Field-level land-use adaptation to local weather trends

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Abstract. The intersection of agriculture and climate has been well researched for at least the last couple of decades. Largely, the motivation for previous research has been the potential impact on food security for the world's (growing) population. Many studies have predicted unfavorable yield scenarios for particular geographic regions. As a result, another common research theme is farmer adaptation to a changing climate. Typically, these studies are concerned with what farmers could or should do to adapt to adverse outcomes. However, research examining whether farmers do respond to weather patterns has largely been ignored. Answers to this question can help provide more accurate food security analysis: If farmers do respond to changing patterns through cropping decisions, for instance, the global food supply outcome will be different than a world in which they do not respond. This article aims to provide insights into what and how farmers' cropping decisions respond to weather patterns. The study region is a set of 11 Kansas counties. The article provides an important step towards more credible estimates of global food supplies under changing climates and the methods themselves translate to other areas. Results suggest that land-use responses to changing weather patterns will vary across time and space.

Keywords. Climate Change, Weather, Adaptation, Agriculture, Kansas, Crop Choice

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Given the importance of agriculture, combined with its susceptibility to weather patterns, it is not surprising that the intersection of agriculture, weather, and climate has been well researched (e.g., Mendelsohn, Nordhaus, and Shaw 1994; Lal 2004; Long et al. 2006; Lobell et al. 2008; Searchinger et al. 2008; Schlenker and Roberts 2009; Deschênes and Greenstone 2007). Much research to date has focused on yield impacts on food supplies (e.g., Rosenzweig et al. 1994; Long et al. 2006; Lobell et al. 2008; and Schlenker and Roberts 2009). Though many of these studies do not paint an overall-favorable picture for global or regional food supply response under assessed climate and weather scenarios, impacts tend to be spatially heterogeneous, with "winners" and "losers" determined by local phenomena. There has also been considerable research regarding potential adaptation and/or mitigation strategies for agriculture in the face of climate change and adverse weather (such as Smit and Skinner 2002; Bradshaw, Dolan, and Smit 2004; Howden et al. 2007; Lin 2011). Still others have examined climate change perceptions and beliefs held by farmers and the factors that shape them (e.g., Diggs 1991; Haden et al. 2012; Arbuckle, Morton, and Hobbs 2015; Sanderson et al. 2018).

In addition to crop yields, the effect of climate change on agricultural output will be impacted by planted acreage. Considering this, a gap exists in the current literature on empirical analyses investigating if and how farmer land-use decisions respond to changes in weather and climate patterns, rather than if they should or could do so. Past literature has shown that farmers respond in some way to weather and climate, but there is ambiguity about the extent to which these responses manifest in farm-level decision-making (Morton, McGuire and Cast 2017). Morton et al. (2015) suggest that many climate forecasts may have little relevance to farmers as they are more global in nature with considerably less predictive power at a more local level. Furthermore, it is unclear if farmers are responding to short term weather changes (shocks) or longer-term weather and climate changes (Burke and Emerick 2016). This is further complicated by how long a weather event or shock effects farmers' memory and in turn their land use decisions. The relevance of whether farmers recognize and respond to changing weather and climate is compounded as many countries use incentive-based approaches to climate-change adaptation and thus the adaptation process relies – at least in part – on farmer climate and weather perceptions (Haden et al. 2012). The speed at which farmers adapt to or how they respond to changes in weather and climate will likely have shorter to longer term food security implications through direct effects on crop yields and supplies. In addition, it could impact the formulation of incentive-based agricultural policies targeting climate-change resilience (Schleussner et al. 2018).

The purpose of this article is to investigate whether land-use decisions in a set of limited-irrigation counties in the Smoky Hill Watershed in Kansas, USA have been influenced by weather trends over time and, if so, how do past time horizons used in forming future weather expectations impact these decisions. If farmers' land-use decisions do respond to weather patterns, these responses are likely to be more noticeable and occur first in dryland cropping systems and regions, which may be more susceptible to impacts from weather and climate change. As such, this article focuses on dryland cropping decisions. Through the inclusion of different average and extreme precipitation and temperature histories, insights are gained as to how agricultural production in a region may respond or adapt to changing climate or changing weather conditions. This work contributes to the existing climate-change and land-use literature by providing a more inclusive dynamic land-use conceptual framework assuming risk-neutral producers and adaptive-weather expectations that allows for the examination of multiple land uses or management regimes and the incorporation of different historical weather patterns.

The findings from this study provide several novel insights into how farmers may adapt to weather over time and how they may respond to adverse weather events, given the increased occurrence of extreme weather events (e.g., drought and heat stress) now and in the future due to climate change (Mann, et al.

2018; Reynolds et al. 2016). First, results from the study highlight a process by which extreme and adverse weather events and shocks could affect a farmer's land use decision-making both immediately and for a considerable period. Moreover, the short- and long-term reactions may be quite different, which could lead to a more volatile adaptation process if future weather is characterized by an increased frequency of severe events. Relatedly, results show how a shift in climate or a persistent (over time) adverse weather event will impact farmer land-use decisions in the long term, but adaptation to these conditions may lag the event's onset by a few years (or growing seasons) due to countervailing short-term responses, potentially impacting adaption-policy effectiveness. These results suggest that in modeling farmer decision-making, researchers should account for this longer-term memory of weather events.

Background

Common motivations for previous research on the agriculture-climate change relationship include food security concerns, agriculture's potential to compound or mitigate adverse climate-change scenarios, and the economic impacts on agricultural producers. Some negative impacts are estimated to have occurred already, such as 3.8 and 5.5% production declines from 1980 to 2008 in maize and wheat, respectively (Lobell, et al., 2008). Others are expected to be coming. Crops including corn, rice, sorghum, soybeans, and wheat, for example, are expected to see yield decreases from higher temperatures and decreased soil moisture despite some yield benefits from direct fertilization caused by higher carbon-dioxide (CO_2) levels (Long, Ainsworth, Leakey, Nosberger, & Ort, 2006). Global-yield decreases by 2099 may be as large as 30 to 82% for corn, soybeans, and cotton, depending on the speed of climate change (Schlenker & Roberts, 2009). Despite commonality amongst global conclusions such as yield reductions, the distribution of impacts is unlikely to be globally or regionally homogenous (Parry, Rosenzweig, Iglesias, Livermore, & Fischer, 2004). In a country the size of the United States, this spatial heterogeneity will likely mean some areas may see economic gains while others experience losses (Deschênes &

Greenstone, 2007). A common theme in much of this literature, however, is the omission of climate change-induced changes or adaptations in land-use patterns.

Due to potential food-security ramifications and, to a lesser extent, the role agriculture may play in compounding adverse weather and climate scenarios (see, e.g., Searchinger et al. 2008; Bellarby, Foereid, and Hastings 2008), numerous studies have looked at climate-change adaptation or mitigation strategies that could be employed at the farm level. The focus of this article is adaptation, which may be realized in numerous ways and may "encompass a wide range of forms (technical, financial, managerial), scales (global, regional, local) and participants (governments, industries, farmers)" (Smit & Skinner, 2002, p. 86). Adaptation can refer to any response by farmers as an adjustment in their farming operation or decision-making to a change in the environment that takes advantage of beneficial opportunities or moderates adverse impacts (Burke and Emerick 2015; Burke and Lobell 2010; Zilberman, Zhao and Heiman 2012). Olesen and Bindi (2002, pp. 252-253) identify several adaptation strategies including "short-term adjustments" such as modified planting schedules, input adjustments, and water-conserving practices such as reduced-tillage or irrigation management; and "long-term adaptations" such as changes in land allocations or a move away from specialized production. With respect to changes in land allocations, Olesen and Bindi (2002) suggest that crops with highly variable production could be substituted for crops with more stable yields, even if total production is lower. Given the data used in this article, it is not possible to identify specific management-based adaptation strategies, such as tillage or crop varietal changes. Adaptation strategies that are captured in the current study would include changes in crop rotations, use of fallow periods (possibly for water conservation), and substitution between crop types (e.g., to more drought resistant crops like sorghum) (Smith et al. 2008). For example, Staggenborg, Dhuyvetter, and Gordon (2008) find that sorghum may be a better crop choice in regions with erratic rainfall and high temperatures. In the study region for this analysis, sorghum may be frequently used as silage or a feed grain due to limited rainfall and irrigation, as well as the large number of cattle in the region. As such, sorghum (and more infrequently corn for silage) may be a more viable low-rainfall option for dryland farmers than more water-intensive land uses.

Despite potential global ramifications and localized incentives to adapt, there is little research to indicate how farm production and land-use decisions will respond. Most climate-change scenarios or measures are global, and thus may have little actual or perceived relevance to individual farmers (Morton et al. 2015). As a result, some farmers may be slow to respond or perhaps not respond at all. Relatedly, some may have a lack of faith in future projections, perhaps due to short-term forecast accuracy. Weather forecasts 10 days out, for example, may only have a 40% forecast skill, defined as the correlation between forecasts and a verifying analysis (Bauer, Thorpe, and Brunet 2015). Whatever the reasons, previous research indicates a sizable portion of the farming community has doubts regarding climate change (Arbuckle, Morton and Hobbs 2013b; Arbuckle et al. 2013c), which is an obvious barrier to timely adaptation.

Regardless of beliefs about the issue, we should expect individual farmers to react to local climate change if it creates negative economic outcomes. The question then becomes: Are farmers responding to weather patterns? Some, such as Burke and Emerick (2016), suggest that farmers have not adapted to climate changes, despite negative impacts on crop productivity. If, however, farmers are responding, the next question is: To what are they responding? To put this second question another way, Bradshaw, Dolan, and Smit (2004, p. 123) ask "will farmers differentiate between the so-called 'signal' and 'noise'?" In other words, will farmers differentiate between long-term weather trends and patterns (the signal) and short-term variations around this trend (the noise)? Bradshaw, Dolan, and Smit (2004) note that the answer to this question may be unimportant if farmers' adaptations leave them better prepared for long-term trends, but important if farmers respond to variability which masks slower, underlying trends, potentially leading to complacency, inefficient adaptation, or maladaptation. A final question then is what if farmers react to both? For example, it may be that weather expectations are largely formed by the "signal", but "noise" components indirectly play a role as well and may do so more directly if they include a severe shock, such as a drought or flood. The third question then is asking: What are the consequences for the adaptation path under such a scenario?

The question of how and to what – if anything – are farmers responding is the central question of this article. An answer to this question will provide insights as to the speed at which farmers might employ adaptation measures. Additionally, results will provide insights into how land-use patterns may shift under various climate change and weather scenarios, accounting for potential adaptation. Taken together, these results can guide future researchers in conducting more thorough assessments of climate-change impacts.

In attempting to answer these types of questions, however, researchers are faced with many challenges, such as identifying "how the dependent variable of interest changes with the weather…" and with "…forecasts of the weather" (Lemoine 2017, p. 13). Lemoine (2017) notes that in analyses of weather impacts on agricultural profits, for example, an omitted variable bias is created because profits are a function of land-use decisions, which in turn will be a function of the weather. In our approach, we attempt to avoid this concern by focusing on the land-use decisions themselves. That is, we focus on the field crop category to gain insights into how specific land uses within that group may respond to weather events and climate change.

Conceptual Framework

This section of the article provides a farmer-based land-use conceptual framework that starts with an assumption of a risk-neutral farmer who seeks to maximize expected profit. Under this assumption, each farmer n must decide what crop to plant in field i in year t to maximize field-level expected profits. Letting

$j = 0, \ldots, J$ denote the crop choices available and $\Pi_{i,t}$ denote expected profits on field i in year t, farmer n's problem in year t for field i can be represented as:

$$(1) \quad \max \Pi_{i,t} = \sum_{j=0}^{J} d_{i,t}^{j} \left(p_t^j q_{i,t}^j - \mathbf{w}_{i,t}' \mathbf{x}_{i,t}^j \right) \ \text{s.t.} \sum_{j=0}^{J} d_{i,t}^{j} = 1$$

where $d_{i,t}^j = 1$ if crop j is planted in year t and 0 otherwise; p_t^j is the expected price for crop j in year t; $q_{i,t}^j = Q^j\left(\mathbf{x}_{i,t}^j, \mathbf{s}_{i,t}, \mathbf{c}_{i,t}\right) + B_{i,t}^j$ is expected output on field i for crop choice j in year t; $\mathbf{x}_{i,t}^j$ is an $M \times 1$ vector of inputs used to produce crop j in year t on field i with individual elements $x_{i,m,t}^j \geq 0$ for $m = 1, \ldots, M$; $\mathbf{s}_{i,t}$ is a vector of site characteristics; $\mathbf{c}_{i,t}$ is a vector of expected weather outcomes for year t; and $\mathbf{w}_{i,t}'$ is a $1 \times M$ vector of input costs. We assume local weather is exogenous to the expected prices, p_t^j, and that $Q^j(\cdot)$ is a twice differentiable concave production function in the inputs and weather variables for crop j. Site characteristic variables could be those related to overall soil health and productivity, such as organic matter content or drainage. Weather variables are assumed to be a key factor in determining yields and could include precipitation measures (e.g., Schlenker and Roberts 2009; Hendricks, Smith, and Sumner 2014; Isik and Devadoss 2006), growing degree days (e.g., Reynolds et al. 2000), daily solar radiation (e.g., Kaminski, Kan, and Fleischer 2012), etc. We further assume that farmers have adaptive expectations (Nerlove, 1958) with respect to weather, i.e., expectations for current weather are based on past weather history.

Growing crops in rotation can have substantial benefits (e.g. Roozeboom et al. 2009). Thus, we assume a linearly additive rotational effect, B, to crop output on a given field with crops grown in rotation following Hennessy (2006) and Hendricks, Smith, and Sumner (2014). Yield boosts are assumed to have a one-year memory and be dependent on the past and current crop, so the rotational effect on crop j in field i in year t is $B_{i,t}^j = \alpha_{0,i}^j + \boldsymbol{\alpha}_{1,i}' \mathbf{d}_{i,t-1}$, where $\alpha_{0,i}^j$ is the base yield adjustment for crop j being in rotation and

$\boldsymbol{\alpha}'_{1,i}\mathbf{d}_{i,t-1}$ is the linear additive adjustment for the effect of the crop planted in year $t-1$, with $\mathbf{d}_{i,t-1} = \left[d^0_{i,t-1}\ d^1_{i,t-1} \cdots\ d^J_{i,t-1}\right]'$; and $\boldsymbol{\alpha}_{1,i} = \left[\alpha^0_{1,i}\ \alpha^1_{1,i} \cdots\ \alpha^J_{1,i}\right]'$.

The assumption that farmers have adaptive weather expectations draws on previous literature that suggests farmers respond to biophysical events and patterns, such as local climate and weather, both in the short and long term, which can influence decision-making (Morton, McGuire and Cast 2017). That is, they form their expectations of weather in year t based on past weather and incorporate these expectations into production decisions. Wilke and Morton (2017) found through interviews with farmers in the Midwestern US that future climate and weather expectations are based on reference to past historical weather events and cycles. This is further supported in the literature (e.g., Arbuckle et al., 2013b, 2014; Morton et al. 2015; Niles, Lubell, and Haden 2013)). Wilke and Morton (2017, p. 40) also suggest that "…farmers do seem to delineate the recent past from the historical past…" This suggests farmers will not place equal importance on each past weather event and thus a simple average of past weather is not an accurate forecast of a farmer's expectations. The weights put on past events will depend on, for example, cognitive processes, level of ambiguity, etc. (Hogarth and Einhorn 1990). We assume then that weather expectations in time t for covariate k in location i will be of the form:

$$(2) \quad c_{i,k,t} = \omega_0 + \omega_s W\left(\ddot{c}_{i,k,t-1}, \dots, \ddot{c}_{i,k,t-r}\right) + \omega_l W\left(\ddot{c}_{i,k,t-r-1}, \dots, \ddot{c}_{i,k,t-R}\right),$$

where $\ddot{c}_{i,k,t-r}$ are actual past weather events for $r = 1, \dots, R$; ω_0 is a reference expectation; ω_s is the farmer's weight assigned to the recent past (time periods $t-1$to $t-r$); ω_l is the weight assigned to a more distant past (up to time horizon R); and $W(\cdot)$ is a weighting function (e.g., annual mean). Findings by Hu et al. (2006) suggest that the immediate past may only have a moderate influence on planting decisions. However, it is unclear how farmers weight a longer-term history, except that it does play into forming their expectations and decision-making (Wilke and Morton 2017). It is generally held that localized climate and weather will likely influence farmer decision-making, but the evidence is inconclusive (Haigh et al. 2015; Morton et al. 2015). It should be noted that within the context of the expected-weather-formation process, a "longer-term" history in reality likely will not be – and by construction is not for the variables used in this analysis – equivalent to a climatological notion of "long-term".

Returning to the farmer's objective, problem (1) can be solved sequentially by first solving the sub-problems to obtain the maximum expected profit for each crop and then setting $d_{i,t}^{j} = 1$ for the j^{th} crop with the highest expected profit. First-order conditions (FOCs) for the sub-problems associated with each crop are given by $p_t^j \, \partial Q^j / \partial x_{i,m,t}^j = w_{i,m,t}$, yielding a system of equations with optimal solution (Hennessy 2006):

$$(3) \quad \mathbf{x}_{i,t}^{j,*} = \mathbf{g}^j\left(\mathbf{w}_{i,t}^j, \mathbf{s}_{i,t}, \mathbf{c}_{i,t}\right) \equiv \mathbf{g}^j$$

where $\mathbf{w}_{i,t}^j$ is a vector of price ratios with individual element $w_{i,m,t}^j = w_{i,m,t}/p_t^j \, , m = 1, \dots, M$. Using equation (3), maximum expected profit for crop j on field i in year t can be expressed as:

$$(4) \quad \Pi_{i,t}^j = p_t^j \times \left(Q^j\left(\mathbf{g}^j, \mathbf{s}_{i,t}, \mathbf{c}_{i,t}\right) + B_{i,t}^j\right) - \mathbf{w}_{i,t}\mathbf{g}^j.$$

A farmer will decide to plant crop j on field i in time t if the following condition holds:

$$(5) \quad \Pi_{i,t}^j - \Pi_{i,t}^k > 0 \quad \forall k \neq j.$$

It should be noted that the problem represented in (1) and the solution given by condition (5) represents a simplified version of the farmer decision-making process. Particularly, it assumes the farmer's decision is only concerned with the current year's expected profit given the past year's cropping decision.[1] While this framework simplifies the dynamics of the crop-rotation decision-making process, it does allow for the emergence of crop rotations so long as $\boldsymbol{\alpha}_{1,i}'$ remains fixed over time. In addition, this framework allows for adjustments to planned crop rotations due to changes in weather and/or market conditions, of which the former is the primary interest of this paper.[2]

The above framework provides a basis for examining the impacts of weather on land-use decisions. Consider the weather expectation for the k^{th} weather variable, c_k. Suppressing field and time subscripts, the impact of a change in this expectation on the decision to plant crop j can be represented by $\partial\left(\Pi^j - \Pi^h\right)/\partial c_k = \partial\Pi^j/\partial c_k - \partial\Pi^h/\partial c_k$, where

$$(6) \quad \frac{\partial\Pi^j}{\partial c_k} = p^j\frac{\partial Q^j}{\partial c_k} + \left[p^j\left(\frac{\partial Q^j}{\partial \mathbf{g}^j}\right)' - \mathbf{w}_t\right]\frac{\partial \mathbf{g}^j}{\partial c_k}.$$

The first component in equation (6) is the direct impact on expected marginal revenue from changes in expected crop output (yield) due to a change in expected weather. The second component (an indirect effect) is the change in marginal profit due to a shift in the (expected) optimal input quantities due to a change in expected weather. Whether $\partial\left(\Pi^j - \Pi^h\right)/\partial c_k > 0$ will dictate the impact on the likelihood a farmer opts for land-use j rather than land-use h. In addition, the magnitude of the effect will depend on how long ago the weather event occurred and whether it is taken to be a short-term "shock" or indicative of a long-term trend. For example, a weather event in the recent past (e.g. a one-period drought) in period $t - r$, will change weather expectations by $\partial c_{i,k,t}/\partial \ddot{c}_{i,k,t-r} = \omega_s\, \partial\mathrm{W}/\partial \ddot{c}_{i,k,t-r}$ based on equation (2). If a farmer heavily discounts recent, short-term weather, then ω_s will be very small, potentially resulting in a negligible expected impact on marginal profits. If the weather event occurred in the longer, more distant past, then $\partial c_{i,k,t}/\partial \ddot{c}_{i,k,t-r} = \omega_l\, \partial\mathrm{W}/\partial \ddot{c}_{i,k,t-r}$. Wilke and Morton (2017) indicate that extreme past events (e.g., the Dust Bowl or severe drought in the Midwestern US in 2012) may have long-term memory, in which case ω_l may be significantly larger and play a more dominant role in weather expectation formation, resulting in potentially significant marginal changes from persistent past weather events. Regardless of which dominates, capturing the impacts of these distinct weather-expectations components on land-use decisions can help to assess impacts of weather and climate changes for food security and land use policy purposes.

Dynamic-Multinomial Logit with Random Effects

From the researcher's perspective, $\Pi_{i,t}^{j}, j = 0, \ldots, J$ are random variables. It is assumed $\Pi_{i,t}^{j}$ can be decomposed into a known systematic component, $\pi_{i,t}^{j} = \pi\left(\mathbf{p}_{\boldsymbol{t}}, \mathbf{w}_{i,t}^{j}, \mathbf{s}_{i,t}, \mathbf{c}_{i,t}, \mathbf{d}_{i,t-1}\right)$, and a random component, $\varepsilon_{i,t}^{j}$. Condition (5), which states option j will be chosen over option k if it provides greater expected profits, can be rewritten as:

$$(7) \quad \Delta\pi_{i,t}^{j,k} = \pi_{i,t}^{j} - \pi_{i,t}^{k} > \varepsilon_{i,t}^{k} - \varepsilon_{i,t}^{j} \quad \forall k \neq j,$$

It is assumed that the error terms ($\varepsilon_{i,t}^{j}$) are mean zero and distributed IID Gumbel. Assuming that the systematic component of the profit function can be sufficiently approximated by $\Delta\pi_{i,t}^{j,k} = \mathbf{z}_{i,t}'\boldsymbol{\beta}_j$ where $\mathbf{z}_{i,t} = \left[\mathbf{p}_{\boldsymbol{t}}, \mathbf{w}_{i,t}, \mathbf{s}_{i,t}, \mathbf{c}_{i,t}, \mathbf{d}_{i,t-1}\right]'$ and $\boldsymbol{\beta}_j$ is a set of parameters specific to land use j.

The probability that field i is planted to crop j in year t can be represented as $\mathbb{P}_{i,t}^{j} = \mathbb{P}\left(\Delta\pi_{i,t}^{j,k} > \varepsilon_{i,t}^{k} - \varepsilon_{i,t}^{j}\right) = \mathbb{P}\left(\mathbf{z}_{i,t}'\boldsymbol{\beta}_j > \varepsilon_{i,t}^{k} - \varepsilon_{i,t}^{j}\right) \;\; \forall k \neq j$. Following Train (2009), these probabilities can be estimated using a multinomial logit model:

$$(8) \quad \mathbb{P}_{i,t}^{j} = \frac{\exp\left(\mathbf{z}_{i,t}'\boldsymbol{\beta}_j\right)}{1 + \sum_{h=1}^{J}\exp\left(\mathbf{z}_{i,t}'\boldsymbol{\beta}_h\right)},$$

where the parameters for land use $j = 0$, a reference land use chosen by the researcher, are normalized to zero (i.e., $\boldsymbol{\beta}_0 = \mathbf{0}$) to ensure identifiability of the other model parameters (Greene 2012).

A significant issue in modeling land-use is unobserved heterogeneity across fields. This problem is compounded due to the absence of farmer-specific and field-specific data, and thus the inability to control for field-specific characteristics such as the farmer's management ability or resource constraints, soil characteristics, etc. One method to capture unobserved heterogeneity is to adopt a random effects approach to equation (8), where the land-use specific intercept is replaced with $a_{i,j}$, a field specific random intercept associated with land use *j* that is assumed to follow a given distribution $h(a_{i,j})$. Under this assumption, the logit probability given in equation (8), conditional on $\mathbf{a}_i = [a_{i,1} \dots a_{i,J}]'$, becomes (Train 2009):

$$(9) \quad \mathbb{P}_{i,t}^{j} = \frac{\exp(\mathbf{z}_{i,t}'\boldsymbol{\beta}_j + a_{i,j})}{1 + \sum_{r=1}^{J} \exp(\mathbf{z}_{i,t}'\boldsymbol{\beta}_r + a_{i,r})}$$

We will assume that $a_{i,j} \sim N(\bar{a}_j, \sigma_j^2)$ for $j = 1, \dots, J$. The specific random intercept terms allow the model to capture unobserved differences across fields in a parsimonious way, by capturing unobserved farmer-specific characteristics, cultural differences, operational management specificities, and field-specific conditions.

With the inclusion of memory in crop rotations and yield boosts in the model, temporal dynamics come into play. To better present the dynamic nature of the model, consider the reformulation of $\mathbb{P}_{i,t}^{j}$ as $\mathbb{P}_{i,t}^{j} = \mathbb{P}(\mathbf{z}_{i,t}'\overline{\boldsymbol{\beta}}_j + \mathbf{d}_{i,t-1}'\boldsymbol{\rho}_j + a_{i,j} > \varepsilon_{i,t}^{k} - \varepsilon_{i,t}^{j}) \;\; \forall k \neq j$ where $\boldsymbol{\rho}_j$ are the parameters associated with the lagged-dependent variables and $\overline{\boldsymbol{\beta}}_j$ is the vector of parameters from $\boldsymbol{\beta}_j$ less $\boldsymbol{\rho}_j$. Letting Λ denote the multinomial logistic cumulative density function and suppressing the field subscript i, the joint density for a field is (Wooldridge 2010):

$$(10) \quad f(y_1, \dots, y_T \mid y_0, \mathbf{Z}, \mathbf{a}; \overline{\boldsymbol{\beta}}, \boldsymbol{\rho}) = \prod_{t=1}^{T} \prod_{j=0}^{J} \left(\Lambda(\mathbf{z}_t, \mathbf{d}_{t-1}, \mathbf{a}; \overline{\boldsymbol{\beta}}_j, \boldsymbol{\rho}_j)\right)^{d_t^j}.$$

where $y_t = [d_t^0, d_t^1, \dots, d_t^J]$ for $t = 1, \dots, T$ is the vector of land use decisions in time period t such that $\sum_{j=0}^{J} d_{i,t}^{j} = 1$. Wooldridge (2010) notes that, for the binary case, the presence of unobserved heterogeneity (or effects) does not allow for a log-likelihood function that can be used to consistently estimate $\overline{\boldsymbol{\beta}} = [\overline{\boldsymbol{\beta}}_{\mathbf{1}}, \dots, \overline{\boldsymbol{\beta}}_{\boldsymbol{J}}]$ and $\boldsymbol{\rho} = [\boldsymbol{\rho}_{\mathbf{1}}, \dots, \boldsymbol{\rho}_{\boldsymbol{J}}]$. Instead, Wooldridge (2010) suggests the unobserved effects be integrated out of the distribution, which creates another issue of how to deal with the initial observations, y_0 (Wooldridge 2010). This is generally referred to as the initial conditions problem[3].

To integrate out the unobserved effects, Wooldridge (2005) suggests using the density $f(y_1, \dots, y_T \mid y_0, \mathbf{Z})$, because $f(y_1, \dots, y_T \mid y_0, \mathbf{Z}, \mathbf{a})$ has already been specified using equation (10).[4]. Then, all that must be done is to specify an alternative density for $\mathbf{a}$, the vector of random effects, that is conditional on y_0 and $\mathbf{Z}$. Letting $\mathbb{P}(\mathbf{a} \mid y_0, \mathbf{Z}; \mathbf{\Theta}) = h(\mathbf{a} \mid y_0, \mathbf{Z}; \mathbf{\Theta})$, then following Wooldridge (2005), $f(y_1, \dots, y_T | y_0, \mathbf{Z}; \overline{\boldsymbol{\beta}}, \mathbf{\Theta}, \boldsymbol{\rho})$ is given by:

$$(11) \quad \int_{R^J} f(y_1, y_2, \dots, y_T \mid y_0, \mathbf{Z}, \mathbf{a}; \overline{\boldsymbol{\beta}}, \boldsymbol{\rho}) h(\mathbf{a} \mid y_0, \mathbf{Z}; \mathbf{\Theta}) \eta(d\mathbf{a}),$$

which after substituting into equation (10) becomes:

$$(12) \quad \int_{R^J} \prod_{t=1}^{T} \prod_{j=0}^{J} \left(\Lambda(\mathbf{z}_t', \mathbf{d}_{t-1}', \mathbf{a}; \overline{\boldsymbol{\beta}}_j, \boldsymbol{\rho}_j)\right)^{d_t^j} h(\mathbf{a} \mid y_0, \mathbf{Z}; \mathbf{\Theta}) \eta(d\mathbf{a}).$$

The density function $h(\cdot)$ can be specified in such a way that the model can be estimated using a standard random effects or mixed logit approach. A specification for $h(\cdot)$ that accomplishes this is $a_{i,j} \sim N(\theta_{0,j} + \mathbf{d}_{i,0}' \mathbf{\Theta}_{1,j} + \mathbf{z}_i' \mathbf{\Theta}_{2,j}, \sigma_j^2)$, where $\mathbf{z}_i = [\mathbf{z}_{i,0}' \ \mathbf{z}_{i,1}' \cdots \mathbf{z}_{i,T}']'$ is a vector of contemporaneous explanatory variables. Under this specification, the vector of random intercepts follows $\mathbf{a}_i \sim N(\bar{\mathbf{a}}, \boldsymbol{\Gamma}\boldsymbol{\Gamma}')$, where $\bar{\mathbf{a}}$ is a vector of conditional means with elements $\bar{a}_j = \theta_{0,j} + \mathbf{d}_{i,0}' \mathbf{\Theta}_{1,j} + \mathbf{z}_i' \mathbf{\Theta}_{2,j}$. We assume for estimation purposes that $\boldsymbol{\Gamma}\boldsymbol{\Gamma}'$ is a diagonal matrix with $\sigma_j^2, j = 1, \dots, J$ along the diagonal. Equation (12) along with the specification for $h(\cdot)$ is referred to as a dynamic-multinomial logit model with random effects (DML-RE).

Farmer-specific weather expectations and the process by which they form these expectations are likely unique to the individual. Thus, the weather-expectation process is another justification for the unobserved heterogeneity assumption as farmers may hold different weather expectations for the upcoming season even if they have experienced identical weather histories due to unobserved cognitive, social, and cultural processes. Under this scenario, the two farmers may make different land-use decisions in any given year, even if all other variables are identical. As mentioned previously, potential differences in operational management and field-specific conditions provide additional justification. These factors and the assumed importance of crop rotations justify the approach suggested by Wooldridge (2005).

To assist with capturing additional spatial heterogeneity and improve the robustness of model estimations, we estimate a separate DML-RE model for each county in the study region in Kansas. The counties included are Barton, Ellis, Ellsworth, Gove, Lincoln, Ness, Ottawa, Rush, Russell, Saline, and Trego (see figure 1). Differences across counties in model estimates could arise due to spatial heterogeneity resulting from differences in local agricultural conditions and conservation policies (e.g., the USDA Environmental Quality Incentives Program has been historically administered at the county level), as well as differences in agricultural extension efforts, markets, and services.

Data

Analysis for this article is based on the subset of Kansas counties, which are depicted along with the Ogallala Aquifer boundary in figure 1. The primary reason for choosing these counties is that their combined boundaries largely encompass two central Kansas watersheds that are the subject of an ongoing research project[5]. Motivation for using this set of counties follows from the fact that Kansas exhibits a strong precipitation gradient moving from east to west, allowing for potentially greater variation in precipitation histories. These counties also see little irrigated crop production (USGS 2017) and are thus less susceptible to bias from omitted irrigation variables. As mentioned previously, we focus on dryland agriculture systems based on an assumption that these systems will be more responsive to weather trends.

Land-use Decision Variables

Land-use observations are based on a detailed, field-level database. Land-use decisions within field boundaries are based upon the United States Department of Agriculture National Agricultural Statistics

Service's (2016) Cropland Data Layer (CDL) and Farm Service Agency (FSA) data for the years 2003 to 2012. The study region depicted consists of 157,207 unique fields, developed by the Kansas Biological Survey. For each field, the crop assigned to a field represented the dominant crop (the crop with the most planted acreage).[6] Any fields that were at any time period classified to a land use other than those of interest – alfalfa, corn and sorghum, soybeans and double crop (soybeans and wheat), fallow, and wheat – were dropped. The land-use classifiers include a category for alfalfa, double cropped (primarily with soybeans), fallow, corn, sorghum, soybeans, and wheat. Any fields that had an irrigated land-use in any year were dropped to further the effort of limiting the analysis to dryland agriculture. Observations from 2003 are set aside as the initial period and fields of less than 5 acres are dropped, leaving a balanced panel set of 38,506 fields and a total of 346,554 observations (nine observations per field) across all counties for model estimations.

Dependent variables are the five land uses described above and are denoted A_t for alfalfa, CS_t for corn or sorghum, F_t for fallow, SD_t for soybeans or double cropped (soybeans and wheat), and W_t for wheat. These land uses and land-use groupings were chosen to create categories that, within the study region, may respond differently to different weather scenarios. Corn and sorghum, for example, were grouped together, because in western Kansas, a wheat-feed grain-fallow rotation is common (Aiken and O'Brien 2009). Much of the dryland corn grown in this area of Kansas – due to limited water conditions – is used for forage (Roozeboom and Fjell 2007) and is a less intensive land use than corn grown for grain, which is predominantly irrigated in western Kansas. Summary statistics for these categories can be found in table 1. Wheat was the dominant land use over the period examined, with an average of 53% of fields devoted to wheat each year. With an average share of 3% of fields, alfalfa was generally the most infrequent land use. Land-use acre shares were nearly identical to the field shares.

Expected Output Prices

We use expected prices to represent the price a farmer expects to receive at harvest given the information available at the time a crop is planted. Following the approach of Hendricks, Smith, and Sumner (2014), expected prices for sorghum, soybeans, and wheat were calculated as a futures price at the time of planting plus an expectation of the basis at harvest[7]:

$$(15) \quad E(p_t^j) = fp_t^j + E(basis_t^j).$$

The futures price component (fp_t^j) is an average daily futures price for each crop across “planting months”[8]. Corn futures prices were used for sorghum as sorghum futures prices were not available for this time period. The expected basis was set equal to the harvest-time basis from the previous harvest. Thus, we again are assuming adaptive expectations, albeit with a shorter memory for expected basis. This choice was partly dictated by data limitations, but evidence from Taylor, Dhuyvetter, and Kastens (2006) suggests that a “naïve” basis forecast using just the previous season’s basis often offered better predictions for current-year basis than forecasts using longer-term averages. Spot price data for basis calculations came from 961 elevator locations across Kansas[9]. This process created three of the price variables used in analysis: p_{Sor}, p_{Soy}, and p_W. An expected alfalfa price, p_A, is also used, and was set equal to the April alfalfa price in the current year using USDA-NASS data. Summary statistics for the included expected-price variables can be found in table 2.

It is recognized that input prices are important in determining the net returns to the different land uses. Due to data limitations and limited spatial variation from available data sources, input prices were not included. Hendricks, Smith, and Sumner (2014) show that changes in fertilizer prices have a much smaller impact on relative crop returns than output prices and that their results were robust to the exclusion of input prices[10], so it is assumed these omitted variables do not pose a serious concern.

Weather Variables

Included weather variables were calculated using daily data provided by Schlenker and Roberts (2009), which were created using data from the PRISM Weather Group. The daily weather data provided by PRISM are interpolated values based on weather stations located throughout the United States and are provided for gridded units that are roughly 16 km^2 in size. Individual fields were assigned weather data from the closest PRISM grid cell based on centroid distances. For the grid cells ultimately used in analysis, an average of about 26 fields were assigned to each cell. Summary statistics are provided in table 2.

Included weather variables are meant to capture – from the farmer's perspective – recent, shorter-term and more distant, longer-term weather patterns with respect to precipitation and temperatures and each is defined and calculated in terms of a growing season defined as February to September. The first four variables, *Prec1to3* and *Prec4to10* and their squared counterparts, provide the average annual growing season precipitation (100 mm) based on years $t-1$ to $t-3$ and $t-4$ to $t-10$, respectively. To provide context as to how these levels may impact land-use decisions, a table from Stone and Schlegel (2006) is reproduced in table 3. This table is based on research conducted in western Kansas and is thus applicable to the current study region. The table indicates lower threshold evapotranspiration (ET) levels for soybeans and grain sorghum of 7.8 inches (~198 mm) and 6.9 inches (~175 mm) respectively, where threshold ET is defined as the ET level below which seed yield is zero (Stone and Schlegel 2006). Max ET, defined as ET from emergence to physiological maturity (Stone and Schlegel, 2006, p. 173), was estimated to be highest for corn at 25 inches (~635 mm) and lowest for grain sorghum at 21 inches (~533 mm). Max ET for winter wheat and soybeans fell in the middle, estimated at 24 inches (~609 mm) for both. The estimates from Stone and Schlegel (2006) offer validation to the conclusions reached by Staggenborg, Dhuyvetter, and Gordon (2008). Growing season temperatures are captured by growing degree days variables, *GDD1to3* and *GDD4to10*, which measure degree days between 10°C and 30°C. These were calculated using a cosine interpolation of daily temperature exposures using the daily minimum and maximum temperatures from PRISM[11].

The next two variables, *PrecLow1to3* and *PrecLow4to10*, attempt to capture the average number of "low-precipitation days" using the same lag structures. A low-precipitation day was defined as any day which received less than 1 mm of precipitation. The 1 mm threshold for defining a low precipitation is in line with thresholds elsewhere in the literature (e.g., Bin, Murty, and Hoan 1994; Garcia et al. 2007; Nguyen et al. 2016). This threshold was chosen as it may capture frequency of little to no rainfall during the crop growing season, but an agronomic basis for the threshold could not be identified in the literature. Future research should seek to identify (potentially) more appropriate thresholds. This would likely be crop dependent, e.g., what is considered a beneficial amount of rainfall for one crop may provide no benefits to another crop, further complicating the threshold choice for the current analysis. Similarly, *GDDHigh1to3* and *GDDHigh4to10*, are meant to capture exposure to extreme temperatures. Specifically, these variables measure growing-degree days above 30°C (~86°F), calculated using the same approach used for *GDD1to3* and *GDD4to10*. This choice of threshold may not be ideal, as what constitutes an extreme temperature has been reported to vary across crops, e.g., 29°C for corn, 30°C for soybeans, 33°C for sorghum, and 34°C for wheat (Tack, Lingenfelser, and Jagadish, 2017).

The spatial and temporal variations in *Prec1to3* and *Prec4to10* are depicted in figures 2 and 3, figures for the remaining variables are provided in figures SA1 through SA6 in the supplementary appendix. The figures highlight the spatial variation along an east to west gradient, as well as the temporal variation of weather patterns within the study region. A separate set of weather variables were constructed for additional model runs using the same approaches as above, but with different lag structures for examining the time horizons of expectation formation in the paper and as a robustness check. These variables are *Prec1to5, Prec6to20, PrecLow1to5, PrecLow6to20, GDD1to5, GDD6to20, GDDHigh1to5,* and *GDDHigh6to20.*

With respect to each of these variables, there is little guidance as to how people form expectations regarding weather that will occur several months into the future, and as such our choice to use lags of 1 to 3 and 4 to 10 or 1 to 5 and 6 to 20 are subject to criticism; better structures may well exist. Our attempt here is twofold: (1) to capture a shorter-term measure from the recent past that is subject to more variability and a longer-term measure from the more distant past and (2) to construct measures (lag structures) that could plausibly be used by a farmer drawing from personal experiences. Importantly, both the shorter- and longer-term measures are a part of the same "signal" and separating them thus allows for the more complex adaptive-weighting process. From a more objective or scientific perspective, these may likely represent short- or medium-run weather histories.

Post-Estimation Inference

Average Partial Effects and Simulating Weather Changes

This study uses average partial effects (APEs) as one tool to help discern the impact of variables on land-use decisions. The magnitudes and signs of these APEs with respect to the climate variables can give an indication as to the direction and severity of impacts on land-use probabilities from a weather shock or change in the short-term, recent past or the longer-term, more distant past. As such, they can provide insights as to how the occurrence of an extreme event, e.g., a severe drought, or how a more persistent change will impact crop choice. If $\mathbf{z}'_{i,t}\boldsymbol{\beta}_j$ in (9) is linear with respect to a weather variable $c_{i,t,k}$, then the individual level partial effect for land-use j (for field i in year t) is given by:

$$(16) \quad PE^{j}_{i,t,k} = \frac{\partial P^{j}_{i,t}}{\partial c_{i,t,k}} = P^{j}_{i,t}\left(\beta_{j,k} - \sum_{h=1}^{J} \beta_{h,k} P^{h}_{i,t}\right).$$

If $\mathbf{z}'_{i,t}\boldsymbol{\beta}_j$ is nonlinear with respect to the weather variable $c_{i,t,k}$, precipitation in this case, then $\beta_{j,k}$ and $\beta_{h,k}$ are replaced with $\frac{\partial \mathbf{z}'_{i,t}\boldsymbol{\beta}_j}{\partial c_{i,t,k}}$ and $\frac{\partial \mathbf{z}'_{i,t}\boldsymbol{\beta}_h}{\partial c_{i,t,k}}$ in equation (16), respectively. The APE associated with land-use j and

$c_{i,t,k}$ then is estimated as:

$$(17) \quad APE_k^j = \frac{1}{T \times N} \sum_{t=1}^{T} \sum_{i=1}^{N} PE_{i,t,k} \,.$$

Because $c_{i,t,k}$ represents an average across some lag structures, its APE is most easily interpreted as the average change (across fields and years) in the probability of observing land-use j had $c_{i,t,k}$ been, on average, (marginally) larger over the history.

The impact of weather in the current framework depends on if the weather event or shock is for a single year, over multiple years, or a more permanent shift. An alternative and more readily accessible way to evaluate the impact of a weather event is through simulation. Of interest here is to see the effect of a weather event on the probability of choosing land-use *j* through time, *ceteris paribus*. That is the impact of an event as it moves farther back in time from $t - 1$ to say $t - 10$. To achieve this, we simulate a one-year, two-year, and three-year adverse weather event based on the 2012 drought in Kansas and compare it to a baseline scenario based on long-term averages, *ceteris paribus*. In the baseline scenario, the weather variables for every field in every year are replaced with their respective study-region averages over the 1974-2003 period. For example, for the PRISM grid cells used in the analysis, the average total precipitation (February-September) across the 1974-2003 period was about 542 mm. Thus, in the baseline scenario, *Prec1to3* and *Prec1to5* are assigned a value of 5.42 for all fields and years. The remaining baseline weather variables are constructed in a similar manner, while all remaining variables are maintained at their original values over space and time. This forms our period-t baseline data. A key assumption built into these values is that the actual weather values in $t - 1$ through $t - 10$ are equal to these long-term averages (LTAs). For the one-year shock, the 2012 drought-like event is assumed to occur in period t, and then weather returns to the LTA. This shock will lead to a change in *Prec1to3*, *PrecLow1to3*, *GDD1to3*, and *GDDHigh1to3* in periods $t + 1$, $t + 2$, and $t + 3$, and then they return to the LTAs. Conversely, *Prec4to10*, *PrecLow4to10*, *GDD4to10*, and *GDDHigh4to10* remain at the LTAs for periods $t+1$, $t+2$, and $t+3$, and change to a "shocked" level in $t+4$ through $t+10$. Continuing with *Prec1to3* and *Prec4to10*, this pattern of values is given by:

$$(18) \quad Prec1to3_{t+r} = \frac{1}{3} Prec_{2012} + \frac{2}{3} Prec_{LTA} \; for \; r = 1,2,3$$

$$(19) \quad Prec1to3_{t+r} = Prec_{LTA} \; for \; r = 4, \dots, 10$$

$$(20) \quad Prec4to10_{t+r} = Prec_{LTA} \; for \; r = 1,2,3$$

$$(21) \quad Prec4to10_{t+r} = \frac{1}{7} Prec_{2012} + \frac{6}{7} Prec_{LTA} \; for \; r = 4, \dots, 10$$

The remaining weather variables can be defined and computed similarly. For the two- and three-year events, the 2012 weather is assumed to occur in t through $t+1$ and t through $t+2$, respectively, followed by returns to the LTAs. For the permanent shock, 2012 weather is assumed to persist, i.e., there is no return to the LTAs. The underlying, study-region averages are presented in table 4 and the resulting period-by-period values used for each of the weather variables in each of the scenarios are provided in table SA1 of the supplementary appendix. We simulate the impact of the weather event for all observations and each hypothetical time period. The benefit of the simulations is that it allows for the capture of changes in multiple weather covariates, which is more realistic and flexible when examining changes in weather and representing actual weather events. Another way to view the simulations is as a comparison between two counterfactuals – one where actual weather is replaced by the LTAs and one where it is replaced by a combination of the LTAs and the 2012 drought – on farmers' land-use decisions.

