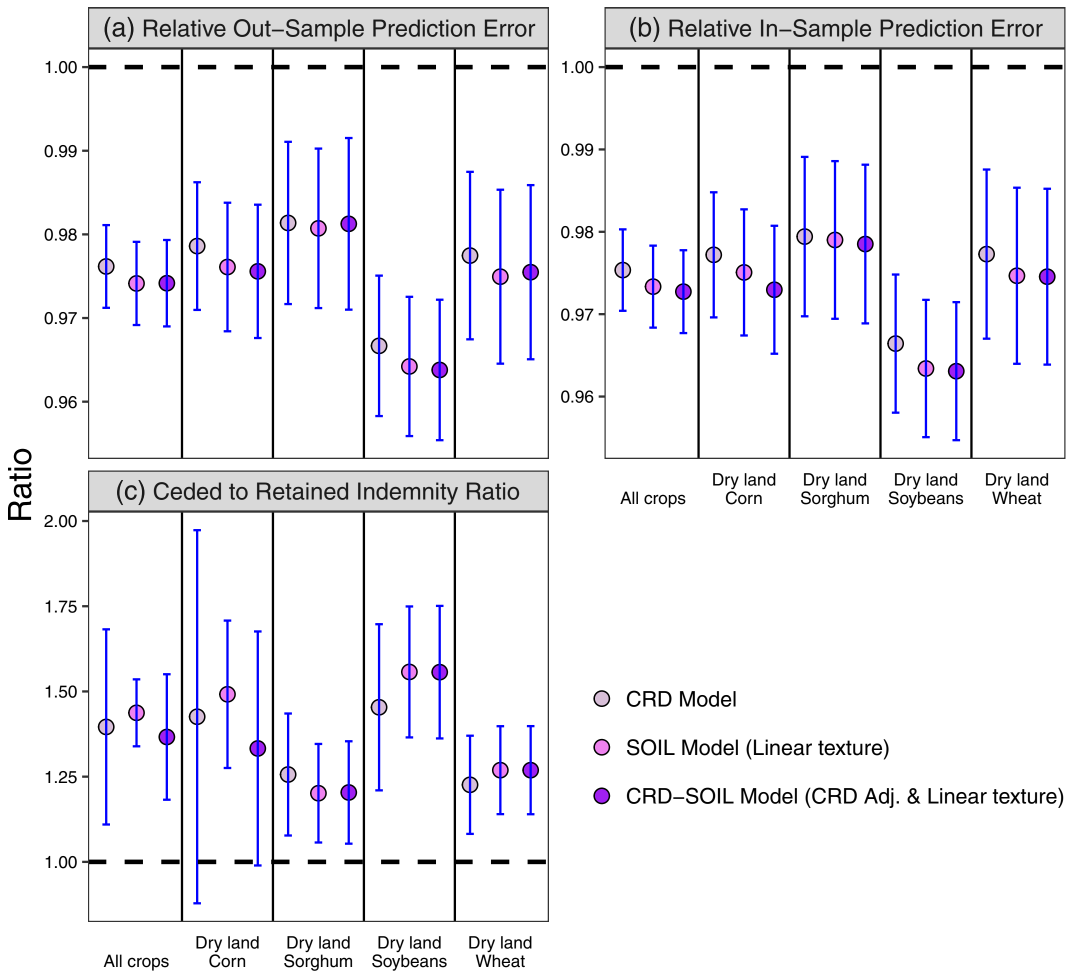

Figure 3. Predictive and economic performance of alternative models for estimating continuous rating exponents in Kansas

Notes: Graph shows the predictive (A and B) and economic (C) performance of crop insurance continuous rating exponents estimated from our models (CRD Model–Crop reporting district [CRD] conditioned exponents, SOIL Model–Linear soil texture conditioned exponents, and CRD-Soil Model–CRD and Linear soil texture conditioned exponents). Panels A and B are evaluated in terms of relative performance to exponents provided by USDA Risk Management Agency (RMA) for 2019. Panel C is based on Coble, Dismukes, and Glauber (2007) and Harri et al. (2011) and measures the level of forgone economic rents as the ratio of indemnities from ceded to that of retained policies under a simplified Standard Reinsurance Agreement (SRA) scenario. For Panels A and B values less than one indicate how well our exponents perform better than that of the RMA, and for panel C, values greater than one indicate a relatively higher level of forgone economic rents. The error bars represent the bootstrap (1,000) 95% confidence interval (CI) for the estimates, and the dashed black line marks the reference for one. Estimates with their 95% CI overlapping with the reference line are not statistically significant. Farm-level data were provided by the Kansas Farm Management Association (KFMA).