The implications from the APEs and simulations may be non-trivial. If farmer expectations are dominated by more persistent trends – i.e., "signals" – they may be more likely to undertake appropriate land-use adaptations, but adaptations may be slow, resulting in more significant impacts from climate change than would otherwise occur if beneficial changes were made in a timelier fashion. Furthermore, land-use responses in the short-run may be prone to being inefficient adaptations or maladaptations from a climate-change perspective if farmers do not respond in a way that lessens impacts from climate change or adverse weather events. Recall that the two lag structures (e.g., 1 to 3 and 4 to 10) are both components of the overall signal. Thus, in the context of this analysis, reacting to just the overall signal would imply that the APEs would have the same sign and be of (approximately) equal magnitudes.

Average Transition Probabilities

Because the lagged-dependent variables represent multiple mutually exclusive scenarios $\left(\sum_{j=1}^{J} d_{i,t-1}^{j} = 1\right)$, the standard approach to calculating APEs for the lagged-binary-dependent variables via discrete differences is not appropriate. Instead, this article presents estimates of average-transition probabilities (ATPs) that provide the average-conditional probabilities of a field being allocated to land use j in year t given the field was allocated to land use k in year $t-1$. These values were calculated as:

$$(22) \quad \overline{\mathbb{P}}^{j|k} = \frac{1}{N}\sum_{i=1}^{N} \overline{\mathbb{P}}_i\left(d_{t,i}^{j} = 1 \mid d_{t-1,i}^{k} = 1, \mathbf{z}_i \right) \quad j,k = 0, \dots, 4.$$

These transition probabilities are functions of past weather and will change as weather changes. While this is not the primary focus of the paper, it provides a means for land use modelers to utilize the framework developed here for land-use modeling under different weather and climate scenarios.

Results

Separate DML-RE models and associated ATPs and APEs were estimated for each county in the study region using the two sets of lag structures for the weather variables. The two lag structures were (1) “1to3” (the near past of one to three years) and “4to10” (the longer term past of 4 to 10 years); and (2) “1to5” (the near past of one to five years) and “6to20” (the longer term past of 6 to 20 years). DML-RE model estimations were carried out in LIMDEP 10. General estimation results are presented in this section; more detailed results, as well as tables and figures for the second lag structure ("1to5" and "6to20") can be found in the supplementary appendix. For brevity, given the large number of parameter estimates and numerical results, we focus primarily on the "1to3" and "4to10" models, presenting results for APEs, the proposed simulations, and ATPs, given the limited interpretability of multinomial model coefficient estimates. Subsections present selected APEs, simulation results, and estimated ATPs for the chosen model. Due to estimation difficulties, fallow was dropped completely from the Ottawa County model, the F_{t-1} and F_0 variables were dropped from the Saline County model, F_{t-1} was dropped from the Lincoln County model, and at least one initial-conditions variable was dropped (usually SD_0) from each of the other county models. Estimation challenges are discussed further in the supplementary appendix, section A.1.

Model Estimates

Multiple model specifications were estimated for the DML-RE, but some were ruled out due to estimation challenges (see supplementary appendix for further explanation). In the preferred model, referred to as NL-DML-RE, the following variables were included: *Acres*, p_A, p_{Sor}, p_{Soy}, p_W, *Prec1to3*, *Prec1to3* squared, *Prec4to10*, *Prec4to10* squared, *PrecLow1to3*, *PrecLow4to10*, *GDD1to3*, *GDD4to10*, *GDDHigh1to3*, *GDDHigh4to10*, the initial conditions and lagged-dependent variables, and a trend variable (*Trend*). The alfalfa category was chosen as the base case. To allow for additional spatial heterogeneity, a separate model was estimated for each county in the study area as previously discussed. Model parameter estimates are available in the supplementary appendix (tables SA2 through SA12). Inclusion of the nonlinear squared terms for *Prec1to3* and *Prec4to10* are supported by the statistical significance of these terms in the model estimation results.

Three additional models were estimated for each county as robustness checks.

1. LIN-DML-RE: Same variables as NL-DML-RE less the squared precipitation terms, estimated using the DML-RE model in NLOGIT.
2. NL-OLS-FE: Same variables as NL-DML-RE, estimated using equation-by-equation OLS with field-level fixed effects in Stata.
3. LIN-OLS-FE: Same variables as LIN-DML-RE, estimated using equation-by-equation OLS with field-level fixed effects in Stata.

All four models were estimated using both the “1to3, 4to10” and the “1to5, 6to20” lag structures. Estimated APEs across model categories for the weather variables, the focus of this study, are provided in the supplementary appendix. Overall, across model specifications signs and general magnitudes of the APEs agreed, with differences between the lag structures. At times magnitudes of APEs between the linear probability model specifications using (2) and (3) differed, but signs of the APES remained the same. Differences likely arise due to the assumption of linearity with the linear probability models and that they were estimated equation-by-equation, which assumed independence between crop categories.

APEs for Weather Covariates

Results varied across land uses and counties. Estimated APE values are provided in table SA13 in the supplementary appendix. Many of the APEs are statistically significant for both lag structures, but statistical significance varies by weather variable and across counties. For the APEs, recall that we assume the weather variables based on lags 1 to 3 (or 1 to 5) represent the shorter-term reactions to past weather events, which incorporates the “noise”, while those based on lags 4 to 10 (or 6 to 20) represent longer-term reactions to past weather events. The “signal” though will include information from both the short-term and the long-term. A possibly better way to assess reaction to changes in the “signal” are through a combined effect from the shorter- and longer-term reactions.

To get an idea of longer-term impacts of persistent weather changes (i.e., like climatic changes or persistent weather effects), we can look at the net impact of adding APEs together from the two lag structures. These net impacts are depicted in figure 4. Another way to view this is to assume that the weather variable of interest, *Var*, exhibits a persistent annual increase such that after ten periods $\Delta Var1to3 = \Delta Var4to10 = 1$ given they are computed as simple averages of the past weather histories over the given lag structure. Then, the change in the probability of observing a given crop or land-use *j* given the change in the "signal" associated with weather-variable Var could be computed as (suppressing the indices *i* and *t*):

$\Delta \mathbb{P}_k^j = \frac{\partial \mathbb{P}^j}{\partial Var1to3} + \frac{\partial \mathbb{P}^j}{\partial Var4to10}$, where $\frac{\partial \mathbb{P}^j}{\partial Var1to3}$ and $\frac{\partial \mathbb{P}^j}{\partial Var4to10}$ are APEs for $Var1to3$ and $Var4to10$. This interpretation of the APEs provides a way to examine the impacts of a shift (in the longer term or "signal"), such as a climate shift, in a weather variable and assess the impact on land use decision-making, *ceteris paribus.*

Under this view, the combined APE effect of *GDDHigh1to3* and *GDDHigh4to10* suggest that long-term increases, or changes in the "signal" in daily temperatures above 30°C will, ceteris paribus, lead to an increased probability that a field is planted to alfalfa (in 9 of 11 counties), corn/sorghum (in 7 of 11 counties), soybeans/double cropped (in 7 of 11 counties) and wheat (in 6 of 11 counties), with a decrease in the probability of fallow (lower probability in 8 of 10 counties). The double crop result may be unexpected due to the lower threshold temperature at which there may be yield reductions but be partially explainable if the *GDDHigh* variables are correlated with longer growing seasons. In general, the *GDDHigh1to5* and *GDDHigh6to20* results follow those for the "1to3" and "4to10" lag structure.

A combined long-term increase in *GDD1to3* and *GDD4to10* will, *ceteris paribus*, lead to an increased probability of soybeans/double cropped (in 7 of 11 counties) and fallow (7 of 10 counties). It will lead to a decreased probability of alfalfa (in 7 of 11 counties) and corn/sorghum (in 7 of 11 counties). For wheat, the results where more mixed, with the net effect on the probability of wheat being positive in 5 counties and negative in 6 counties. On average, changes using *GDD1to5* and *GDD6to20* were similar but differed by county at times. For example, for wheat, the sign on $\Delta \mathbb{P}_k^j$ was flipped in 4 counties. This may result due to the change in lag structure. The change from *GDD1to3* to *GDD1to5* represents (1) a change in the breakpoint between the recent and distant past and (2) doubles the length of the total period examined, resulting in potentially different impacts than the "1to3" and "4to10" lag structure.

The potential land-use changes due to shifts in *GDD* (temperature) variables are somewhat consistent with changes in crop yields that may be experienced under different climate-change scenarios. Evidence from Long et al. (2006) suggests that soybean and wheat yields may respond more positively under typical climate-change scenarios relative to corn and sorghum. Tack, Lingenfelser, and Jagadish (2017) find that sorghum may not be as adaptable and heat resistant as anticipated under different climate warming scenarios using current cultivars. Across the study-region counties, the combined APE results based on an increase in average growing-season growing degree days general resulted in a lower probability of planting corn/sorghum and alfalfa and an increase for fallow and soybeans/double crop, while the results for wheat are mixed. Drought stress and extreme heat stress are likely to be more frequent under many climate change scenarios (Reynolds et al. 2016), and changes in crop yields due to temperature changes will directly impact the relative profitability of crops on a per acre basis, altering the economic incentives of which crops to plant or land uses to select on a given field. These relative changes will be spatially heterogeneous (Deschênes and Greenstone 2007), which is evidenced in the differences in responses across counties to a warming increase.

The long-term, equal combined unit increase in *PrecLow1to3* and *PrecLow4to10* was estimated to decrease the probability a field is planted to corn/sorghum in most counties (9 of 11) and increase fallow probability (6 of 10) while results were mostly mixed for the other land uses, each of which saw an increase in probability in 6 (of 11) counties[12]. This could indicate marginal shifts away from wheat-corn/sorghum-fallow rotations towards wheat-fallow rotations. However, it should be kept in mind what the *ceteris paribus* implies here: There is an increase in the number of "low-precipitation" days, but there is no change in total precipitation received. Thus, the assumption here implies an increased number of heavy precipitation events.

Patterns in the *Prec1to3* and *Prec4to10* results from a combined long-term equal increase were more noticeable and suggest an increase in the probability of alfalfa (in 6 of 11 counties), soybeans/double crop (in 8 of 11 counties), and wheat (in 9 of 11 counties) and decreases in the probability of corn/sorghum (in 10 of 11 counties) and fallow (in 9 of 10 counties). This suggests under long-term (and *ceteris paribus*) precipitation increases producers would more likely choose what are – for the region – higher value land uses. Conversely, under long-term precipitation decreases, producers would switch to corn/sorghum – with corn likely used as silage – or to fallow, which can increase soil water recharge (Aiken et al. 2013). The long-term increase results were similar using *Prec1to5* and *Prec6to20.*

Weather Simulations

To examine farmer land-use response for dryland copping systems to more extreme and adverse weather events that are predicted to occur more often, we simulate a significant one-, two- and three-year drought event in the study region based on the severe 2012 drought in Kansas. In addition, we examine a scenario to see what would happen if the drought was persistent over the entire time period. Recall, the simulations are conducted assuming a deviation from a 30-year weather trend as outlined in the methods section. The results of the simulated drought shocks using NL-DML-RE and the 1-3, 4-10 lag structure are presented in figures 5 through 8. Similar figures for the 1-5, 6-20 lag structure are included in figures SA7 through SA10 in the supplementary appendix. These findings allow us to better examine the response to simultaneous changes in multiple weather variables that occur during adverse and extreme weather events, as well as how the effect of these events on decision-making may change as a producer becomes more temporally removed from the event or they become more persistent.

For the one-year drought, the shorter- (1 to 3 years post shock) and longer-term (4 to 10 years post shock) tend to be minor in many cases (figure 5). Two of the more noticeable patterns include a significant short-term probability decrease for corn/sorghum in many counties and an increase in the likelihood of planting wheat, after which both tend to revert towards baseline levels or to a slight increase (decrease) in the likelihood of planting corn/sorghum (wheat). Another pattern of interest, but not observed as often, was a decrease in the likelihood of the use of fallow periods in the short run. The longer-term impacts – shifts away from wheat and towards corn/sorghum – are in-line with expectations (e.g., Staggenborg, Dhuyvetter, and Gordon, 2008). The short-term impacts may be less intuitive. One possible explanation is that immediately following the shock, farmers expect it to be just that – a shock – and thus expect weather to return to a "normal", less droughty year. Thus, there may be an impetus to capitalize on what are expected to be favorable weather conditions in the near future to regain potential economic losses during the drought year. The response to weather is also likely influenced by farmer perceptions, farmer age, understanding of meteorological events, and farmer demographics, which was data not available for this study, but is an area of future research (Taylor, Stewart, and Downton, 1988).

A stronger response is evidenced in the 2-year and 3-year simulated drought events. Probabilities see slightly more across-the-board impacts under these drought shocks (figures 6 and 7), but some similar patterns emerge for corn/sorghum, wheat, and fallow in the short term. The longer-term impacts on corn/sorghum and wheat probabilities are more pronounced, with corn/sorghum probabilities generally seeing modest increases and wheat probabilities modest decreases. A less prominent pattern in these scenarios is a short-term decrease in fallow probabilities, followed by a large spike in year $t + 4$ before returning to roughly the baseline levels. For the permanent-shock scenario, the impacts are often much larger and present across more land-uses (figure 8). A couple of scenarios emerge from the simulation of the persistent shock: greater shifts to the likelihood of planting continuous alfalfa (Lincoln, Ness, Ottawa, and Saline counties) and large shifts away from wheat in most other counties over time. The results from the persistent shock should be taken with some caution though, as it would represent a very significant and prolonged extreme event (or a dramatic shift in climate).

The short-term response in many of the simulations for corn/sorghum, wheat and fallow may seem maladaptive and contrary to what one may expect in these situations. Taylor, Steward, and Downton (1988) suggest that while such a response may seem counterintuitive or maladaptive, it may be a rational decision for the farmer based on how they perceive and form weather expectations. The average age of farmers is increasing, and Diggs (1991) finds evidence that farmers with more experience tend to have lower expectations (e.g., less likely to occur and/or impact their operation) concerning the severity of future drought events. Crane et al. (2010) interviewed farmers about use of climate and weather information and found that their risk-management production strategies tended to be based on longer-term strategies that are meant to be in place over longer time periods and producers preferred management that emphasized consistency over year-to-year changes. These results may suggest that deviations in land-use decisions from shorter-term weather changes are less likely, which could mean a greater likelihood of keeping with current cropping and land-use practices in the short term. Farmers also tend to discount weather and climate forecasts (Crane et al. 2010). Gebrehiwot and Veen (2015) indicate that the likelihood of adaptation will be driven by the expectation of the severity of an event and the ability to cope with necessary changes for adaptation. If the perceived cost of adaptation is too high, which may be the case in the short run if producers tend to develop management strategies that look longer term with respect to weather, then it may take longer to adapt to more severe weather shocks or persistent changes in weather. Thus, adaptation may be delayed until a significant amount of "experience" has been built up over time to initiate a change in management strategies. That is, impacts from adverse weather events may need to be experienced for a longer period or more often for adaptation to occur.

Price Effects

NL-DML-RE APEs associated with crop prices and the 1-3, 4-10 lag structure are presented in table SA14 in the supplementary appendix. The expected alfalfa price, p_A, had a negligible impact on the probability of observing any land use and alfalfa in general was unresponsive to all prices. An increase in p_{Sor} increases the probability of observing corn/sorghum in 7 out of 11 counties. An increase in p_{Soy} increased the probability of observing soybeans or double cropping (soybeans and wheat) in all counties, and an increase in p_W increased the probability of observing wheat in 10 of 11 counties. The probability of observing fallow generally increased with increases in p_{Sor} (in 7 of 10 counties) and p_W (7 of 10) and decreased with increases in p_{Soy} (in 8 of 10 counties).

Land-use Transition Probabilities

The estimated NL-DML-RE ATPs are depicted in figure 9 shown in table SA15 in the supplementary appendix. Because F_{t-1} was dropped in the Lincoln and Saline County models, but all dependent variables remained, there is an alfalfa/fallow lagged-land-use category for these counties. Though there are many potential patterns that can be inferred from the figure and table, some are more obvious. One example is continuous wheat, which is indicated by an ATP of 0.50 or greater in six of the eleven counties. Continuous alfalfa is also seen in some counties, but a more noticeable pattern with alfalfa is the low probability of transitioning into alfalfa from another land use. Perhaps the strongest ATP pattern is the transition from fallow to wheat: The smallest fallow-to-wheat ATP was about 0.84 in Gove county (excluding Ottawa County where fallow was dropped entirely and Saline County where the base category is alfalfa/fallow). The probability of going into fallow, meanwhile, is generally highest when preceded by corn/sorghum.

Taken together, these last two results are consistent with a wheat-sorghum-fallow or wheat-corn-fallow rotation. In western Kansas, more intensive crop sequences such as the incorporation of a feed grain into a wheat-fallow rotation – e.g., wheat-sorghum-fallow or wheat-corn silage-fallow – may be used to increase crop access to precipitation (Aiken & O'Brien 2009). These results are in line with previous research that indicates the importance of crop rotations (e.g., Hennessy 2006; Hendricks, Smith, and Sumner 2014). ATPs for models using the set of "1to5" and "6to20" variables were very similar to those presented here and are presented in figure SA11.

Limitations

It is worth noting some limitations to the current analysis when interpreting these results. First, the study region represents a small geographic area and thus the results here are not necessarily indicative of what to expect in other regions – this is demonstrated by the intra-county heterogeneity of results in this region. The study though does highlight that weather effects are localized and may experience significant heterogeneity over space. This study serves largely to provide a more holistic framework for thinking about and analyzing the impacts of climate change, specifically, by accounting for producer land-use responses. Second, none of these scenarios – changes in temperatures, in total precipitation, in "low" precipitation days – are likely to occur in a vacuum. That is, the *ceteris paribus* assumption for average partial effects does not represent the future state of the world. The simulated drought scenarios alleviate this problem to some extent and provide some indications as to how various drought shocks may impact land-use patterns in the region. Similarly, as noted in the conceptual framework and in the results, rotations matter. However, it is easily recognized that rotations in western Kansas are different from rotations in, for example, the Corn Belt due to differences in the physical environment. Then, given sufficient changes in climate patterns, there could be drastic changes in transition probabilities. The current model – due to estimation difficulties and (parameter) constraints – may not be able to capture these effects due to the lack of non-linear and interaction terms in the model.

Moreover, weather variables associated with such scenarios may fall well outside the range of values for this region and thus produce very uncertain simulation results. The threshold choices for the *GDDHigh* and *PrecLow* variables are difficult to identify, particularly given the number of land uses in this study, and so may not necessarily be optimal threshold values. Lastly, though a simulation across a climate scenario may eventually reach a "steady state", there are likely to be some interesting short-run results – particularly in those counties where the 1 to 3 and 4 to 10 APEs work in opposite directions. This is suggested but not fully captured by the drought simulations conducted here.

Discussion and Conclusion

Climate change has been the subject of much research, primarily as it relates to food security, but also with respect to adaptation or mitigation measures that farmers can take in response to changing climates. Little, however, has been done to examine to which, if any, and how farmers are responding to climate and weather patterns via their land-use decisions. If a farmer is skeptical about climate change, (s)he may not believe there is any need, or at least be less willing, to take adaptive measures, as found by Arbuckle et al. (2013b) and Arbuckle et al. (2013c). This has potential ramifications for any study seeking to examine food security or other issues under climate change scenarios: How farmer land-use decisions respond will have consequences on food supplies, environmental impacts, etc. There may also be farm-level ramifications: If farmers are responding to short-term variations in weather rather than longer-term trends, their adaptation path may be more erratic and potentially prone to maladaptations, at least in a given year. This article provides a framework for assessing the climate/weather patterns to which farmers respond, and, using this framework, examined the influence of multiple weather variables on field-level land-use decisions for 11 counties in central Kansas. Two sets of weather variables were utilized, one using three- and seven-year and the other using five and 15-year non-overlapping but adjacent histories, to provide insights into what shapes producer weather expectations and how this may ultimately shape the trajectory of climate-change induced land-use adaptation.

Empirical analysis was done using a dynamic-multinomial logit with random effects (DML-RE) approach based on the dynamic multinomial probit model with random effects proposed by Wooldridge (2005). This article appears to be the first to employ the DML-RE model for representing farmer land-use decisions, which offers a better empirical approach as the presence of unobserved heterogeneity combined with lagged-dependent variables gives rise to an initial conditions problem that can play a crucial role in determining the entire path of outcomes and render more traditional estimators inconsistent (Greene 2012). A separate DML-RE model was estimated for each county in the study region and for both sets of lag structures for the weather variables. Additional DML-RE models with different functional forms for the index function as well as linear probability models were estimated as robustness checks for each county and lag structure.

The combined net effects from the shorter- (three- or five-year) and longer-term (seven- or 15-year) average partial effects (APEs) from the estimated models provided insights as to how sustained changes in a weather variable (e.g., precipitation or temperatures) could impact land-use patterns in the region. In general, the results suggest that under sufficiently extreme changes in climate the region could see significant changes in land-use patters, particularly for corn/sorghum, fallow, and wheat. Individual shorter- and longer-term APEs, however, did not move in the same direction for some county-land-use combinations, suggesting that the short- and long-run reactions in these instances may bear little resemblance to each other.

To further parse some of these effects, this study looked at simulated probabilities from weather shocks based on the 2012 drought. Four different shock timeframes were considered: 1-year shock, 2-year shock, 3-year shock, and a permanent shock. These results also suggest differences in short- and long-term responses. Despite this, over a longer-term, the drought scenarios suggest the region may see shifts away from wheat and towards corn/sorghum. Under a permanent shock scenario, results suggest there may also be a shift to continuous alfalfa in some counties.

Several important implications may arise from the results of this article. The most obvious is the implication for food security research. How, and at what speed, farmers adapt land-use decisions to a changing climate will play a key role in determining long-term food supply trends. However, climate scenarios are not heterogeneous across space nor, as this study has shown, will be producer responses. As such, similar research in other key agricultural regions must be conducted before more definitive statements can be made.

A second implication could be the impacts on or for crop insurance. It is plausible that crop insurance may dampen the economic incentives to respond to a changing climate, at least for a period. Crop insurance could have a chronological-shifting effect, wherein the adaptation process follows a similar trend with or without crop insurance, but, with insurance, the process is shifted later in time (Annan and Schlenker, 2015). The process by which farmers adapt could also impact crop insurance indemnity payments. This will apply to region-land use combinations that are more responsive to short-term fluctuations than longer-term trends. The impacts on crop insurance will depend on the program structure and thus warrant further research.

This study focused on dryland agriculture, and thus a final implication and area for further research are the impacts on or from irrigation and water conservation. As with crop insurance, it seems likely that the ability to irrigate a field would impact how and at what speed farmers adapt to a changing climate. On the other hand, in areas where irrigation is possible – e.g., portions of western Kansas which rely on the Ogallala aquifer – if future weather is characterized by lower rainfall, this could potentially increase irrigation rates and thus lead to quicker depletion of the aquifer (Elliott et al. 2015). Actual outcomes will depend on actual weather trends and on state or local laws, such as water rights, irrigation limits, etc. Obviously, forcing adaptation by dictating land uses is not politically feasible or desirable, but incentivizing it may be. Policies to promote water conservation practices or increased irrigation efficiency, to the extent that this has not already been done, may also be warranted. Again, additional research is needed in this area to better understand adaptive land-use behaviors and their impacts.

Tables

Table 1. Share of Fields by Land-Use Category and Year in the Study Region

Year	Alfalfa	Corn or Sorghum	Fallow	Soybeans or Double Crop	Wheat
2004	0.05	0.22	0.13	0.07	0.53
2005	0.05	0.11	0.09	0.09	0.66
2006	0.03	0.17	0.22	0.02	0.56
2007	0.03	0.20	0.17	0.02	0.58
2008	0.03	0.23	0.16	0.04	0.55
2009	0.03	0.24	0.19	0.06	0.48
2010	0.02	0.23	0.17	0.09	0.49
2011	0.02	0.24	0.18	0.09	0.47
2012	0.02	0.27	0.18	0.07	0.45
All	0.03	0.21	0.17	0.06	0.53

Table 2. Descriptions and Summary Statistics for Dependent and Explanatory Variables

Variable	Description	Mean	Standard Deviation
Acres	Size of field in acres	51.15	44.54
p_A	Expected price of alfalfa	113.33	41.32
p_{Sor}	Expected price of sorghum	3.66	1.32
p_{Soy}	Expected price of soybeans	8.74	2.66
p_W	Expected price of wheat	5.53	1.67
Prec1to3	Average total Feb-Sep precipitation (100 mm) years $t-1$ to $t-3$.	5.40	0.88
Prec4to10	Average total Feb-Sep precipitation (100 mm) years $t-4$ to $t-10$.	5.44	0.64
PrecLow1to3	Average number of days (100 day), Feb-Sep, with precipitation <1 mm, years $t-1$ to $t-3$.	1.79	0.08
PrecLow4to10	Average number of days (100 day), Feb-Sep, with precipitation <1 mm, years $t-4$ to $t-10$.	1.78	0.07
GDD1to3	Average number of growing degree days (1000 gdd) between 10°C and 30°C, Feb-Sep, years $t-1$ to $t-3$.	2.06	0.09
GDD4to10	Average number of growing degree days (1000 gdd) between 10°C and 30°C, Feb-Sep, years $t-4$ to $t-10$.	2.08	0.08
GDDHigh1to3	Average number of growing degree days (100 gdd) above 30°C, Feb-Sep, years $t-1$ to $t-3$.	0.89	0.19
GDDHigh4to10	Average number of growing degree days (100 gdd) above 30°C, Feb-Sep, years $t-4$ to $t-10$.	0.99	0.11
Prec1to5	Average total Feb-Sep precipitation (100 mm) years $t-1$ to $t-5$.	5.40	0.77
Prec6to20	Average total Feb-Sep precipitation (100 mm) years $t-6$ to $t-20$.	5.71	0.56
PrecLow1to5	Average number of days (100 day), Feb-Sep, with precipitation <1 mm, years $t-1$ to $t-5$.	1.79	0.08

PrecLow6to20	Average number of days (100 day), Feb-Sep, with precipitation <1 mm, years $t-6$ to $t-20$.	1.74	0.07
GDD1to5	Average number of growing degree days (1000 gdd) between 10°C and 30°C, Feb-Sep, years $t-1$ to $t-5$.	2.08	0.07
GDD6to20	Average number of growing degree days (1000 gdd) between 10°C and 30°C, Feb-Sep, years $t-6$ to $t-20$.	2.05	0.08
GDDHigh1to5	Average number of growing degree days (100 gdd) above 30°C, Feb-Sep, years $t-1$ to $t-5$.	0.93	0.16
GDDHigh6to20	Average number of growing degree days (100 gdd) above 30°C, Feb-Sep, years $t-6$ to $t-20$.	0.86	0.09

Table 3. Yield vs. Evapotranspiration Relationship for Crops of the Central High Plains

Crop	Max ET for full-season variety	Threshold ET	Slope of yield vs. ET
Corn	25 in.	10.9 in.	16.9 bu./ac./in.
Grain Sorghum	21 in.	6.9 in.	12.2 bu./ac./in.
Soybeans	24 in.	7.8 in.	4.6 bu./ac./in.
Wheat	24 in.	10.0 in.	6.0 bu./ac./in.

Table 4. Long-term Average and 2012 Drought Weather Variable Values

	Prec	PrecLow	GDD	GDDHigh
1974-2003 LTA	5.42	1.75	2.04	0.90
2012 Drought	3.85	2.00	2.28	1.67
Change	-29%	14%	12%	85%

Figures

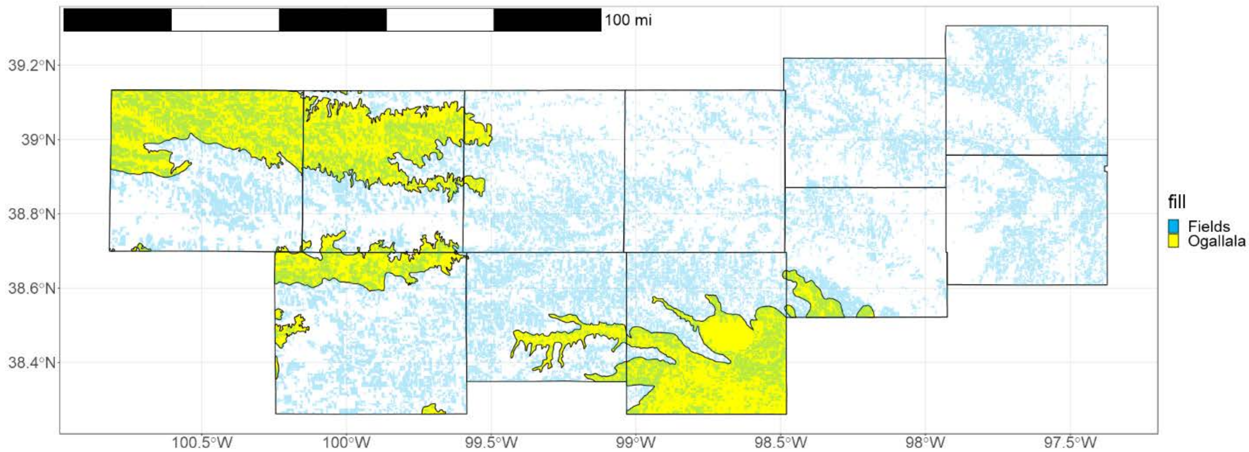

Figure 1. Study area in Kansas and fields used in analysis

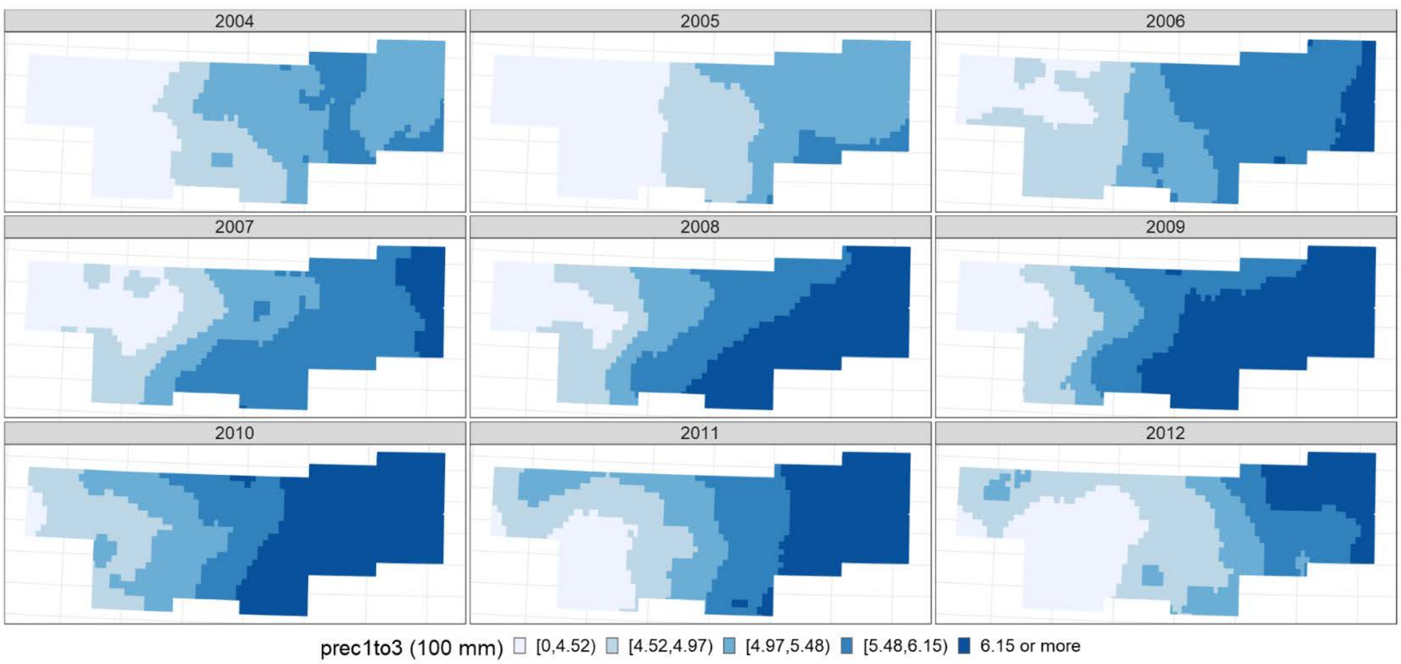

Figure 2. Spatial and temporal variation in three-year average total growing-season precipitation, using lags 1 through 3 (used to create *Prec1to3*).

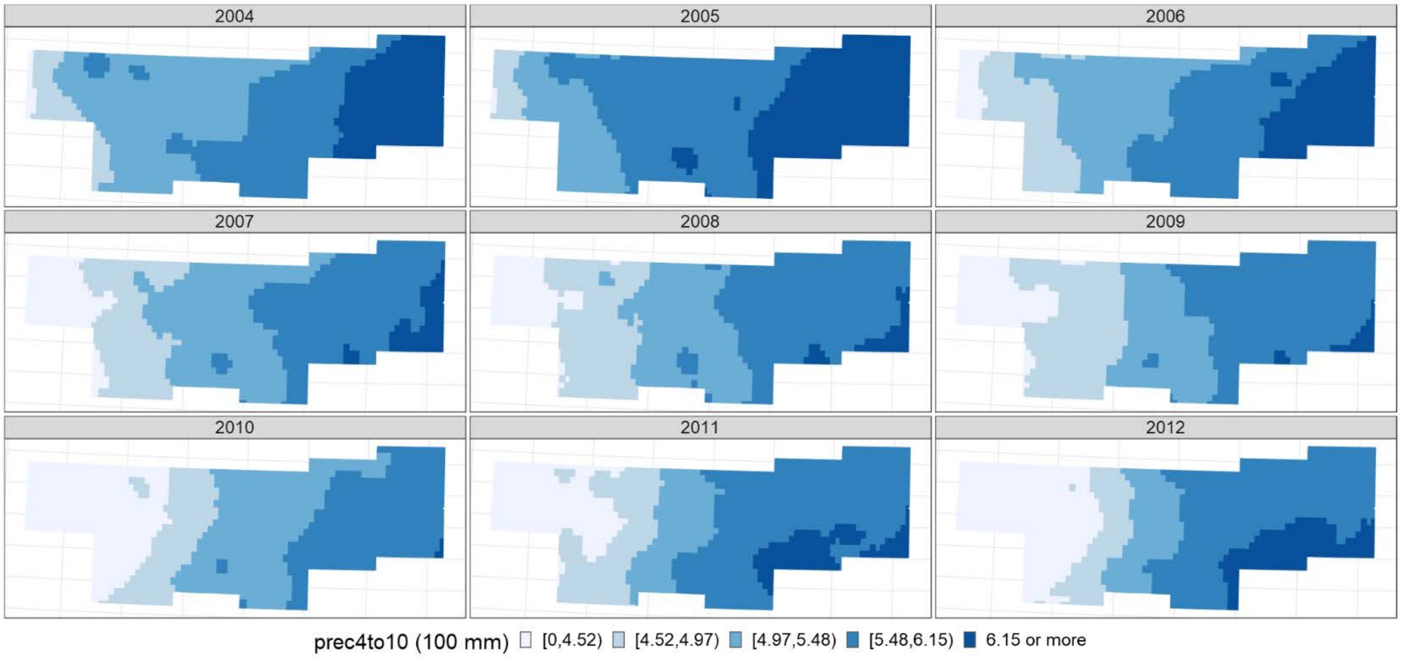

Figure 3. Spatial and temporal variation in seven-year average total growing season precipitation, lags 4 through 10 (used to create *Prec4to10*).

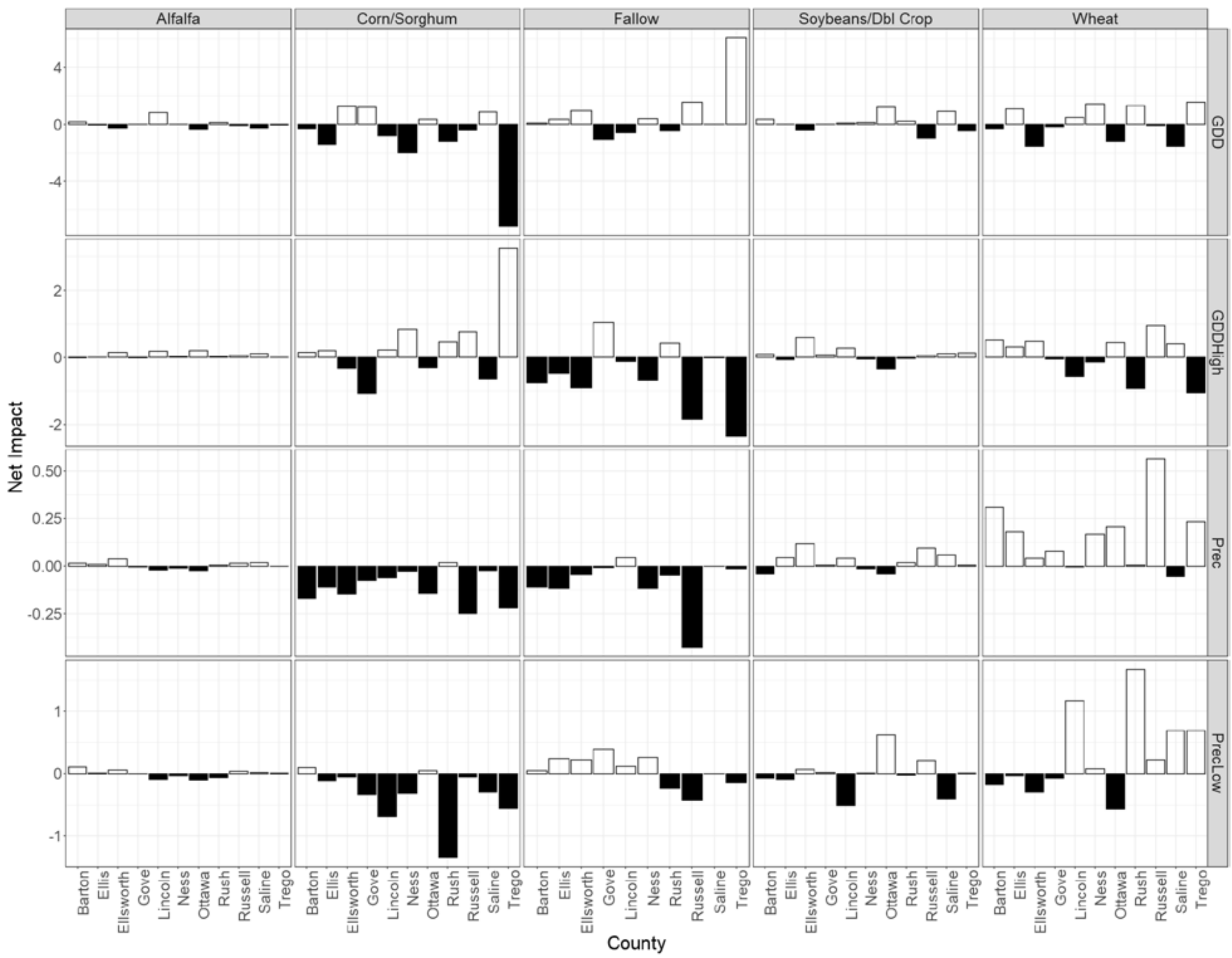

Figure 4. Net impacts of one-unit change in weather variables, NL-DML-RE, 1-3 and 4-10 lag structure

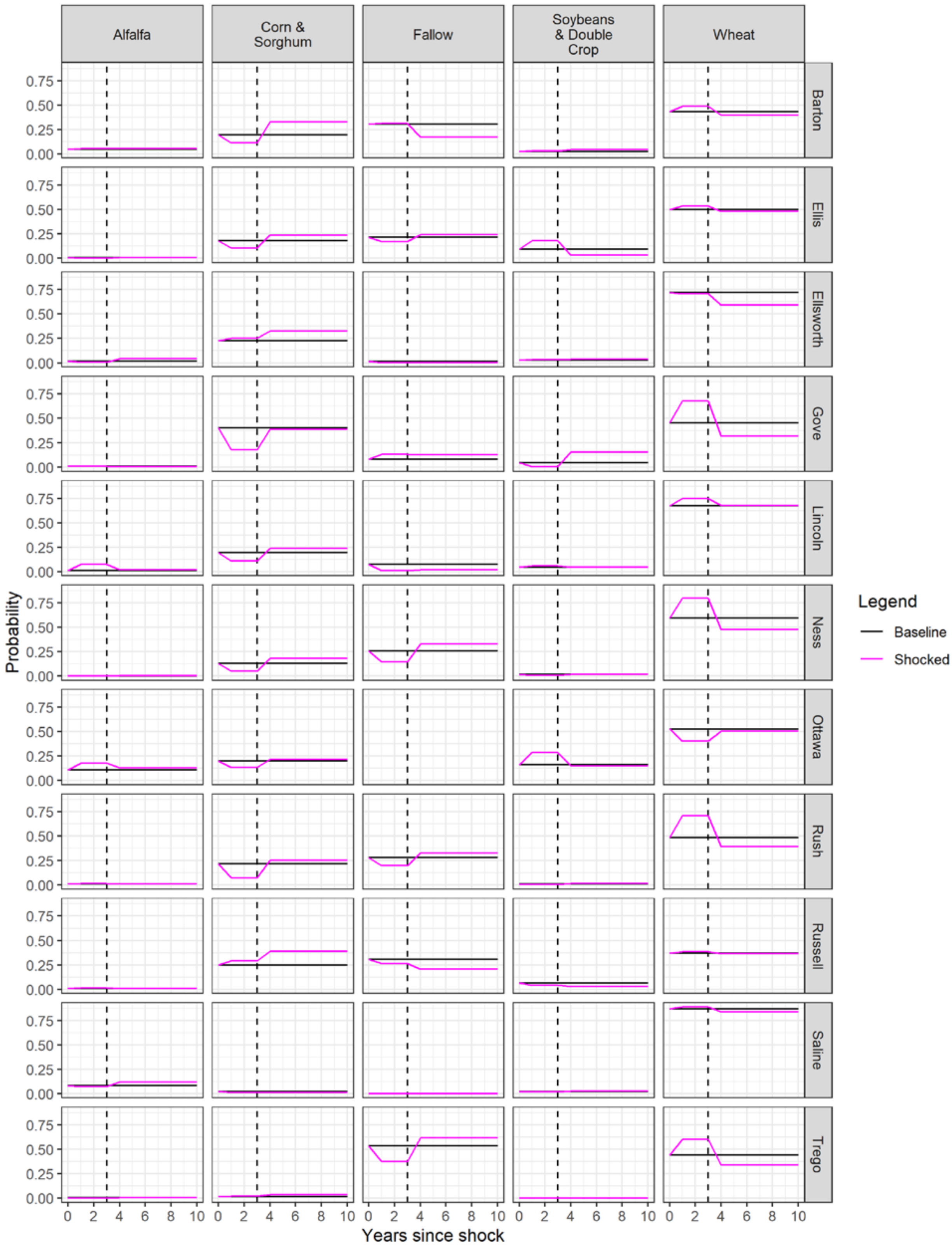

Figure 5. Simulated probabilities from drought lasting one year, NL-DML-RE, 1-3 and 4-10 lag structure

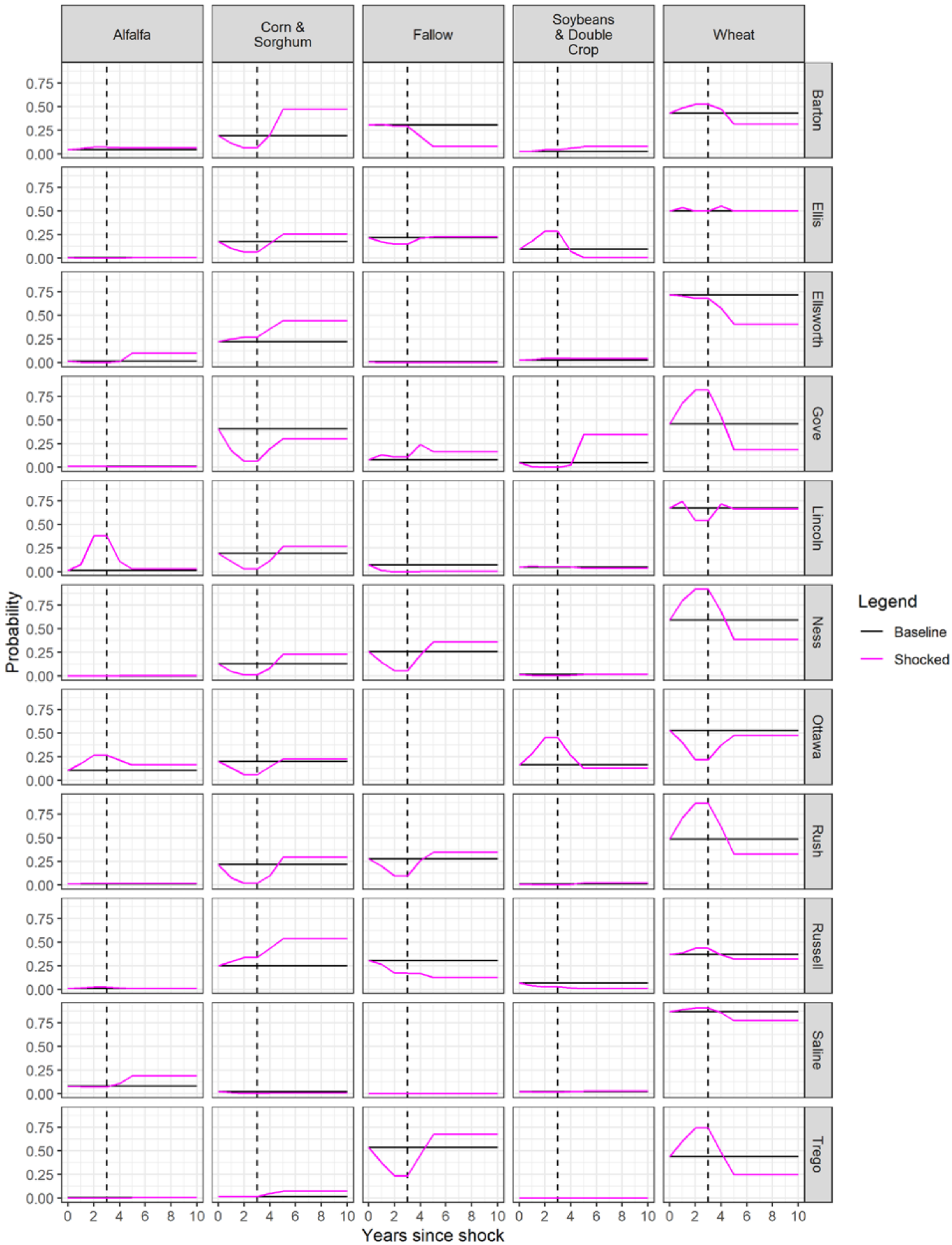

Figure 6. Simulated probabilities from drought lasting two years, NL-DML-RE, 1-3 and 4-10 lag structure

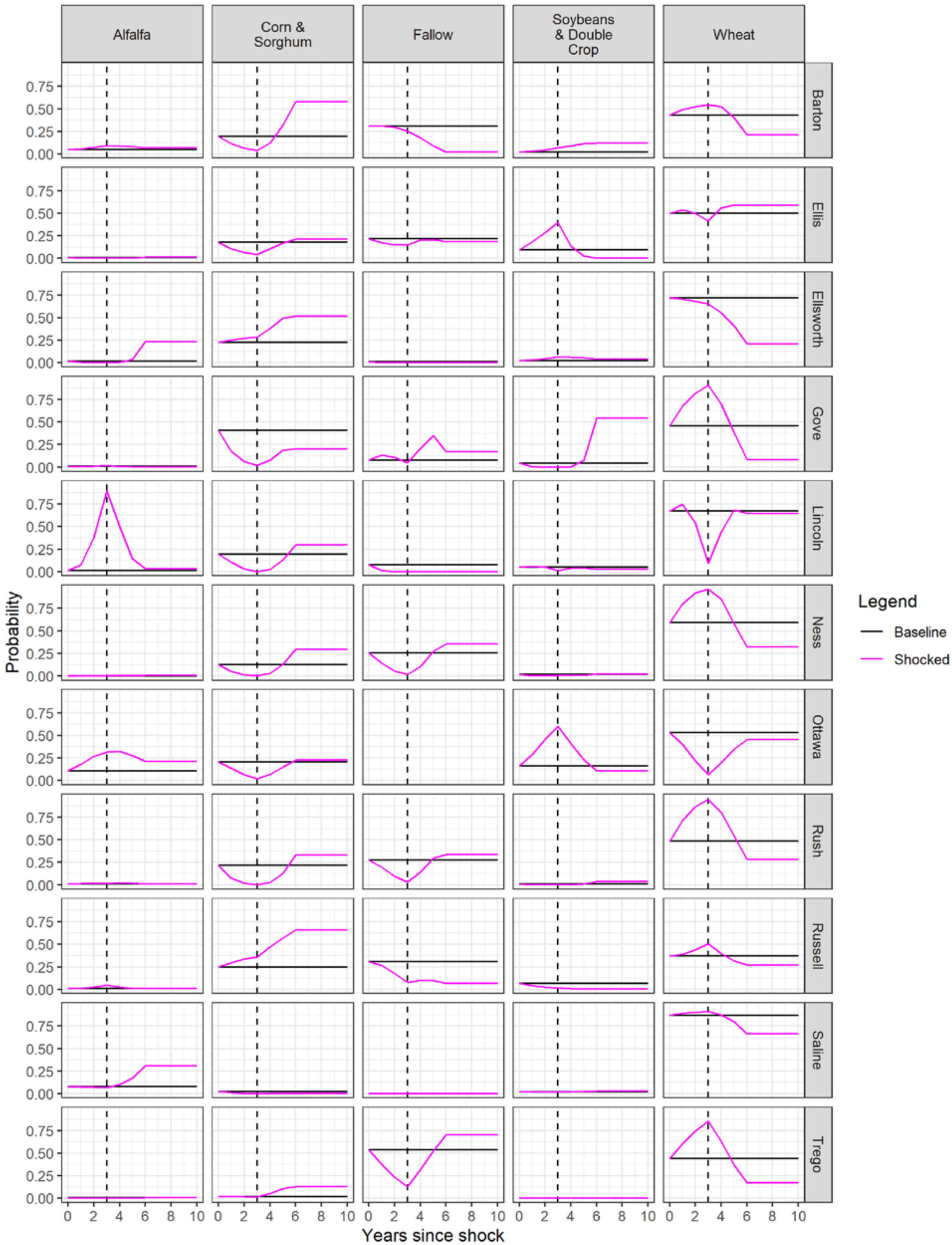

Figure 7. Simulated probabilities from drought lasting three years, NL-DML-RE, 1-3 and 4-10 lag structure

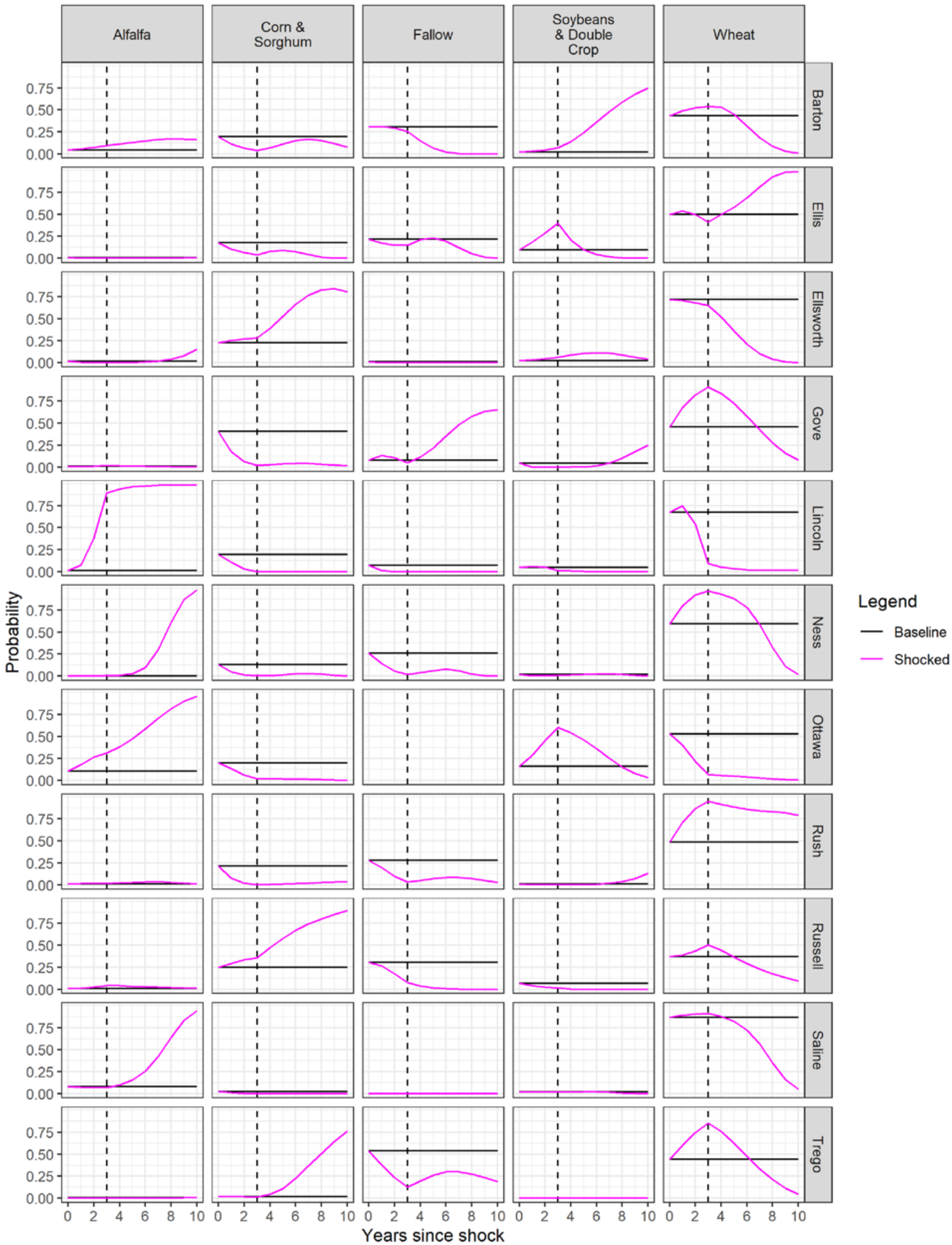

Figure 8. Simulated probabilities from permanent drought, NL-DML-RE, 1-3 and 4-10 lag structure

Figure 9. Average transition probabilities, NL-DML-RE, 1-3 and 4-10 lag structure

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[1] The empirical model can capture a longer history, as it incorporates initial conditions in the model.

[2] It should be noted that the conceptual framework does hold on-farm capital as fixed. Changes in on-farm capital could be another adaptation strategy, but this is beyond the scope of this study given the data used.

[3] Greene (2012) notes that the initial conditions can have a crucial impact on the entire path of outcomes and, additionally, standard estimators are no longer consistent. To address the initial conditions problem, an alternative model was proposed by Wooldridge (2005) for the binary case. Though other techniques are available, such as that from Heckman (1981), the approach from Wooldridge (2005) is appealing as it results in a specification which is estimable by standard econometric software.

[4] Alternativelty, Wooldridge (2005) notes another popular approach is to specify a density $g(\, y_0 \mid \mathbf{z}, \mathbf{u}\,)$ to yield: $f(y_0, y_1, \ldots, y_T \mid \mathbf{z}, \mathbf{u}, \overline{\boldsymbol{\beta}}, \boldsymbol{\rho}) = \prod_{t=1}^{T} \prod_{j=0}^{J} \left(\Lambda(\mathbf{z}_t', \mathbf{d}_{t-1}', \mathbf{u}; \overline{\boldsymbol{\beta}}_j, \boldsymbol{\rho}_j)\right)^{d_t^j} g(\, y_0 \mid \mathbf{z}, \mathbf{u}\,)$. This expression can then be integrated with respect to a density $h(\,\mathbf{u} \mid \mathbf{z}\,)$ – specified by the researcher – to obtain $f(y_0, y_1, \ldots, y_T \mid \mathbf{z})$ (Wooldridge, 2005). While the resulting density can be estimated via maximum likelihood, the density $g(\, y_0 \mid \mathbf{z}, \mathbf{u}\,)$ is extremely difficult – if not impossible – to define (Wooldridge 2010).

[5] The original counties were adjusted slightly. Specifically, Sheridan County was dropped, and Ottawa County was brought in. This was done to limit the effects of irrigation, which are not captured in the empirical model. For the included counties, irrigated cropland averaged about 2% of total cropland from 2000 to 2015; Sheridan County averaged about 21% (USGS 2017).

[6] Fields could have had multiple crops represented, but only the dominant crop was reported in the final land-use data set used for this study.

[7] September and October of the previous calendar year for corn, sorghum, and soybeans and June and July of the same calendar year for wheat.

[8] March and April for corn, sorghum and soybeans and September and October for wheat.

[9] Expected prices were calculated for each of the 961 elevator locations. The expected-crop price for a given field was set equal to the price of the nearest elevator for which data was available. Data were not available for every crop-year-elevator combination, and so the expected price for a field across crops may come from different elevator locations both within and across years.

[10] Additionally, Hendricks, Smith, and Sumner (2014) noted that with a short panel – 11 years in their case – the inclusion of fertilizer creates limitations in the ability to identify the impact of crop prices.

[11] Thanks to Dr. Jesse Tack of Kansas State University for his assistance with this.

[12] A one unit increase in the average number low precipitation days (*PrecLow*) is equal to 100 additional days throughout the growing season with 1 mm or less of precipitation.

Supplementary Appendix

A.1 Model Estimation Challenges

Estimation challenges arose when estimating the DML-RE land-use models. Some difficulties resulted from the software chosen, while others appear to be data driven. With respect to LIMDEP 10, one limitation with LIMDEP was that the multinomial logit with random parameters estimation procedure was limited to 150 parameters. In many applications this likely does not present a problem. However, with five outcome categories (which realistically could be further divided), the number of included variables could be constrained. Due to data-driven difficulties, the 150-parameter constraint was not binding for this article, but it could be in similar studies with different data. For example, in random effects models, it is generally recommended that a full set of time-specific dummy variables be included (Wooldridge 2010). Additionally, the model could include either the means or the full history of the time-varying explanatory variables, as suggested by Wooldridge (2005). An advantage of using LIMDEP 10 is that it provides APEs (through the PARTIALS command) and can be prompted to give individual-specific estimates of the random intercept for each category. When data-driven issues manifested, they at times resulted in a singular covariance matrix and at others resulted in the program crashing. In addition, the use of many binary variables (e.g. initial conditions and lagged dependent variables) can result in near collinearity between covariates, resulting in numerical issues during estimation, which likely resulted in some of the estimation issues encountered. The models were estimated in other statistical software as an additional robustness check, e.g. STATA, but similar estimation issues were encountered. Additionally, it was not clear that the field-specific intercepts were available as outputs in these other software packages. Based on use of different algorithms and tolerance criteria, LIMDEP 10, provided the most robust estimation results for the models.

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Tables

Table SA1. Weather variable values for drought-shock simulations

	t	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$	$t+6$	$t+7$	$t+8$	$t+9$	$t+10$
Baseline											
Prec1to3	5.42	5.42	5.42	5.42	5.42	5.42	5.42	5.42	5.42	5.42	5.42
Prec4to10	5.42	5.42	5.42	5.42	5.42	5.42	5.42	5.42	5.42	5.42	5.42
PrecLow1to3	1.75	1.75	1.75	1.75	1.75	1.75	1.75	1.75	1.75	1.75	1.75
PrecLow4to10	1.75	1.75	1.75	1.75	1.75	1.75	1.75	1.75	1.75	1.75	1.75
GDD1to3	2.04	2.04	2.04	2.04	2.04	2.04	2.04	2.04	2.04	2.04	2.04
GDD4to10	2.04	2.04	2.04	2.04	2.04	2.04	2.04	2.04	2.04	2.04	2.04
GDDHigh1to3	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90
GDDHigh4to10	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90
1-Year Shock											
Prec1to3	5.42	4.90	4.90	4.90	5.42	5.42	5.42	5.42	5.42	5.42	5.42
Prec4to10	5.42	5.42	5.42	5.42	5.20	5.20	5.20	5.20	5.20	5.20	5.20
PrecLow1to3	1.75	1.83	1.83	1.83	1.75	1.75	1.75	1.75	1.75	1.75	1.75
PrecLow4to10	1.75	1.75	1.75	1.75	1.79	1.79	1.79	1.79	1.79	1.79	1.79
GDD1to3	2.04	2.12	2.12	2.12	2.04	2.04	2.04	2.04	2.04	2.04	2.04
GDD4to10	2.04	2.04	2.04	2.04	2.07	2.07	2.07	2.07	2.07	2.07	2.07
GDDHigh1to3	0.90	1.15	1.15	1.15	0.90	0.90	0.90	0.90	0.90	0.90	0.90
GDDHigh4to10	0.90	0.90	0.90	0.90	1.01	1.01	1.01	1.01	1.01	1.01	1.01
2-Year Shock											
Prec1to3	5.42	4.90	4.37	4.37	4.90	5.42	5.42	5.42	5.42	5.42	5.42
Prec4to10	5.42	5.42	5.42	5.42	5.20	4.97	4.97	4.97	4.97	4.97	4.97
PrecLow1to3	1.75	1.83	1.92	1.92	1.83	1.75	1.75	1.75	1.75	1.75	1.75
PrecLow4to10	1.75	1.75	1.75	1.75	1.79	1.82	1.82	1.82	1.82	1.82	1.82
GDD1to3	2.04	2.12	2.20	2.20	2.12	2.04	2.04	2.04	2.04	2.04	2.04
GDD4to10	2.04	2.04	2.04	2.04	2.07	2.11	2.11	2.11	2.11	2.11	2.11
GDDHigh1to3	0.90	1.15	1.41	1.41	1.15	0.90	0.90	0.90	0.90	0.90	0.90
GDDHigh4to10	0.90	0.90	0.90	0.90	1.01	1.12	1.12	1.12	1.12	1.12	1.12
3-Year Shock											
Prec1to3	5.42	4.90	4.37	3.85	4.37	4.90	5.42	5.42	5.42	5.42	5.42
Prec4to10	5.42	5.42	5.42	5.42	5.20	4.97	4.75	4.75	4.75	4.75	4.75
PrecLow1to3	1.75	1.83	1.92	2.00	1.92	1.83	1.75	1.75	1.75	1.75	1.75
PrecLow4to10	1.75	1.75	1.75	1.75	1.79	1.82	1.86	1.86	1.86	1.86	1.86
GDD1to3	2.04	2.12	2.20	2.28	2.20	2.12	2.04	2.04	2.04	2.04	2.04
GDD4to10	2.04	2.04	2.04	2.04	2.07	2.11	2.14	2.14	2.14	2.14	2.14
GDDHigh1to3	0.90	1.15	1.41	1.67	1.41	1.15	0.90	0.90	0.90	0.90	0.90
GDDHigh4to10	0.90	0.90	0.90	0.90	1.01	1.12	1.23	1.23	1.23	1.23	1.23
Persistent Shock											
Prec1to3	5.42	4.90	4.37	3.85	3.85	3.85	3.85	3.85	3.85	3.85	3.85
Prec4to10	5.42	5.42	5.42	5.42	5.20	4.97	4.75	4.52	4.30	4.07	3.85
PrecLow1to3	1.75	1.83	1.92	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00
PrecLow4to10	1.75	1.75	1.75	1.75	1.79	1.82	1.86	1.89	1.93	1.97	2.00
GDD1to3	2.04	2.12	2.20	2.28	2.28	2.28	2.28	2.28	2.28	2.28	2.28
GDD4to10	2.04	2.04	2.04	2.04	2.07	2.11	2.14	2.18	2.21	2.25	2.28
GDDHigh1to3	0.90	1.15	1.41	1.67	1.67	1.67	1.67	1.67	1.67	1.67	1.67
GDDHigh4to10	0.90	0.90	0.90	0.90	1.01	1.12	1.23	1.34	1.45	1.56	1.67

Table SA2. NL-DML-RE Parameter Estimates, Barton County

	CS_t	F_t	SD_t	W_t
Trend	-0.27799	0.42800**	-0.0934	-0.03459
	(-1.63)	(2.31)	(-0.50)	(-0.21)
Acres	-0.22269***	-0.63705***	-0.16274*	-0.20731***
	(-2.99)	(-7.19)	(-1.88)	(-2.95)
P_A	1.82282*	-2.31538**	0.3554	-0.36337
	(1.80)	(-2.13)	(0.32)	(-0.37)
P_{Sor}	0.36064*	1.20585***	-0.78318***	-0.08488
	(1.82)	(5.57)	(-3.51)	(-0.44)
P_{Soy}	0.10767	-1.20661***	0.71410***	-0.03103
	(0.60)	(-6.21)	(3.53)	(-0.18)
P_W	-0.32436*	0.86856***	-0.36693*	0.23453
	(-1.87)	(4.67)	(-1.90)	(1.40)
Prec1to3	1.63327	5.78968***	-0.52678	3.78280***
	(1.43)	(4.47)	(-0.43)	(3.51)
Prec1to3^2	-0.13389	-0.44690***	0.03266	-0.29409***
	(-1.51)	(-4.42)	(0.34)	(-3.52)
Prec4to10	8.95169	14.7589**	0.13994	13.2912***
	(1.63)	(2.37)	(0.02)	(2.62)
Prec4to10^2	-0.91475**	-1.56534***	-0.13323	-1.17527***
	(-1.97)	(-2.97)	(-0.25)	(-2.74)
PrecLow1to3	-1.7699	0.56632	-1.10239	0.23169
	(-1.32)	(0.38)	(-0.74)	(0.19)
PrecLow4to10	-0.76488	-2.95739*	-3.20227*	-3.64649***
	(-0.51)	(-1.72)	(-1.90)	(-2.61)
GDD1to3	-8.19214***	-7.36785**	-1.36968	-2.53276
	(-3.00)	(-2.49)	(-0.45)	(-0.96)
GDD4to10	1.16017	3.51677	2.65717	-3.69328*
	(0.57)	(1.53)	(1.17)	(-1.94)
GDDHigh1to3	-0.38935	3.03825	-0.35799	1.08986
	(-0.20)	(1.48)	(-0.17)	(0.58)
GDDHigh4to10	0.65258	-15.2057***	0.62163	-0.1077
	(0.32)	(-6.73)	(0.27)	(-0.05)
CS_{t-1}	5.29217***	6.73368***	5.88337***	3.97136***
	(42.04)	(41.35)	(40.74)	(37.00)
F_{t-1}	2.62361***	1.82293***	1.95238***	5.09212***
	(13.72)	(7.83)	(7.17)	(33.29)
SD_{t-1}	4.93716***	5.06418***	4.63882***	4.67451***
	(30.64)	(25.50)	(27.93)	(31.45)
W_{t-1}	5.03563***	3.92585***	3.73450***	4.44175***
	(54.65)	(28.22)	(32.67)	(76.08)
CS_0	0.96181***	0.85116***	0.31559***	0.50957***
	(10.10)	(7.46)	(2.9)	(5.63)
F_0	1.92865***	2.69253***	1.66695***	1.47101***
	(8.87)	(11.74)	(7.14)	(6.97)
W_0	0.57520***	1.30168***	0.35372***	0.75967***
	(9.99)	(17.17)	(5.00)	(14.55)
Means and standard deviations for random intercepts				
$\hat{a}_{CS}$	-10.9783	$\hat{\sigma}_{CS}$	0.51064***	
	(-0.61)		(41.27)	
$\hat{a}_F$	-28.7704	$\hat{\sigma}_F$	1.07834***	
	(-1.42)		(53.44)	
$\hat{a}_{SD}$	5.15183	$\hat{\sigma}_{SD}$	0.73635***	
	(0.25)		(36.35)	
$\hat{a}_W$	-32.2240*	$\hat{\sigma}_W$	0.26611***	
	(-1.93)		(25.57)	

Table SA3. NL-DML-RE Parameter Estimates, Ellis County

	CS_t	F_t	SD_t	W_t
Trend	0.73236	1.16585*	1.10547	0.84896
	(1.11)	(1.77)	(1.62)	(1.29)
Acres	0.57164	0.5208	0.19608	0.71447
	(0.83)	(0.76)	(0.28)	(1.04)
P_A	-5.13303	-7.09901*	-10.2759***	-6.32205*
	(-1.39)	(-1.91)	(-2.67)	(-1.71)
P_{Sor}	-0.79059	-0.33079	-6.60792***	-1.34122
	(-0.64)	(-0.27)	(-5.01)	(-1.08)
P_{Soy}	0.10111	-0.5324	2.96317***	0.27166
	(0.15)	(-0.81)	(4.20)	(0.41)
P_W	-0.08597	0.2222	0.15832	-0.05251
	(-0.11)	(0.29)	(0.20)	(-0.07)
Prec1to3	4.03571	2.45221	9.35816	8.60753
	(0.33)	(0.20)	(0.76)	(0.71)
Prec1to3^2	-0.47886	-0.3492	-0.97196	-0.98111
	(-0.41)	(-0.30)	(-0.82)	(-0.84)
Prec4to10	64.6132*	58.3029*	19.6935	20.609
	(1.83)	(1.65)	(0.55)	(0.58)
Prec4to10^2	-6.61131*	-5.97171*	-2.06501	-2.19388
	(-1.94)	(-1.76)	(-0.60)	(-0.65)
PrecLow1to3	-13.4797*	-19.9271***	-24.0993***	-17.1626**
	(-1.87)	(-2.76)	(-3.20)	(-2.38)
PrecLow4to10	9.60951	17.9855**	15.5600**	13.6804*
	(1.31)	(2.45)	(2.06)	(1.87)
GDD1to3	1.23936	3.0642	17.7216**	6.32265
	(0.15)	(0.37)	(1.99)	(0.77)
GDD4to10	10.9446	17.885	3.8627	16.4549
	(0.85)	(1.38)	(0.29)	(1.28)
GDDHigh1to3	8.53006	10.8759*	13.8774**	9.78691
	(1.31)	(1.67)	(2.08)	(1.50)
GDDHigh4to10	-13.6278*	-19.7917***	-24.3928***	-14.7191**
	(-1.88)	(-2.72)	(-3.22)	(-2.03)
CS_{t-1}	6.45125***	8.45485***	6.50931***	5.82840***
	(9.67)	(10.86)	(8.74)	(8.04)
F_{t-1}	5.85823***	5.74981***	5.54801***	9.09574***
	(6.64)	(6.01)	(5.89)	(10.28)
SD_{t-1}	5.46653***	6.62219***	5.23727***	5.23669***
	(7.27)	(8.37)	(7.31)	(6.95)
W_{t-1}	7.46280***	7.16099***	6.00323***	7.36073***
	(14.56)	(11.47)	(10.80)	(16.73)
CS_0	0.73011	0.8201	-0.33765	0.59765
	(1.38)	(1.53)	(-0.60)	(1.13)
F_0	1.61013***	3.01534***	1.59190***	1.65080***
	(2.82)	(5.25)	(2.66)	(2.92)
W_0	1.09646***	2.35386***	0.74211*	1.74368***
	(2.98)	(6.37)	(1.91)	(4.78)
Means and standard deviations for random intercepts				
$\hat{a}_{CS}$	-175.089*	$\hat{\sigma}_{CS}$	0.86969***	
	(-1.85)		(52.50)	
$\hat{a}_F$	-171.702*	$\hat{\sigma}_F$	1.05202***	
	(-1.81)		(59.67)	
$\hat{a}_{SD}$	-87.14	$\hat{\sigma}_{SD}$	0.68537***	
	(-0.90)		(16.58)	
$\hat{a}_W$	-97.3403	$\hat{\sigma}_W$	0.31764***	
	(-1.03)		(23.46)	

Table SA4. NL-DML-RE Parameter Estimates, Ellsworth County

	CS_t	F_t	SD_t	W_t
Trend	0.89479**	0.6249	0.63609	0.66139*
	(2.25)	(1.41)	(1.55)	(1.73)
Acres	0.27035	-0.31984	0.46223**	0.44568**
	(1.30)	(-1.42)	(2.19)	(2.18)
P_A	-4.99193**	-4.19548	-4.26700*	-4.56484**
	(-2.13)	(-1.61)	(-1.77)	(-2.00)
P_{Sor}	-0.0783	-1.1387	-1.36669*	-1.07785
	(-0.11)	(-1.55)	(-1.88)	(-1.59)
P_{Soy}	-0.64081	-0.45053	0.21087	-0.07149
	(-1.59)	(-1.00)	(0.49)	(-0.19)
P_W	0.80257*	1.29213**	0.56059	0.80321*
	(1.71)	(2.54)	(1.15)	(1.75)
Prec1to3	1.06627	8.34525**	-0.4901	0.60936
	(0.31)	(2.22)	(-0.13)	(0.18)
Prec1to3^2	-0.12272	-0.73260**	0.0638	-0.10906
	(-0.46)	(-2.53)	(0.23)	(-0.42)
Prec4to10	-2.49944	49.2329***	9.21483	15.3965
	(-0.21)	(3.69)	(0.74)	(1.33)
Prec4to10^2	-0.0862	-4.36152***	-0.85646	-1.46664
	(-0.09)	(-4.04)	(-0.85)	(-1.57)
PrecLow1to3	5.03506*	0.89026	8.63970***	4.39537*
	(1.90)	(0.32)	(3.03)	(1.73)
PrecLow4to10	-10.4686***	-1.27082	-11.8175***	-10.2946***
	(-3.13)	(-0.36)	(-3.38)	(-3.17)
GDD1to3	12.8932**	24.4461***	3.47132	16.6839***
	(2.42)	(4.09)	(0.61)	(3.30)
GDD4to10	17.9086***	18.6223***	11.4068**	1.80886
	(3.25)	(3.07)	(1.98)	(0.34)
GDDHigh1to3	1.10741	-6.26842	4.29399	-1.07227
	(0.28)	(-1.41)	(1.05)	(-0.29)
GDDHigh4to10	-18.2152***	-26.9655***	-8.15077*	-12.3604***
	(-4.39)	(-5.72)	(-1.85)	(-3.09)
CS_{t-1}	5.37460***	7.36059***	5.65903***	3.95793***
	(16.54)	(16.72)	(18.01)	(14.57)
F_{t-1}	2.44871***	1.03524	1.66394**	5.69775***
	(4.59)	(1.52)	(2.55)	(12.68)
SD_{t-1}	4.35564***	5.42948***	3.85345***	4.35791***
	(11.83)	(11.92)	(11.98)	(14.69)
W_{t-1}	5.14169***	4.21175***	3.84589***	5.07659***
	(21.86)	(11.58)	(15.16)	(28.84)
CS_0	-0.05325	-0.42972*	-0.55865**	-0.16003
	(-0.24)	(-1.65)	(-2.32)	(-0.75)
SD_0	-0.35607	-0.85305***	-0.20929	-0.80314***
	(-1.37)	(-2.77)	(-0.76)	(-3.21)
W_0	0.69165***	1.26085***	0.62168***	0.93631***
	(4.31)	(6.88)	(3.42)	(6.16)
Means and standard deviations for random intercepts				
$\hat{a}_{CS}$	-22.6399	$\hat{\sigma}_{CS}$	0.34240***	
	(-0.54)		(17.51)	
$\hat{a}_F$	-53.9722	$\hat{\sigma}_F$	0.31419***	
	(-1.35)		(18.54)	
$\hat{a}_{SD}$	-46.6558	$\hat{\sigma}_{SD}$	0.88550***	
	(-1.08)		(26.58)	
$\hat{a}_W$	-222.580***	$\hat{\sigma}_W$	1.43991***	
	(-4.92)		(37.86)	

Table SA5. NL-DML-RE Parameter Estimates, Gove County

	CS_t	F_t	SD_t	W_t
Trend	-0.99961	-1.07182	-1.1367	-0.02521
	(-0.94)	(-1.00)	(-1.01)	(-0.02)
Acres	1.86127***	1.76784***	1.52177**	1.78492***
	(2.98)	(2.83)	(2.42)	(2.86)
P_A	4.04601	3.12713	2.09504	-1.58318
	(0.75)	(0.58)	(0.37)	(-0.30)
P_{Sor}	-0.45606	-0.49098	-2.79585**	-0.08736
	(-0.49)	(-0.53)	(-2.31)	(-0.09)
P_{Soy}	0.89734	0.95727	2.84568***	0.04711
	(1.37)	(1.46)	(3.36)	(0.07)
P_W	-1.1173	-1.52324*	-1.80972**	-0.20114
	(-1.40)	(-1.90)	(-1.98)	(-0.25)
Prec1to3	14.2365	26.9723**	4.14886	16.7627
	(1.15)	(2.18)	(0.32)	(1.36)
Prec1to3^2	-1.4676	-2.84146**	-0.62552	-1.75762
	(-1.03)	(-1.98)	(-0.41)	(-1.23)
Prec4to10	3.59399	7.84898	18.3317	4.3224
	(0.25)	(0.53)	(1.20)	(0.29)
Prec4to10^2	-0.44258	-0.9852	-1.53153	-0.43341
	(-0.32)	(-0.71)	(-1.06)	(-0.31)
PrecLow1to3	5.04127	5.12276	-5.09271	2.19571
	(0.66)	(0.67)	(-0.63)	(0.29)
PrecLow4to10	-4.55484	-1.21863	8.52409	-1.07531
	(-0.45)	(-0.12)	(0.80)	(-0.11)
GDD1to3	-4.0715	-12.5432	-20.3776	-2.40607
	(-0.25)	(-0.77)	(-1.12)	(-0.15)
GDD4to10	3.76	2.01521	14.3054	-2.8267
	(0.20)	(0.11)	(0.70)	(-0.15)
GDDHigh1to3	-5.67074	0.60868	-4.99787	1.42022
	(-0.61)	(0.07)	(-0.51)	(0.15)
GDDHigh4to10	5.66371	9.0735	18.132	1.80312
	(0.38)	(0.60)	(1.12)	(0.12)
CS_{t-1}	6.53220***	7.64102***	6.43518***	5.75360***
	(13.15)	(11.83)	(6.40)	(9.67)
F_{t-1}	6.57590***	5.32554***	7.37384***	9.12315***
	(7.09)	(5.02)	(5.93)	(8.53)
SD_{t-1}	5.54420***	6.01609***	5.16444***	4.68787***
	(4.89)	(5.01)	(4.39)	(4.30)
W_{t-1}	7.39445***	5.33363***	5.75094***	5.85055***
	(14.47)	(10.92)	(5.89)	(11.38)
CS_0	1.46277***	1.96981***	0.54926	1.32160***
	(3.82)	(4.78)	(1.06)	(3.45)
F_0	2.26658***	4.14123***	1.11428*	2.20710***
	(4.33)	(7.72)	(1.76)	(4.19)
W_0	1.55158***	3.04133***	0.59978	1.90115***
	(3.99)	(7.74)	(1.25)	(4.77)
Means and standard deviations for random intercepts				
$\hat{a}_{CS}$	-44.8042	$\hat{\sigma}_{CS}$	0.70047***	
	(-1.06)		(45.79)	
$\hat{a}_F$	-74.3747*	$\hat{\sigma}_F$	0.95911***	
	(-1.75)		(51.98)	
$\hat{a}_{SD}$	-70.6708	$\hat{\sigma}_{SD}$	0.85780***	
	(-1.60)		(15.16)	
$\hat{a}_W$	-45.4059	$\hat{\sigma}_W$	0.33040***	
	(-1.07)		(20.18)	

Table SA6. NL-DML-RE Parameter Estimates, Lincoln County

	CS_t	F_t	SD_t	W_t
Trend	-0.39082^{**}	0.17665	-0.88906^{***}	-0.41076^{**}
	(-2.22)	(0.75)	(-5.03)	(-2.51)
Acres	-0.12932	-0.70901^{***}	-0.08686	-0.11354
	(-1.30)	(-4.95)	(-0.82)	(-1.26)
P_A	1.61278^{***}	-1.32458	2.64924^{***}	1.17746^{**}
	(2.69)	(-1.54)	(4.45)	(2.15)
P_{Sor}	0.89839^{**}	0.82166^{*}	-0.99917^{***}	0.68634^{*}
	(2.53)	(1.79)	(-2.65)	(1.95)
P_{Soy}	-0.26787	-0.96435^{***}	1.05483^{***}	-0.26481
	(-1.30)	(-3.67)	(4.83)	(-1.30)
P_W	0.17496	1.19398^{***}	-0.17012	0.24277
	(1.07)	(5.43)	(-1.02)	(1.52)
Prec1to3	9.68654^{***}	27.3783^{***}	0.70505	6.46160^{**}
	(2.89)	(6.64)	(0.20)	(2.03)
Prec1to3^2	-0.74476^{***}	-2.15573^{***}	-0.02617	-0.49432^{*}
	(-2.70)	(-6.37)	(-0.09)	(-1.88)
Prec4to10	-15.2202^{***}	10.6212	0.14998	-14.2679^{***}
	(-3.25)	(1.61)	(0.03)	(-3.31)
Prec4to10^2	1.26523^{***}	-0.83606	0.03938	1.21739^{***}
	(3.26)	(-1.51)	(0.10)	(3.42)
PrecLow1to3	-14.3818^{***}	-20.0625^{***}	-8.12596^{***}	-7.63963^{***}
	(-6.93)	(-7.55)	(-3.81)	(-3.86)
PrecLow4to10	13.0065^{***}	26.4286^{***}	5.05276^{**}	12.5807^{***}
	(6.11)	(9.49)	(2.31)	(6.19)
GDD1to3	-8.94863^{***}	-4.75975	-5.00788^{**}	-2.80225
	(-3.82)	(-1.60)	(-2.06)	(-1.25)
GDD4to10	-28.7799^{***}	-55.4249^{***}	-27.5654^{***}	-28.1493^{***}
	(-10.31)	(-12.78)	(-9.32)	(-10.98)
GDDHigh1to3	-1.97909^{**}	-2.20774^{*}	-5.28851^{***}	-4.01682^{***}
	(-2.32)	(-1.86)	(-6.11)	(-5.20)
GDDHigh4to10	-3.36960^{***}	-9.57205^{***}	1.61570^{**}	-3.63384^{***}
	(-4.90)	(-10.38)	(2.21)	(-5.66)
CS_{t-1}	5.64296^{***}	7.94957^{***}	5.72504^{***}	2.63023^{***}
	(30.29)	(24.11)	(30.42)	(15.66)
SD_{t-1}	5.07680^{***}	6.35002^{***}	4.68328^{***}	3.58299^{***}
	(24.76)	(18.14)	(25.74)	(20.76)
W_{t-1}	5.05344^{***}	4.61686^{***}	3.85136^{***}	3.59002^{***}
	(33.54)	(14.70)	(27.07)	(31.23)
CS_0	1.22812^{***}	1.49156^{***}	0.63425^{***}	1.39862^{***}
	(11.49)	(9.14)	(5.42)	(14.34)
W_0	0.68472^{***}	1.37539^{***}	0.34602^{***}	1.06578^{***}
	(9.50)	(11.02)	(4.43)	(17.24)
Means and standard deviations for random intercepts				
$\hat{a}_{CS}$	96.1607^{***}	$\hat{\sigma}_{CS}$	0.00246	
	(6.20)		(0.15)	
$\hat{a}_F$	-0.394	$\hat{\sigma}_F$	1.21511^{***}	
	(-0.02)		(29.20)	
$\hat{a}_{SD}$	65.0568^{***}	$\hat{\sigma}_{SD}$	0.40894^{***}	
	(3.94)		(28.94)	
$\hat{a}_W$	83.2925^{***}	$\hat{\sigma}_W$	0.74334^{***}	
	(5.72)		(33.71)	

Table SA7. NL-DML-RE Parameter Estimates, Ness County

	CS_t	F_t	SD_t	W_t
Trend	-0.55753	-0.50398	-0.76213	-0.08891
	(-0.31)	(-0.28)	(-0.41)	(-0.05)
Acres	1.26967**	1.48033***	0.71448	1.26321**
	(2.53)	(2.94)	(1.37)	(2.51)
P_A	3.24111	2.25745	-1.01897	0.38603
	(0.33)	(0.23)	(-0.10)	(0.04)
P_{Sor}	-0.75168	-0.44297	-2.48677	-0.91613
	(-0.48)	(-0.28)	(-1.39)	(-0.58)
P_{Soy}	0.70915	0.35969	2.02303	0.29659
	(0.53)	(0.27)	(1.40)	(0.22)
P_W	-0.06016	0.13974	-0.4038	0.50527
	(-0.04)	(0.10)	(-0.27)	(0.36)
Prec1to3	18.3187	18.7503	0.90592	19.2609
	(0.74)	(0.76)	(0.04)	(0.78)
Prec1to3^2	-1.86385	-1.89873	-0.12158	-1.95801
	(-0.72)	(-0.74)	(-0.05)	(-0.76)
Prec4to10	24.7339	35.6285	11.5384	19.1033
	(0.80)	(1.16)	(0.36)	(0.62)
Prec4to10^2	-2.1444	-3.32296	-0.74295	-1.4621
	(-0.72)	(-1.12)	(-0.24)	(-0.49)
PrecLow1to3	-4.6072	-2.19887	-4.46654	0.15083
	(-0.32)	(-0.15)	(-0.30)	(0.01)
PrecLow4to10	18.9782	19.6169	22.6584	16.7867
	(1.04)	(1.07)	(1.21)	(0.92)
GDD1to3	0.71623	4.84982	11.4635	15.1384
	(0.04)	(0.28)	(0.62)	(0.87)
GDD4to10	-13.0996	-3.25816	8.44741	-5.70046
	(-0.74)	(-0.18)	(0.44)	(-0.32)
GDDHigh1to3	-5.54555	-6.11409	-7.55585	-4.96098
	(-0.37)	(-0.41)	(-0.49)	(-0.33)
GDDHigh4to10	-2.56249	-9.99891	-11.2349	-9.47055
	(-0.24)	(-0.92)	(-0.94)	(-0.87)
CS_{t-1}	6.36173***	8.95998***	7.41472***	6.22235***
	(9.39)	(9.93)	(4.04)	(9.05)
F_{t-1}	6.33537***	6.41541***	8.22039***	9.83532***
	(5.55)	(6.23)	(4.22)	(8.53)
SD_{t-1}	4.82968***	6.39144***	6.49056***	4.47398***
	(4.87)	(5.77)	(4.68)	(4.20)
W_{t-1}	7.58218***	7.75465***	6.75817***	6.94108***
	(12.94)	(11.44)	(4.12)	(11.58)
CS_0	1.0658	1.67376**	0.23707	1.20503*
	(1.63)	(2.52)	(0.29)	(1.83)
F_0	-0.08234	2.24129***	-0.80833	0.67375
	(-0.17)	(4.60)	(-1.16)	(1.39)
W_0	0.13674	2.21381***	0.02863	1.23718***
	(0.31)	(4.60)	(0.04)	(2.81)
Means and standard deviations for random intercepts				
$\hat{a}_{CS}$	-112.997	$\hat{\sigma}_{CS}$	1.19704***	
	(-0.99)		(59.39)	
$\hat{a}_F$	-165.614	$\hat{\sigma}_F$		
	(-1.45)		0.99074***(58.68)	
$\hat{a}_{SD}$	-102.081	$\hat{\sigma}_{SD}$	0.39007***	
	(-0.87)		(6.50)	
$\hat{a}_W$	-145.502	$\hat{\sigma}_W$	0.17551***	
	(-1.27)		(11.10)	