variation obscures the soil information in the "signal." A somewhat similar situation arises for sorghum as well since it is sown under hotter conditions than soybeans and is also harvested later under colder conditions (sometimes into December). Nonetheless, all three models produce very similar economic gains for each crop, suggesting that the adjustment based on soil covariates alone is robust to including an additional adjustment at the CRD level.

One might suspect that the economic gains from including soil information are likely to decline with the amount of historical yield information provided by the farm. Soil effects are largely time invariant and thus can likely be captured with a long enough yield history; however, it is unclear how short a history must be for soil to provide additional information not already captured by the rate yield. To investigate this, the indemnities within the ceded and retained pools are grouped by the number of years that were used in the rate yield calculation and the cede/retain ratios for each group are reported in figure 5. Results suggest that economic gains do indeed decrease as yield histories become longer.

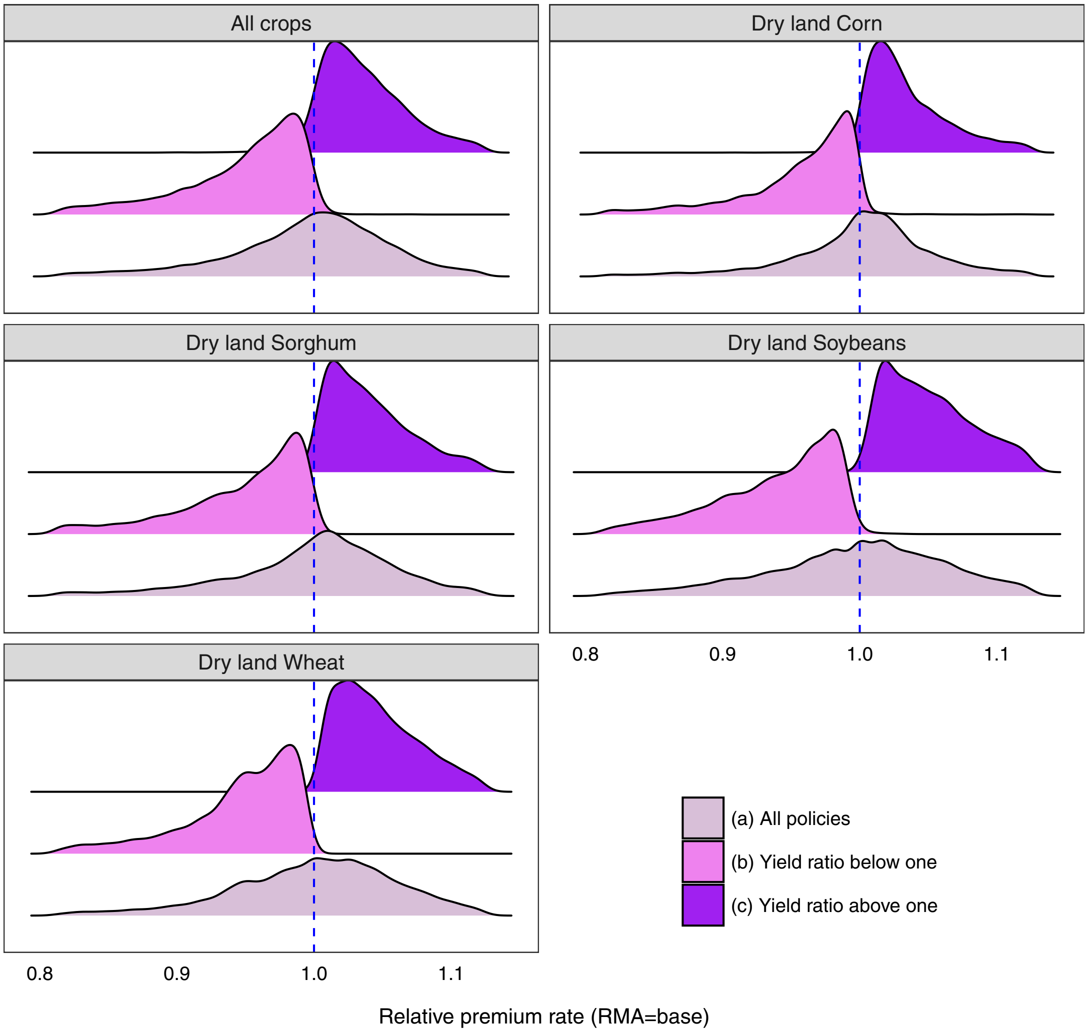

Figure 4. Distribution of farm level relative premium rates

Notes: Graph show distribution of mean farm level rates from the SOIL Model (Linear soil texture conditioned exponents), relative to rates from the exponents provided by RMA for 2019. For each panel, the top [middle] distribution is for those policies with mean relative yield ratios above [below] one, and the bottom is for the entire sample. The dashed blue reference line is the point at which rates from the SOIL Model are equal to those from the RMA. The vertical axis of the pdfs has been omitted. Farm-level data were provided by the Kansas Farm Management Association (KFMA).

Additionally, the rate of decline is striking as gains are essentially zero across all crops for the group with rate yields based on ten years of data. Focusing on the all-crop aggregate, the percentage reduction in economic gains between rate-yields based on a ten-year history, the maximum allowable by the RMA, is approximately 63%, 42%, and 28%, respectively for 0–3-, 4-, and 5–9-year history.

Robustness of Main Finding

Figure S11 shows that the pattern of declining economic gains as yield history length increases is robust across different dimensions of the empirical analysis. First, we consider a wide range of alternative soil features both alone and alongside the soil texture measures. These features include root zone depth, available water storage, slope, exchangeable cations, soil organic carbon, and the NCCPI. Second, although the analysis assumed a 75% coverage level because it was the largest enrolled across the four crops in Kansas since 2002 (RMA 2020), we also consider a full range of alternatives from 50%–85% in five-unit increments. The third set of robustness checks extends the linear soil texture model to include polynomials of