Table SA8. NL-DML-RE Parameter Estimates, Ottawa County

	CS_t	SD_t	W_t
Trend	-0.51021**	-0.20173	-0.30943*
	(-2.50)	(-1.07)	(-1.73)
Acres	0.12836	-0.08633	0.26319***
	(1.28)	(-0.87)	(2.87)
P_A	1.52064*	0.23139	0.85808
	(1.89)	(0.31)	(1.20)
P_{Sor}	-0.11505	-1.01941***	0.34499
	(-0.37)	(-3.27)	(1.19)
P_{Soy}	0.1716	.58452***	-0.26474
	(0.80)	(2.79)	(-1.36)
P_W	-0.17584	-0.05922	-0.02609
	(-1.01)	(-0.35)	(-0.16)
Prec1to3	3.2069	-3.31163	4.31513
	(0.87)	(-0.92)	(1.28)
Prec1to3^2	-0.29278	0.23284	-0.33237
	(-0.98)	(0.79)	(-1.21)
Prec4to10	11.1442***	14.5688***	6.86406*
	(2.62)	(3.63)	(1.87)
Prec4to10^2	-.92523***	-1.14678***	-0.48520*
	(-2.74)	(-3.61)	(-1.67)
PrecLow1to3	-0.65301	1.97554	-0.13718
	(-0.28)	(0.88)	(-0.06)
PrecLow4to10	4.63919*	5.83437**	1.96364
	(1.70)	(2.22)	(0.77)
GDD1to3	2.21915	4.97747**	-0.04877
	(0.91)	(2.11)	(-0.02)
GDD4to10	12.0252***	14.9914***	7.98328***
	(4.43)	(5.67)	(3.32)
GDDHigh1to3	-4.86337***	-4.37021***	-2.83673***
	(-4.14)	(-3.97)	(-2.69)
GDDHigh4to10	-4.81997***	-5.37339***	-3.06671***
	(-4.15)	(-4.83)	(-2.99)
CS_{t-1}	5.83568***	6.14390***	4.26638***
	(22.31)	(23.66)	(16.92)
SD_{t-1}	5.00811***	4.45516***	4.63379***
	(24.07)	(24.81)	(26.31)
W_{t-1}	3.82568***	3.38087***	4.64185***
	(26.63)	(26.44)	(44.69)
CS_0	0.94382***	0.90498***	0.77399***
	(5.46)	(5.40)	(4.79)
SD_0	0.32028	0.55403***	-0.09571
	(1.55)	(2.92)	(-0.52)
W_0	0.35766***	0.34393***	0.38994***
	(3.63)	(3.70)	(4.53)
$\hat{a}_{CS}$	-71.7648***	$\hat{\sigma}_{CS}$	0.00055
	(-4.26)		(0.03)
$\hat{a}_{SD}$	-83.3522***	$\hat{\sigma}_{SD}$	0.68633***
	(-5.09)		(32.40)
$\hat{a}_W$	-51.4653***	$\hat{\sigma}_W$	0.47032***
	(-3.44)		(27.51)

Table SA9. NL-DML-RE Parameter Estimates, Rush County

	CS_t	F_t	SD_t	W_t
Trend	-0.09428	0.5638	-0.67336	0.42995
	(-0.17)	(1.02)	(-1.12)	(0.79)
Acres	0.00972	0.28667*	-0.35834*	-0.074
	(0.06)	(1.72)	(-1.80)	(-0.45)
P_A	-2.96906	-6.24362*	-1.34468	-6.81049**
	(-0.91)	(-1.91)	(-0.38)	(-2.11)
P_{Sor}	1.24435***	1.72317***	-0.81263	1.05316**
	(2.66)	(3.67)	(-1.56)	(2.27)
P_{Soy}	-0.77357*	-1.55350***	0.69637	-1.21272***
	(-1.92)	(-3.83)	(1.57)	(-3.03)
P_W	0.50707	0.93929*	0.06794	1.05933*
	(0.91)	(1.69)	(0.12)	(1.94)
Prec1to3	1.29759	6.18539	-5.39835	2.51301
	(0.33)	(1.55)	(-1.22)	(0.63)
Prec1to3^2	0.04425	-0.43822	0.62589	-0.12778
	(0.12)	(-1.18)	(1.51)	(-0.35)
Prec4to10	-18.3516	-3.00739	-24.0678*	-24.1038**
	(-1.54)	(-0.25)	(-1.95)	(-2.04)
Prec4to10^2	1.42946	-0.02661	2.10573*	2.00558*
	(1.34)	(-0.02)	(1.90)	(1.90)
PrecLow1to3	-6.2571	-11.2476**	-2.34059	-2.50712
	(-1.10)	(-1.97)	(-0.39)	(-0.45)
PrecLow4to10	8.48505*	18.3032***	10.1936**	17.4143***
	(1.87)	(4.02)	(2.13)	(3.88)
GDD1to3	-31.6542***	-32.9571***	-21.6278***	-19.0426***
	(-4.40)	(-4.56)	(-2.87)	(-2.65)
GDD4to10	5.0272	8.98058	15.2821**	3.09786
	(0.92)	(1.63)	(2.52)	(0.57)
GDDHigh1to3	9.81871*	14.8356***	4.62341	11.2720**
	(1.73)	(2.61)	(0.75)	(2.01)
GDDHigh4to10	-11.9341**	-16.2037***	-10.3748**	-19.0601***
	(-2.52)	(-3.40)	(-2.07)	(-4.07)
CS_{t-1}	4.68534***	6.89657***	5.30546***	4.31597***
	(16.71)	(18.78)	(14.72)	(16.20)
F_{t-1}	3.31807***	2.23369***	3.51938***	6.94621***
	(7.98)	(4.92)	(6.95)	(17.90)
SD_{t-1}	4.15105***	5.11926***	3.60653***	4.44263***
	(11.74)	(10.94)	(10.10)	(13.14)
W_{t-1}	5.54018***	4.76565***	3.74446***	5.21268***
	(25.47)	(16.02)	(11.93)	(31.20)
CS_0	1.12079***	1.50508***	0.19812	1.18103***
	(5.55)	(7.25)	(0.85)	(6.24)
F_0	1.82908***	3.57350***	1.48187***	1.98275***
	(7.49)	(14.47)	(5.24)	(8.29)
W_0	1.13471***	2.88440***	0.79644***	1.94966***
	(7.07)	(17.15)	(4.03)	(12.63)
Means and standard deviations for random intercepts				
$\hat{a}_{CS}$	104.225**	$\hat{\sigma}_{CS}$	0.91292***	
	(2.28)		(52.47)	
$\hat{a}_F$	38.8063	$\hat{\sigma}_F$	1.20174***	
	(0.85)		(61.08)	
$\hat{a}_{SD}$	82.1243*	$\hat{\sigma}_{SD}$	0.92242***	
	(1.72)		(21.99)	
$\hat{a}_W$	81.4738*	$\hat{\sigma}_W$	0.03376**	
	(1.80)		(2.41)	

Table SA10. NL-DML-RE Parameter Estimates, Russell County

	CS_t	F_t	SD_t	W_t
Trend	-0.12132	0.31724	-0.57202	-0.38826
	(-0.19)	(0.49)	(-0.88)	(-0.60)
Acres	0.04474	0.03614	-0.16934	0.01997
	(0.09)	(0.07)	(-0.33)	(0.04)
P_A	0.68709	-1.04567	1.32201	0.74404
	(0.22)	(-0.33)	(0.41)	(0.24)
P_{Sor}	0.88737	1.37421*	-1.23522*	0.49411
	(1.26)	(1.95)	(-1.73)	(0.70)
P_{Soy}	-0.38545	-1.12914**	1.09838**	-0.27123
	(-0.72)	(-2.10)	(2.03)	(-0.51)
P_W	-0.4334	-0.01561	-0.77886	-0.16091
	(-0.71)	(-0.03)	(-1.25)	(-0.26)
Prec1to3	0.89002	9.18632	-0.24105	-2.15189
	(0.09)	(0.91)	(-0.02)	(-0.22)
Prec1to3^2	-0.08281	-0.87082	0.04216	0.20655
	(-0.09)	(-0.96)	(0.05)	(0.23)
Prec4to10	-7.39428	-15.6741	15.6443	-1.5843
	(-0.35)	(-0.73)	(0.72)	(-0.08)
Prec4to10^2	0.25341	0.75804	-1.5658	-0.01957
	(0.14)	(0.40)	(-0.83)	(-0.01)
PrecLow1to3	-5.45199	-8.61306	-4.05978	-5.25567
	(-0.90)	(-1.41)	(-0.67)	(-0.87)
PrecLow4to10	-3.89487	-4.56620*	-0.80844	-3.05025
	(-1.42)	(-1.67)	(-0.30)	(-1.12)
GDD1to3	-9.25641	3.49543	-6.8049	-9.51538
	(-1.12)	(0.42)	(-0.81)	(-1.16)
GDD4to10	25.2031***	28.6204***	4.86143	26.4219***
	(2.67)	(2.98)	(0.50)	(2.82)
GDDHigh1to3	1.31632	-3.10249	-2.41354	0.8509
	(0.20)	(-0.46)	(-0.36)	(0.13)
GDDHigh4to10	-12.5260**	-29.9857***	-12.3161**	-11.7066**
	(-2.36)	(-5.58)	(-2.29)	(-2.21)
CS_{t-1}	7.55932***	9.15188***	7.43274***	6.44302***
	(11.59)	(14.02)	(11.20)	(10.03)
F_{t-1}	5.00363***	3.83832***	4.96031***	8.52605***
	(4.51)	(3.50)	(4.36)	(7.81)
SD_{t-1}	5.14397***	5.19480***	4.34486***	4.87212***
	(11.92)	(10.48)	(11.04)	(12.40)
W_{t-1}	6.79216***	5.22165***	4.91102***	6.26974***
	(19.61)	(12.96)	(13.48)	(20.15)
CS_0	2.23283**	2.15331**	1.65209*	2.29224***
	(2.51)	(2.40)	(1.85)	(2.58)
F_0	1.85504*	2.89643***	1.61914	1.76243
	(1.66)	(2.59)	(1.42)	(1.59)
W_0	0.48792**	1.42030***	0.3757	0.93861***
	(2.09)	(5.93)	(1.54)	(4.03)
Means and standard deviations for random intercepts				
$\hat{a}_{CS}$	24.8646	$\hat{\sigma}_{CS}$	0.57925***	
	(0.31)		(31.63)	
$\hat{a}_F$	5.5885	$\hat{\sigma}_F$	0.22113***	
	(0.07)		(13.57)	
$\hat{a}_{SD}$	-14.2399	$\hat{\sigma}_{SD}$	0.71943***	
	(-0.17)		(21.99)	
$\hat{a}_W$	28.6275	$\hat{\sigma}_W$	1.30600***	
	(0.35)		(47.59)	

Table SA11. NL-DML-RE Parameter Estimates, Saline County

	CS_t	F_t	SD_t	W_t
Trend	0.09299	-0.36549	-0.07071	0.12828
	(0.44)	(-0.32)	(-0.37)	(0.71)
Acres	0.57393***	-0.65805	0.61069***	0.83867***
	(4.13)	(-0.76)	(4.60)	(6.60)
P_A	-1.93446*	-6.17833	-1.21343	-1.63217*
	(-1.83)	(-1.20)	(-1.24)	(-1.79)
P_{Sor}	-0.31179	-3.43459***	-0.53763	0.4149
	(-0.91)	(-2.85)	(-1.64)	(1.32)
P_{Soy}	-0.31234	0.90858	0.01856	-0.68437***
	(-1.51)	(1.05)	(0.10)	(-3.74)
P_W	0.75166***	2.59325**	0.55511**	0.61261***
	(3.10)	(2.56)	(2.46)	(2.86)
Prec1to3	4.58158*	8.97614	-0.97893	1.28765
	(1.73)	(0.79)	(-0.40)	(0.56)
Prec1to3^2	-0.34573*	-0.89671	0.07969	-0.08995
	(-1.69)	(-1.09)	(0.42)	(-0.50)
Prec4to10	16.2188***	63.1567**	14.7003***	13.1478***
	(3.40)	(2.26)	(3.47)	(3.26)
Prec4to10^2	-1.34351***	-5.11679**	-1.16394***	-1.09254***
	(-3.69)	(-2.33)	(-3.61)	(-3.58)
PrecLow1to3	-2.97745	-12.4439	-2.43315	1.38391
	(-1.63)	(-1.51)	(-1.39)	(0.87)
PrecLow4to10	-1.76726	1.86395	-2.25247	-0.81411
	(-0.92)	(0.19)	(-1.21)	(-0.48)
GDD1to3	7.44180**	7.181	-0.66044	-1.96057
	(2.11)	(0.50)	(-0.21)	(-0.63)
GDD4to10	12.9705***	4.29609	18.4658***	7.77144**
	(3.66)	(0.31)	(5.40)	(2.38)
GDDHigh1to3	-1.39954	-2.66405	0.29803	1.60556
	(-0.71)	(-0.27)	(0.17)	(0.96)
GDDHigh4to10	-10.7474***	-11.9115	-4.63083**	-5.38777***
	(-5.11)	(-1.46)	(-2.31)	(-2.77)
CS_{t-1}	6.31044***	5.82347***	5.99892***	3.89574***
	(20.34)	(6.56)	(19.95)	(13.36)
SD_{t-1}	5.40731***	4.35303***	4.28659***	4.19688***
	(23.20)	(5.39)	(23.26)	(23.86)
W_{t-1}	3.87746***	2.85394***	3.16929***	4.08745***
	(19.90)	(3.39)	(24.14)	(39.19)
CS_0	0.75415***	-1.70942	0.60202***	0.41634**
	(3.69)	(-1.17)	(3.00)	(2.14)
SD_0	0.33574*	0.07691	0.37504**	-0.0759
	(1.75)	(0.10)	(2.00)	(-0.43)
W_0	0.65150***	0.00867	0.45274***	0.92060***
	(6.86)	(0.02)	(5.08)	(11.57)
Means and standard deviations for random intercepts				
$\hat{a}_{CS}$	-89.9609***	$\hat{\sigma}_{CS}$	0.27639***	
	(-5.52)		(12.30)	
$\hat{a}_F$	-214.978***	$\hat{\sigma}_F$	1.42037***	
	(-2.69)		(8.59)	
$\hat{a}_{SD}$	-71.6026***	$\hat{\sigma}_{SD}$	0.61492***	
	(-4.66)		(29.17)	
$\hat{a}_W$	-52.3242***	$\hat{\sigma}_W$	0.64465***	
	(-3.65)		(34.77)	

Table SA12. NL-DML-RE Parameter Estimates, Trego County

	CS_t	F_t	SD_t	W_t
Trend	-0.79686	-1.17719	-0.9241	-0.37786
	(-0.39)	(-0.57)	(-0.43)	(-0.18)
Acres	3.90516***	4.06853***	2.63640*	3.84980**
	(2.60)	(2.71)	(1.74)	(2.56)
P_A	-0.74363	0.66436	-5.28404	-2.45658
	(-0.07)	(0.06)	(-0.46)	(-0.22)
P_{Sor}	-2.23099	-1.6879	-6.16284***	-2.72775
	(-1.06)	(-0.80)	(-2.60)	(-1.29)
P_{Soy}	1.20254	0.84407	3.62832**	1.19521
	(0.97)	(0.68)	(2.53)	(0.96)
P_W	-0.28553	-0.23812	0.30934	0.14786
	(-0.16)	(-0.13)	(0.15)	(0.08)
Prec1to3	30.8611*	28.4407*	14.9701	29.8634*
	(1.78)	(1.65)	(0.83)	(1.73)
Prec1to3^2	-3.26209*	-3.0153	-1.49224	-3.17347*
	(-1.74)	(-1.62)	(-0.76)	(-1.70)
Prec4to10	30.8442*	30.6393*	21.5009	34.4630**
	(1.84)	(1.83)	(1.21)	(2.06)
Prec4to10^2	-3.41419**	-3.28518*	-2.24101	-3.49488**
	(-1.97)	(-1.90)	(-1.23)	(-2.02)
PrecLow1to3	6.03004	6.04292	22.1255	11.8977
	(0.46)	(0.46)	(1.62)	(0.91)
PrecLow4to10	-13.9018	-12.2869	-24.7065	-12.3866
	(-0.81)	(-0.72)	(-1.41)	(-0.72)
GDD1to3	-23.8529	-12.0579	-31.6528	-6.74393
	(-1.13)	(-0.57)	(-1.36)	(-0.32)
GDD4to10	27.6376	77.686	10.7181	51.4882
	(0.46)	(1.30)	(0.17)	(0.86)
GDDHigh1to3	8.04941	1.25106	7.68757	2.69603
	(0.35)	(0.05)	(0.33)	(0.12)
GDDHigh4to10	-0.8009	-20.1133	1.40581	-16.6098
	(-0.04)	(-0.93)	(0.06)	(-0.77)
CS_{t-1}	7.93146***	10.3323***	7.00070***	7.56889***
	(9.22)	(9.93)	(5.28)	(7.08)
F_{t-1}	6.24079***	6.38619***	5.24380***	9.84086***
	(7.21)	(5.88)	(3.88)	(9.51)
SD_{t-1}	7.19339***	8.68895***	5.85761***	6.24335***
	(3.78)	(4.59)	(3.81)	(3.39)
W_{t-1}	9.12747***	8.52477***	6.38305***	8.13886***
	(12.38)	(9.15)	(5.42)	(10.30)
CS_0	2.39860***	2.58039***	2.20704**	2.14348***
	(3.43)	(3.64)	(2.48)	(2.97)
SD_0	2.48354***	3.63568***	3.03570***	2.22613***
	(3.78)	(5.39)	(3.52)	(3.28)
W_0	1.83489***	2.94215***	1.75247**	2.20325***
	(2.94)	(4.59)	(2.10)	(3.43)
Means and standard deviations for random intercepts				
$\hat{a}_{CS}$	-141.943	$\hat{\sigma}_{CS}$	0.83550***	
	(-1.34)		(48.11)	
$\hat{a}_F$	-240.547**	$\hat{\sigma}_F$	0.82347***	
	(-2.26)		(47.35)	
$\hat{a}_{SD}$	-58.427	$\hat{\sigma}_{SD}$	1.02800***	
	(-0.49)		(15.55)	
$\hat{a}_W$	-231.367**	$\hat{\sigma}_W$	0.52389***	
	(-2.18)		(29.65)	

Table SA13. Average Partial Effects, Weather Variables

			Lag Structure							
			Short = 1 to 3, Long = 4 to 10				Lag structure: Short = 1 to 5, Long = 6 to 20			
			Models							
Land-use	**County**	**Variable**	**LIN-DML-RE**	**NL-DML-RE**	**LIN-OLS-FE**	**NL-OLS-FE**	**LIN-DML-RE**	**NL-DML-RE**	**LIN-OLS-FE**	**NL-OLS-FE**
Alfalfa	Barton	*Prec* – Short	-0.002	-0.009*	-0.031***	-0.046***	0.006	0.011	-0.038***	-0.007
			(-0.58)	(-1.68)	(-6.16)	(-6.32)	(0.70)	(1.28)	(-4.57)	(-0.75)
		Prec – Long	0.039***	0.022***	-0.065***	-0.087***	0.063***	0.069***	-0.063	-0.029
			(5.53)	(2.59)	(-6.45)	(-6.61)	(5.02)	(4.91)	(-1.53)	(-0.67)
		PrecLow – Short	0.002	0.006	-0.204***	-0.178***	-0.031	-0.013	0.126*	0.150**
			(0.05)	(0.16)	(-3.68)	(-3.18)	(-0.67)	(-0.28)	(1.65)	(1.97)
		PrecLow – Long	0.111***	0.098**	0.125	0.180**	0.151***	0.138***	1.252***	0.905***
			(2.59)	(2.23)	(1.63)	(2.23)	(3.30)	(2.93)	(4.68)	(3.31)
		GDD – Short	0.127	0.116	-0.103	0.027	0.514***	0.519***	0.494***	0.069
			(1.60)	(1.38)	(-1.18)	(0.28)	(4.97)	(4.74)	(2.97)	(0.38)
		GDD – Long	-0.060	0.065	-2.061***	-1.897***	-0.485***	-0.526***	-2.766***	-3.319***
			(-1.35)	(1.08)	(-11.39)	(-9.94)	(-5.33)	(-5.21)	(-7.83)	(-9.13)
		GDDHigh – Short	-0.012	-0.026	-0.028	-0.113	0.109**	0.143***	0.178***	0.291***
			(-0.23)	(-0.44)	(-0.46)	(-1.64)	(2.13)	(2.74)	(2.90)	(4.46)
		GDDHigh – Long	0.143***	0.021	0.100	-0.040	0.041	0.065	0.093	0.159
			(2.98)	(0.33)	(1.52)	(-0.46)	(0.92)	(1.40)	(0.80)	(1.36)
	Ellis	*Prec* – Short	0.001	0.002	0.006**	0.007**	0.000	0.042***	0.013***	0.011**
			(0.39)	(0.83)	(2.10)	(2.23)	(0.05)	(4.77)	(2.65)	(2.26)
		Prec – Long	0.005**	0.006**	0.016***	0.017***	0.006	-0.024*	0.036**	0.023
			(2.00)	(2.00)	(3.51)	(3.67)	(1.28)	(-1.65)	(2.24)	(1.32)
		PrecLow – Short	0.030*	0.034**	0.045***	0.048***	0.006	-0.027	0.008	0.008
			(1.78)	(2.53)	(2.82)	(3.00)	(0.35)	(-0.60)	(0.40)	(0.39)
		PrecLow – Long	-0.025*	-0.027*	-0.009	-0.015	0.010	0.157***	0.025	0.017
			(-1.72)	(-1.90)	(-0.38)	(-0.63)	(0.55)	(3.51)	(0.34)	(0.23)
		GDD – Short	-0.001	-0.010	-0.067**	-0.064**	0.094**	0.411***	0.026	0.023
			(-0.05)	(-0.60)	(-2.50)	(-2.32)	(2.50)	(3.44)	(0.71)	(0.64)
		GDD – Long	-0.043	-0.028	-0.042	-0.024	-0.058	0.264**	-0.088	-0.033
			(-1.63)	(-1.11)	(-0.66)	(-0.33)	(-1.30)	(2.17)	(-1.21)	(-0.43)
		GDDHigh – Short	-0.021*	-0.020	0.001	-0.005	0.003	0.223***	-0.015	0.006
			(-1.90)	(-1.53)	(0.09)	(-0.28)	(0.22)	(4.01)	(-0.54)	(0.21)
		GDDHigh – Long	0.032**	0.032**	0.080***	0.076***	-0.010	-0.377***	-0.061	-0.035
			(2.46)	(2.26)	(3.90)	(3.50)	(-0.44)	(-8.46)	(-1.30)	(-0.71)
	Ellsworth	*Prec* – Short	0.007***	0.007*	-0.013**	-0.021***	0.006	0.009	-0.026***	-0.024**
			(2.58)	(1.78)	(-2.52)	(-3.22)	(0.73)	(1.06)	(-2.76)	(-2.29)

	Prec – Long	0.033	0.030***	-0.033***	-0.042***	0.043***	0.053***	-0.081*	-0.074
		(6.37)	(5.44)	(-2.84)	(-3.51)	(4.49)	(4.92)	(-1.87)	(-1.61)
	PrecLow – Short	-0.053*	-0.054*	-0.001	0.006	-0.056*	-0.039	-0.035	-0.042
		(-1.86)	(-1.87)	(-0.02)	(0.12)	(-1.69)	(-1.05)	(-0.71)	(-0.79)
	PrecLow – Long	0.121***	0.114***	0.250***	0.213***	0.147***	0.155***	0.000	0.045
		(3.37)	(3.13)	(3.78)	(3.15)	(4.63)	(4.62)	(0.00)	(0.26)
	GDD – Short	-0.168***	-0.171***	0.152	0.266**	0.029	-0.017	-0.102	-0.091
		(-3.14)	(-3.05)	(1.63)	(2.51)	(0.24)	(-0.13)	(-0.70)	(-0.59)
	GDD – Long	-0.105**	-0.067	-1.296***	-0.854***	-0.140*	-0.134*	-2.073***	-2.026***
		(-2.02)	(-1.12)	(-6.16)	(-3.35)	(-1.85)	(-1.71)	(-7.06)	(-6.78)
	GDDHigh – Short	0.007	0.005	-0.301***	-0.343***	0.052	0.091*	-0.256***	-0.255***
		(0.17)	(0.12)	(-5.24)	(-5.34)	(1.13)	(1.83)	(-4.44)	(-3.91)
	GDDHigh – Long	0.187***	0.152***	-0.121*	-0.258***	0.063	0.124***	-0.539***	-0.535***
		(4.28)	(3.40)	(-1.69)	(-3.02)	(1.58)	(2.61)	(-5.67)	(-5.12)
Gove	*Prec* – Short	-0.003	-0.004	-0.003	-0.001	-0.004	-0.006	0.003	0.003
		(-1.00)	(-0.98)	(-1.02)	(-0.18)	(-0.70)	(-0.87)	(0.56)	(0.59)
	Prec – Long	0.002	0.000	-0.001	0.013**	0.003	0.000	0.019	0.025
		(0.70)	(0.10)	(-0.24)	(2.05)	(0.74)	(-0.03)	(1.36)	(1.53)
	PrecLow – Short	0.001	-0.009	-0.022	-0.030*	-0.055**	-0.053*	-0.071***	-0.068***
		(0.07)	(-0.50)	(-1.34)	(-1.74)	(-1.98)	(-1.95)	(-2.99)	(-2.64)
	PrecLow – Long	-0.001	0.005	-0.039	-0.039*	0.069*	0.063*	0.027	0.030
		(-0.03)	(0.22)	(-1.64)	(-1.65)	(1.85)	(1.71)	(0.49)	(0.53)
	GDD – Short	0.006	0.014	-0.028	-0.081***	0.127***	0.128***	0.155***	0.149***
		(0.19)	(0.38)	(-1.11)	(-2.84)	(2.85)	(2.72)	(3.73)	(3.55)
	GDD – Long	-0.022	-0.004	-0.063	-0.103	-0.093	0.001	0.028	0.003
		(-0.51)	(-0.09)	(-0.94)	(-1.22)	(-1.38)	(0.01)	(0.29)	(0.03)
	GDDHigh – Short	0.006	0.005	0.019	0.026	0.019	-0.011	0.102***	0.101***
		(0.29)	(0.22)	(1.02)	(1.36)	(1.07)	(-0.27)	(3.76)	(3.63)
	GDDHigh – Long	-0.011	-0.013	0.037	0.130***	-0.053	-0.086	0.146***	0.144***
		(-0.39)	(-0.38)	(1.37)	(3.68)	(-1.30)	(-1.49)	(3.04)	(2.77)
Lincoln	*Prec* – Short	-0.005	-0.016***	0.013*	0.013	-0.011	-0.009	0.013	0.020*
		(-1.05)	(-3.01)	(1.73)	(1.58)	(-1.63)	(-1.13)	(1.32)	(1.75)
	Prec – Long	-0.019***	-0.005	-0.005	-0.008	-0.027***	-0.055***	-0.086**	-0.080**
		(-4.47)	(-1.05)	(-0.48)	(-0.67)	(-5.03)	(-8.92)	(-2.26)	(-2.07)
	PrecLow – Short	0.194***	0.219***	-0.033	-0.040	0.114**	0.117**	-0.214**	-0.176*
		(4.61)	(4.29)	(-0.52)	(-0.62)	(2.42)	(2.00)	(-2.15)	(-1.68)
	PrecLow – Long	-0.292***	-0.308***	-0.346***	-0.375***	-0.327***	-0.403***	-0.581**	-0.639**
		(-6.60)	(-5.89)	(-3.03)	(-3.03)	(-5.63)	(-6.08)	(-2.56)	(-2.48)
	GDD – Short	0.094*	0.095	-0.250***	-0.237***	0.123	0.158*	-0.485***	-0.502***
		(1.91)	(1.64)	(-4.08)	(-3.67)	(1.61)	(1.80)	(-4.89)	(-4.99)
	GDD – Long	0.297***	0.733***	-0.360*	-0.301	0.368***	0.900***	-1.239***	-1.586***
		(4.67)	(11.30)	(-1.73)	(-1.17)	(4.21)	(9.34)	(-3.66)	(-3.82)

	GDDHigh – Short	0.061***	0.102***	0.119***	0.113***	0.031	0.043**	0.200***	0.208***
		(3.52)	(5.16)	(3.95)	(3.56)	(1.63)	(2.09)	(5.54)	(5.68)
	GDDHigh – Long	0.055***	0.080***	0.182***	0.166***	0.133***	0.199***	0.065	0.050
		(3.29)	(4.86)	(3.68)	(3.01)	(5.37)	(7.91)	(0.75)	(0.57)
Ness	*Prec* – Short	-0.001	-0.003	-0.000	-0.003	-0.002	-0.003	0.000	-0.004
		(-0.28)	(-0.45)	(-0.21)	(-1.15)	(-0.31)	(-1.22)	(0.05)	(-1.38)
	Prec – Long	-0.006*	-0.008	0.002	0.002	-0.009	-0.014*	-0.004	-0.016**
		(-1.84)	(-1.54)	(0.55)	(0.59)	(-1.03)	(-1.70)	(-1.06)	(-1.97)
	PrecLow – Short	0.006	0.004	-0.006	0.002	0.018	0.000	0.013	0.002
		(0.22)	(0.15)	(-0.39)	(0.09)	(0.40)	(0.01)	(0.69)	(0.10)
	PrecLow – Long	-0.035	-0.035	-0.041	-0.035	-0.055	0.030	-0.029	0.030
		(-1.13)	(-1.01)	(-1.43)	(-1.17)	(-0.90)	(0.58)	(-1.46)	(0.58)
	GDD – Short	-0.009	-0.014	-0.037	-0.016	-0.016	-0.019	0.083	-0.021
		(-0.32)	(-0.43)	(-1.43)	(-0.58)	(-0.21)	(-0.47)	(0.97)	(-0.51)
	GDD – Long	-0.001	0.013	0.015	0.079	-0.017	-0.116*	-0.162*	-0.114*
		(-0.03)	(0.39)	(0.33)	(1.54)	(-0.28)	(-1.71)	(-1.65)	(-1.68)
	GDDHigh – Short	0.010	0.011	0.011	0.005	0.003	0.012	-0.005	0.012
		(0.38)	(0.37)	(0.91)	(0.38)	(0.19)	(0.85)	(-0.18)	(0.85)
	GDDHigh – Long	0.017	0.014	0.054***	0.043**	0.022	0.018	0.067*	0.013
		(0.91)	(0.71)	(2.81)	(2.15)	(1.22)	(0.71)	(1.83)	(0.51)
Ottawa	*Prec* – Short	-0.004	-0.002	0.006	0.008	-0.022*	-0.014	-0.013	-0.038*
		(-0.38)	(-0.21)	(0.51)	(0.59)	(-1.76)	(-0.99)	(-0.63)	(-1.71)
	Prec – Long	-0.010	-0.023**	-0.014	-0.013	0.020**	0.005	-0.023	-0.071
		(-1.26)	(-2.52)	(-0.88)	(-0.66)	(2.32)	(0.49)	(-0.48)	(-1.30)
	PrecLow – Short	-0.022	-0.006	0.205**	0.206**	-0.173***	-0.128**	0.148	0.232*
		(-0.35)	(-0.09)	(2.39)	(2.38)	(-2.85)	(-2.00)	(1.22)	(1.86)
	PrecLow – Long	-0.085	-0.092	0.244	0.243	0.044	-0.051	0.189	0.414*
		(-1.15)	(-1.22)	(1.27)	(1.25)	(0.57)	(-0.60)	(0.97)	(1.93)
	GDD – Short	-0.028	-0.037	-0.283***	-0.307**	0.143	0.095	-0.149	-0.148
		(-0.43)	(-0.56)	(-2.84)	(-2.39)	(1.58)	(1.04)	(-1.07)	(-1.02)
	GDD – Long	-0.342***	-0.297***	-0.627**	-0.737	-0.608***	-0.541***	-0.864***	-0.607*
		(-4.93)	(-4.16)	(-2.12)	(-1.57)	(-5.75)	(-5.06)	(-2.64)	(-1.78)
	GDDHigh – Short	0.079***	0.102***	0.263***	0.273***	0.068**	0.064*	0.310***	0.283***
		(2.93)	(3.29)	(5.71)	(4.77)	(2.34)	(1.95)	(4.57)	(4.10)
	GDDHigh – Long	0.141***	0.113***	0.309***	0.335***	0.220***	0.226***	0.688***	0.775***
		(5.06)	(3.69)	(4.69)	(3.02)	(6.22)	(5.86)	(4.34)	(4.75)
Rush	*Prec* – Short	-0.007**	-0.009**	-0.021***	-0.020***	0.003	0.003	-0.015**	-0.007
		(-2.16)	(-2.45)	(-3.80)	(-3.56)	(0.68)	(0.67)	(-2.24)	(-0.93)
	Prec – Long	0.014***	0.014***	-0.010	-0.015	0.016*	0.015*	-0.031	-0.038*
		(4.51)	(4.47)	(-1.01)	(-1.35)	(1.95)	(1.87)	(-1.58)	(-1.88)
	PrecLow – Short	0.024	0.034	-0.028	-0.048	0.082**	0.092*	0.030	-0.019
		(0.64)	(0.89)	(-0.81)	(-1.32)	(2.19)	(1.80)	(0.74)	(-0.45)

	PrecLow – Long	-0.089***	-0.097***	0.071	0.085*	-0.232***	-0.249***	-0.146	-0.175
		(-3.00)	(-3.22)	(1.45)	(1.69)	(-6.21)	(-5.34)	(-1.11)	(-1.32)
	GDD – Short	0.139***	0.169***	0.098*	0.074	0.296***	0.284***	0.455***	0.325***
		(4.19)	(3.51)	(1.69)	(1.27)	(3.41)	(3.16)	(4.24)	(2.83)
	GDD – Long	-0.026	-0.039	-0.399***	-0.533***	-0.106	-0.076	-0.832***	-0.951***
		(-0.96)	(-1.07)	(-5.74)	(-7.08)	(-1.22)	(-0.75)	(-5.71)	(-6.34)
	GDDHigh – Short	-0.064*	-0.073*	-0.021	-0.062	0.001	-0.006	-0.032	0.005
		(-1.73)	(-1.94)	(-0.59)	(-1.68)	(0.02)	(-0.18)	(-0.63)	(0.10)
	GDDHigh – Long	0.080***	0.106***	0.105***	0.071*	0.056**	0.053*	-0.086	-0.088
		(2.91)	(3.40)	(3.07)	(1.83)	(2.02)	(1.83)	(-1.19)	(-1.20)
Russell	*Prec* – Short	0.000	0.000	-0.012***	-0.011***	0.000	0.000	-0.004	-0.002
		(0.00)	(0.05)	(-3.18)	(-2.89)	(0.00)	(-0.03)	(-0.70)	(-0.33)
	Prec – Long	0.016***	0.015***	-0.024***	-0.023***	0.021**	0.017	-0.007	0.004
		(3.52)	(2.83)	(-3.01)	(-2.9)	(2.11)	(1.51)	(-0.28)	(0.15)
	PrecLow – Short	0.031	0.027	-0.010	-0.017	0.024	0.014	-0.070	-0.064
		(1.22)	(0.91)	(-0.31)	(-0.55)	(0.72)	(0.37)	(-1.18)	(-1.07)
	PrecLow – Long	0.017	0.015	-0.012	-0.013	0.061**	0.054*	-0.094	-0.071
		(1.26)	(1.11)	(-1.17)	(-1.22)	(2.01)	(1.89)	(-0.51)	(-0.38)
	GDD – Short	0.042	0.039	0.118**	0.105**	0.321***	0.307***	0.205**	0.196**
		(1.31)	(0.95)	(2.33)	(2.03)	(4.39)	(3.82)	(2.15)	(2.03)
	GDD – Long	-0.112**	-0.114**	-0.406***	-0.475***	-0.174***	-0.183***	-0.497**	-0.587**
		(-2.32)	(-2.40)	(-4.20)	(-4.41)	(-2.66)	(-2.74)	(-2.25)	(-2.52)
	GDDHigh – Short	-0.002	0.000	-0.076**	-0.065	0.031	0.034	-0.008	-0.007
		(-0.06)	(0.01)	(-1.98)	(-1.64)	(1.10)	(1.18)	(-0.13)	(-0.11)
	GDDHigh – Long	0.068***	0.068***	-0.038	-0.019	0.003	-0.002	-0.137*	-0.127*
		(2.58)	(2.59)	(-1.03)	(-0.48)	(0.06)	(-0.05)	(-1.78)	(-1.65)
Saline	*Prec* – Short	-0.004	-0.004	0.003	0.010	-0.030***	-0.024**	-0.035**	-0.051***
		(-0.80)	(-0.67)	(0.29)	(0.85)	(-3.10)	(-2.52)	(-1.98)	(-2.74)
	Prec – Long	0.033***	0.022***	0.003	-0.004	0.057***	0.045***	0.084	0.023
		(5.42)	(3.17)	(0.15)	(-0.19)	(4.34)	(3.16)	(1.62)	(0.40)
	PrecLow – Short	-0.052	-0.011	0.172*	0.114	-0.036	-0.020	0.665***	0.605***
		(-1.27)	(-0.26)	(1.80)	(1.17)	(-0.65)	(-0.36)	(4.62)	(4.22)
	PrecLow – Long	0.053	0.030	0.358***	0.190	0.106	0.085	1.255***	1.052***
		(1.18)	(0.66)	(3.32)	(1.49)	(1.46)	(1.19)	(3.87)	(3.20)
	GDD – Short	-0.035	0.028	-0.278***	-0.428***	0.473***	0.460***	0.265*	0.087
		(-0.43)	(0.34)	(-2.65)	(-2.98)	(4.32)	(3.75)	(1.85)	(0.48)
	GDD – Long	-0.380***	-0.267***	-1.89***	-2.244***	-0.682***	-0.613***	-3.210***	-3.329***
		(-5.12)	(-3.09)	(-6.46)	(-4.73)	(-5.36)	(-4.53)	(-7.99)	(-8.13)
	GDDHigh – Short	0.006	-0.031	0.098**	0.175**	-0.056	-0.040	-0.358***	-0.330***
		(0.14)	(0.70)	(2.05)	(2.56)	(-1.24)	(-0.87)	(-3.86)	(-3.45)
	GDDHigh – Long	0.225***	0.152***	0.376***	0.480***	0.135**	0.106*	-0.106	-0.132
		(4.53)	(2.96)	(5.22)	(4.30)	(2.35)	(1.86)	(-0.62)	(-0.78)

	Trego	*Prec* – Short	-0.001	-0.002	0.001	-0.001	0.001	0.001	0.012***	0.011**
			(-0.34)	(-0.99)	(0.43)	(-0.52)	(0.36)	(0.35)	(2.79)	(2.45)
		Prec – Long	0.002	0.002	0.013***	0.009**	0.003	0.003	0.049***	0.045***
			(0.64)	(0.57)	(3.23)	(2.02)	(0.48)	(0.51)	(3.48)	(3.02)
		PrecLow – Short	-0.002	-0.014	-0.019	-0.021	-0.013	-0.005	-0.005	0.007
			(-0.12)	(-0.68)	(-1.34)	(-1.44)	(-0.65)	(-0.23)	(-0.22)	(0.28)
		PrecLow – Long	0.007	0.021	0.032	0.038*	0.034	0.027	-0.114**	-0.084
			(0.31)	(0.76)	(1.63)	(1.85)	(1.26)	(0.92)	(-2.13)	(-1.53)
		GDD – Short	0.003	0.022	-0.025	0.015	0.168***	0.187***	0.150***	0.187***
			(0.11)	(0.69)	(-1.17)	(0.56)	(3.86)	(2.94)	(5.06)	(5.72)
		GDD – Long	-0.178***	-0.074	-0.001	0.121	-0.097	-0.088	0.061	0.132**
			(-3.07)	(-0.84)	(-0.01)	(1.36)	(-1.38)	(-1.12)	(1.00)	(1.98)
		GDDHigh – Short	0.013	-0.007	0.030*	0.001	0.009	0.004	0.003	-0.024
			(0.36)	(-0.18)	(1.81)	(0.04)	(0.39)	(0.16)	(0.15)	(-0.98)
		GDDHigh – Long	0.046**	0.018	0.055***	0.007	-0.043	-0.045	-0.040	-0.076
			(2.08)	(0.56)	(2.96)	(0.29)	(-1.16)	(-1.04)	(-0.86)	(-1.57)
Corn, Sorghum	Barton	*Prec* – Short	-0.009	-0.037***	0.032***	0.020	-0.142***	-0.177***	0.013	-0.019
			(-1.26)	(-3.92)	(2.80)	(1.22)	(-9.74)	(-11.57)	(0.71)	(-0.90)
		Prec – Long	-0.092***	-0.131***	0.018	0.013	0.134***	0.008	0.282***	0.150
			(-6.11)	(-6.48)	(0.81)	(0.44)	(4.83)	(0.26)	(3.09)	(1.57)
		PrecLow – Short	-0.251***	-0.277***	-0.217	-0.206	-0.285***	-0.467***	-0.104	-0.149
			(-3.09)	(-3.39)	(-1.77)	(-1.66)	(-2.72)	(-4.38)	(-0.62)	(-0.88)
		PrecLow – Long	0.298***	0.378***	-0.028	0.042	0.622***	0.615***	1.017*	1.361**
			(3.28)	(4.02)	(-0.17)	(0.24)	(6.39)	(6.04)	(1.72)	(2.26)
		GDD – Short	-0.883***	-0.758***	-1.153***	-1.041***	-0.117	-0.280	-2.655***	-2.397***
			(-6.63)	(-5.55)	(-6.00)	(-4.77)	(-0.56)	(-1.34)	(-7.23)	(-5.99)
		GDD – Long	0.348***	0.465***	0.380	0.432	-0.252	0.339	-2.375***	-1.759**
			(3.46)	(3.77)	(0.95)	(1.03)	(-1.13)	(1.43)	(-3.05)	(-2.19)
		GDDHigh – Short	-0.099	-0.225**	-0.182	-0.248	-0.599***	-0.811***	-0.301**	-0.316**
			(-1.13)	(-2.42)	(-1.32)	(-1.63)	(-6.30)	(-8.21)	(-2.22)	(-2.20)
		GDDHigh – Long	0.571***	0.379***	0.71***	0.686***	1.297***	1.026***	0.496*	0.450*
			(5.92)	(3.30)	(4.87)	(3.62)	(15.22)	(11.63)	(1.93)	(1.74)
	Ellis	*Prec* – Short	0.129***	0.056***	0.164***	0.147***	-0.148***	-0.177***	-0.179***	-0.216***
			(9.04)	(3.53)	(6.59)	(5.57)	(-8.25)	(-11.36)	(-4.22)	(-4.96)
		Prec – Long	-0.112***	-0.168***	-0.076	-0.119***	0.304***	-0.007	-0.228	-0.487***
			(-6.81)	(-10.12)	(-1.87)	(-2.92)	(9.67)	(-0.20)	(-1.61)	(-3.21)
		PrecLow – Short	0.937***	0.697***	0.852***	0.673***	0.028	-0.495***	-0.264	-0.293*
			(8.43)	(6.07)	(5.98)	(4.69)	(0.24)	(-4.57)	(-1.52)	(-1.67)
		PrecLow – Long	-0.991***	-0.821***	-1.224***	-0.89***	-0.411***	0.635***	-1.954***	-2.008***
			(-9.48)	(-7.59)	(-5.71)	(-4.09)	(-3.67)	(6.14)	(-3.03)	(-3.09)
		GDD – Short	-0.962***	-0.597***	-0.975***	-1.336***	-2.085***	-0.313	-2.846***	-2.870***
			(-8.69)	(-5.06)	(-4.09)	(-5.42)	(-7.87)	(-1.46)	(-8.84)	(-8.90)

	GDD – Long	-0.602***	-0.825***	-1.814***	-3.79***	-1.478***	0.395	-6.994***	-6.095***
		(-4.33)	(-5.61)	(-3.17)	(-5.86)	(-7.14)	(1.64)	(-10.84)	(-8.93)
	GDDHigh – Short	-0.347***	-0.249***	-0.454***	0.012	-1.068***	-0.786***	-0.390	-0.030
		(-4.69)	(-3.31)	(-3.23)	(0.08)	(-13.58)	(-7.83)	(-1.62)	(-0.12)
	GDDHigh – Long	0.603***	0.456***	0.613***	1.032***	2.147***	1.028***	2.435***	2.863***
		(6.85)	(5.06)	(3.35)	(5.31)	(18.41)	(11.35)	(5.79)	(6.59)
Ellsworth	*Prec* – Short	0.013	0.024*	0.047***	0.052**	0.003	0.006	0.069**	0.086**
		(1.15)	(1.85)	(2.62)	(2.35)	(0.13)	(0.24)	(2.15)	(2.38)
	Prec – Long	-0.115***	-0.172***	-0.130***	-0.151***	0.033	0.039	0.262*	0.303*
		(-5.57)	(-6.78)	(-3.25)	(-3.67)	(1.04)	(1.11)	(1.75)	(1.91)
	PrecLow – Short	0.099	0.087	-0.117	-0.030	-0.031	-0.031	-0.419**	-0.307*
		(1.05)	(0.91)	(-0.72)	(-0.18)	(-0.28)	(-0.26)	(-2.46)	(-1.70)
	PrecLow – Long	-0.051	-0.135	0.010	-0.036	0.235*	0.241*	-0.030	0.011
		(-0.45)	(-1.18)	(0.05)	(-0.16)	(1.70)	(1.69)	(-0.05)	(0.02)
	GDD – Short	-0.280	-0.397*	-0.587	-0.567	-1.760***	-1.800***	-1.776***	-2.067***
		(-1.28)	(-1.76)	(-1.82)	(-1.56)	(-4.39)	(-4.02)	(-3.52)	(-3.88)
	GDD – Long	1.203***	1.652***	-2.742***	-1.735**	1.735***	1.742***	-0.582	-0.62
		(6.31)	(7.23)	(-3.78)	(-1.98)	(5.99)	(5.93)	(-0.58)	1(-0.60)
	GDDHigh – Short	0.132	0.274	-0.239	-0.125	-0.182	-0.158	-0.364*	-0.215
		(0.80)	(1.51)	(-1.21)	(-0.56)	(-1.29)	(-0.94)	(-1.84)	(-0.96)
	GDDHigh – Long	-0.206	-0.592***	-0.777***	-1.027***	0.701***	0.726***	-0.172	0.020
		(-1.22)	(-3.01)	(-3.14)	(-3.49)	(4.51)	(4.14)	(-0.53)	(0.06)
Gove	*Prec* – Short	-0.040**	-0.047***	-0.117***	-0.112***	-0.128***	-0.128***	-0.001	-0.096*
		(-2.24)	(-2.58)	(-4.18)	(-3.89)	(-4.85)	(-4.77)	(-0.02)	(-1.85)
	Prec – Long	0.004	-0.027	-0.364***	-0.301***	0.179***	0.175***	-0.003	-0.364**
		(0.23)	(-1.20)	(-8.50)	(-5.02)	(8.01)	(7.34)	(-0.03)	(-2.47)
	PrecLow – Short	0.497***	0.235**	0.247*	0.133	-0.248*	-0.387***	0.750***	0.182
		(5.04)	(2.15)	(1.65)	(0.86)	(-1.73)	(-2.61)	(3.45)	(0.78)
	PrecLow – Long	-0.805***	-0.573***	-0.226	-0.232	0.260	0.339*	-0.406	-1.188**
		(-7.05)	(-4.63)	(-1.05)	(-1.08)	(1.52)	(1.93)	(-0.81)	(-2.31)
	GDD – Short	0.421***	0.626***	-0.647***	-0.373	1.185***	1.121***	-0.374	-0.782**
		(2.85)	(3.96)	(-2.82)	(-1.43)	(4.13)	(3.90)	(-0.99)	(-2.04)
	GDD – Long	0.010	0.594***	-3.487***	-1.696**	-1.993***	-1.791***	-8.741***	-8.457***
		(0.05)	(2.81)	(-5.66)	(-2.21)	(-4.83)	(-4.13)	(-9.78)	(-9.27)
	GDDHigh – Short	-1.034***	-1.042***	-0.564***	-0.543***	-0.108	-0.254**	-0.557**	-0.179
		(-10.38)	(-9.67)	(-3.28)	(-3.15)	(-1.02)	(-2.05)	(-2.26)	(-0.71)
	GDDHigh – Long	0.093	-0.035	0.560**	0.475	0.369**	0.512***	-1.266***	-0.029
		(0.74)	(-0.23)	(2.30)	(1.47)	(2.11)	(2.81)	(-2.89)	(-0.06)
Lincoln	*Prec* – Short	0.012	0.024**	0.009	0.013	-0.036**	-0.029*	0.018	0.027
		(1.09)	(1.96)	(0.41)	(0.59)	(-2.25)	(-1.70)	(0.63)	(0.86)
	Prec – Long	-0.070***	-0.082***	-0.037	-0.030	-0.038**	-0.030	0.501***	0.507***
		(-5.49)	(-5.40)	(-1.38)	(-0.98)	(-2.03)	(-1.37)	(4.77)	(4.77)

	PrecLow – Short	-0.985***	-0.879***	-0.448**	-0.423**	-0.893***	-0.614***	-0.879***	-0.790***
		(-9.26)	(-7.82)	(-2.54)	(-2.38)	(-6.80)	(-3.92)	(-3.20)	(-2.72)
	PrecLow – Long	0.327***	0.190	1.475***	1.553***	0.194	-0.140	0.744	0.746
		(2.91)	(1.60)	(4.68)	(4.55)	(1.11)	(-0.72)	(1.19)	(1.05)
	GDD – Short	-0.842***	-0.810***	-0.859***	-0.909***	-1.479***	-1.470***	-0.842***	-0.862***
		(-7.91)	(-7.46)	(-5.06)	(-5.11)	(-6.95)	(-6.75)	(-3.08)	(-3.10)
	GDD – Long	-0.035	0.011	-0.416	-0.745	0.346	0.295	4.661***	4.052***
		(-0.20)	(0.06)	(-0.72)	(-1.05)	(1.40)	(1.13)	(4.98)	(3.53)
	GDDHigh – Short	0.327***	0.299***	0.537***	0.553***	0.064	0.066	0.229**	0.240**
		(5.51)	(4.94)	(6.44)	(6.30)	(1.18)	(1.22)	(2.29)	(2.38)
	GDDHigh – Long	-0.074*	-0.065	0.225*	0.291*	0.102	0.129**	1.333***	1.311***
		(-1.66)	(-1.45)	(1.65)	(1.90)	(1.63)	(2.02)	(5.54)	(5.40)
Ness	*Prec* – Short	-0.013	-0.007	0.006	-0.006	-0.087***	0.005	-0.154***	0.000
		(-0.95)	(-0.47)	(0.30)	(-0.25)	(-4.72)	(0.20)	(-6.36)	(-0.01)
	Prec – Long	0.000	-0.019	-0.151***	-0.128***	0.133***	0.047	0.193***	0.033
		(0.02)	(-1.16)	(-5.11)	(-4.12)	(6.44)	(0.63)	(6.45)	(0.44)
	PrecLow – Short	-0.402***	-0.374***	0.255*	0.295*	-0.176	-0.495**	-0.188	-0.470**
		(-4.55)	(-4.15)	(1.67)	(1.88)	(-1.37)	(-2.40)	(-1.20)	(-2.26)
	PrecLow – Long	0.076	0.053	1.077***	1.271***	-0.311**	0.263	-0.007	0.291
		(0.87)	(0.60)	(4.04)	(4.54)	(-2.38)	(0.55)	(-0.04)	(0.60)
	GDD – Short	-0.905***	-0.915***	-1.065***	-1.099***	-0.033	-1.870***	-1.305*	-1.849***
		(-8.92)	(-8.83)	(-4.36)	(-4.27)	(-0.12)	(-4.92)	(-1.83)	(-4.78)
	GDD – Long	-1.142***	-1.047***	-2.942***	-3.109***	-2.110***	-5.243***	-0.023	-5.210***
		(-9.42)	(-8.00)	(-7.11)	(-6.44)	(-7.49)	(-8.24)	(-0.03)	(-8.16)
	GDDHigh – Short	0.032	0.015	0.170	0.224*	-0.088	0.453***	0.361	0.450***
		(0.41)	(0.19)	(1.48)	(1.90)	(-1.18)	(3.44)	(1.41)	(3.42)
	GDDHigh – Long	0.858***	0.829***	0.358**	0.464**	1.095***	1.010***	0.300	0.995***
		(13.00)	(12.43)	(2.00)	(2.48)	(14.27)	(4.35)	(0.99)	(4.23)
Ottawa	*Prec* – Short	-0.044***	-0.049***	-0.041	-0.032	0.007	-0.021	-0.064	-0.048
		(-2.63)	(-2.88)	(-1.84)	(-1.29)	(0.25)	(-0.73)	(-1.58)	(-1.10)
	Prec – Long	-0.117***	-0.094***	-0.056	-0.087**	-0.080***	-0.062***	-0.126	-0.086
		(-5.86)	(-3.88)	(-1.81)	(-2.32)	(-3.96)	(-2.76)	(-1.35)	(-0.80)
	PrecLow – Short	-0.117	-0.121	0.151	0.187	0.067	-0.033	0.194	0.141
		(-0.93)	(-0.97)	(0.89)	(1.10)	(0.48)	(-0.24)	(0.82)	(0.58)
	PrecLow – Long	0.183	0.173	0.755**	0.793**	-0.331*	-0.120	-0.586	-0.700*
		(1.39)	(1.31)	(1.99)	(2.09)	(-1.90)	(-0.67)	(-1.54)	(-1.66)
	GDD – Short	0.056	0.085	0.459**	0.474*	-0.297	-0.155	-0.226	-0.203
		(0.41)	(0.61)	(2.35)	(1.88)	(-1.41)	(-0.73)	(-0.83)	(-0.71)
	GDD – Long	0.341**	0.245	1.120*	0.654	0.103	0.029	1.435**	1.277*
		(2.15)	(1.46)	(1.93)	(0.71)	(0.43)	(0.12)	(2.23)	(1.91)
	GDDHigh – Short	-0.153**	-0.18***	-0.164	-0.137	-0.256***	-0.330***	0.002	0.023
		(-2.41)	(-2.60)	(-1.81)	(-1.22)	(-4.07)	(-4.68)	(0.02)	(0.17)

	GDDHigh – Long	-0.165***	-0.128*	-0.302**	-0.356	0.055	0.096	0.730**	0.689**
		(-2.65)	(-1.86)	(-2.34)	(-1.64)	(0.76)	(1.23)	(2.35)	(2.15)
Rush	*Prec* – Short	0.058***	0.066***	0.038	0.032	-0.187***	-0.213***	-0.057*	-0.089**
		(3.33)	(3.72)	(1.46)	(1.20)	(-7.89)	(-8.80)	(-1.73)	(-2.53)
	Prec – Long	-0.027**	-0.047***	-0.076	-0.068	0.229***	0.248***	-0.178*	-0.154
		(-1.96)	(-3.19)	(-1.52)	(-1.24)	(8.01)	(8.34)	(-1.89)	(-1.60)
	PrecLow – Short	-0.132	-0.129	-0.214	-0.165	0.402***	0.599***	0.136	0.318
		(-1.01)	(-0.96)	(-1.30)	(-0.94)	(2.64)	(3.56)	(0.70)	(1.54)
	PrecLow – Long	-1.218***	-1.220***	-0.745***	-0.824***	-1.035***	-1.044***	-0.699	-0.593
		(-11.65)	(-10.81)	(-3.13)	(-3.38)	(-8.27)	(-8.04)	(-1.10)	(-0.93)
	GDD – Short	-0.975***	-1.145***	-1.150***	-1.059***	0.984***	1.235***	-1.556***	-1.071*
		(-8.17)	(-8.31)	(-4.10)	(-3.76)	(3.32)	(4.01)	(-3.01)	(-1.94)
	GDD – Long	-0.176	-0.037	-1.735***	-1.185***	-0.778***	-0.881***	-5.192***	-4.753***
		(-1.20)	(-0.24)	(-5.18)	(-3.26)	(-2.71)	(-2.90)	(-7.41)	(-6.58)
	GDDHigh – Short	-0.434***	-0.318**	-0.276	-0.123	-1.273***	-1.369***	0.123	-0.017
		(-3.00)	(-2.18)	(-1.58)	(-0.69)	(-10.31)	(-10.77)	(0.50)	(-0.07)
	GDDHigh – Long	0.823***	0.792***	0.914***	1.001***	0.616***	0.689***	1.793***	1.801***
		(7.38)	(6.56)	(5.57)	(5.38)	(5.92)	(6.44)	(5.17)	(5.08)
Russell	*Prec* – Short	-0.007	-0.003	0.129***	0.134***	-0.137***	-0.135***	0.062*	0.031
		(-0.54)	(-0.24)	(5.28)	(5.35)	(-6.78)	(-6.57)	(1.85)	(0.89)
	Prec – Long	-0.241***	-0.245***	0.088*	0.066	0.105***	0.069	-0.122	-0.287*
		(-9.98)	(-9.16)	(1.76)	(1.29)	(2.83)	(1.56)	(-0.77)	(-1.68)
	PrecLow – Short	0.020	0.065	0.358*	0.365*	-0.206	-0.179	-0.381	-0.488
		(0.13)	(0.43)	(1.81)	(1.82)	(-1.20)	(-0.99)	(-1.01)	(-1.29)
	PrecLow – Long	-0.115**	-0.111**	0.132**	0.147**	0.315***	0.266***	-1.307	-1.595
		(-2.33)	(-2.24)	(1.97)	(2.19)	(3.58)	(2.76)	(-1.11)	(-1.35)
	GDD – Short	-0.522***	-0.459***	-1.992***	-1.995***	-0.433	-0.372	-2.734***	-2.663***
		(-3.78)	(-3.08)	(-6.16)	(-6.07)	(-1.31)	(-1.11)	(-4.48)	(-4.33)
	GDD – Long	0.028	0.028	2.107***	2.423***	-1.866***	-1.934***	-2.198	-0.906
		(0.10)	(0.10)	(3.41)	(3.51)	(-7.06)	(-7.18)	(-1.56)	(-0.61)
	GDDHigh – Short	0.304**	0.252*	1.813***	1.790***	-0.735***	-0.723***	1.585***	1.576***
		(2.13)	(1.75)	(7.36)	(7.12)	(-5.15)	(-4.99)	(4.05)	(4.03)
	GDDHigh – Long	0.523***	0.503***	1.935***	1.812***	0.964***	0.974***	4.214***	4.061***
		(4.22)	(4.02)	(8.32)	(7.27)	(4.84)	(4.73)	(8.59)	(8.23)
Saline	*Prec* – Short	0.000	-0.003	-0.014	-0.014	-0.004	-0.021	0.061*	0.053
		(0.05)	(-0.31)	(-0.82)	(-0.70)	(-0.21)	(-1.08)	(1.92)	(1.59)
	Prec – Long	-0.036***	-0.020	-0.032	-0.038	-0.043*	-0.013	0.006	0.033
		(-3.22)	(-1.42)	(-0.96)	(-1.10)	(-1.77)	(-0.46)	(0.07)	(0.32)
	PrecLow – Short	-0.207***	-0.250***	-0.206	-0.224	-0.196**	-0.206**	-0.476*	-0.489*
		(-2.82)	(-3.30)	(-1.21)	(-1.29)	(-1.97)	(-2.04)	(-1.86)	(-1.93)
	PrecLow – Long	-0.039	-0.044	-0.440**	-0.520**	-0.070	-0.103	-1.119*	-1.446**
		(-0.51)	(-0.57)	(-2.30)	(-2.30)	(-0.57)	(-0.80)	(-1.94)	(-2.48)

		GDD – Short	0.799***	0.691***	0.574***	0.582**	0.641***	0.800***	0.696***	0.881***
			(5.64)	(4.68)	(3.09)	(2.29)	(3.33)	(3.68)	(2.74)	(2.72)
		GDD – Long	0.485***	0.186	1.819***	1.930**	0.606***	0.346	0.592	0.497
			(3.76)	(1.28)	(3.50)	(2.30)	(3.01)	(1.53)	(0.83)	(0.68)
		GDDHigh – Short	-0.300***	-0.200**	-0.011	-0.011	-0.438***	-0.463***	-0.265	-0.268
			(-3.83)	(-2.29)	(-0.14)	(-0.09)	(-5.35)	(-5.52)	(-1.61)	(-1.58)
		GDDHigh – Long	-0.549***	-0.438***	-0.337***	-0.339	-0.511***	-0.497***	-0.488	-0.377
			(-6.82)	(-5.16)	(-2.64)	(-1.71)	(-5.50)	(-5.24)	(-1.61)	(-1.26)
	Trego	*Prec* – Short	0.022	0.028**	0.015	0.043*	-0.117***	-0.106***	0.109**	0.115**
			(1.63)	(1.99)	(0.62)	(1.68)	(-6.65)	(-5.95)	(2.43)	(2.48)
		Prec – Long	-0.250***	-0.249***	-0.187***	-0.096**	-0.159***	-0.127***	0.521***	0.553***
			(-17.81)	(-17.10)	(-4.64)	(-2.07)	(-5.27)	(-4.13)	(3.67)	(3.67)
		PrecLow – Short	-0.373***	-0.359***	-0.288**	-0.131	-0.369***	-0.356***	-0.276	-0.224
			(-3.60)	(-3.37)	(-2.02)	(-0.89)	(-3.29)	(-3.09)	(-1.14)	(-0.91)
		PrecLow – Long	-0.166	-0.202*	0.275	0.388*	-0.764***	-0.798***	-0.425	-0.262
			(-1.54)	(-1.85)	(1.37)	(1.88)	(-6.92)	(-7.17)	(-0.78)	(-0.47)
		GDD – Short	-1.817***	-1.898***	-2.309***	-2.864***	-2.841***	-2.322***	-2.977***	-2.810***
			(-12.06)	(-12.21)	(-10.85)	(-10.80)	(-10.37)	(-7.99)	(-9.95)	(-8.52)
		GDD – Long	-4.816***	-5.245***	-4.039***	-5.084***	-7.959***	-7.250***	-8.524***	-8.231***
			(-14.83)	(-13.08)	(-5.11)	(-5.64)	(-23.17)	(-20.41)	(-13.88)	(-12.22)
		GDDHigh – Short	0.778***	0.843***	1.085***	1.499***	0.460***	0.262**	1.527***	1.359***
			(7.01)	(7.29)	(6.45)	(7.29)	(4.41)	(2.41)	(6.60)	(5.41)
		GDDHigh – Long	2.280***	2.412***	2.800***	3.406***	3.999***	3.789***	5.363***	5.081***
			(16.92)	(15.76)	(14.94)	(13.00)	(25.44)	(23.64)	(11.39)	(10.34)
Fallow	Barton	*Prec* – Short	0.004	0.022***	-0.019**	-0.026**	-0.021**	-0.045***	-0.088***	-0.167***
			(0.83)	(3.63)	(-2.43)	(-2.34)	(-2.44)	(-4.98)	(-6.86)	(-11.20)
		Prec – Long	-0.172***	-0.134***	-0.088***	-0.130***	-0.300***	-0.385***	-0.102	-0.248***
			(-17.39)	(-9.46)	(-5.7)	(-6.46)	(-17.65)	(-18.90)	(-1.60)	(-3.75)
		PrecLow – Short	0.046	0.070	-0.118	-0.083	0.150**	0.075	-0.707***	-0.780***
			(0.90)	(1.36)	(-1.39)	(-0.96)	(2.22)	(1.10)	(-6.03)	(-6.66)
		PrecLow – Long	0.042	-0.022	-0.701***	-0.743***	0.096	-0.002	-3.153***	-2.285***
			(0.70)	(-0.35)	(-5.95)	(-6.02)	(1.58)	(-0.03)	(-7.69)	(-5.46)
		GDD – Short	-0.093	-0.199**	1.057***	1.095***	-1.805***	-1.953***	0.347	1.308***
			(-1.08)	(-2.26)	(7.93)	(7.24)	(-13.87)	(-14.73)	(1.36)	(4.71)
		GDD – Long	0.397***	0.277***	4.542***	4.815***	1.821***	2.239***	7.684***	9.109***
			(5.69)	(3.32)	(16.39)	(16.49)	(12.71)	(14.55)	(14.19)	(16.35)
		GDDHigh – Short	0.085	0.159***	0.101	0.057	-0.318***	-0.417***	-0.071	-0.294***
			(1.59)	(2.88)	(1.06)	(0.54)	(-5.30)	(-6.66)	(-0.75)	(-2.94)
		GDDHigh – Long	-1.107***	-0.923***	-0.979***	-1.262***	-0.476***	-0.587***	1.537***	1.383***
			(-18.39)	(-12.51)	(-9.69)	(-9.62)	(-9.12)	(-10.98)	(8.60)	(7.72)
	Ellis	*Prec* – Short	0.041***	-0.004	0.028	-0.019	-0.089***	-0.046***	-0.236***	-0.248***
			(3.25)	(-0.33)	(1.20)	(-0.74)	(-5.72)	(-5.08)	(-5.81)	(-5.95)

	Prec – Long	-0.048***	-0.114***	0.100***	0.055	-0.014	-0.400***	-0.332**	-0.426***
		(-3.13)	(-7.05)	(2.60)	(1.41)	(-0.50)	(-19.54)	(-2.46)	(-2.94)
	PrecLow – Short	-0.357***	-0.518***	-0.383***	-0.519***	-0.536***	0.084	-0.990***	-0.994***
		(-3.61)	(-5.13)	(-2.83)	(-3.80)	(-5.13)	(1.22)	(-5.96)	(-5.93)
	PrecLow – Long	0.616***	0.753***	0.361*	0.625***	0.634***	-0.001	-2.209***	-2.254***
		(6.62)	(7.92)	(1.77)	(3.02)	(6.33)	(-0.02)	(-3.59)	(-3.63)
	GDD – Short	-0.352***	-0.183*	0.515**	0.546**	-2.747***	-2.008***	-1.961***	-1.977***
		(-3.41)	(-1.68)	(2.27)	(2.33)	(-12.02)	(-14.99)	(-6.38)	(-6.42)
	GDD – Long	0.492***	0.541***	5.562***	5.486***	1.613***	2.275***	4.754***	5.128***
		(3.95)	(4.06)	(10.22)	(8.92)	(8.99)	(14.72)	(7.72)	(7.86)
	GDDHigh – Short	0.099	0.189***	-0.025	0.140	-0.591***	-0.418***	-0.509**	-0.366
		(1.46)	(2.73)	(-0.19)	(0.98)	(-8.15)	(-6.63)	(-2.22)	(-1.51)
	GDDHigh – Long	-0.550***	-0.652***	-1.114***	-1.107***	0.477***	-0.592***	1.610***	1.789***
		(-6.77)	(-7.85)	(-6.40)	(-5.99)	(4.46)	(-10.96)	(4.01)	(4.31)
Ellsworth	*Prec* – Short	-0.026***	-0.017**	0.052***	0.068***	0.052***	0.049***	0.034	0.043*
		(-3.64)	(-2.13)	(4.21)	(4.46)	(4.25)	(3.61)	(1.55)	(1.72)
	Prec – Long	-0.079***	-0.027*	0.157***	0.163***	-0.327***	-0.338***	-0.095	-0.063
		(-6.34)	(-1.87)	(5.74)	(5.77)	(-15.97)	(-14.84)	(-0.92)	(-0.58)
	PrecLow – Short	-0.278***	-0.192***	-0.160	-0.129	0.000	-0.007	0.281**	0.290**
		(-5.29)	(-3.51)	(-1.42)	(-1.13)	(0.00)	(-0.10)	(2.41)	(2.34)
	PrecLow – Long	0.338***	0.409***	0.049	0.093	-0.006	-0.017	0.988***	1.134***
		(4.82)	(5.79)	(0.32)	(0.58)	(-0.07)	(-0.20)	(2.63)	(2.81)
	GDD – Short	0.605***	0.497***	0.169	-0.024	-1.930***	-1.856***	-1.304***	-1.343***
		(4.33)	(3.34)	(0.77)	(-0.09)	(-8.27)	(-7.48)	(-3.76)	(-3.67)
	GDD – Long	1.061***	0.478***	4.545***	4.247***	1.677***	1.674***	3.143***	3.276***
		(9.70)	(3.45)	(9.15)	(7.05)	(9.87)	(9.72)	(4.52)	(4.63)
	GDDHigh – Short	-0.427***	-0.297***	-0.273**	-0.141	-0.129*	-0.174**	-0.398***	-0.359**
		(-4.24)	(-2.64)	(-2.01)	(-0.93)	(-1.68)	(-1.98)	(-2.92)	(-2.32)
	GDDHigh – Long	-1.116***	-0.613***	-0.592***	-0.470**	-1.142***	-1.186***	-0.823***	-0.759***
		(-11.55)	(-5.23)	(-3.49)	(-2.33)	(-12.38)	(-11.26)	(-3.65)	(-3.07)
Gove	*Prec* – Short	0.096***	0.109***	0.138***	0.132***	-0.068***	-0.068***	0.030	0.013
		(5.83)	(6.51)	(5.49)	(5.13)	(-2.91)	(-2.88)	(0.67)	(0.27)
	Prec – Long	-0.162***	-0.116***	0.081***	-0.002	-0.140***	-0.146***	0.616***	0.570***
		(-11.83)	(-6.11)	(2.12)	(-0.03)	(-7.30)	(-7.14)	(5.32)	(4.30)
	PrecLow – Short	-0.151*	0.147	-0.016	0.147	0.688***	0.620***	0.745***	0.646***
		(-1.76)	(1.56)	(-0.12)	(1.06)	(5.49)	(4.81)	(3.81)	(3.05)
	PrecLow – Long	0.519***	0.246**	0.403***	0.413**	-0.874***	-0.830***	0.545	0.401
		(5.20)	(2.32)	(2.09)	(2.15)	(-5.83)	(-5.42)	(1.20)	(0.86)
	GDD – Short	-0.787***	-1.080***	-0.199	-0.645***	-4.315***	-4.379***	-2.793***	-2.904***
		(-5.83)	(-7.61)	(-0.97)	(-2.76)	(-16.71)	(-16.96)	(-8.20)	(-8.42)
	GDD – Long	0.729***	0.013	4.448***	1.765**	4.869***	5.062***	9.603***	9.537***
		(3.97)	(0.07)	(8.04)	(2.56)	(13.18)	(13.01)	(11.93)	(11.60)

	GDDHigh – Short	0.463***	0.503***	0.510***	0.484***	-0.580***	-0.675***	-1.859***	-1.788***
		(5.31)	(5.32)	(3.31)	(3.12)	(-6.22)	(-6.29)	(-8.38)	(-7.86)
	GDDHigh – Long	0.372***	0.545***	0.298	0.494*	0.677***	0.730***	-0.599	-0.360
		(3.48)	(4.18)	(1.36)	(1.70)	(4.58)	(4.77)	(-1.52)	(-0.85)
Lincoln	*Prec* – Short	0.021***	0.018***	0.003	0.007	0.055***	0.050***	0.014	-0.135***
		(5.45)	(4.67)	(0.30)	(0.69)	(9.66)	(8.90)	(1.07)	(-3.78)
	Prec – Long	0.014***	0.025***	0.027***	0.043***	-0.063***	-0.029***	0.126***	-0.444***
		(3.08)	(5.11)	(2.17)	(2.95)	(-8.82)	(-3.56)	(2.58)	(-3.67)
	PrecLow – Short	-0.269***	-0.225***	-0.302***	-0.267***	0.037	0.191***	0.048	0.205
		(-6.77)	(-5.29)	(-3.69)	(-3.23)	(0.79)	(3.35)	(0.38)	(0.62)
	PrecLow – Long	0.447***	0.342***	-0.003	0.147	-0.093	-0.257***	0.398	0.621
		(10.00)	(7.25)	(-0.02)	(0.93)	(-1.34)	(-3.33)	(1.36)	(0.77)
	GDD – Short	-0.069	0.010	0.354***	0.286***	-0.563***	-0.395***	0.175	1.053***
		(-1.64)	(0.24)	(4.49)	(3.46)	(-6.47)	(-4.32)	(1.38)	(3.34)
	GDD – Long	-0.408***	-0.604***	2.336***	2.071***	0.261***	-0.032	3.620***	-0.481
		(-5.15)	(-7.30)	(8.72)	(6.26)	(2.75)	(-0.30)	(8.32)	(-0.37)
	GDDHigh – Short	0.052***	0.031	-0.055	-0.024	0.014	-0.008	-0.203***	-0.038
		(2.60)	(1.46)	(-1.43)	(-0.58)	(0.71)	(-0.41)	(-4.37)	(-0.33)
	GDDHigh – Long	-0.182***	-0.160***	-0.552***	-0.472***	-0.151***	-0.154***	-0.001	-0.755***
		(-11.27)	(-9.82)	(-8.68)	(-6.66)	(-6.08)	(-6.13)	(-0.01)	(-2.74)
Ness	*Prec* – Short	0.053***	0.019	0.031	-0.031	-0.105***	0.027	0.061***	0.011
		(3.49)	(1.08)	(1.44)	(-1.25)	(-5.03)	(0.90)	(2.29)	(0.38)
	Prec – Long	-0.188***	-0.137***	-0.095***	0.007	-0.166***	0.850***	-0.264***	0.841***
		(-12.08)	(-7.56)	(-2.92)	(0.21)	(-7.34)	(10.41)	(-8.04)	(10.06)
	PrecLow – Short	0.165	0.013	0.156	0.371**	-0.722***	-0.339	-0.468***	-0.26
		(1.53)	(0.12)	(0.93)	(2.15)	(-4.68)	(-1.50)	(-2.74)	2(-1.14)
	PrecLow – Long	0.112	0.245**	0.322	1.198***	0.981***	0.724	0.609***	0.867
		(1.04)	(2.23)	(1.10)	(3.90)	(6.48)	(1.37)	(3.39)	(1.63)
	GDD – Short	-0.677***	-0.440***	0.439	0.400	-2.857***	-2.999***	-0.884	-2.844***
		(-5.58)	(-3.52)	(1.64)	(1.42)	(-8.95)	(-7.19)	(-1.13)	(-6.70)
	GDD – Long	1.250***	0.831***	3.110***	2.722***	3.154***	6.752***	0.748	6.883***
		(8.98)	(5.57)	(6.83)	(5.14)	(9.84)	(9.67)	(0.83)	(9.82)
	GDDHigh – Short	-0.118	-0.120	-0.702***	-0.497***	-0.507***	-0.367**	0.095	-0.378***
		(1.35)	(1.35)	(-5.59)	(-3.83)	(-5.79)	(-2.54)	(0.34)	(-2.61)
	GDDHigh – Long	-0.674***	-0.567***	-1.302***	-0.897***	-0.619***	1.167***	-0.559*	1.203***
		(8.77)	(7.25)	(-6.61)	(-4.37)	(-6.86)	(4.58)	(-1.67)	(4.66)
Rush	*Prec* – Short	0.044***	0.020	0.114***	0.148***	-0.142***	-0.131***	-0.130***	-0.088***
		(2.92)	(1.28)	(4.68)	(5.98)	(-7.03)	(-6.36)	(-4.18)	(-2.65)
	Prec – Long	-0.102***	-0.067***	0.095**	0.285***	-0.198***	-0.264***	0.046	-0.047
		(-8.20)	(-5.14)	(2.06)	(5.57)	(-7.98)	(-9.87)	(0.52)	(-0.52)
	PrecLow – Short	-0.995***	-0.802***	-0.587***	-0.132	-1.148***	-1.023***	-1.252***	-1.309***
		(-9.15)	(-7.14)	(-3.82)	(-0.81)	(-8.91)	(-6.96)	(-6.90)	(-6.81)

	PrecLow – Long	0.816***	0.559***	0.899***	1.323***	0.410***	0.273**	0.702	0.494
		(9.10)	(5.69)	(4.05)	(5.83)	(3.80)	(2.44)	(1.18)	(0.83)
	GDD – Short	-1.522***	-0.977***	-1.626***	-1.605***	-3.241***	-3.658***	-3.674***	-4.456***
		(-14.04)	(-7.83)	(-6.21)	(-6.12)	(-12.87)	(-13.93)	(-7.61)	(-8.64)
	GDD – Long	0.831***	0.507***	2.275***	1.660***	2.822***	3.312***	4.479***	4.433***
		(6.31)	(3.62)	(7.28)	(4.91)	(11.40)	(12.67)	(6.84)	(6.58)
	GDDHigh – Short	0.608***	0.506***	0.124	0.180	-0.136	-0.165	-0.290	0.027
		(5.00)	(4.14)	(0.76)	(1.08)	(-1.28)	(-1.52)	(-1.26)	(0.11)
	GDDHigh – Long	-0.400***	-0.072	-0.509***	0.172	0.583***	0.474***(5.	0.827**	1.149***
		(-4.20)	(-0.69)	(-3.32)	(0.99)	(6.39)	06)	(2.56)	(3.47)
Russell	*Prec* – Short	-0.060***	-0.059***	-0.051***	-0.024	-0.020	-0.028*	0.119***	0.161***
		(-6.28)	(-6.08)	(-2.63)	(-1.21)	(-1.38)	(-1.91)	(4.47)	(5.69)
	Prec – Long	-0.366***	-0.367***	-0.254***	-0.280***	-0.432***	-0.330***	0.862***	1.095***
		(-21.22)	(-19.02)	(-6.38)	(-6.91)	(-17.04)	(-10.27)	(6.79)	(8.05)
	PrecLow – Short	-0.333***	-0.295***	-0.105	-0.267	0.000	0.173	-0.377	-0.234
		(-3.19)	(-2.79)	(-0.67)	(-1.67)	(0.00)	(1.26)	(-1.25)	(-0.77)
	PrecLow – Long	-0.123***	-0.125***	-0.038	-0.028	-0.762***	-0.615***	1.008	1.448
		(-3.78)	(-3.82)	(-0.71)	(-0.53)	(-12.58)	(-9.19)	(1.07)	(1.53)
	GDD – Short	0.868***	1.067***	1.646***	1.344***	-1.435***	-1.292***	-0.048	-0.192
		(8.77)	(10.04)	(6.39)	(5.14)	(-6.26)	(-5.50)	(-0.10)	(-0.39)
	GDD – Long	0.485**	0.474**	3.506***	2.449***	1.434***	1.568***	14.409***	12.542***
		(2.29)	(2.24)	(7.13)	(4.47)	(7.41)	(8.01)	(12.81)	(10.55)
	GDDHigh – Short	-0.363***	-0.318***	-0.659***	-0.436**	-0.165	-0.234**	0.514*	0.533*
		(-3.56)	(-3.10)	(-3.36)	(-2.18)	(-1.56)	(-2.20)	(1.65)	(1.71)
	GDDHigh – Long	-1.566***	-1.528***	-2.098***	-1.868***	-0.091	0.083	3.070***	3.282***
		(-17.96)	(-17.14)	(-11.34)	(-9.43)	(-0.60)	(0.53)	(7.85)	(8.34)
Saline	*Prec* – Short		-0.002		-0.006**		-0.002		-0.005
			(-1.58)		(-2.13)		(-0.24)		(-0.99)
	Prec – Long		0.000		-0.003		-0.002		-0.021
			(0.34)		(-0.62)		(-0.25)		(-1.32)
	PrecLow – Short		-0.008		-0.050		-0.010		-0.099***
			(-1.40)		(-1.93)		(-0.23)		(-2.60)
	PrecLow – Long		0.002		-0.010		0.007		-0.049
			(0.31)		(-0.30)		(0.20)		(-0.56)
	GDD – Short		0.005		0.056		-0.011		-0.043
			(0.50)		(1.48)		(-0.23)		(-0.90)
	GDD – Long		-0.004		0.164		0.020		0.305***
			(-0.45)		(1.31)		(0.23)		(2.81)
	GDDHigh – Short		-0.002		-0.023		-0.007		0.013
			(-0.35)		(-1.29)		(-0.23)		(0.51)
	GDDHigh – Long		-0.004		-0.070**		-0.005		-0.030
			(-0.77)		(-2.35)		(-0.24)		(-0.66)

	Trego	*Prec* – Short	-0.010	-0.010	0.016	0.009	-0.075***	-0.073***	-0.117***	-0.114**
			(-0.74)	(-0.74)	(0.68)	(0.37)	(-4.34)	(-4.17)	(-2.67)	(-2.50)
		Prec – Long	0.000	-0.006	-0.015	-0.020	0.003	0.007	-0.097	-0.081
			(0.01)	(-0.40)	(-0.39)	(-0.45)	(0.10)	(0.23)	(-0.70)	(-0.55)
		PrecLow – Short	-0.273***	-0.309***	-0.792***	-0.783***	-0.308***	-0.348***	-0.740***	-0.752***
			(-2.69)	(-2.96)	(-5.70)	(-5.41)	(-2.86)	(-3.13)	(-3.13)	(-3.12)
		PrecLow – Long	0.116	0.160	0.147	0.185	0.265**	0.281***	-0.016	-0.037
			(1.18)	(1.60)	(0.75)	(0.91)	(2.51)	(2.62)	(-0.03)	(-0.07)
		GDD – Short	0.633***	0.730***	0.691***	0.796***	-2.086***	-2.150***	-3.390***	-3.423***
			(4.45)	(4.92)	(3.32)	(3.07)	(-7.73)	(-7.57)	(-11.55)	(-10.57)
		GDD – Long	4.907***	5.340***	4.881***	5.285***	3.814***	3.826***	4.083***	4.012***
			(16.33)	(14.16)	(6.31)	(5.99)	(11.59)	(11.11)	(6.77)	(6.07)
		GDDHigh – Short	-0.545***	-0.617***	-0.546***	-0.624***	-0.740***	-0.731***	0.090	0.104
			(-5.06)	(-5.51)	(-3.32)	(-3.10)	(-7.30)	(-6.89)	(0.40)	(0.42)
		GDDHigh – Long	-1.614***	-1.742***	-1.853***	-1.987***	-0.118	-0.105	2.350***	2.353***
			(-12.96)	(-12.02)	(-10.11)	(-7.75)	(-0.75)	(-0.65)	(5.09)	(4.88)
Soybeans, Double Crop	Barton	*Prec* – Short	-0.008*	-0.022***	0.021***	-0.011	-0.024***	-0.023***	0.057***	0.069***
			(-1.71)	(-4.20)	(3.03)	(-1.14)	(-2.82)	(-2.68)	(4.96)	(5.19)
		Prec – Long	0.013	-0.019*	0.057***	0.000	0.093***	0.123***	-0.096*	-0.117**
			(1.55)	(-1.90)	(4.11)	(0.01)	(5.35)	(6.30)	(-1.68)	(-1.97)
		PrecLow – Short	-0.023	-0.042	0.169**	0.230***	0.245***	0.266***	0.523***	0.526***
			(-0.52)	(-0.96)	(2.22)	(2.98)	(4.41)	(4.67)	(4.98)	(5.00)
		PrecLow – Long	-0.039	-0.031	0.777***	0.880***	-0.445***	-0.411***	1.302***	1.160***
			(-0.77)	(-0.61)	(7.34)	(7.94)	(-8.12)	(-7.16)	(3.54)	(3.09)
		GDD – Short	0.158**	0.170**	-0.515***	-0.235	0.811***	0.824***	-1.084***	-1.316***
			(2.02)	(2.08)	(-4.3)	(-1.73)	(6.78)	(6.81)	(-4.74)	(-5.28)
		GDD – Long	0.017	0.173**	-0.532**	-0.126	-0.466***	-0.560***	-2.666***	-2.868***
			(0.30)	(2.50)	(-2.14)	(-0.48)	(-3.64)	(-4.16)	(-5.49)	(-5.73)
		GDDHigh – Short	-0.032	-0.067	0.273***	0.087	-0.220***	-0.197***	0.321***	0.402***
			(-0.63)	(-1.24)	(3.18)	(0.91)	(-4.14)	(-3.67)	(3.81)	(4.49)
		GDDHigh – Long	0.330***	0.165***	0.441***	0.084	0.374***	0.415***	0.157	0.191
			(5.90)	(2.61)	(4.86)	(0.71)	(7.41)	(7.89)	(0.98)	(1.19)
	Ellis	*Prec* – Short	0.007	0.012**	-0.095***	-0.097***	0.017**	-0.021**	-0.058***	-0.052***
			(1.26)	(2.16)	(-10.48)	(-4.91)	(2.44)	(-2.50)	(-3.68)	(-3.26)
		Prec – Long	0.017**	0.030***	-0.097***	-0.100***	0.025**	0.115***	-0.166***	-0.113**
			(2.24)	(3.21)	(-6.58)	(6.03)	(2.19)	(5.93)	(-3.20)	(-2.03)
		PrecLow – Short	-0.123***	-0.117***	-0.335***	-0.346***	-0.070	0.246***	0.104	0.098
			(-2.91)	(-2.72)	(-6.43)	(-5.18)	(-1.57)	(4.36)	(1.62)	(1.52)
		PrecLow – Long	0.037	0.027	0.406***	0.428***	0.057	-0.397***	1.312***	1.368***
			(1.02)	(0.73)	(5.17)	(1.56)	(1.36)	(-6.93)	(5.53)	(5.72)
		GDD – Short	0.236***	0.221***	0.265***	0.248***	0.534***	0.777***	1.227***	1.244***
			(4.18)	(3.84)	(3.04)	(3.04)	(4.45)	(6.46)	(10.36)	(10.48)

	GDD – Long	-0.183***	-0.193***	-1.934***	-2.033***	-0.275***	-0.473***	-1.681***	-1.948***
		(-3.51)	(-3.49)	(-9.23)	(-7.12)	(-2.82)	(-3.54)	(-7.08)	(-7.75)
	GDDHigh – Short	0.093***	0.068**	-0.016	0.010	0.108***	-0.187***	0.038	-0.057
		(3.37)	(2.39)	(-0.32)	(-1.77)	(4.55)	(-3.53)	(0.43)	(-0.61)
	GDDHigh – Long	-0.156***	-0.142***	0.036	0.056	-0.235***	0.398***	-1.193***	-1.323***
		(-4.01)	(-3.61)	(0.53)	(2.54)	(-5.72)	(7.59)	(-7.71)	(-8.27)
Ellsworth	*Prec* – Short	0.052***	0.046***	0.068***	0.044***	0.005	0.014	0.066***	0.030
		(8.67)	(6.62)	(5.68)	(2.98)	(0.37)	(1.00)	(3.13)	(1.24)
	Prec – Long	0.082***	0.070***	0.134***	0.123***	0.145***	0.164***	0.222**	0.121
		(7.52)	(5.56)	(5.02)	(4.49)	(7.99)	(8.43)	(2.23)	(1.15)
	PrecLow – Short	0.240***	0.211***	-0.012	-0.054	0.460***	0.427***	0.485***	0.314***
		(4.05)	(3.46)	(-0.11)	(-0.49)	(7.84)	(6.42)	(4.29)	(2.61)
	PrecLow – Long	-0.132**	-0.143**	0.223	0.152	-0.218***	-0.159**	-0.852**	-1.100***
		(-1.98)	(-2.12)	(1.47)	(0.98)	(-3.24)	(-2.26)	(-2.34)	(-2.81)
	GDD – Short	-0.625***	-0.582***	-1.528***	-1.225***	0.968***	0.848***	0.007	0.473
		(-5.12)	(-4.64)	(-7.13)	(-5.06)	(4.35)	(3.58)	(0.02)	(1.33)
	GDD – Long	-0.010	0.143	-0.082	0.455	-0.711***	-0.699***	0.043	-0.074
		(-0.09)	(1.19)	(-0.17)	(0.78)	(-4.42)	(-4.30)	(0.06)	(-0.11)
	GDDHigh – Short	0.324***	0.251***	0.621***	0.424***	0.014	0.087	0.180	-0.085
		(4.14)	(2.87)	(4.72)	(2.87)	(0.19)	(0.98)	(1.36)	(-0.57)
	GDDHigh – Long	0.464***	0.336***	0.988***	0.779***	0.559***	0.642***	0.603***	0.245
		(5.21)	(3.31)	(6.00)	(3.98)	(6.73)	(6.85)	(2.76)	(1.02)
Gove	*Prec* – Short	-0.026***	-0.031***	-0.062***	-0.055***	-0.012	-0.008	0.009	0.025*
		(-6.09)	(-6.31)	(-8.20)	(-7.02)	(-1.15)	(-0.77)	(0.63)	(1.73)
	Prec – Long	0.026***	0.036***	0.041***	0.092***	0.026***	0.020**	0.055	0.099**
		(7.71)	(8.79)	(3.54)	(5.66)	(3.11)	(2.30)	(1.57)	(2.46)
	PrecLow – Short	-0.048**	-0.080***	-0.137***	-0.182***	-0.033	-0.011	-0.210***	-0.120*
		(-2.10)	(-3.25)	(-3.36)	(-4.34)	(-1.05)	(-0.34)	(-3.54)	(-1.87)
	PrecLow – Long	0.056*	0.096***	0.193***	0.191***	0.064*	0.045	0.268*	0.398***
		(1.84)	(2.98)	(3.30)	(3.27)	(1.65)	(1.11)	(1.95)	(2.82)
	GDD – Short	-0.074	-0.129**	-0.534***	-0.597***	-0.084	-0.015	0.055	0.151
		(-1.20)	(-2.01)	(-8.57)	(-8.42)	(-0.63)	(-0.11)	(0.53)	(1.44)
	GDD – Long	0.105	0.119*	-0.304	0.035	0.230	0.150	-0.498**	-0.453*
		(1.58)	(1.77)	(-1.82)	(0.17)	(1.20)	(0.76)	(-2.04)	(-1.81)
	GDDHigh – Short	0.030	-0.033	-0.041	-0.020	0.145***	0.172***	0.573***	0.509***
		(1.09)	(-1.05)	(-0.89)	(-0.44)	(4.94)	(5.20)	(8.51)	(7.37)
	GDDHigh – Long	-0.010	0.115**	0.086	0.292***	-0.150**	-0.199***	0.131	-0.084
		(-0.24)	(2.35)	(1.29)	(3.33)	(-1.99)	(-2.59)	(1.09)	(-0.65)
Lincoln	*Prec* – Short	0.008	-0.011	0.000	-0.013	-0.005	0.006	0.071***	0.027
		(1.01)	(-1.20)	(-0.02)	(-0.72)	(-0.42)	(0.46)	(3.08)	(0.86)
	Prec – Long	0.024***	0.053***	-0.037	0.023	0.085***	0.050***	-0.096	0.507***
		(2.95)	(5.12)	(-1.69)	(0.93)	(6.56)	(3.27)	(-1.12)	(4.77)