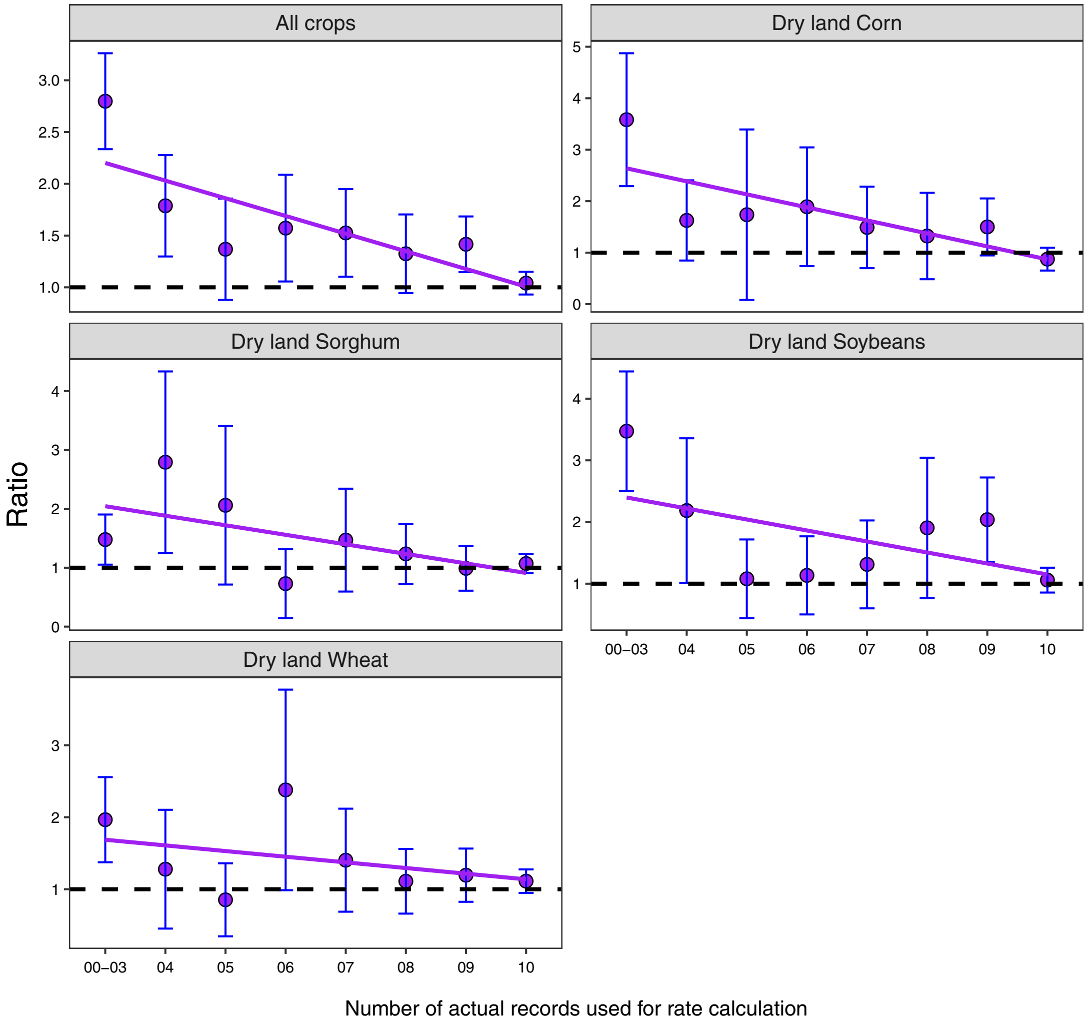

Figure 5. Relationship between actual production history length and economic performance of soil texture conditioned continuous rating exponents in Kansas

Notes: Graph shows the economic performance of crop insurance continuous rating exponents estimated from the SOIL Model (Linear soil texture conditioned exponents) across all crops, summarized by the length of actual production history. The performance is based on Coble, Dismukes, and Glauber (2007) and Harri et al. (2011) and measures the level of forgone economic rents as the ratio of indemnities from ceded to that of retained policies under a simplified Standard Reinsurance Agreement (SRA) scenario. Values greater than one indicate a relatively higher level of forgone economic rents. The error bars represent the bootstrap (1,000) 95% confidence interval (CI) for the estimates, and the dashed black line marks the reference for one. Estimates with their 95% CI overlapping with the reference line are not statistically significant. Farm-level data were provided by the Kansas Farm Management Association (KFMA).

degree two to four in the adjustment function *f*(.). The fourth set of robustness checks focuses on a key assumption of the measurement of soil information, in which the use of farm mailing addresses instead of specific geo-referenced field locations is used to match yield histories with soil data. Specifically, the buffer for aggregating soil information given the farms mailing address was varied from a 0.5- to 3-mile radius; and separably, all farms whose mailing address was in an urban area were dropped.[15] The final set of robustness checks are reported in figure

[15]Depending on the radius used, 8–9.5% of the sample used fell within areas designated as urban by the Census Bureau. However, as shown in Note S1, soil information is aggregated over the area with each buffer that overlaps with the gridded crop frequency layer from NASS CropScape. For robustness checks, farms whose mailing address spatially intersected with Census Bureau's Urban Area Reference Maps were dropped regardless of their overlap with the crop frequency layer. The Census Bureau identifies two types of urban areas: (*a*) urbanized areas (UAs) of 50,000 or more people; and (*b*) urban clusters (UCs) of at least 2,500 and less than 50,000 people.

S12 and use loss ratios (indemnities over premiums) in the cede–retain measure instead of indemnities alone because it is a more complete measure of economic rents and is commonly used in the literature. Overall, the pattern of results from the robustness checks in figures S11 and S12 are consistent with the main findings in the manuscript.

Conclusion

We extend the crop insurance rating literature by incorporating topographic and soil information into rating procedures. A novel econometric approach based on RMA's procedures for pricing insurance at the farm level was developed and applied to a sample of 149,267 farm-level observations in Kansas spanning 1973–2018. The results show that including such information improves rate predictions on average and that the revised rates are economically different in the sense of a commonly used cede–retain game.