	PrecLow – Short	0.414***	0.173**	0.437***	0.461***	0.039	-0.127	0.451**	-0.790***
		(5.93)	(2.16)	(3.06)	(3.19)	(0.45)	(-1.16)	(2.02)	(-2.72)
	PrecLow – Long	-0.936***	-0.685***	-1.153***	-0.740***	-0.376***	-0.228	-1.695***	0.746
		(-12.08)	(-7.98)	(-4.50)	(-2.67)	(-3.04)	(-1.63)	(-3.32)	(1.05)
	GDD – Short	0.159*	-0.027	0.410***	0.399***	0.638***	0.452***	0.104	-0.862***
		(1.95)	(-0.32)	(2.98)	(2.76)	(4.19)	(2.86)	(0.47)	(-3.10)
	GDD – Long	-0.167	0.125	-1.347***	0.182	-0.719***	-0.330*	-4.690***	4.052***
		(-1.29)	(0.95)	(-2.87)	(0.31)	(-3.99)	(-1.73)	(-6.17)	(3.53)
	GDDHigh – Short	-0.232***	-0.180***	-0.579***	-0.491***	-0.033	-0.016	-0.213***	0.240**
		(-6.04)	(-4.52)	(-8.55)	(-6.89)	(-0.87)	(-0.42)	(-2.62)	(2.38)
	GDDHigh – Long	0.450***	0.459***	-0.008	-0.063	0.417***	0.456***	-0.600***	1.311***
		(13.48)	(13.74)	(-0.07)	(-0.50)	(9.12)	(9.76)	(-3.07)	(5.40)
Ness	*Prec* – Short	-0.013***	-0.02**	0.008	0.006	0.012*	-0.020***	0.006	-0.022***
		(-2.65)	(-2.32)	(1.48)	(1.00)	(1.71)	(-2.80)	(0.92)	(-3.03)
	Prec – Long	0.006	0.007	0.040***	0.037***	-0.012	-0.166***	-0.017**	-0.182***
		(1.60)	(1.39)	(5.00)	(4.43)	(-1.57)	(-8.29)	(-2.21)	(-8.90)
	PrecLow – Short	-0.039	-0.024	-0.114***	-0.108**	0.051	-0.052	0.135***	-0.046
		(-1.33)	(-0.66)	(-2.78)	(-2.57)	(1.39)	(-0.94)	(3.45)	(-0.83)
	PrecLow – Long	0.047	0.037	-0.232***	-0.249***	-0.051	-0.254**	-0.154***	-0.269**
		(1.42)	(0.96)	(-3.24)	(-3.32)	(-1.32)	(-1.96)	(-3.75)	(-2.07)
	GDD – Short	0.053	0.022	-0.678***	-0.644***	0.083	-0.439***	-0.027	-0.469***
		(1.04)	(0.40)	(-10.34)	(-9.32)	(0.77)	(-4.30)	(-0.15)	(-4.51)
	GDD – Long	0.056	0.117**	-0.205	-0.092	-0.015	-1.409***	0.194	-1.412***
		(1.05)	(1.99)	(-1.84)	(-0.71)	(-0.13)	(-8.25)	(0.94)	(-8.24)
	GDDHigh – Short	-0.018	-0.017	0.248***	0.232***	0.050**	0.242***	0.109*	0.243***
		(-0.61)	(-0.52)	(8.07)	(7.30)	(2.15)	(6.85)	(1.69)	(6.86)
	GDDHigh – Long	-0.009	-0.022	0.626***	0.597***	-0.063*	0.207***	-0.152**	0.172***
		(-0.24)	(-0.55)	(13.01)	(11.88)	(-1.91)	(3.32)	(-1.98)	(2.71)
Ottawa	*Prec* – Short	-0.034**	-0.045***	-0.029	-0.078***	0.028	-0.012	0.130***	0.101**
		(-2.10)	(-2.79)	(-1.24)	(-2.95)	(1.08)	(-0.45)	(3.11)	(2.20)
	Prec – Long	-0.013	0.006	-0.135***	-0.099**	-0.027	-0.019	0.536***	0.452***
		(-0.73)	(0.25)	(-4.18)	(-2.52)	(-1.33)	(-0.88)	(5.48)	(4.03)
	PrecLow – Short	0.280**	0.253**	0.541***	0.459***	0.474***	0.380***	-0.534**	-0.432*
		(2.47)	(2.22)	(3.06)	(2.58)	(3.86)	(3.02)	(-2.15)	(-1.68)
	PrecLow – Long	0.382***	0.363***	0.484	0.448	-0.213	0.083	-2.477***	-2.269***
		(3.13)	(2.97)	(1.22)	(1.13)	(-1.37)	(0.50)	(-6.20)	(-5.14)
	GDD – Short	0.423***	0.494***	0.468**	0.890***	0.465**	0.757***	0.930***	0.873***
		(3.21)	(3.72)	(2.28)	(3.36)	(2.37)	(3.79)	(3.26)	(2.93)
	GDD – Long	0.683***	0.707***	-2.575***	0.291	0.476**	0.373*	2.021***	2.324***
		(4.55)	(4.46)	(-4.22)	(0.30)	(2.18)	(1.68)	(3.00)	(3.32)
	GDDHigh – Short	0.027	-0.126**	-0.103	-0.346***	-0.019	-0.208***	-0.100	-0.141

		(0.50)	(-2.10)	(-1.09)	(-2.93)	(-0.34)	(-3.22)	(-0.72)	(-1.00)
	GDDHigh – Long	-0.320***	-0.222***	-0.378***	-0.752***	-0.270***	-0.159**	-0.302	-0.229
		(-5.62)	(-3.48)	(-2.79)	(-3.30)	(-3.96)	(-2.13)	(-0.93)	(-0.68)
Rush	*Prec* – Short	-0.003	-0.007	0.005	-0.001	0.009	0.003	0.025*	0.010
		(-0.65)	(-1.40)	(0.53)	(-0.09)	(1.40)	(0.48)	(1.91)	(0.69)
	Prec – Long	0.024***	0.026***	0.067***	0.0290	0.018*	0.022**	-0.296***	-0.265***
		(6.25)	(6.40)	(3.42)	(1.33)	(1.92)	(2.31)	(-8.00)	(-7.02)
	PrecLow – Short	0.054	0.058	-0.117	-0.209***	0.067	0.099*	-0.184**	-0.156*
		(1.37)	(1.45)	(-1.81)	(-3.06)	(1.42)	(1.92)	(-2.41)	(-1.94)
	PrecLow – Long	-0.103***	-0.075**	-0.173	-0.253***	-0.031	-0.024	-0.517**	-0.444*
		(-3.21)	(-2.26)	(-1.85)	(-2.65)	(-0.81)	(-0.61)	(-2.08)	(-1.78)
	GDD – Short	0.158***	0.062	-0.291***	-0.299***	0.404***	0.443***	-0.223	0.055
		(4.38)	(1.44)	(-2.65)	(-2.71)	(3.62)	(3.97)	(-1.10)	(0.25)
	GDD – Long	0.072*	0.157***	-0.257**	-0.160	-0.124	-0.154	-1.915***	-1.878***
		(1.76)	(3.39)	(-1.96)	(-1.12)	(-1.09)	(-1.34)	(-6.96)	(-6.63)
	GDDHigh – Short	-0.115***	-0.110***	0.122*	0.104	-0.019	-0.031	0.738***	0.628***
		(-2.81)	(-2.67)	(1.79)	(1.49)	(-0.56)	(-0.86)	(7.64)	(6.26)
	GDDHigh – Long	0.098***	0.085**	0.542***	0.403***	0.020	0.037	0.809***	0.705***
		(3.39)	(2.55)	(8.43)	(5.53)	(0.64)	(1.19)	(5.95)	(5.07)
Russell	*Prec* – Short	0.017**	0.015**	-0.025	-0.028	0.015	0.019	-0.047**	-0.053***
		(2.53)	(2.05)	(-1.78)	(-1.93)	(1.13)	(1.43)	(-2.47)	(-2.62)
	Prec – Long	0.075***	0.082***	-0.077***	-0.050	0.142***	0.101***	-0.166*	-0.207**
		(6.47)	(6.93)	(-2.69)	(-1.71)	(5.66)	(3.51)	(-1.82)	(-2.12)
	PrecLow – Short	0.081	0.087	-0.102	-0.131	0.089	0.068	0.085	0.069
		(1.17)	(1.24)	(-0.90)	(-1.14)	(0.93)	(0.68)	(0.39)	(0.32)
	PrecLow – Long	0.127***	0.123***	0.137***	0.118***	0.200***	0.152***	0.338	0.230
		(4.82)	(4.64)	(3.57)	(3.06)	(3.98)	(2.83)	(0.50)	(0.34)
	GDD – Short	-0.052	-0.031	-0.439**	-0.473**	0.568***	0.595***	0.160	0.228
		(-0.67)	(-0.38)	(-2.36)	(-2.50)	(2.95)	(3.07)	(0.46)	(0.64)
	GDD – Long	-0.929***	-0.937***	-3.627***	-4.183***	-0.957***	-1.041***	-5.407***	-5.034***
		(-6.62)	(-6.67)	(-10.22)	(-10.56)	(-6.49)	(-6.69)	(-6.68)	(-5.88)
	GDDHigh – Short	-0.079	-0.106	-0.188	-0.129	0.053	0.081	-0.127	-0.136
		(-1.07)	(-1.40)	(-1.33)	(-0.89)	(0.79)	(1.18)	(-0.57)	(-0.60)
	GDDHigh – Long	0.150**	0.170***	0.222*	0.417***	-0.021	-0.026	-1.332***	-1.366***
		(2.53)	(2.85)	(1.66)	(2.91)	(-0.21)	(-0.26)	(-4.73)	(-4.82)
Saline	*Prec* – Short	-0.003	-0.003	-0.074***	-0.065***	0.041**	0.064***	-0.156***	-0.106***
		(-0.26)	(-0.31)	(-3.65)	(-2.82)	(2.30)	(3.37)	(-4.24)	(-2.77)
	Prec – Long	0.068***	0.062***	-0.082**	-0.046	-0.003	-0.038	-0.217**	-0.168
		(5.62)	(4.47)	(-2.18)	(-1.16)	(-0.10)	(-1.25)	(-2.03)	(-1.40)
	PrecLow – Short	-0.264***	-0.277***	-0.009	0.178	-0.413***	-0.408***	0.807***	0.971***
		(-3.06)	(-3.18)	(-0.05)	(0.89)	(-3.70)	(-3.63)	(2.73)	(3.32)
	PrecLow – Long	-0.165*	-0.126	0.010	0.542**	0.165	0.204	0.952	1.793***

			(-1.88)	(-1.43)	(0.05)	(2.08)	(1.23)	(1.48)	(1.43)	(2.67)
		GDD – Short	-0.109	-0.083	0.510**	0.404	-0.047	-0.215	-0.794***	-0.875***
			(-0.74)	(-0.56)	(2.37)	(1.38)	(-0.23)	(-0.95)	(-2.70)	(-2.35)
		GDD – Long	0.815***	0.985***	-0.777	-1.646	1.118***	1.359***	-0.786	-0.091
			(5.36)	(6.07)	(-1.29)	(-1.70)	(4.68)	(5.29)	(-0.95)	(-0.11)
		GDDHigh – Short	0.012	-0.057	-0.479***	-0.427***	0.261***	0.255***	-0.196	-0.150
			(0.16)	(-0.70)	(-4.89)	(-3.05)	(3.30)	(3.17)	(-1.03)	(-0.77)
		GDDHigh – Long	0.208**	0.167*	-0.164	0.000	-0.004	0.002	0.405	0.471
			(2.28)	(1.81)	(-1.11)	(0.00)	(-0.04)	(0.02)	(1.16)	(1.36)
	Trego	*Prec* – Short	-0.002	-0.009*	-0.022***	-0.030***	-0.003	-0.004	-0.018	-0.025**
			(-0.51)	(-1.94)	(-3.44)	(-4.35)	(-0.78)	(-0.81)	(-1.50)	(-1.99)
		Prec – Long	0.007**	0.014***	0.041***	0.023*	0.023***	0.027***	0.027	-0.001
			(2.04)	(2.99)	(3.82)	(1.82)	(3.10)	(3.29)	(0.70)	(-0.03)
		PrecLow – Short	0.090***	0.099***	0.13***	0.105***	-0.091***	-0.083**(-	-0.036	-0.011
			(3.54)	(3.59)	(3.42)	(2.64)	(-2.89)	2.49)	(-0.55)	(-0.16)
		PrecLow – Long	-0.080***	-0.086***	-0.126**	-0.134**	0.133***	0.112***	0.279*	0.328**(2
			(-3.05)	(-3.05)	(-2.34)	(-2.41)	(4.35)	(3.21)	(1.90)	.20)
		GDD – Short	-0.124*	-0.133*	-0.188***	-0.047	-0.071	-0.083	1.175***	1.247***
			(-1.94)	(-1.87)	(-3.30)	(-0.67)	(-0.76)	(-0.89)	(14.59)	(14.04)
		GDD – Long	-0.411***	-0.315**	-0.798***	-0.457	0.337***	0.365***	0.008	0.159
			(-3.29)	(-2.36)	(-3.76)	(-1.89)	(3.56)	(3.55)	(0.05)	(0.87)
		GDDHigh – Short							-	-
			0.035	0.030	0.099**	-0.006	0.253***	0.264***	0.171***(	0.208***
			(1.26)	(1.07)	(2.19)	(-0.12)	(5.03)	(4.61)	-2.75)	(-3.07)
		GDDHigh – Long	0.142**	0.109	0.359***	0.197***	-0.380***	-0.383***	-1.331***	-1.355***
			(2.47)	(1.62)	(7.14)	(2.81)	(-6.79)	(-5.56)	(-10.50)	(-10.24)
Wheat	Barton	*Prec* – Short	0.015*	0.045***	-0.002	0.064***	0.182***	0.234***	0.056***	0.124***
			(1.73)	(4.00)	(-0.19)	(3.49)	(11.03)	(13.71)	(2.66)	(5.07)
		Prec – Long	0.213***	0.262***	0.078***	0.204***	0.010	0.184***	-0.021	0.245**
			(12.54)	(12.04)	(3.07)	(6.16)	(0.33)	(5.12)	(-0.20)	(2.25)
		PrecLow – Short	0.226**	0.243***	0.369***	0.237*	-0.079	0.139	0.162	0.253
			(2.47)	(2.64)	(2.65)	(1.68)	(-0.68)	(1.18)	(0.84)	(1.32)
		PrecLow – Long	-0.413***	-0.424***	-0.172	-0.359	-0.424***	-0.340***	-0.418	-1.141*(-
			(-4.08)	(-4.04)	(-0.89)	(-1.77)	(-3.91)	(-3.02)	(-0.62)	1.66)
		GDD – Short	0.690***	0.671***	0.715***	0.153	0.598***	0.891***	2.898***	2.337***
			(4.41)	(4.16)	(3.26)	(0.62)	(2.63)	(3.85)	(6.92)	(5.13)
		GDD – Long	-0.702***	-0.980***	-2.329***	-3.225***	-0.618***	-1.492***	0.124	-1.163
			(-6.66)	(-7.33)	(-5.11)	(-6.72)	(-2.60)	(-5.91)	(0.14)	(-1.27)
		GDDHigh – Short	0.059	0.159	-0.163	0.217	1.028***	1.281***	-0.127	-0.083
			(0.56)	(1.41)	(-1.04)	(1.25)	(9.55)	(11.57)	(-0.82)	(-0.51)
		GDDHigh – Long	0.063	0.358***	-0.273	0.532**	-1.236***	-0.920***	-2.283***	-2.183***
			(0.57)	(2.77)	(-1.64)	(2.47)	(-12.63)	(-9.01)	(-7.79)	(-7.42)

Ellis	*Prec* – Short	-0.177***	-0.066***	-0.103***	-0.038	0.220***	0.202***	0.460***	0.506***
		(-11.80)	(-4.03)	(-3.89)	(-1.34)	(12.14)	(10.91)	(10.19)	(10.93)
	Prec – Long	0.137***	0.246***	0.057	0.148***	-0.321***	0.315***	0.690***	1.004***
		(7.31)	(12.24)	(1.34)	(3.42)	(-9.94)	(8.16)	(4.60)	(6.23)
	PrecLow – Short	-0.486***	-0.096	-0.178	0.144	0.572***	0.193	1.143***	1.181***
		(-4.06)	(-0.79)	(-1.18)	(0.95)	(4.54)	(1.53)	(6.19)	(6.34)
	PrecLow – Long	0.363***	0.068	0.466**	-0.147	-0.290**	-0.395***	2.826***	2.877***
		(3.26)	(0.60)	(2.04)	(-0.64)	(-2.46)	(-3.24)	(4.13)	(4.17)
	GDD – Short	1.079***	0.569***	0.261	0.606**	4.204***	1.133***	3.554***	3.580***
		(9.01)	(4.37)	(1.03)	(2.32)	(16.24)	(4.45)	(10.41)	(10.46)
	GDD – Long	0.336**	0.504***	-1.772***	0.361	0.199	-2.460***	4.009***	2.948***
		(2.36)	(3.32)	(-2.91)	(0.53)	(0.96)	(-8.93)	(5.85)	(4.07)
	GDDHigh – Short	0.177**	0.012	0.494***	-0.157	1.548***	1.169***	0.876***	0.446*
		(2.22)	(0.15)	(3.31)	(-0.99)	(20.32)	(9.65)	(3.43)	(1.66)
	GDDHigh – Long	0.072	0.306***	0.386**	-0.058	-2.379***	-0.457***	-2.791***	-3.295***
		(0.76)	(3.20)	(1.98)	(-0.28)	(-20.88)	(-4.13)	(-6.25)	(-7.14)
Ellsworth	*Prec* – Short	-0.046***	-0.060***	-0.154***	-0.143***	-0.066**	-0.078***	-0.144***	-0.135***
		(-3.67)	(-4.08)	(-7.36)	(-5.55)	(-2.48)	(-2.72)	(-3.87)	(-3.20)
	Prec – Long	0.079***	0.099***	-0.128***	-0.093	0.107***	0.082**	-0.308*	-0.287
		(3.49)	(3.66)	(-2.75)	(-1.94)	(3.09)	(2.11)	(-1.77)	(-1.55)
	PrecLow – Short	-0.008	-0.051	0.290	0.207	-0.372***	-0.350**	-0.312	-0.256
		(-0.08)	(-0.50)	(1.52)	(1.07)	(-2.94)	(-2.54)	(-1.58)	(-1.21)
	PrecLow – Long	-0.276**	-0.245*	-0.533**	-0.421	-0.158	-0.220	-0.106	-0.089
		(-2.20)	(-1.92)	(-2.01)	(-1.56)	(-1.05)	(-1.42)	(-0.17)	(-0.13)
	GDD – Short	0.467**	0.654***	1.793***	1.550***	2.693***	2.825***	3.176***	3.028***
		(1.99)	(2.71)	(4.79)	(3.66)	(6.13)	(5.85)	(5.41)	(4.88)
	GDD – Long	-2.150***	-2.207***	-0.424	-2.114**	-2.561***	-2.582***	-0.531	-0.554
		(-10.88)	(-9.29)	(-0.50)	(-2.07)	(-8.22)	(-8.14)	(-0.45)	(-0.46)
	GDDHigh – Short	-0.036	-0.233	0.192	0.186	0.244	0.154	0.839***	0.914***
		(-0.20)	(-1.20)	(0.83)	(0.72)	(1.58)	(0.86)	(3.63)	(3.49)
	GDDHigh – Long	0.670***	0.717***	0.503*	0.975***	-0.181	-0.306	0.932**	1.028**
		(3.62)	(3.34)	(1.75)	(2.85)	(-1.10)	(-1.62)	(2.44)	(2.45)
Gove	*Prec* – Short	-0.026*	-0.027*	0.044*	0.035	0.212***	0.210***	-0.041	0.056
		(-1.71)	(-1.68)	(1.82)	(1.40)	(9.50)	(9.39)	(-0.93)	(1.22)
	Prec – Long	0.131***	0.107***	0.243***	0.197***	-0.068***	-0.049**	-0.687***	-0.330**
		(10.62)	(6.16)	(6.51)	(3.78)	(-3.79)	(-2.56)	(-6.12)	(-2.57)
	PrecLow – Short	-0.299***	-0.294***	-0.072	-0.068	-0.351***	-0.169	-1.213***	-0.640***
		(-3.79)	(-3.36)	(-0.55)	(-0.50)	(-3.03)	(-1.41)	(-6.40)	(-3.13)
	PrecLow – Long	0.232**	0.226**	-0.332	-0.333	0.482***	0.384***	-0.433	0.360
		(2.53)	(2.31)	(-1.78)	(-1.78)	(3.50)	(2.72)	(-0.99)	(0.80)
	GDD – Short	0.435***	0.569***	1.409***	1.696***	3.087***	3.145***	2.957***	3.386***
		(3.58)	(4.32)	(7.06)	(7.47)	(13.32)	(13.60)	(8.95)	(10.14)

	GDD – Long	-0.823***	-0.722***	-0.593	-0.002	-3.014***	-3.422***	-0.392	-0.631
		(-4.68)	(-3.90)	(-1.11)	(0.00)	(-8.81)	(-9.35)	(-0.50)	(-0.79)
	GDDHigh – Short	0.536***	0.567***	0.076	0.054	0.524***	0.769***	1.741***	1.357***
		(6.49)	(6.37)	(0.51)	(0.36)	(5.98)	(7.58)	(8.09)	(6.16)
	GDDHigh – Long	-0.444***	-0.612***	-0.981***	-1.392***	-0.843***	-0.958***	1.589***	0.329
		(-4.04)	(-4.50)	(-4.62)	(-4.95)	(-5.54)	(-6.05)	(4.16)	(0.80)
Lincoln	*Prec* – Short	-0.037***	-0.015	-0.025	-0.020	-0.003	-0.019	-0.116***	-0.135***
		(-3.02)	(-1.06)	(-1.02)	(-0.79)	(-0.16)	(-0.93)	(-3.62)	(-3.78)
	Prec – Long	0.05***	0.008	0.051*	-0.028	0.043**	0.064***	-0.445***	-0.444***
		(3.77)	(0.52)	(1.69)	(-0.79)	(2.15)	(2.65)	(-3.74)	(-3.67)
	PrecLow – Short	0.647***	0.712***	0.345*	0.270	0.703***	0.434**	0.593*	0.205
		(5.59)	(5.57)	(1.73)	(1.34)	(4.88)	(2.42)	(1.90)	(0.62)
	PrecLow – Long	0.454***	0.461***	0.027	-0.586	0.602***	1.028***	1.133	0.621
		(3.63)	(3.35)	(0.08)	(-1.51)	(3.12)	(4.57)	(1.59)	(0.77)
	GDD – Short	0.657***	0.732***	0.345*	0.461**	1.281***	1.255***	1.047***	1.053***
		(5.53)	(5.78)	(1.79)	(2.28)	(5.45)	(5.11)	(3.37)	(3.34)
	GDD – Long	0.313	-0.265	-0.212	-1.207	-0.255	-0.834***	-2.351**	-0.481
		(1.64)	(-1.31)	(-0.32)	(-1.49)	(-0.95)	(-2.84)	(-2.22)	(-0.37)
	GDDHigh – Short	-0.208***	-0.251***	-0.021	-0.151	-0.075	-0.085	-0.013	-0.038
		(-3.28)	(-3.76)	(-0.23)	(-1.52)	(-1.28)	(-1.40)	(-0.12)	(-0.33)
	GDDHigh – Long	-0.25***	-0.313***	0.153	0.078	-0.501***	-0.629***	-0.796***	-0.755***
		(-4.99)	(-5.97)	(0.98)	(0.45)	(-7.08)	(-8.42)	(-2.92)	(-2.74)
Ness	*Prec* – Short	-0.025*	0.011	-0.044**	0.033	0.181***	-0.008	0.087***	0.015
		(-1.88)	(0.71)	(-2.23)	(1.46)	(10.20)	(-0.30)	(3.72)	(0.56)
	Prec – Long	0.188***	0.156***	0.205***	0.082***	0.054***	-0.718***	0.091***	-0.676***
		(14.36)	(10.46)	(6.86)	(2.62)	(2.76)	(-9.60)	(3.13)	(-8.84)
	PrecLow – Short	0.270***	0.381***	-0.291	-0.560***	0.829***	0.885***	0.508***	0.776***
		(3.00)	(4.13)	(-1.88)	(-3.54)	(6.61)	(4.27)	(3.36)	(3.71)
	PrecLow – Long	-0.200**	-0.299***	-1.126***	-2.184***	-0.564***	-0.763	-0.419***	-0.918*
		(-2.20)	(-3.22)	(-4.18)	(-7.75)	(-4.48)	(-1.58)	(-2.63)	(-1.88)
	GDD – Short	1.538***	1.347***	1.341***	1.359***	2.823***	5.328***	2.134***	5.183***
		(14.75)	(12.55)	(5.44)	(5.24)	(10.55)	(13.95)	(3.08)	(13.33)
	GDD – Long	-0.162	0.087	0.023	0.399	-1.013***	0.016	-0.757	-0.146
		(-1.40)	(0.69)	(0.05)	(0.82)	(-3.75)	(0.03)	(-0.95)	(-0.23)
	GDDHigh – Short	0.094	0.111	0.274**	0.036	0.541***	-0.340**(-	-0.560**	-0.327**
		(1.27)	(1.49)	(2.37)	(0.30)	(7.62)	2.57)	(-2.25)	(-2.47)
	GDDHigh – Long	-0.192***	-0.254***	0.264	-0.207	-0.435***	-2.402***	0.343	-2.382***
		(-2.79)	(-3.56)	(1.46)	(-1.10)	(-5.47)	(-10.30)	(1.16)	(-10.07)
Ottawa	*Prec* – Short	0.082***	0.096***	0.064**	0.103***	-0.013	0.047	-0.054	-0.015
		(4.02)	(4.62)	(2.35)	(3.32)	(-0.39)	(1.38)	(-1.10)	(-0.27)
	Prec – Long	0.140***	0.111***	0.205***	0.199***	0.087***	0.076***	-0.387***	-0.295**
		(6.07)	(4.08)	(5.40)	(4.32)	(3.46)	(2.81)	(-3.37)	(-2.24)

	PrecLow – Short	-0.142	-0.125	-0.897***	-0.852***	-0.368**	-0.218	0.192	0.059
		(-0.95)	(-0.83)	(-4.33)	(-4.08)	(-2.26)	(-1.31)	(0.66)	(0.20)
	PrecLow – Long	-0.480***	-0.444***	-1.484***	-1.484***	0.499**	0.088	2.874***	2.556***
		(-2.94)	(-2.72)	(-3.19)	(-3.18)	(2.38)	(0.39)	(6.13)	(4.93)
	GDD – Short	-0.451***	-0.542***	-0.644***	-1.057***	-0.311	-0.697***	-0.555*	-0.522
		(-2.70)	(-3.18)	(-2.68)	(-3.41)	(-1.28)	(-2.84)	(-1.66)	(-1.49)
	GDD – Long	-0.682***	-0.656***	2.082***	-0.208	0.029	0.138	-2.591***	-2.994***
		(-3.74)	(-3.39)	(2.91)	(-0.18)	(0.10)	(0.49)	(-3.28)	(-3.65)
	GDDHigh – Short	0.047	0.203**	0.004	0.209	0.207***	0.474***	-0.212	-0.164
		(0.63)	(2.46)	(0.04)	(1.52)	(2.78)	(5.60)	(-1.29)	(-0.99)
	GDDHigh – Long	0.344***	0.237***	0.371**	0.773***	-0.005	-0.163*	-1.116***	-1.235***
		(4.79)	(3.00)	(2.34)	(2.89)	(-0.06)	(-1.71)	(-2.92)	(-3.14)
Rush	*Prec* – Short	-0.092***	-0.069***	-0.137***	-0.159***	0.316***	0.338***	0.178***	0.174***
		(-5.20)	(-3.80)	(-4.91)	(-5.63)	(13.45)	(14.01)	(5.02)	(4.63)
	Prec – Long	0.091***	0.075***	-0.076	-0.230***	-0.065**	-0.022	0.459***	0.503***
		(6.50)	(4.95)	(-1.44)	(-3.94)	(-2.14)	(-0.68)	(4.58)	(4.91)
	PrecLow – Short	1.049***	0.839***	0.946***	0.554***	0.597***	0.233	1.270***	1.167***
		(7.74)	(6.01)	(5.38)	(2.97)	(3.66)	(1.29)	(6.14)	(5.32)
	PrecLow – Long	0.594***	0.833***	-0.053	-0.332	0.888***	1.043***	0.661	0.719
		(5.52)	(7.30)	(-0.21)	(-1.28)	(6.68)	(7.60)	(0.98)	(1.06)
	GDD – Short	2.200***	1.891***	2.969***	2.889***	1.557***	1.697***	4.998***	5.148***
		(18.21)	(12.97)	(9.92)	(9.63)	(5.02)	(5.29)	(9.08)	(8.75)
	GDD – Long	-0.700***	-0.588***	0.116	0.218	-1.814***	-2.200***	3.460***	3.149***
		(-4.71)	(-3.63)	(0.33)	(0.56)	(-6.18)	(-7.04)	(4.63)	(4.10)
	GDDHigh – Short	0.005	-0.005	0.051	-0.099	1.428***	1.571***	-0.538**	-0.643**
		(0.03)	(-0.04)	(0.28)	(-0.52)	(11.60)	(12.40)	(-2.05)	(-2.36)
	GDDHigh – Long	-0.601***	-0.911***	-1.052***	-1.647***	-1.275***	-1.253***	-3.343***	-3.567***
		(-5.34)	(-7.35)	(-6.01)	(-8.30)	(-11.71)	(-11.21)	(-9.06)	(-9.45)
Russell	*Prec* – Short	0.050***	0.048***	-0.041	-0.071***	0.142***	0.143***	-0.130***	-0.137***
		(3.74)	(3.43)	(-1.58)	(-2.70)	(6.66)	(6.66)	(-3.70)	(-3.68)
	Prec – Long	0.517***	0.515***	0.266***	0.287***	0.164***	0.143***	-0.567***	-0.604***
		(21.84)	(20.10)	(5.07)	(5.37)	(4.19)	(3.03)	(-3.39)	(-3.37)
	PrecLow – Short	0.201	0.115	-0.141	0.051	0.093	-0.077	0.742*	0.717*
		(1.37)	(0.76)	(-0.68)	(0.24)	(0.51)	(-0.41)	(1.87)	(1.80)
	PrecLow – Long	0.094**	0.098**	-0.219***	-0.224***	0.186**	0.142	0.054	-0.011
		(1.98)	(2.06)	(-3.12)	(-3.18)	(1.99)	(1.40)	(0.04)	(-0.01)
	GDD – Short	-0.335**	-0.616***	0.668**	1.019***	0.979***	0.762**	2.417***	2.432***(
		(-2.33)	(-3.87)	(1.97)	(2.95)	(3.08)	(2.37)	(3.77)	3.76)
	GDD – Long	0.528*	0.549*	-1.581**	-0.213	1.563***	1.590***	-6.307***	-6.015***
		(1.84)	(1.89)	(-2.44)	(-0.29)	(5.93)	(5.88)	(-4.25)	(-3.84)
	GDDHigh – Short	0.140	0.172	-0.890***	-1.160***	0.816***	0.843***	-1.964***	-1.966***
		(0.90)	(1.09)	(-3.44)	(-4.40)	(5.46)	(5.57)	(-4.77)	(-4.77)

	GDDHigh – Long	0.825***	0.787***	-0.022	-0.342	-0.855***	-1.028***	-5.815***	-5.849***
		(6.36)	(6.02)	(-0.09)	(-1.31)	(-4.29)	(-5.02)	(-11.27)	(-11.26)
Saline	*Prec* – Short	0.007	0.012	0.086***	0.076***	-0.008	-0.017	0.131***	0.110**
		(0.59)	(0.9)	(3.62)	(2.81)	(-0.34)	(-0.68)	(3.04)	(2.44)
	Prec – Long	-0.064***	-0.064***	0.111**	0.091**	-0.012	0.008	0.126	0.132
		(-4.19)	(-3.53)	(2.53)	(1.96)	(-0.35)	(0.21)	(1.01)	(0.94)
	PrecLow – Short	0.523***	0.545***	0.043	-0.018	0.645***	0.643***	-0.996***	-0.988***
		(5.00)	(5.11)	(0.19)	(-0.08)	(4.65)	(4.58)	(-2.89)	(-2.89)
	PrecLow – Long	0.151	0.139	0.072	-0.202	-0.200	-0.194	-1.088	-1.350*
		(1.38)	(1.26)	(0.28)	(-0.66)	(-1.16)	(-1.09)	(-1.40)	(-1.72)
	GDD – Short	-0.654***	-0.640***	-0.807***	-0.614	-1.066***	-1.034***	-0.167	-0.049
		(3.49)	(3.37)	(-3.22)	(-1.79)	(-4.29)	(-3.79)	(-0.49)	(-0.11)
	GDD – Long	-0.92***	-0.900***	0.848	1.797	-1.043***	-1.111***	3.404***	2.618***
		(5.00)	(4.51)	(1.21)	(1.59)	(-3.58)	(-3.54)	(3.54)	(2.68)
	GDDHigh – Short	0.282***	0.290***	0.392***	0.286*	0.233**	0.255**	0.819***	0.735***
		(2.78)	(2.61)	(3.44)	(1.75)	(2.18)	2.31)	(3.69)	(3.22)
	GDDHigh – Long	0.116	0.123	0.126	-0.072	0.380***	0.393***	0.190	0.068
		(1.01)	(1.06)	(0.73)	(-0.27)	(2.90)	(2.98)	(0.47)	(0.17)
Trego	*Prec* – Short	-0.010	-0.006	-0.010	-0.021	0.194***	0.181***	0.014	0.012
		(-0.81)	(-0.47)	(-0.45)	(-0.92)	(12.83)	(11.97)	(0.35)	(0.29)
	Prec – Long	0.241***	0.238***	0.149***	0.084**	0.130***	0.089***	-0.500***	-0.516***
		(19.72)	(19.13)	(4.10)	(2.03)	(4.71)	(3.20)	(-3.92)	(-3.81)
	PrecLow – Short	0.558***	0.583***	0.968***	0.831***	0.782***	0.792***	1.057***	0.979***
		(6.15)	(6.20)	(7.58)	(6.25)	(8.39)	(8.33)	(4.89)	(4.45)
	PrecLow – Long	0.122	0.106	-0.328	-0.476**	0.332***	0.378***	0.277	0.055
		(1.36)	(1.17)	(-1.82)	(-2.57)	(3.60)	(4.08)	(0.57)	(0.11)
	GDD – Short	1.304***	1.279***	1.831***	2.101***	4.830***	4.367***	5.043***	4.799***
		(10.09)	(9.60)	(9.58)	(8.82)	(21.82)	(18.71)	(18.79)	(16.21)
	GDD – Long	0.499*	0.294	-0.044	0.135	3.904***	3.147***	4.373***	3.929***
		(1.82)	(0.86)	(-0.06)	(0.17)	(13.55)	(10.52)	(7.93)	(6.50)
	GDDHigh – Short	-0.280***	-0.250**	-0.668***	-0.869***	0.018	0.200**	-1.449***	-1.231***
		(-2.93)	(-2.52)	(-4.42)	(-4.70)	(0.21)	(2.23)	(-6.98)	(-5.46)
	GDDHigh – Long	-0.855***	-0.797***	-1.360***	-1.624***	-3.459***	-3.256***	-6.342***	-6.003***
		(-7.55)	(-6.13)	(-8.08)	(-6.90)	(-25.87)	(-24.09)	(-15.01)	(-13.62)

Table SA14. NL-DML-RE Partial Effects, Price Variables, 1-3 and 4-10 lag structure

County	Land use	P_A	P_{Sor}	P_{Soy}	P_W
Barton	Alfalfa	0.001	0.000	0.000	-0.004
		(0.03)	(0.01)	(0.03)	(0.74)
	Corn/Sorghum	0.34^{***}	0.049^{***}	0.032^{***}	-0.083^{***}
		(6.85)	(4.80)	(3.76)	(9.64)
	Fallow	-0.164^{***}	0.075^{***}	-0.080^{***}	0.054^{***}
		(5.62)	(11.52)	(10.72)	(10.72)
	Soybeans/Double Crop	0.024	-0.052^{***}	0.046^{***}	-0.028^{***}
		(0.82)	(8.27)	(8.30)	(5.32)
	Wheat	-0.201^{***}	-0.072^{***}	0.002	0.061^{***}
		(3.39)	(5.81)	(0.20)	(5.90)
Ellis	Alfalfa	0.013^{*}	0.003	-0.001	0.000
		(1.72)	(1.09)	(-0.41)	(-0.02)
	Corn/Sorghum	0.224^{***}	0.043^{***}	0.010	-0.020^{**}
		(4.74)	(3.41)	(1.43)	(-2.54)
	Fallow	-0.145^{***}	0.120^{***}	-0.104^{***}	0.035^{***}
		(-3.27)	(10.39)	(-17.09)	(4.68)
	Soybeans/Double Crop	-0.067^{***}	-0.094^{***}	0.049^{***}	0.002
		(-3.43)	(-11.15)	(10.15)	(0.62)
	Wheat	-0.025	-0.072^{***}	0.046^{***}	-0.017^{*}
		(-0.48)	(-5.00)	(6.06)	(-1.94)
Ellsworth	Alfalfa	0.052^{**}	0.011	0.002	-0.009^{*}
		(2.03)	(1.42)	(0.38)	(-1.76)
	Corn/Sorghum	-0.067	0.123^{***}	-0.067^{***}	-0.002
		(-0.71)	(5.82)	(-3.85)	(-0.14)
	Fallow	0.017	-0.013	-0.012	0.024^{**}
		(0.30)	(-1.07)	(-1.14)	(2.39)
	Soybeans/Double Crop	0.010	-0.023^{*}	0.021^{**}	-0.013
		(0.22)	(-1.85)	(2.33)	(-1.61)
	Wheat	-0.011	-0.097^{***}	0.057^{***}	0.001
		(-0.11)	(-4.10)	(2.98)	(0.05)
Gove	Alfalfa	-0.005	0.001	-0.002	0.002
		(-0.39)	(0.47)	(-1.13)	(1.22)
	Corn/Sorghum	0.494^{***}	-0.017	0.052^{***}	-0.032^{***}
		(8.67)	(-1.41)	(5.97)	(-3.00)
	Fallow	0.110^{**}	-0.013	0.036^{***}	-0.085^{***}
		(2.26)	(-1.32)	(4.85)	(-9.49)
	Soybeans/Double Crop	0.004	-0.022^{***}	0.020^{***}	-0.008^{**}
		(0.20)	(-3.13)	(4.04)	(-2.01)
	Wheat	-0.603^{***}	0.051^{***}	-0.106^{***}	0.123^{***}
		(-12.67)	(4.79)	(-14.60)	(13.56)
Lincoln	Alfalfa	-0.035^{**}	-0.014	0.003	-0.005
		(-2.50)	(-1.51)	(0.64)	(-1.25)
	Corn/Sorghum	0.045	0.074^{***}	-0.030^{***}	-0.005
		(1.17)	(5.11)	(-3.24)	(-0.68)
	Fallow	-0.065^{***}	0.010^{*}	-0.022^{***}	0.024^{***}
		(-4.50)	(1.84)	(-6.22)	(7.66)
	Soybeans/Double Crop	0.130^{***}	-0.147^{***}	0.115^{***}	-0.037^{***}
		(5.46)	(-11.99)	(15.05)	(-6.93)
	Wheat	-0.074^{*}	0.077^{***}	-0.066^{***}	0.024^{***}
		(-1.76)	(4.11)	(-5.58)	(2.72)
Ness	Alfalfa	-0.003	0.001	-0.001	0.000
		(-0.19)	(0.49)	(-0.37)	(-0.14)
	Corn/Sorghum	0.198^{***}	-0.013	0.041^{***}	-0.038^{***}
		(3.93)	(-1.15)	(4.45)	(-4.37)
	Fallow	0.072	0.061^{***}	-0.025^{**}	-0.010
		(1.24)	(4.72)	(-2.38)	(-0.98)
	Soybeans/Double Crop	-0.021	-0.014^{**}	0.013^{***}	-0.005
		(-0.86)	(-2.06)	(2.78)	(-1.15)
	Wheat	-0.245^{***}	-0.035^{***}	-0.028^{***}	0.053^{***}
		(-4.92)	(-2.86)	(-2.99)	(6.04)

Ottawa	Alfalfa	-0.025	-0.001	0.001	0.002
		(-1.17)	(-0.08)	(0.23)	(0.33)
	Corn/Sorghum	0.094**	-0.005	0.019	-0.015*
		(2.09)	(-0.35)	(1.64)	(-1.69)
	Soybeans/Double Crop	-0.086**	-0.137***	0.080***	0.001
		(-2.19)	(-8.63)	(6.96)	(0.09)
	Wheat	0.017	0.143***	-0.101***	0.013
		(0.33)	(7.12)	(-6.93)	(1.12)
Rush	Alfalfa	0.035	-0.007**	0.007***	-0.005
		(1.61)	(-2.26)	(2.45)	(-1.46)
	Corn/Sorghum	0.475***	0.005	0.067***	-0.066***
		(5.62)	(0.43)	(7.08)	(-4.46)
	Fallow	-0.146**	0.076***	-0.069***	0.018
		(-2.06)	(7.64)	(-8.15)	(1.43)
	Soybeans/Double Crop	0.065***	-0.033***	0.029***	-0.012***
		(2.75)	(-8.49)	(8.83)	(-3.17)
	Wheat	-0.428***	-0.041***	-0.035***	0.065***
		(-4.93)	(-3.31)	(-3.41)	(4.33)
Russell	Alfalfa	-0.003	-0.002	0.001	0.002
		(-0.21)	(-0.55)	(0.29)	(0.52)
	Corn/Sorghum	0.047	0.053***	-0.005	-0.041***
		(0.71)	(3.64)	(-0.51)	(-3.28)
	Fallow	-0.156***	0.080***	-0.084***	0.028***
		(-3.24)	(7.48)	(-11.47)	(3.24)
	Soybeans/Double Crop	0.046	-0.090***	0.071***	-0.026***
		(1.30)	(-10.89)	(10.33)	(-3.87)
	Wheat	0.066	-0.041***	0.018	0.036***
		(0.89)	(-2.67)	(1.55)	(2.74)
Saline	Alfalfa	0.043*	-0.005	0.014***	-0.017***
		(1.75)	(-0.63)	(2.97)	(-2.89)
	Corn/Sorghum	-0.035	-0.034***	0.012	0.013
		(-0.81)	(-2.84)	(1.46)	(1.33)
	Fallow	-0.003	-0.002**	0.001	0.001*
		(-0.90)	(-2.38)	(1.46)	(1.81)
	Soybeans/Double Crop	0.041	-0.077***	0.058***	-0.006
		(0.93)	(-5.90)	(7.08)	(-0.62)
	Wheat	-0.046	0.118***	-0.086***	0.009
		(-0.79)	(6.68)	(-7.65)	(0.63)
Trego	Alfalfa	0.002	0.004	-0.002	0.000
		(0.12)	(1.13)	(-0.95)	(0.04)
	Corn/Sorghum	-0.006	-0.009	0.025***	-0.030***
		(-0.11)	(-0.58)	(3.13)	(-3.08)
	Fallow	0.270***	0.102***	-0.051***	-0.016
		(4.97)	(7.36)	(-6.81)	(-1.64)
	Soybeans/Double Crop	-0.031*	-0.028***	0.018***	0.003
		(-1.80)	(-3.40)	(3.60)	(0.42)
	Wheat	-0.235***	-0.069***	0.010	0.042***
		(-4.87)	(-5.09)	(1.38)	(4.95)

Table SA15. County-average land-use transition probabilities, NL-DML-RE, 1 to 3 and 4 to 10 lag structure

		Current Land-Use				
County	Lagged Land-Use	Alfalfa	Corn/Sorghum	Fallow	Soybeans/Double Crop	Wheat
Barton	Alfalfa	0.60	0.06	0.04	0.03	0.27
	Corn/Sorghum	0.01	0.20	0.33	0.18	0.27
	Fallow	0.02	0.02	0.00	0.00	0.96
	Soybeans/Double Crop	0.02	0.18	0.10	0.07	0.64
	Wheat	0.02	0.25	0.04	0.03	0.65
Ellis	Alfalfa	0.45	0.15	0.12	0.03	0.24
	Corn/Sorghum	0.00	0.18	0.64	0.04	0.14
	Fallow	0.00	0.03	0.02	0.00	0.94
	Soybeans/Double Crop	0.00	0.24	0.44	0.03	0.28
	Wheat	0.00	0.34	0.19	0.01	0.46
Ellsworth	Alfalfa	0.39	0.08	0.04	0.06	0.44
	Corn/Sorghum	0.01	0.19	0.35	0.18	0.27
	Fallow	0.00	0.01	0.00	0.00	0.98
	Soybeans/Double Crop	0.01	0.13	0.13	0.06	0.68
	Wheat	0.01	0.16	0.03	0.03	0.78
Gove	Alfalfa	0.36	0.20	0.25	0.01	0.17
	Corn/Sorghum	0.00	0.25	0.63	0.01	0.11
	Fallow	0.00	0.11	0.04	0.01	0.84
	Soybeans/Double Crop	0.00	0.34	0.51	0.01	0.14
	Wheat	0.00	0.69	0.14	0.01	0.16
Lincoln	Alfalfa/Fallow	0.29	0.04	0.00	0.04	0.63
	Corn/Sorghum	0.01	0.27	0.14	0.33	0.25
	Soybeans/Double Crop	0.01	0.16	0.03	0.14	0.66
	Wheat	0.01	0.18	0.01	0.07	0.73
Ness	Alfalfa	0.54	0.15	0.16	0.00	0.16
	Corn/Sorghum	0.00	0.10	0.80	0.01	0.09
	Fallow	0.00	0.04	0.04	0.01	0.92
	Soybeans/Double Crop	0.01	0.19	0.64	0.03	0.14
	Wheat	0.00	0.35	0.42	0.01	0.22
Ottawa	Alfalfa	0.55	0.07		0.11	0.27
	Corn/Sorghum	0.01	0.26		0.51	0.23
	Soybeans/Double Crop	0.01	0.21		0.20	0.57
	Wheat	0.02	0.09		0.11	0.78
Rush	Alfalfa	0.34	0.17	0.19	0.02	0.27
	Corn/Sorghum	0.00	0.13	0.68	0.05	0.14
	Fallow	0.00	0.02	0.01	0.00	0.97
	Soybeans/Double Crop	0.01	0.19	0.40	0.02	0.38
	Wheat	0.00	0.36	0.19	0.01	0.44
Russell	Alfalfa	0.43	0.11	0.13	0.07	0.27
	Corn/Sorghum	0.00	0.18	0.55	0.11	0.16
	Fallow	0.00	0.01	0.01	0.01	0.97
	Soybeans/Double Crop	0.01	0.23	0.24	0.07	0.45
	Wheat	0.00	0.35	0.09	0.03	0.53
Saline	Alfalfa/Fallow	0.43	0.04	0.00	0.11	0.43
	Corn/Sorghum	0.01	0.23	0.00	0.47	0.29
	Soybeans/Double Crop	0.01	0.18	0.00	0.18	0.63
	Wheat	0.02	0.06	0.00	0.10	0.82
Trego	Alfalfa	0.51	0.18	0.14	0.02	0.14
	Corn/Sorghum	0.00	0.14	0.76	0.01	0.09
	Fallow	0.00	0.05	0.03	0.00	0.92
	Soybeans/Double Crop	0.00	0.26	0.63	0.01	0.09
	Wheat	0.00	0.55	0.23	0.01	0.21

Figures

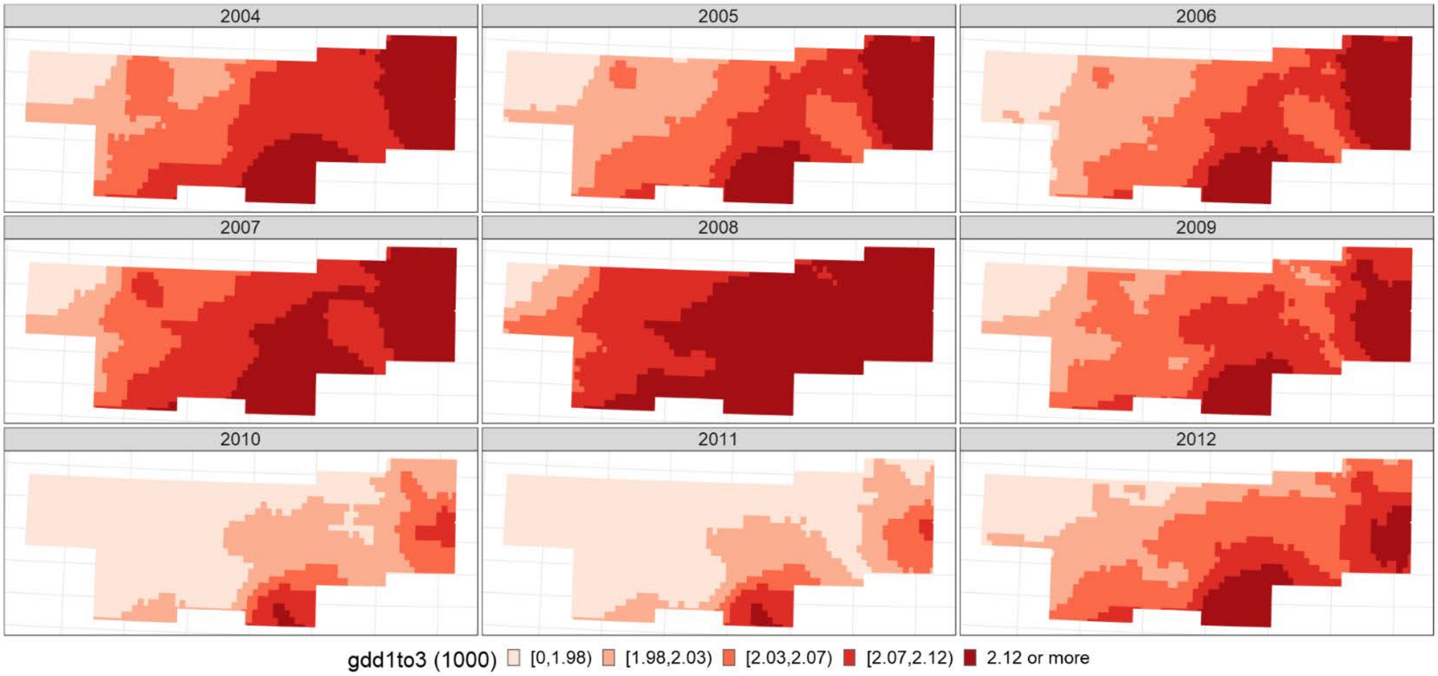

Figure SA1. Spatial and temporal variation in three-year average total growing-season growing degree days between 10°C and 30°C, lags 1 through 3 (used to create *GDD1to3*).

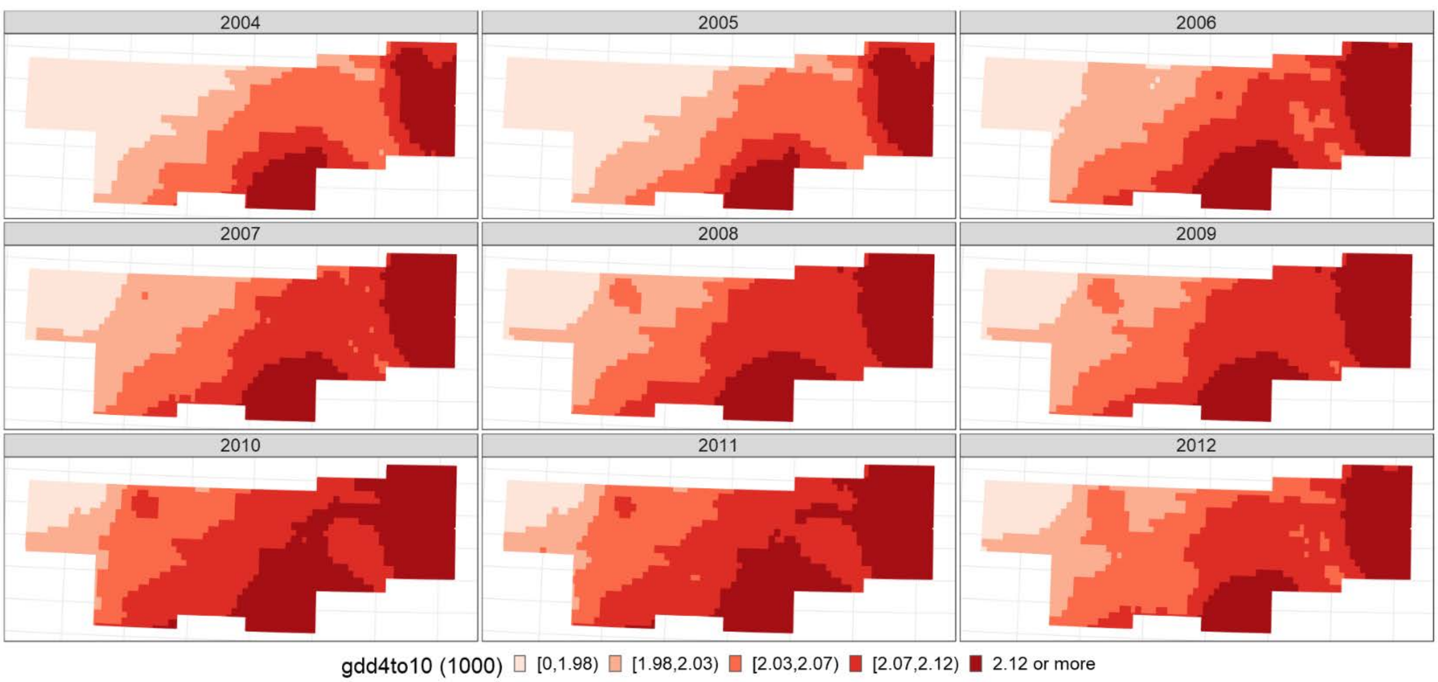

Figure SA2. Spatial and temporal variation in seven-year average total growing-season growing degree days between 10°C and 30°C, lags 4 through 10 (used to create *GDD4to10*).

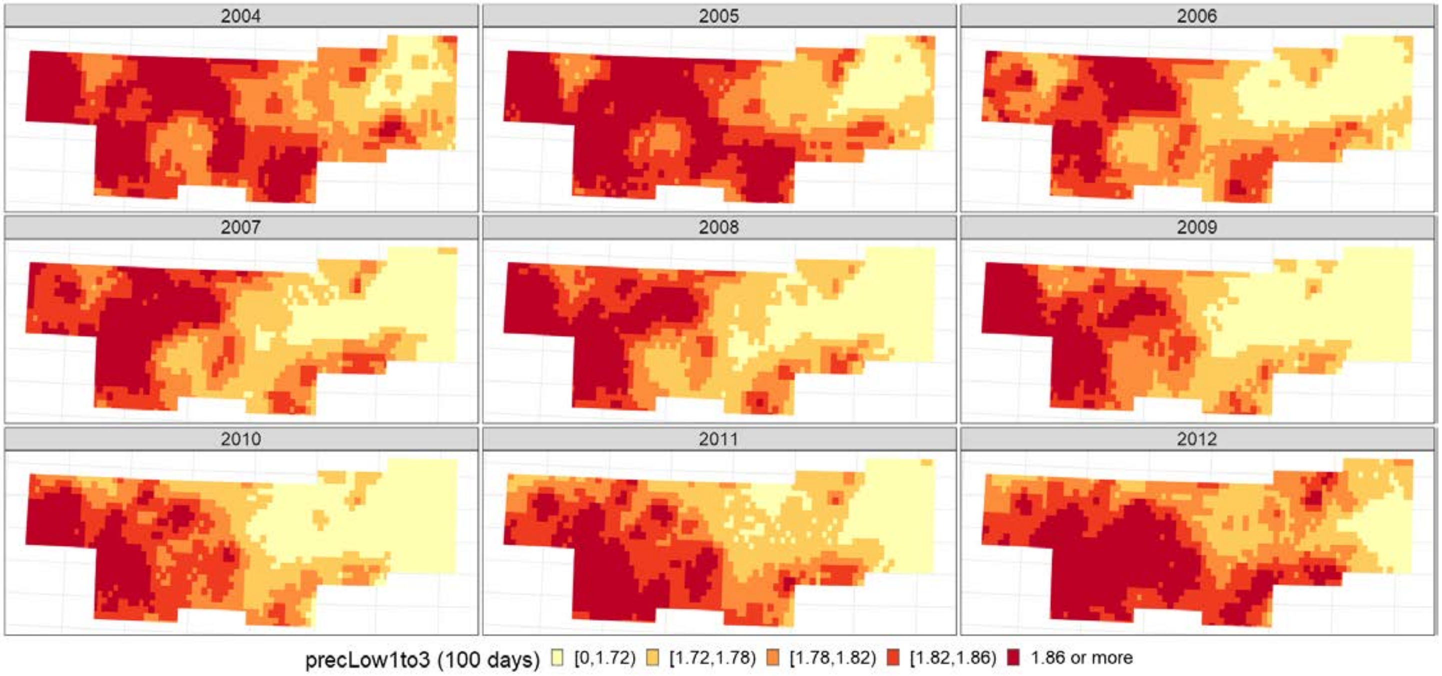

Figure SA3. Spatial and temporal variation in three-year average number of days with precipitation less than 1 mm, lags 1 through 3 (used to create *PrecLow1to3*).

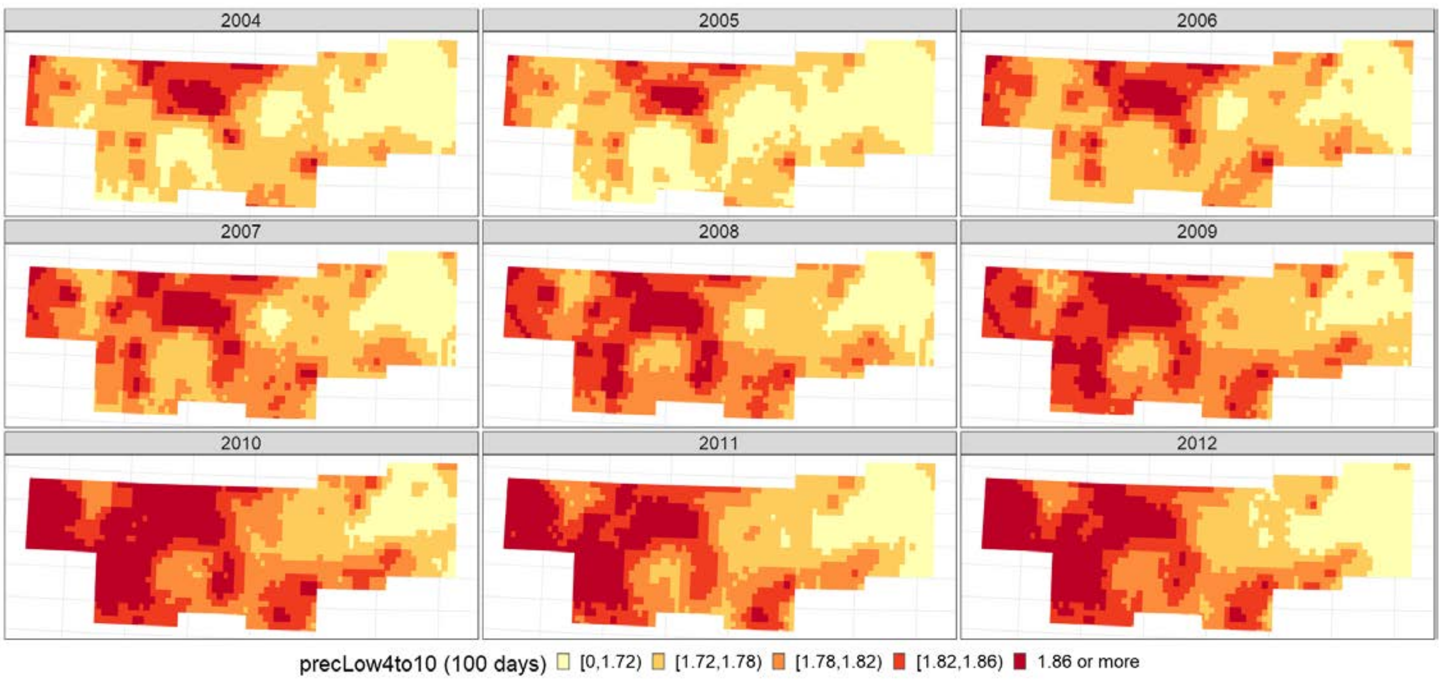

Figure SA4. Spatial and temporal variation in seven-year average number of days with precipitation less than 1 mm, lags 4 through 10 (used to create *PrecLow4to10*).

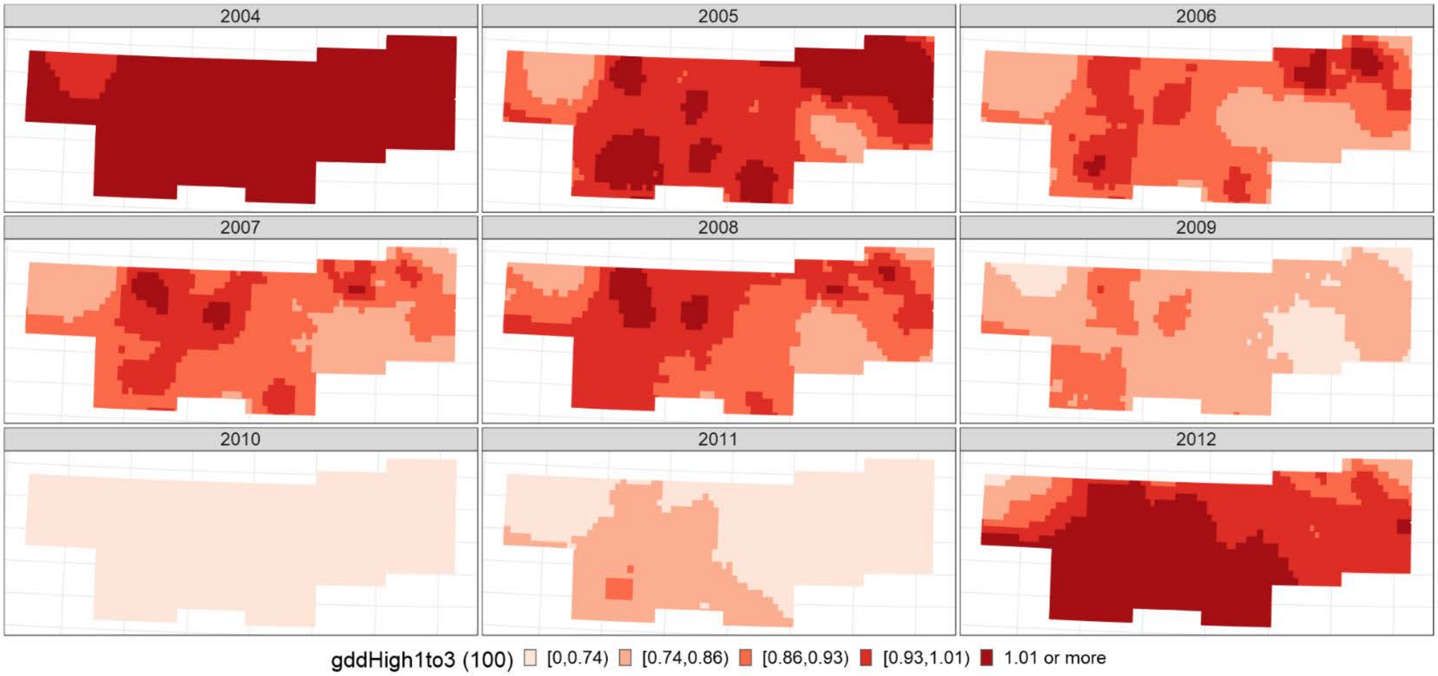

Figure SA5. Spatial and temporal variation in three-year average growing-season growing degree days above 30°C, lags 1 through 3 (used to create *GDDHigh1to3*).

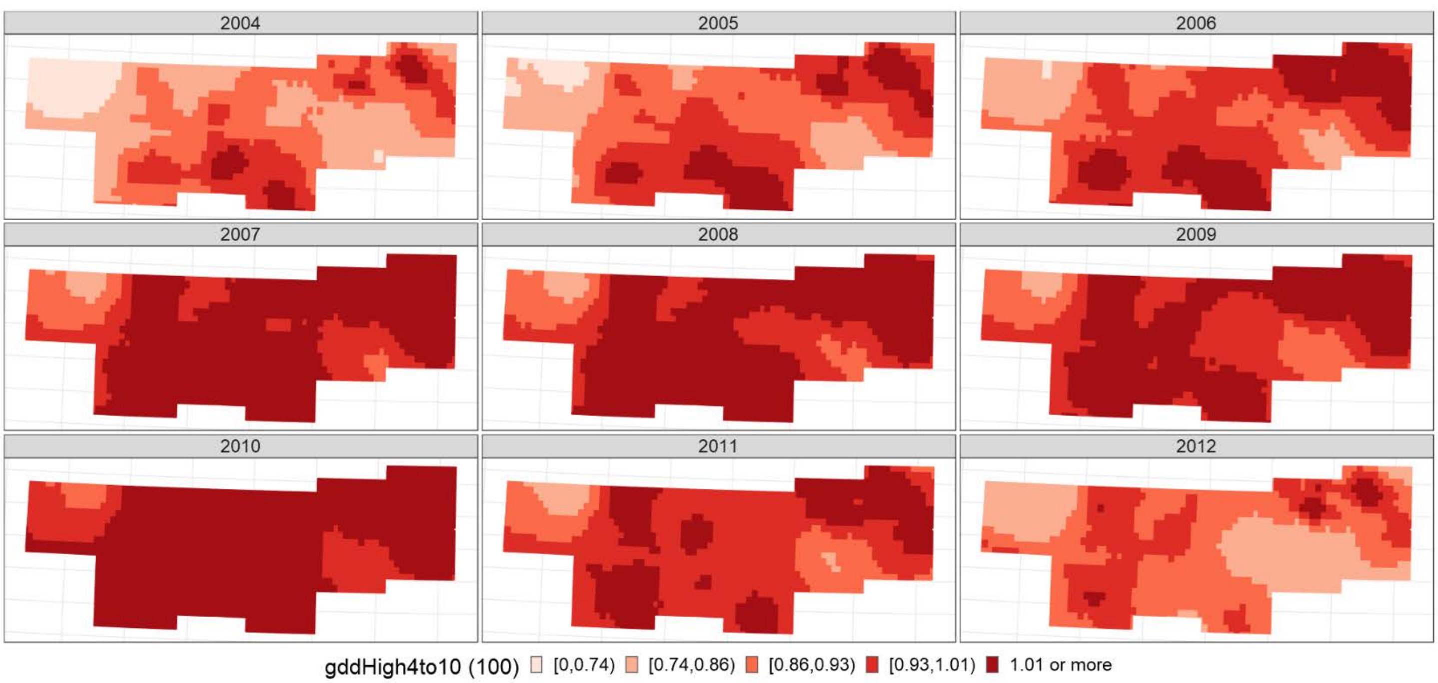

Figure SA6. Spatial and temporal variation in seven-year average growing-season growing degree days above 30°C, lags 4 through 10 (used to create *GDDHigh4to10*).

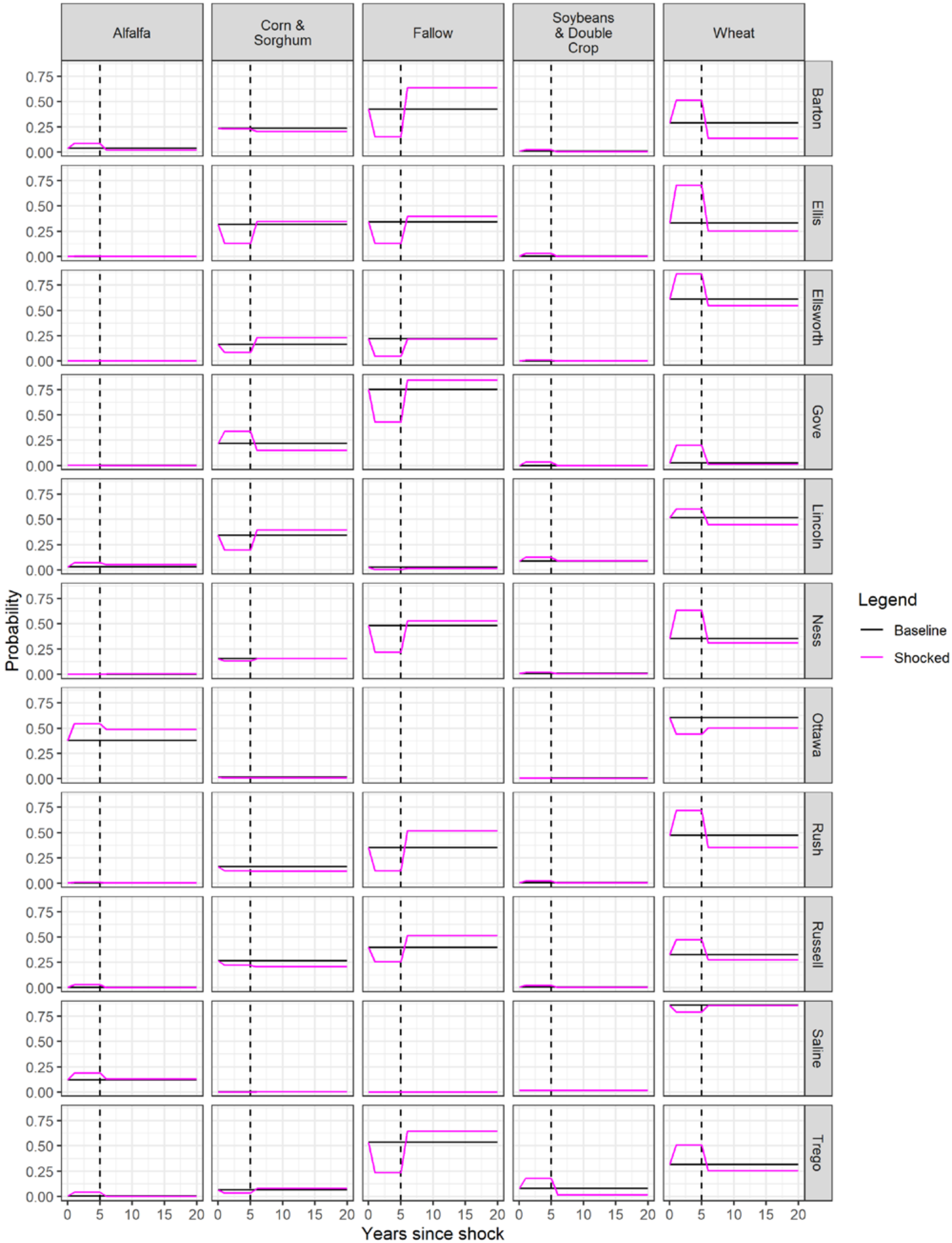

Figure SA7. Simulated probabilities from drought lasting one year, NL-DML-RE, 1-5 and 6-20 lag structure

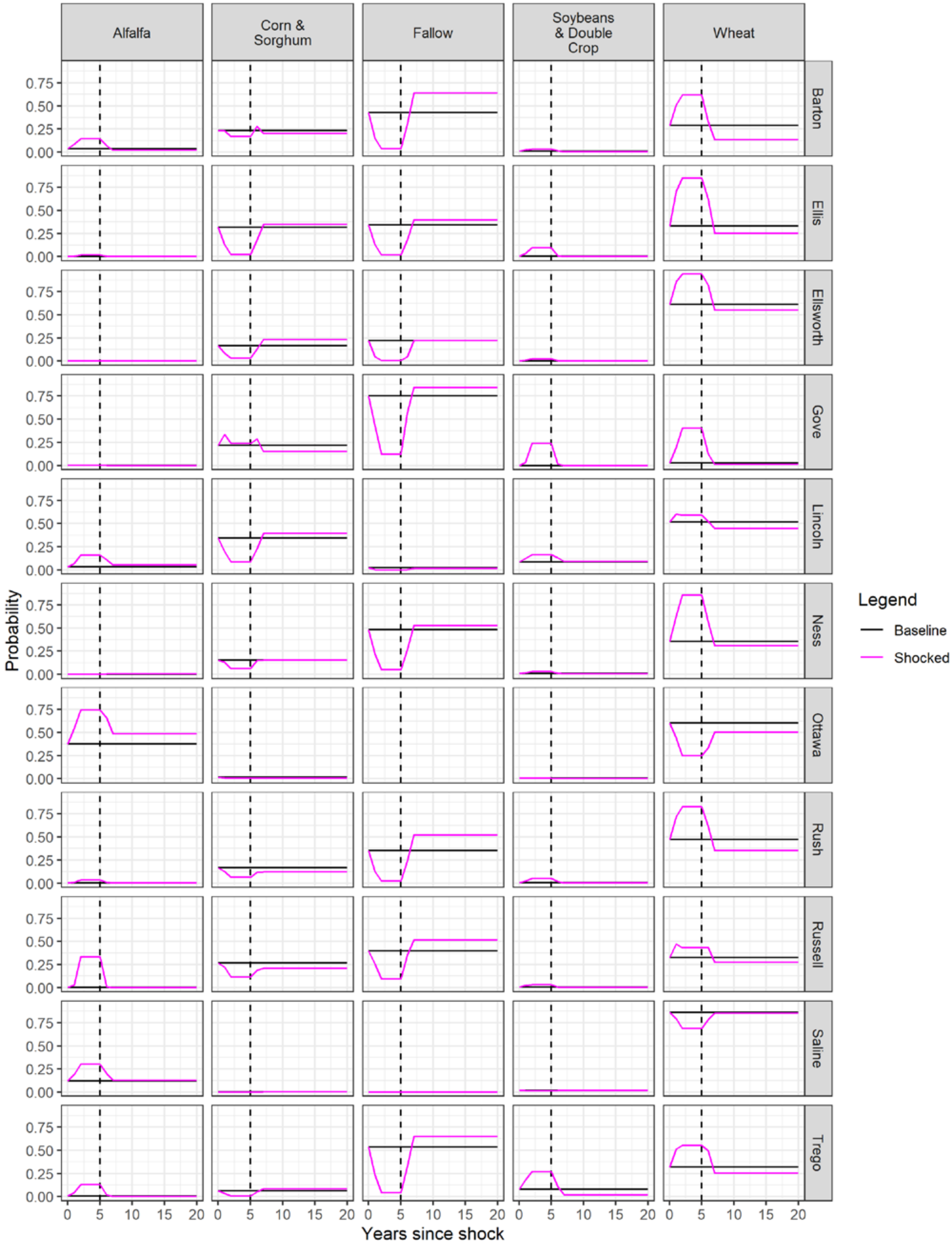

Figure SA8. Simulated probabilities from drought lasting two years, NL-DML-RE, 1-5 and 6-20 lag structure

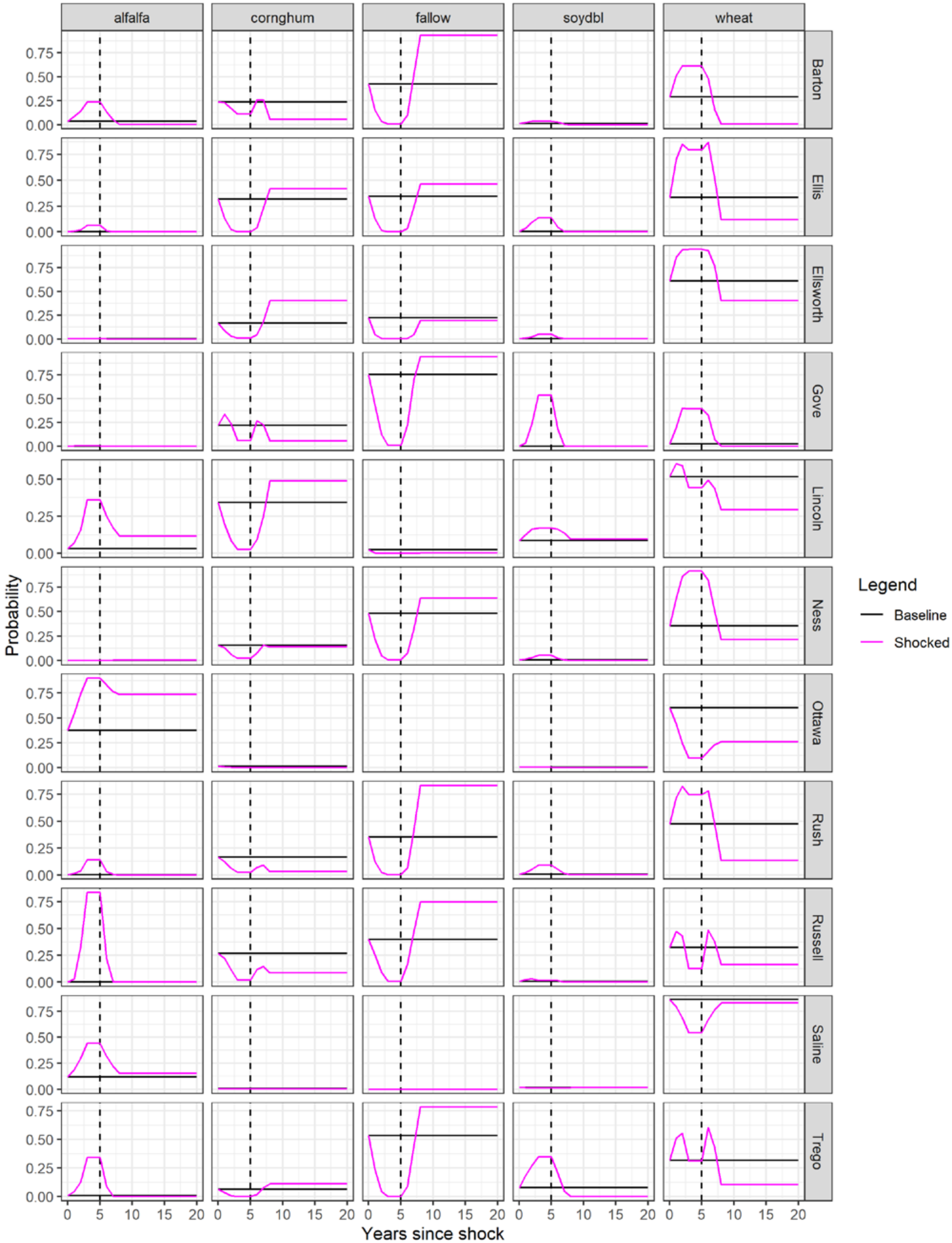

Figure SA9. Simulated probabilities from drought lasting three years, NL-DML-RE, 1-5 and 6-20 lag structure

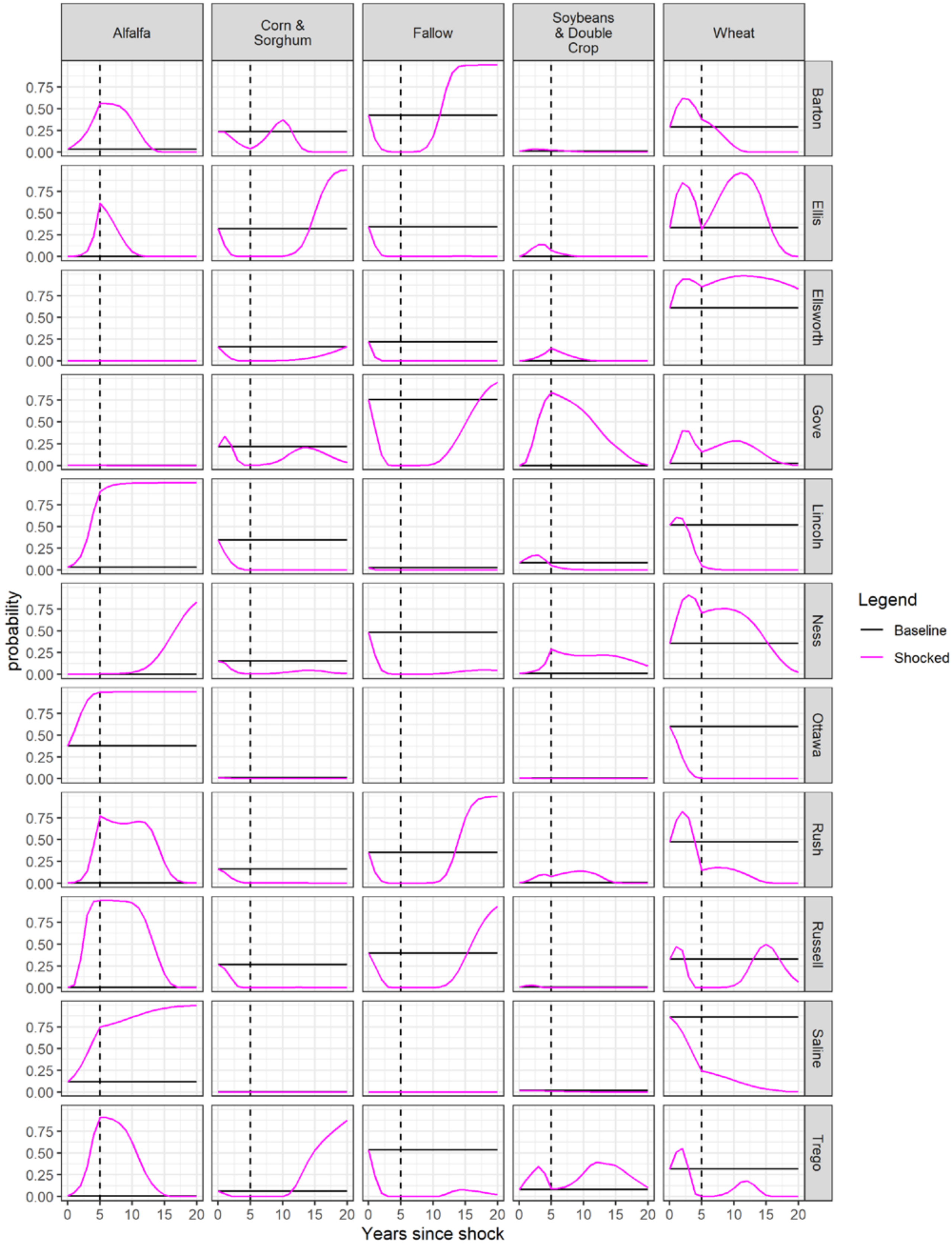

Figure SA10. Simulated probabilities from permanent drought, NL-DML-RE, 1-5 and 6-20 lag structure

Figure SA11. Average transition probabilities, NL-DML-RE, 1-5 and 6-20 lag structure

Field-level land-use adaptation to local weather trends - Supplementary Appendix

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Model Estimation Challenges

Estimation challenges arose when estimating the DML-RE land-use models. Some difficulties resulted from the software chosen, while others appear to be data driven. With respect to LIMDEP 10, one limitation with LIMDEP was that the multinomial logit with random parameters estimation procedure was limited to 150 parameters. In many applications this likely does not present a problem. However, with five outcome categories (which realistically could be further divided), the number of included variables could be constrained. Due to data-driven difficulties, the 150-parameter constraint was not binding for this article, but it could be in similar studies with different data. For example, in random effects models, it is generally recommended that a full set of time-specific dummy variables be included (Wooldridge 2010). Additionally, the model could include either the means or the full history of the time-varying explanatory variables, as suggested by Wooldridge (2005). An advantage of using LIMDEP 10 is that it provides APEs (through the PARTIALS command) and can be prompted to give individual-specific estimates of the random intercept for each category. When data-driven issues manifested, they at times resulted in a singular covariance matrix and at others resulted in the program crashing. In addition, the use of many binary variables (e.g. initial conditions and lagged dependent variables) can result in near collinearity between covariates, resulting in numerical issues during estimation, which likely resulted in some of the estimation issues encountered. The models were estimated in other statistical software as an additional robustness check, e.g. STATA, but similar estimation issues were encountered. Additionally, it was not clear that the field-specific intercepts were available as outputs in these other software packages. Based on use of different algorithms and tolerance criteria, LIMDEP 10, provided the most robust estimation results for the models.

References

Wooldridge, Jeffrey M. 2005. “Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity.” *Journal of applied econometrics* 20 (1): 39–54.

Wooldridge, Jeffrey M. 2010. *Econometric analysis of cross section and panel data.* MIT press.