Overall, the results are largely in line with previous findings in the literature with the one key exception being that economic gains from including soil information rapidly decline with the yield history of the farm, with no gains associated with farms that provide ten years of historical yield data. This finding highlights a crucial dimension in the debate surrounding whether RMA should incorporate soil information into their rating procedures as it suggests that the proportion of policies for which ten years of data are available is an important variable in this decision.

Neither in this study nor RMA's database more generally can it be assumed that entrance into the data is only driven by new farmers as there exist experienced farms that simply choose not to participate in various programs. So, it cannot be stated specifically from this study that the results apply directly to new farmers as a limited yield history could be driven by selection into the KFMA. However, to the extent that a combination of experienced and new farmers are driving the result, and that the benefit of including soil information for new farmers is at least as large as experienced farmers in a limited yield history context, then our results would provide a lower bound on the benefits of including soil information for new farmers. This could be further broken down into a distinction between experienced farmers growing a new crop versus young farmers with essentially no production history. In this view incorporating soil information can be beneficial for both young farmers and farmers who are switching crops, perhaps to adapt to changing environmental, climatic, and/or economic conditions. However, this is an important empirical question that warrants future research.

Although we did only focus on Kansas farms, we suspect that the policy implications are externally valid for other major production states/regions. The results essentially show that yield history length and soil information are substitutes for inferring risk. It is common to control for farm/location "fixed effects" in production applications, and the core insight is that at some point repeated sampling allows you to capture, or control for, time-invariant drivers of production variation. This insight holds for alternative moments of the yield distribution in the context of Just-Pope technology or more general "moments" models as well (Just and Pope 1979; Antle 2010). If one can repeatedly observe sample moments for two farms that are identical in every way except for their soil quality, then at some point one can disentangle the effect of soil on that moment. So, in principle, the more interesting question is how many repeated draws one requires to make this distinction, and it is likely that the amount of weather/pest/disease variation in the data matters a lot for this threshold because they would affect signal-to-noise ratios. In general, dryland crop production in Kansas is considered more variable relative to other major crop-producing regions such as the U.S. Corn Belt, so if it takes ten years of data to capture soil effects here it would probably be less in many other places. However, we again stress that this is an empirical question that warrants future research.

Although we found no evidence of economic gains associated with ten-year yield histories, there are some additional considerations for utilizing soil conditioned rates that were not directly assessed here and thus might be considered by future research. First, incorporating soil information could help guard against moral hazard, as farmers can easily alter yields through various adjustments to production practices (e.g. fertilizer, pest control, seeding rates, etc.), but it is difficult in practice to adjust soil quality, especially within the growing season when moral hazard concerns may be highest (Coble et al. 1997). Second, several studies have shown that federal farm program payments impact land values (Barnard et al. 1997; Lence and Mishra 2003; Roberts, Kirwan, and Hopkins 2003; Taylor and Brester 2005; Latruffe and Le Mouël 2009). Shaik, Helmers, and Atwood (2005) assert that any future efforts to reduce net agriculture subsidies could have large effects on land prices like that of the 1960s or 1970s. Thus, in addition to rates being important from an insurance perspective, getting them right or wrong could have implications for a farm's financial status through land capitalization.

In closing, several caveats to the analysis are worth mentioning. First, it focuses solely on the dryland operations of Kansas farms that produce corn, soybeans, sorghum, or wheat. Subsequent studies can overcome this by expanding the scope of this study to include a wider variety of crops, production practices (e.g., irrigation), and locations; however, it should be noted that the availability of farm-level panel data required for this type of analysis is quite limited. Second, the topographic and soil information used in this study are based on the mailing address of the farms in the KFMA database. Robustness checks in the analysis provide some evidence that this is a plausible working assumption, but future work might consider more tightly matched soil and production information if possible.

Acknowledgments

We are thankful for the assistance of the Kansas Farm Management Association (KFMA); access to Beocat, the High-Performance Computing (HPC) cluster at Kansas State University (https://beocat.ksu.edu/); feedback from friends and colleagues; and editorial guidance from Terry Hurley and three anonymous reviewers. All errors are our own.

Supplementary Material

Supplementary material are available at American Journal of Agricultural Economics *online.*

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