Tables

Table A1. Weather variable values for drought-shock simulations

Variable	$t+0$	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$	$t+6$	$t+7$	$t+8$	$t+9$	$t+10$
Baseline											
$Prec1to3$	5.42	5.42	5.42	5.42	5.42	5.42	5.42	5.42	5.42	5.42	5.42
$Prec4to10$	5.42	5.42	5.42	5.42	5.42	5.42	5.42	5.42	5.42	5.42	5.42
$PrecLow1to3$	1.75	1.75	1.75	1.75	1.75	1.75	1.75	1.75	1.75	1.75	1.75
$PrecLow4to10$	1.75	1.75	1.75	1.75	1.75	1.75	1.75	1.75	1.75	1.75	1.75
$GDD1to3$	2.04	2.04	2.04	2.04	2.04	2.04	2.04	2.04	2.04	2.04	2.04
$GDD4to10$	2.04	2.04	2.04	2.04	2.04	2.04	2.04	2.04	2.04	2.04	2.04
$GDDHigh1to3$	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90
$GDDHigh4to10$	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90
1-Year Shock											
$Prec1to3$	5.42	4.90	4.90	4.90	5.42	5.42	5.42	5.42	5.42	5.42	5.42
$Prec4to10$	5.42	5.42	5.42	5.42	5.20	5.20	5.20	5.20	5.20	5.20	5.20
$PrecLow1to3$	1.75	1.83	1.83	1.83	1.75	1.75	1.75	1.75	1.75	1.75	1.75
$PrecLow4to10$	1.75	1.75	1.75	1.75	1.79	1.79	1.79	1.79	1.79	1.79	1.79
$GDD1to3$	2.04	2.12	2.12	2.12	2.04	2.04	2.04	2.04	2.04	2.04	2.04
$GDD4to10$	2.04	2.04	2.04	2.04	2.07	2.07	2.07	2.07	2.07	2.07	2.07
$GDDHigh1to3$	0.90	1.15	1.15	1.15	0.90	0.90	0.90	0.90	0.90	0.90	0.90
$GDDHigh4to10$	0.90	0.90	0.90	0.90	1.01	1.01	1.01	1.01	1.01	1.01	1.01
2-Year Shock											
$Prec1to3$	5.42	4.90	4.37	4.37	4.90	5.42	5.42	5.42	5.42	5.42	5.42
$Prec4to10$	5.42	5.42	5.42	5.42	5.20	4.97	4.97	4.97	4.97	4.97	4.97
$PrecLow1to3$	1.75	1.83	1.92	1.92	1.83	1.75	1.75	1.75	1.75	1.75	1.75
$PrecLow4to10$	1.75	1.75	1.75	1.75	1.79	1.82	1.82	1.82	1.82	1.82	1.82
$GDD1to3$	2.04	2.12	2.20	2.20	2.12	2.04	2.04	2.04	2.04	2.04	2.04
$GDD4to10$	2.04	2.04	2.04	2.04	2.07	2.11	2.11	2.11	2.11	2.11	2.11
$GDDHigh1to3$	0.90	1.15	1.41	1.41	1.15	0.90	0.90	0.90	0.90	0.90	0.90
$GDDHigh4to10$	0.90	0.90	0.90	0.90	1.01	1.12	1.12	1.12	1.12	1.12	1.12

Table A1 continued

Variable	$t+0$	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$	$t+6$	$t+7$	$t+8$	$t+9$	$t+10$
3-Year Shock											
$Prec1to3$	5.42	4.90	4.37	3.85	4.37	4.90	5.42	5.42	5.42	5.42	5.42
$Prec4to10$	5.42	5.42	5.42	5.42	5.20	4.97	4.75	4.75	4.75	4.75	4.75
$PrecLow1to3$	1.75	1.83	1.92	2.00	1.92	1.83	1.75	1.75	1.75	1.75	1.75
$PrecLow4to10$	1.75	1.75	1.75	1.75	1.79	1.82	1.86	1.86	1.86	1.86	1.86
$GDD1to3$	2.04	2.12	2.20	2.28	2.20	2.12	2.04	2.04	2.04	2.04	2.04
$GDD4to10$	2.04	2.04	2.04	2.04	2.07	2.11	2.14	2.14	2.14	2.14	2.14
$GDDHigh1to3$	0.90	1.15	1.41	1.67	1.41	1.15	0.90	0.90	0.90	0.90	0.90
$GDDHigh4to10$	0.90	0.90	0.90	0.90	1.01	1.12	1.23	1.23	1.23	1.23	1.23
Permanent Shock											
$Prec1to3$	5.42	4.90	4.37	3.85	3.85	3.85	3.85	3.85	3.85	3.85	3.85
$Prec4to10$	5.42	5.42	5.42	5.42	5.20	4.97	4.75	4.52	4.30	4.07	3.85
$PrecLow1to3$	1.75	1.83	1.92	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00
$PrecLow4to10$	1.75	1.75	1.75	1.75	1.79	1.82	1.86	1.89	1.93	1.97	2.00
$GDD1to3$	2.04	2.12	2.20	2.28	2.28	2.28	2.28	2.28	2.28	2.28	2.28
$GDD4to10$	2.04	2.04	2.04	2.04	2.07	2.11	2.14	2.18	2.21	2.25	2.28
$GDDHigh1to3$	0.90	1.15	1.41	1.67	1.67	1.67	1.67	1.67	1.67	1.67	1.67
$GDDHigh4to10$	0.90	0.90	0.90	0.90	1.01	1.12	1.23	1.34	1.45	1.56	1.67

Table A2. NL-DML-RE Parameter Estimates, Barton County

Variable	CS_t	F_t	SD_t	W_t
$Trend$	-0.27799 (-1.63)	0.42800^{**} (2.31)	-0.0934 (-0.50)	-0.03459 (-0.21)
$Acres$	-0.22269^{***} (-2.99)	-0.63705^{***} (-7.19)	-0.16274^{*} (-1.88)	-0.20731^{***} (-2.95)
p_A	1.82282^{*} (1.80)	-2.31538^{**} (-2.13)	0.3554 (0.32)	-0.36337 (-0.37)
p_{Sor}	0.36064^{*} (1.82)	1.20585^{***} (5.57)	-0.78318^{***} (-3.51)	-0.08488 (-0.44)
p_{Soy}	0.10767 (0.60)	-1.20661^{***} (-6.21)	0.71410^{***} (3.53)	-0.03103 (-0.18)
p_W	-0.32436^{*} (-1.87)	0.86856^{***} (4.67)	-0.36693^{*} (-1.90)	0.23453 (1.40)
$Prec1to3$	1.63327 (1.43)	5.78968^{***} (4.47)	-0.52678 (-0.43)	3.78280^{***} (3.51)
$Prec1to3^2$	-0.13389 (-1.51)	-0.44690^{***} (-4.42)	0.03266 (0.34)	-0.29409^{***} (-3.52)
$Prec4to10$	8.95169 (1.63)	14.7589^{**} (2.37)	0.13994 (0.02)	13.2912^{***} (2.62)
$Prec4to10^2$	-0.91475^{**} (-1.97)	-1.56534^{***} (-2.97)	-0.13323 (-0.25)	-1.17527^{***} (-2.74)
$PrecLow1to3$	-1.7699 (-1.32)	0.56632 (0.38)	-1.10239 (-0.74)	0.23169 (0.19)
$PrecLow4to10$	-0.76488 (-0.51)	-2.95739^{*} (-1.72)	-3.20227^{*} (-1.90)	-3.64649^{***} (-2.61)
$GDD1to3$	-8.19214^{***} (-3.00)	-7.36785^{**} (-2.49)	-1.36968 (-0.45)	-2.53276 (-0.96)
$GDD4to10$	1.16017 (0.57)	3.51677 (1.53)	2.65717 (1.17)	-3.69328^{*} (-1.94)
$GDDHigh1to3$	-0.38935 (-0.20)	3.03825 (1.48)	-0.35799 (-0.17)	1.08986 (0.58)
$GDDHigh4to10$	0.65258 (0.32)	-15.2057^{***} (-6.73)	0.62163 (0.27)	-0.1077 (-0.05)
CS_{t-1}	5.29217^{***} (42.04)	6.73368^{***} (41.35)	5.88337^{***} (40.74)	3.97136^{***} (37.00)
F_{t-1}	2.62361^{***} (13.72)	1.82293^{***} (7.83)	1.95238^{***} (7.17)	5.09212^{***} (33.29)
SD_{t-1}	4.93716^{***} (30.64)	5.06418^{***} (25.50)	4.63882^{***} (27.93)	4.67451^{***} (31.45)
W_{t-1}	5.03563^{***} (54.65)	3.92585^{***} (28.22)	3.73450^{***} (32.67)	4.44175^{***} (76.08)
CS_0	0.96181^{***} (10.10)	0.85116^{***} (7.46)	0.31559^{***} (2.9)	0.50957^{***} (5.63)
F_0	1.92865^{***} (8.87)	2.69253^{***} (11.74)	1.66695^{***} (7.14)	1.47101^{***} (6.97)
W_0	0.57520^{***} (9.99)	1.30168^{***} (17.17)	0.35372^{***} (5.00)	0.75967^{***} (14.55)
Means and standard deviations for random intercepts				
Mean (a_j)	-10.9783 (-0.61)	-28.7704 (-1.42)	5.15183 (0.25)	-32.2240^{*} (-1.93)
Std. Dev. (σ_j)	0.51064^{***} (41.27)	1.07834^{***} (53.44)	0.73635^{***} (36.35)	0.26611^{***} (25.57)

Note: Values in parentheses are z-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A3. NL-DML-RE Parameter Estimates, Ellis County

Variable	CS_t	F_t	SD_t	W_t
$Trend$	0.73236 (1.11)	1.16585* (1.77)	1.10547 (1.62)	0.84896 (1.29)
$Acres$	0.57164 (0.83)	0.5208 (0.76)	0.19608 (0.28)	0.71447 (1.04)
p_A	−5.13303 (−1.39)	−7.09901* (−1.91)	−10.2759*** (−2.67)	−6.32205* (−1.71)
p_{Sor}	−0.79059 (−0.64)	−0.33079 (−0.27)	−6.60792*** (−5.01)	−1.34122 (−1.08)
p_{Soy}	0.10111 (0.15)	−0.5324 (−0.81)	2.96317*** (4.20)	0.27166 (0.41)
p_W	−0.08597 (−0.11)	0.2222 (0.29)	0.15832 (0.20)	−0.05251 (−0.07)
$Prec1to3$	4.03571 (0.33)	2.45221 (0.20)	9.35816 (0.76)	8.60753 (0.71)
$Prec1to3^2$	−0.47886 (−0.41)	−0.3492 (−0.30)	−0.97196 (−0.82)	−0.98111 (−0.84)
$Prec4to10$	64.6132* (1.83)	58.3029* (1.65)	19.6935 (0.55)	20.609 (0.58)
$Prec4to10^2$	−6.61131* (−1.94)	−5.97171* (−1.76)	−2.06501 (−0.60)	−2.19388 (−0.65)
$PrecLow1to3$	−13.4797* (−1.87)	−19.9271*** (−2.76)	−24.0993*** (−3.20)	−17.1626** (−2.38)
$PrecLow4to10$	9.60951 (1.31)	17.9855** (2.45)	15.5600** (2.06)	13.6804* (1.87)
$GDD1to3$	1.23936 (0.15)	3.0642 (0.37)	17.7216** (1.99)	6.32265 (0.77)
$GDD4to10$	10.9446 (0.85)	17.885 (1.38)	3.8627 (0.29)	16.4549 (1.28)
$GDDHigh1to3$	8.53006 (1.31)	10.8759* (1.67)	13.8774** (2.08)	9.78691 (1.50)
$GDDHigh4to10$	−13.6278* (−1.88)	−19.7917*** (−2.72)	−24.3928*** (−3.22)	−14.7191** (−2.03)
CS_{t-1}	6.45125*** (9.67)	8.45485*** (10.86)	6.50931*** (8.74)	5.82840*** (8.04)
F_{t-1}	5.85823*** (6.64)	5.74981*** (6.01)	5.54801*** (5.89)	9.09574*** (10.28)
SD_{t-1}	5.46653*** (7.27)	6.62219*** (8.37)	5.23727*** (7.31)	5.23669*** (6.95)
W_{t-1}	7.46280*** (14.56)	7.16099*** (11.47)	6.00323*** (10.80)	7.36073*** (16.73)
CS_0	0.73011 (1.38)	0.8201 (1.53)	−0.33765 (−0.60)	0.59765 (1.13)
F_0	1.61013*** (2.82)	3.01534*** (5.25)	1.59190*** (2.66)	1.65080*** (2.92)
W_0	1.09646*** (2.98)	2.35386*** (6.37)	0.74211* (1.91)	1.74368*** (4.78)
Means and standard deviations for random intercepts				
Mean (a_j)	−175.089* (−1.85)	−171.702* (−1.81)	−87.14 (−0.90)	−97.3403 (−1.03)
Std. Dev. (σ_j)	0.86969*** (52.50)	1.05202*** (59.67)	0.68537*** (16.58)	0.31764*** (23.46)

Note: Values in parentheses are z-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A4. NL-DML-RE Parameter Estimates, Ellsworth County

Variable	CS_t	F_t	SD_t	W_t
$Trend$	0.89479** (2.25)	0.6249 (1.41)	0.63609 (1.55)	0.66139* (1.73)
$Acres$	0.27035 (1.30)	−0.31984 (−1.42)	0.46223** (2.19)	0.44568** (2.18)
p_A	−4.99193** (−2.13)	−4.19548 (−1.61)	−4.26700* (−1.77)	−4.56484** (−2.00)
p_{Sor}	−0.0783 (−0.11)	−1.1387 (−1.55)	−1.36669* (−1.88)	−1.07785 (−1.59)
p_{Soy}	−0.64081 (−1.59)	−0.45053 (−1.00)	0.21087 (0.49)	−0.07149 (−0.19)
p_W	0.80257* (1.71)	1.29213** (2.54)	0.56059 (1.15)	0.80321* (1.75)
$Prec1to3$	1.06627 (0.31)	8.34525** (2.22)	−0.4901 (−0.13)	0.60936 (0.18)
$Prec1to3^2$	−0.12272 (−0.46)	−0.73260** (−2.53)	0.0638 (0.23)	−0.10906 (−0.42)
$Prec4to10$	−2.49944 (−0.21)	49.2329*** (3.69)	9.21483 (0.74)	15.3965 (1.33)
$Prec4to10^2$	−0.0862 (−0.09)	−4.36152*** (−4.04)	−0.85646 (−0.85)	−1.46664 (−1.57)
$PrecLow1to3$	5.03506* (1.90)	0.89026 (0.32)	8.63970*** (3.03)	4.39537* (1.73)
$PrecLow4to10$	−10.4686*** (−3.13)	−1.27082 (−0.36)	−11.8175*** (−3.38)	−10.2946*** (−3.17)
$GDD1to3$	12.8932** (2.42)	24.4461*** (4.09)	3.47132 (0.61)	16.6839*** (3.30)
$GDD4to10$	17.9086*** (3.25)	18.6223*** (3.07)	11.4068** (1.98)	1.80886 (0.34)
$GDDHigh1to3$	1.10741 (0.28)	−6.26842 (−1.41)	4.29399 (1.05)	−1.07227 (−0.29)
$GDDHigh4to10$	−18.2152*** (−4.39)	−26.9655*** (−5.72)	−8.15077* (−1.85)	−12.3604*** (−3.09)
CS_{t-1}	5.37460*** (16.54)	7.36059*** (16.72)	5.65903*** (18.01)	3.95793*** (14.57)
F_{t-1}	2.44871*** (4.59)	1.03524 (1.52)	1.66394** (2.55)	5.69775*** (12.68)
SD_{t-1}	4.35564*** (11.83)	5.42948*** (11.92)	3.85345*** (11.98)	4.35791*** (14.69)
W_{t-1}	5.14169*** (21.86)	4.21175*** (11.58)	3.84589*** (15.16)	5.07659*** (28.84)
CS_0	−0.05325 (−0.24)	−0.42972* (−1.65)	−0.55865** (−2.32)	−0.16003 (−0.75)
SD_0	−0.35607 (−1.37)	−0.85305*** (−2.77)	−0.20929 (−0.76)	−0.80314*** (−3.21)
W_0	0.69165*** (4.31)	1.26085*** (6.88)	0.62168*** (3.42)	0.93631*** (6.16)
Means and standard deviations for random intercepts				
Mean (a_j)	−22.6399 (−0.54)	−53.9722 (−1.35)	−46.6558 (−1.08)	−222.580*** (−4.92)
Std. Dev. (σ_j)	0.34240*** (17.51)	0.31419*** (18.54)	0.88550*** (26.58)	1.43991*** (37.86)

Note: Values in parentheses are z-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A5. NL-DML-RE Parameter Estimates, Gove County

Variable	CS_t	F_t	SD_t	W_t
$Trend$	-0.99961	-1.07182	-1.1367	-0.02521
	(-0.94)	(-1.00)	(-1.01)	(-0.02)
$Acres$	1.86127^{***}	1.76784^{***}	1.52177^{**}	1.78492^{***}
	(2.98)	(2.83)	(2.42)	(2.86)
p_A	4.04601	3.12713	2.09504	-1.58318
	(0.75)	(0.58)	(0.37)	(-0.30)
p_{Sor}	-0.45606	-0.49098	-2.79585^{**}	-0.08736
	(-0.49)	(-0.53)	(-2.31)	(-0.09)
p_{Soy}	0.89734	0.95727	2.84568^{***}	0.04711
	(1.37)	(1.46)	(3.36)	(0.07)
p_W	-1.1173	-1.52324^{*}	-1.80972^{**}	-0.20114
	(-1.40)	(-1.90)	(-1.98)	(-0.25)
$Prec1to3$	14.2365	26.9723^{**}	4.14886	16.7627
	(1.15)	(2.18)	(0.32)	(1.36)
$Prec1to3^2$	-1.4676	-2.84146^{**}	-0.62552	-1.75762
	(-1.03)	(-1.98)	(-0.41)	(-1.23)
$Prec4to10$	3.59399	7.84898	18.3317	4.3224
	(0.25)	(0.53)	(1.20)	(0.29)
$Prec4to10^2$	-0.44258	-0.9852	-1.53153	-0.43341
	(-0.32)	(-0.71)	(-1.06)	(-0.31)
$PrecLow1to3$	5.04127	5.12276	-5.09271	2.19571
	(0.66)	(0.67)	(-0.63)	(0.29)
$PrecLow4to10$	-4.55484	-1.21863	8.52409	-1.07531
	(-0.45)	(-0.12)	(0.80)	(-0.11)
$GDD1to3$	-4.0715	-12.5432	-20.3776	-2.40607
	(-0.25)	(-0.77)	(-1.12)	(-0.15)
$GDD4to10$	3.76	2.01521	14.3054	-2.8267
	(0.20)	(0.11)	(0.70)	(-0.15)
$GDDHigh1to3$	-5.67074	0.60868	-4.99787	1.42022
	(-0.61)	(0.07)	(-0.51)	(0.15)
$GDDHigh4to10$	5.66371	9.0735	18.132	1.80312
	(0.38)	(0.60)	(1.12)	(0.12)
CS_{t-1}	6.53220^{***}	7.64102^{***}	6.43518^{***}	5.75360^{***}
	(13.15)	(11.83)	(6.40)	(9.67)
F_{t-1}	6.57590^{***}	5.32554^{***}	7.37384^{***}	9.12315^{***}
	(7.09)	(5.02)	(5.93)	(8.53)
SD_{t-1}	5.54420^{***}	6.01609^{***}	5.16444^{***}	4.68787^{***}
	(4.89)	(5.01)	(4.39)	(4.30)
W_{t-1}	7.39445^{***}	5.33363^{***}	5.75094^{***}	5.85055^{***}
	(14.47)	(10.92)	(5.89)	(11.38)
CS_0	1.46277^{***}	1.96981^{***}	0.54926	1.32160^{***}
	(3.82)	(4.78)	(1.06)	(3.45)
F_0	2.26658^{***}	4.14123^{***}	1.11428^{*}	2.20710^{***}
	(4.33)	(7.72)	(1.76)	(4.19)
W_0	1.55158^{***}	3.04133^{***}	0.59978	1.90115^{***}
	(3.99)	(7.74)	(1.25)	(4.77)
Means and standard deviations for random intercepts				
Mean (a_j)	-22.6399	-53.9722	-46.6558	-222.580^{***}
	(-0.54)	(-1.35)	(-1.08)	(-4.92)
Std. Dev. (σ_j)	0.34240^{***}	0.31419^{***}	0.88550^{***}	1.43991^{***}
	(17.51)	(18.54)	(26.58)	(37.86)

Note: Values in parentheses are z-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A6. NL-DML-RE Parameter Estimates, Lincoln County

Variable	CS_t	F_t	SD_t	W_t
$Trend$	-0.39082^{**} (-2.22)	0.17665 (0.75)	-0.88906^{***} (-5.03)	-0.41076^{**} (-2.51)
$Acres$	-0.12932 (-1.30)	-0.70901^{***} (-4.95)	-0.08686 (-0.82)	-0.11354 (-1.26)
p_A	1.61278^{***} (2.69)	-1.32458 (-1.54)	2.64924^{***} (4.45)	1.17746^{**} (2.15)
p_{Sor}	0.89839^{**} (2.53)	0.82166^{*} (1.79)	-0.99917^{***} (-2.65)	0.68634^{*} (1.95)
p_{Soy}	-0.26787 (-1.30)	-0.96435^{***} (-3.67)	1.05483^{***} (4.83)	-0.26481 (-1.30)
p_W	0.17496 (1.07)	1.19398^{***} (5.43)	-0.17012 (-1.02)	0.24277 (1.52)
$Prec1to3$	9.68654^{***} (2.89)	27.3783^{***} (6.64)	0.70505 (0.20)	6.46160^{**} (2.03)
$Prec1to3^2$	-0.74476^{***} (-2.70)	-2.15573^{***} (-6.37)	-0.02617 (-0.09)	-0.49432^{*} (-1.88)
$Prec4to10$	-15.2202^{***} (-3.25)	10.6212 (1.61)	0.14998 (0.03)	-14.2679^{***} (-3.31)
$Prec4to10^2$	1.26523^{***} (3.26)	-0.83606 (-1.51)	0.03938 (0.10)	1.21739^{***} (3.42)
$PrecLow1to3$	-14.3818^{***} (-6.93)	-20.0625^{***} (-7.55)	-8.12596^{***} (-3.81)	-7.63963^{***} (-3.86)
$PrecLow4to10$	13.0065^{***} (6.11)	26.4286^{***} (9.49)	5.05276^{**} (2.31)	12.5807^{***} (6.19)
$GDD1to3$	-8.94863^{***} (-3.82)	-4.75975 (-1.60)	-5.00788^{**} (-2.06)	-2.80225 (-1.25)
$GDD4to10$	-28.7799^{***} (-10.31)	-55.4249^{***} (-12.78)	-27.5654^{***} (-9.32)	-28.1493^{***} (-10.98)
$GDDHigh1to3$	-1.97909^{**} (-2.32)	-2.20774^{*} (-1.86)	-5.28851^{***} (-6.11)	-4.01682^{***} (-5.20)
$GDDHigh4to10$	-3.36960^{***} (-4.90)	-9.57205^{***} (-10.38)	1.61570^{**} (2.21)	-3.63384^{***} (-5.66)
CS_{t-1}	5.64296^{***} (30.29)	7.94957^{***} (24.11)	5.72504^{***} (30.42)	2.63023^{***} (15.66)
SD_{t-1}	5.07680^{***} (24.76)	6.35002^{***} (18.14)	4.68328^{***} (25.74)	3.58299^{***} (20.76)
W_{t-1}	5.05344^{***} (33.54)	4.61686^{***} (14.70)	3.85136^{***} (27.07)	3.59002^{***} (31.23)
CS_0	1.22812^{***} (11.49)	1.49156^{***} (9.14)	0.63425^{***} (5.42)	1.39862^{***} (14.34)
W_0	0.68472^{***} (9.50)	1.37539^{***} (11.02)	0.34602^{***} (4.43)	1.06578^{***} (17.24)
Means and standard deviations for random intercepts				
Mean (a_j)	96.1607^{***} (6.20)	-0.394 (-0.02)	65.0568^{***} (3.94)	83.2925^{***} (5.72)
Std. Dev. (σ_j)	0.00246 (0.15)	1.21511^{***} (29.20)	0.40894^{***} (28.94)	0.74334^{***} (33.71)

Note: Values in parentheses are z-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A7. NL-DML-RE Parameter Estimates, Ness County

Variable	CS_t	F_t	SD_t	W_t
$Trend$	-0.55753 (-0.31)	-0.50398 (-0.28)	-0.76213 (-0.41)	-0.08891 (-0.05)
$Acres$	1.26967^{**} (2.53)	1.48033^{***} (2.94)	0.71448 (1.37)	1.26321^{**} (2.51)
p_A	3.24111 (0.33)	2.25745 (0.23)	-1.01897 (-0.10)	0.38603 (0.04)
p_{Sor}	-0.75168 (-0.48)	-0.44297 (-0.28)	-2.48677 (-1.39)	-0.91613 (-0.58)
p_{Soy}	0.70915 (0.53)	0.35969 (0.27)	2.02303 (1.40)	0.29659 (0.22)
p_W	-0.06016 (-0.04)	0.13974 (0.10)	-0.4038 (-0.27)	0.50527 (0.36)
$Prec1to3$	18.3187 (0.74)	18.7503 (0.76)	0.90592 (0.04)	19.2609 (0.78)
$Prec1to3^2$	-1.86385 (-0.72)	-1.89873 (-0.74)	-0.12158 (-0.05)	-1.95801 (-0.76)
$Prec4to10$	24.7339 (0.80)	35.6285 (1.16)	11.5384 (0.36)	19.1033 (0.62)
$Prec4to10^2$	-2.1444 (-0.72)	-3.32296 (-1.12)	-0.74295 (-0.24)	-1.4621 (-0.49)
$PrecLow1to3$	-4.6072 (-0.32)	-2.19887 (-0.15)	-4.46654 (-0.30)	0.15083 (0.01)
$PrecLow4to10$	18.9782 (1.04)	19.6169 (1.07)	22.6584 (1.21)	16.7867 (0.92)
$GDD1to3$	0.71623 (0.04)	4.84982 (0.28)	11.4635 (0.62)	15.1384 (0.87)
$GDD4to10$	-13.0996 (-0.74)	-3.25816 (-0.18)	8.44741 (0.44)	-5.70046 (-0.32)
$GDDHigh1to3$	-5.54555 (-0.37)	-6.11409 (-0.41)	-7.55585 (-0.49)	-4.96098 (-0.33)
$GDDHigh4to10$	-2.56249 (-0.24)	-9.99891 (-0.92)	-11.2349 (-0.94)	-9.47055 (-0.87)
CS_{t-1}	6.36173^{***} (9.39)	8.95998^{***} (9.93)	7.41472^{***} (4.04)	6.22235^{***} (9.05)
F_{t-1}	6.33537^{***} (5.55)	6.41541^{***} (6.23)	8.22039^{***} (4.22)	9.83532^{***} (8.53)
SD_{t-1}	4.82968^{***} (4.87)	6.39144^{***} (5.77)	6.49056^{***} (4.68)	4.47398^{***} (4.20)
W_{t-1}	7.58218^{***} (12.94)	7.75465^{***} (11.44)	6.75817^{***} (4.12)	6.94108^{***} (11.58)
CS_0	1.0658 (1.63)	1.67376^{**} (2.52)	0.23707 (0.29)	1.20503^{*} (1.83)
F_0	-0.08234 (-0.17)	2.24129^{***} (4.60)	-0.80833 (-1.16)	0.67375 (1.39)
W_0	0.13674 (0.31)	2.21381^{***} (4.60)	0.02863 (0.04)	1.23718^{***} (2.81)
Means and standard deviations for random intercepts				
Mean (a_j)	-112.997 (-0.99)	-165.614 (-1.45)	-102.081 (-0.87)	-145.502 (-1.27)
Std. Dev. (σ_j)	1.19704^{***} (59.39)	0.99074^{***} (58.68)	0.39007^{***} (6.50)	0.17551^{***} (11.10)

Note: Values in parentheses are z-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A8. NL-DML-RE Parameter Estimates, Ottawa County

Variable	CS_t	SD_t	W_t
$Trend$	-0.51021^{**} (−2.50)	-0.20173 (−1.07)	-0.30943^{*} (−1.73)
$Acres$	0.12836 (1.28)	-0.08633 (−0.87)	0.26319^{***} (2.87)
p_A	1.52064^{*} (1.89)	0.23139 (0.31)	0.85808 (1.20)
p_{Sor}	-0.11505 (−0.37)	-1.01941^{***} (−3.27)	0.34499 (1.19)
p_{Soy}	0.1716 (0.80)	0.58452^{***} (2.79)	-0.26474 (−1.36)
p_W	-0.17584 (−1.01)	-0.05922 (−0.35)	-0.02609 (−0.16)
$Prec1to3$	3.2069 (0.87)	-3.31163 (−0.92)	4.31513 (1.28)
$Prec1to3^2$	-0.29278 (−0.98)	0.23284 (0.79)	-0.33237 (−1.21)
$Prec4to10$	11.1442^{***} (2.62)	14.5688^{***} (3.63)	6.86406^{*} (1.87)
$Prec4to10^2$	-0.92523^{***} (−2.74)	-1.14678^{***} (−3.61)	-0.48520^{*} (−1.67)
$PrecLow1to3$	-0.65301 (−0.28)	1.97554 (0.88)	-0.13718 (−0.06)
$PrecLow4to10$	4.63919^{*} (1.70)	5.83437^{**} (2.22)	1.96364 (0.77)
$GDD1to3$	2.21915 (0.91)	4.97747^{**} (2.11)	-0.04877 (−0.02)
$GDD4to10$	12.0252^{***} (4.43)	14.9914^{***} (5.67)	7.98328^{***} (3.32)
$GDDHigh1to3$	-4.86337^{***} (−4.14)	-4.37021^{***} (−3.97)	-2.83673^{***} (−2.69)
$GDDHigh4to10$	-4.81997^{***} (−4.15)	-5.37339^{***} (−4.83)	-3.06671^{***} (−2.99)
CS_{t-1}	5.83568^{***} (22.31)	6.14390^{***} (23.66)	4.26638^{***} (16.92)
SD_{t-1}	5.00811^{***} (24.07)	4.45516^{***} (24.81)	4.63379^{***} (26.31)
W_{t-1}	3.82568^{***} (26.63)	3.38087^{***} (26.44)	4.64185^{***} (44.69)
CS_0	0.94382^{***} (5.46)	0.90498^{***} (5.40)	0.77399^{***} (4.79)
SD_0	0.32028 (1.55)	0.55403^{***} (2.92)	-0.09571 (−0.52)
W_0	0.35766^{***} (3.63)	0.34393^{***} (3.70)	0.38994^{***} (4.53)
Means and standard deviations for random intercepts			
Mean (a_j)	-71.7648^{***} (−4.26)	-83.3522^{***} (−5.09)	-51.4653^{***} (−3.44)
Std. Dev. (σ_j)	0.00055 (0.03)	0.68633^{***} (32.40)	0.47032^{***} (27.51)

Note: Values in parentheses are z-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A9. NL-DML-RE Parameter Estimates, Rush County

Variable	CS_t	F_t	SD_t	W_t
$Trend$	-0.09428	0.5638	-0.67336	0.42995
	(-0.17)	(1.02)	(-1.12)	(0.79)
$Acres$	0.00972	0.28667^{*}	-0.35834^{*}	-0.074
	(0.06)	(1.72)	(-1.80)	(-0.45)
p_A	-2.96906	-6.24362^{*}	-1.34468	-6.81049^{**}
	(-0.91)	(-1.91)	(-0.38)	(-2.11)
p_{Sor}	1.24435^{***}	1.72317^{***}	-0.81263	1.05316^{**}
	(2.66)	(3.67)	(-1.56)	(2.27)
p_{Soy}	-0.77357^{*}	-1.55350^{***}	0.69637	-1.21272^{***}
	(-1.92)	(-3.83)	(1.57)	(-3.03)
p_W	0.50707	0.93929^{*}	0.06794	1.05933^{*}
	(0.91)	(1.69)	(0.12)	(1.94)
$Prec1to3$	1.29759	6.18539	-5.39835	2.51301
	(0.33)	(1.55)	(-1.22)	(0.63)
$Prec1to3^2$	0.04425	-0.43822	0.62589	-0.12778
	(0.12)	(-1.18)	(1.51)	(-0.35)
$Prec4to10$	-18.3516	-3.00739	-24.0678^{*}	-24.1038^{**}
	(-1.54)	(-0.25)	(-1.95)	(-2.04)
$Prec4to10^2$	1.42946	-0.02661	2.10573^{*}	2.00558^{*}
	(1.34)	(-0.02)	(1.90)	(1.90)
$PrecLow1to3$	-6.2571	-11.2476^{**}	-2.34059	-2.50712
	(-1.10)	(-1.97)	(-0.39)	(-0.45)
$PrecLow4to10$	8.48505^{*}	18.3032^{***}	10.1936^{**}	17.4143^{***}
	(1.87)	(4.02)	(2.13)	(3.88)
$GDD1to3$	-31.6542^{***}	-32.9571^{***}	-21.6278^{***}	-19.0426^{***}
	(-4.40)	(-4.56)	(-2.87)	(-2.65)
$GDD4to10$	5.0272	8.98058	15.2821^{**}	3.09786
	(0.92)	(1.63)	(2.52)	(0.57)
$GDDHigh1to3$	9.81871^{*}	14.8356^{***}	4.62341	11.2720^{**}
	(1.73)	(2.61)	(0.75)	(2.01)
$GDDHigh4to10$	-11.9341^{**}	-16.2037^{***}	-10.3748^{**}	-19.0601^{***}
	(-2.52)	(-3.40)	(-2.07)	(-4.07)
CS_{t-1}	4.68534^{***}	6.89657^{***}	5.30546^{***}	4.31597^{***}
	(16.71)	(18.78)	(14.72)	(16.20)
F_{t-1}	3.31807^{***}	2.23369^{***}	3.51938^{***}	6.94621^{***}
	(7.98)	(4.92)	(6.95)	(17.90)
SD_{t-1}	4.15105^{***}	5.11926^{***}	3.60653^{***}	4.44263^{***}
	(11.74)	(10.94)	(10.10)	(13.14)
W_{t-1}	5.54018^{***}	4.76565^{***}	3.74446^{***}	5.21268^{***}
	(25.47)	(16.02)	(11.93)	(31.20)
CS_0	1.12079^{***}	1.50508^{***}	0.19812	1.18103^{***}
	(5.55)	(7.25)	(0.85)	(6.24)
F_0	1.82908^{***}	3.57350^{***}	1.48187^{***}	1.98275^{***}
	(7.49)	(14.47)	(5.24)	(8.29)
W_0	1.13471^{***}	2.88440^{***}	0.79644^{***}	1.94966^{***}
	(7.07)	(17.15)	(4.03)	(12.63)
Means and standard deviations for random intercepts				
Mean (a_j)	104.225^{**}	38.8063	82.1243^{*}	81.4738^{*}
	(2.28)	(0.85)	(1.72)	(1.80)
Std. Dev. (σ_j)	0.91292^{***}	1.20174^{***}	0.92242^{***}	0.03376^{**}
	(52.47)	(61.08)	(21.99)	(2.41)

Note: Values in parentheses are z-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A10. NL-DML-RE Parameter Estimates, Russell County

Variable	CS_t	F_t	SD_t	W_t
$Trend$	-0.12132 (-0.19)	0.31724 (0.49)	-0.57202 (-0.88)	-0.38826 (-0.60)
$Acres$	0.04474 (0.09)	0.03614 (0.07)	-0.16934 (-0.33)	0.01997 (0.04)
p_A	0.68709 (0.22)	-1.04567 (-0.33)	1.32201 (0.41)	0.74404 (0.24)
p_{Sor}	0.88737 (1.26)	1.37421^{*} (1.95)	-1.23522^{*} (-1.73)	0.49411 (0.70)
p_{Soy}	-0.38545 (-0.72)	-1.12914^{**} (-2.10)	1.09838^{**} (2.03)	-0.27123 (-0.51)
p_W	-0.4334 (-0.71)	-0.01561 (-0.03)	-0.77886 (-1.25)	-0.16091 (-0.26)
$Prec1to3$	0.89002 (0.09)	9.18632 (0.91)	-0.24105 (-0.02)	-2.15189 (-0.22)
$Prec1to3^2$	-0.08281 (-0.09)	-0.87082 (-0.96)	0.04216 (0.05)	0.20655 (0.23)
$Prec4to10$	-7.39428 (-0.35)	-15.6741 (-0.73)	15.6443 (0.72)	-1.5843 (-0.08)
$Prec4to10^2$	0.25341 (0.14)	0.75804 (0.40)	-1.5658 (-0.83)	-0.01957 (-0.01)
$PrecLow1to3$	-5.45199 (-0.90)	-8.61306 (-1.41)	-4.05978 (-0.67)	-5.25567 (-0.87)
$PrecLow4to10$	-3.89487 (-1.42)	-4.56620^{*} (-1.67)	-0.80844 (-0.30)	-3.05025 (-1.12)
$GDD1to3$	-9.25641 (-1.12)	3.49543 (0.42)	-6.8049 (-0.81)	-9.51538 (-1.16)
$GDD4to10$	25.2031^{***} (2.67)	28.6204^{***} (2.98)	4.86143 (0.50)	26.4219^{***} (2.82)
$GDDHigh1to3$	1.31632 (0.20)	-3.10249 (-0.46)	-2.41354 (-0.36)	0.8509 (0.13)
$GDDHigh4to10$	-12.5260^{**} (-2.36)	-29.9857^{***} (-5.58)	-12.3161^{**} (-2.29)	-11.7066^{**} (-2.21)
CS_{t-1}	7.55932^{***} (11.59)	9.15188^{***} (14.02)	7.43274^{***} (11.20)	6.44302^{***} (10.03)
F_{t-1}	5.00363^{***} (4.51)	3.83832^{***} (3.50)	4.96031^{***} (4.36)	8.52605^{***} (7.81)
SD_{t-1}	5.14397^{***} (11.92)	5.19480^{***} (10.48)	4.34486^{***} (11.04)	4.87212^{***} (12.40)
W_{t-1}	6.79216^{***} (19.61)	5.22165^{***} (12.96)	4.91102^{***} (13.48)	6.26974^{***} (20.15)
CS_0	2.23283^{**} (2.51)	2.15331^{**} (2.40)	1.65209^{*} (1.85)	2.29224^{***} (2.58)
SD_0	1.85504^{*} (1.66)	2.89643^{***} (2.59)	1.61914 (1.42)	1.76243 (1.59)
W_0	0.48792^{**} (2.09)	1.42030^{***} (5.93)	0.3757 (1.54)	0.93861^{***} (4.03)
Means and standard deviations for random intercepts				
Mean (a_j)	24.8646 (0.31)	5.5885 (0.07)	-14.2399 (-0.17)	28.6275 (0.35)
Std. Dev. (σ_j)	0.57925^{***} (31.63)	0.22113^{***} (13.57)	0.71943^{***} (21.99)	1.30600^{***} (47.59)

Note: Values in parentheses are z-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A11. NL-DML-RE Parameter Estimates, Saline County

Variable	CS_t	F_t	SD_t	W_t
$Trend$	0.09299 (0.44)	−0.36549 (−0.32)	−0.07071 (−0.37)	0.12828 (0.71)
$Acres$	0.57393*** (4.13)	−0.65805 (−0.76)	0.61069*** (4.60)	0.83867*** (6.60)
p_A	−1.93446* (−1.83)	−6.17833 (−1.20)	−1.21343 (−1.24)	−1.63217* (−1.79)
p_{Sor}	−0.31179 (−0.91)	−3.43459*** (−2.85)	−0.53763 (−1.64)	0.4149 (1.32)
p_{Soy}	−0.31234 (−1.51)	0.90858 (1.05)	0.01856 (0.10)	−0.68437*** (−3.74)
p_W	0.75166*** (3.10)	2.59325** (2.56)	0.55511** (2.46)	0.61261*** (2.86)
$Prec1to3$	4.58158* (1.73)	8.97614 (0.79)	−0.97893 (−0.40)	1.28765 (0.56)
$Prec1to3^2$	−0.34573* (−1.69)	−0.89671 (−1.09)	0.07969 (0.42)	−0.08995 (−0.50)
$Prec4to10$	16.2188*** (3.40)	63.1567** (2.26)	14.7003*** (3.47)	13.1478*** (3.26)
$Prec4to10^2$	−1.34351*** (−3.69)	−5.11679** (−2.33)	−1.16394*** (−3.61)	−1.09254*** (−3.58)
$PrecLow1to3$	−2.97745 (−1.63)	−12.4439 (−1.51)	−2.43315 (−1.39)	1.38391 (0.87)
$PrecLow4to10$	−1.76726 (−0.92)	1.86395 (0.19)	−2.25247 (−1.21)	−0.81411 (−0.48)
$GDD1to3$	7.44180** (2.11)	7.181 (0.50)	−0.66044 (−0.21)	−1.96057 (−0.63)
$GDD4to10$	12.9705*** (3.66)	4.29609 (0.31)	18.4658*** (5.40)	7.77144** (2.38)
$GDDHigh1to3$	−1.39954 (−0.71)	−2.66405 (−0.27)	0.29803 (0.17)	1.60556 (0.96)
$GDDHigh4to10$	−10.7474*** (−5.11)	−11.9115 (−1.46)	−4.63083** (−2.31)	−5.38777*** (−2.77)
CS_{t-1}	6.31044*** (20.34)	5.82347*** (6.56)	5.99892*** (19.95)	3.89574*** (13.36)
SD_{t-1}	5.40731*** (23.20)	4.35303*** (5.39)	4.28659*** (23.26)	4.19688*** (23.86)
W_{t-1}	3.87746*** (19.90)	2.85394*** (3.39)	3.16929*** (24.14)	4.08745*** (39.19)
CS_0	0.75415*** (3.69)	−1.70942 (−1.17)	0.60202*** (3.00)	0.41634** (2.14)
SD_0	0.33574* (1.75)	0.07691 (0.10)	0.37504** (2.00)	−0.0759 (−0.43)
W_0	0.65150*** (6.86)	0.00867 (0.02)	0.45274*** (5.08)	0.92060*** (11.57)
Means and standard deviations for random intercepts				
Mean (a_j)	−89.9609*** (−5.52)	−214.978*** (−2.69)	−71.6026*** (−4.66)	−52.3242*** (−3.65)
Std. Dev. (σ_j)	0.27639*** (12.30)	1.42037*** (8.59)	0.61492*** (29.17)	0.64465*** (34.77)

Note: Values in parentheses are z-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A12. NL-DML-RE Parameter Estimates, Trego County

Variable	CS_t	F_t	SD_t	W_t
$Trend$	-0.79686	-1.17719	-0.9241	-0.37786
	(-0.39)	(-0.57)	(-0.43)	(-0.18)
$Acres$	3.90516^{***}	4.06853^{***}	2.63640^{*}	3.84980^{**}
	(2.60)	(2.71)	(1.74)	(2.56)
p_A	-0.74363	0.66436	-5.28404	-2.45658
	(-0.07)	(0.06)	(-0.46)	(-0.22)
p_{Sor}	-2.23099	-1.6879	-6.16284^{***}	-2.72775
	(-1.06)	(-0.80)	(-2.60)	(-1.29)
p_{Soy}	1.20254	0.84407	3.62832^{**}	1.19521
	(0.97)	(0.68)	(2.53)	(0.96)
p_W	-0.28553	-0.23812	0.30934	0.14786
	(-0.16)	(-0.13)	(0.15)	(0.08)
$Prec1to3$	30.8611^{*}	28.4407^{*}	14.9701	29.8634^{*}
	(1.78)	(1.65)	(0.83)	(1.73)
$Prec1to3^2$	-3.26209^{*}	-3.0153	-1.49224	-3.17347^{*}
	(-1.74)	(-1.62)	(-0.76)	(-1.70)
$Prec4to10$	30.8442^{*}	30.6393^{*}	21.5009	34.4630^{**}
	(1.84)	(1.83)	(1.21)	(2.06)
$Prec4to10^2$	-3.41419^{**}	-3.28518^{*}	-2.24101	-3.49488^{**}
	(-1.97)	(-1.90)	(-1.23)	(-2.02)
$PrecLow1to3$	6.03004	6.04292	22.1255	11.8977
	(0.46)	(0.46)	(1.62)	(0.91)
$PrecLow4to10$	-13.9018	-12.2869	-24.7065	-12.3866
	(-0.81)	(-0.72)	(-1.41)	(-0.72)
$GDD1to3$	-23.8529	-12.0579	-31.6528	-6.74393
	(-1.13)	(-0.57)	(-1.36)	(-0.32)
$GDD4to10$	27.6376	77.686	10.7181	51.4882
	(0.46)	(1.30)	(0.17)	(0.86)
$GDDHigh1to3$	8.04941	1.25106	7.68757	2.69603
	(0.35)	(0.05)	(0.33)	(0.12)
$GDDHigh4to10$	-0.8009	-20.1133	1.40581	-16.6098
	(-0.04)	(-0.93)	(0.06)	(-0.77)
CS_{t-1}	7.93146^{***}	10.3323^{***}	7.00070^{***}	7.56889^{***}
	(9.22)	(9.93)	(5.28)	(7.08)
F_{t-1}	6.24079^{***}	6.38619^{***}	5.24380^{***}	9.84086^{***}
	(7.21)	(5.88)	(3.88)	(9.51)
SD_{t-1}	7.19339^{***}	8.68895^{***}	5.85761^{***}	6.24335^{***}
	(3.78)	(4.59)	(3.81)	(3.39)
W_{t-1}	9.12747^{***}	8.52477^{***}	6.38305^{***}	8.13886^{***}
	(12.38)	(9.15)	(5.42)	(10.30)
CS_0	2.39860^{***}	2.58039^{***}	2.20704^{**}	2.14348^{***}
	(3.43)	(3.64)	(2.48)	(2.97)
SD_0	2.48354^{***}	3.63568^{***}	3.03570^{***}	2.22613^{***}
	(3.78)	(5.39)	(3.52)	(3.28)
W_0	1.83489^{***}	2.94215^{***}	1.75247^{**}	2.20325^{***}
	(2.94)	(4.59)	(2.10)	(3.43)
Means and standard deviations for random intercepts				
Mean (a_j)	-141.943	-240.547^{**}	-58.427	-231.367^{**}
	(-1.34)	(-2.26)	(-0.49)	(-2.18)
Std. Dev. (σ_j)	0.83550^{***}	0.82347^{***}	1.02800^{***}	0.52389^{***}
	(48.11)	(47.35)	(15.55)	(29.65)

Note: Values in parentheses are z-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A13. Average Partial Effects, Weather Variables

			Lag Structure							
			Short = 1 to 3, Long = 4 to 10				Short = 1 to 5, Long = 6 to 20			
			Models							
Land Use	**County**	**Variable**	**LIN-DML-RE**	**NL-DML-RE**	**LIN-OLS-FE**	**NL-OLS-FE**	**LIN-DML-RE**	**NL-DML-RE**	**LIN-OLS-FE**	**NL-OLS-FE**
Alfalfa	Barton	*Prec* — Short	−0.002	−0.009*	−0.031***	−0.046***	0.006	0.011	−0.038***	−0.007
			(−0.58)	(−1.68)	(−6.16)	(−6.32)	(0.70)	(1.28)	(−4.57)	(−0.75)
		Prec — Long	0.039***	0.022***	−0.065***	−0.087***	0.063***	0.069***	−0.063	−0.029
			(5.53)	(2.59)	(−6.45)	(−6.61)	(5.02)	(4.91)	(−1.53)	(−0.67)
		PrecLow — Short	0.002	0.006	−0.204***	−0.178***	−0.031	−0.013	0.126*	0.15**
			(0.05)	(0.16)	(−3.68)	(−3.18)	(−0.67)	(−0.28)	(1.65)	(1.97)
		PrecLong — Long	0.111***	0.098**	0.125	0.18**	0.151***	0.138***	1.252***	0.905***
			(2.59)	(2.23)	(1.63)	(2.23)	(3.30)	(2.93)	(4.68)	(3.31)
		GDD — Short	0.127	0.116	−0.103	0.027	0.514***	0.519***	0.494***	0.069
			(1.60)	(1.38)	(−1.18)	(0.28)	(4.97)	(4.74)	(2.97)	(0.38)
		GDD — Long	−0.06	0.065	−2.061***	−1.897***	−0.485***	−0.526***	−2.766***	−3.319***
			(−1.35)	(1.08)	(−11.39)	(−9.94)	(−5.33)	(−5.21)	(−7.83)	(−9.13)
		GDDHigh — Short	−0.012	−0.026	−0.028	−0.113	0.109**	0.143***	0.178***	0.291***
			(−0.23)	(−0.44)	(−0.46)	(−1.64)	(2.13)	(2.74)	(2.90)	(4.46)
		GDDHigh — Long	0.143***	0.021	0.1	−0.04	0.041	0.065	0.093	0.159
			(2.98)	(0.33)	(1.52)	(−0.46)	(0.92)	(1.40)	(0.80)	(1.36)
	Ellis	*Prec* — Short	0.001	0.002	0.006**	0.007**	0	0.001	0.013***	0.011**
			(0.39)	(0.83)	(2.10)	(2.23)	(0.05)	(0.39)	(2.65)	(2.26)
		Prec — Long	0.005**	0.006**	0.016***	0.017***	0.006	0.006	0.036**	0.023
			(2.00)	(2.00)	(3.51)	(3.67)	(1.28)	(0.79)	(2.24)	(1.32)
		PrecLow — Short	0.03*	0.034**	0.045***	0.048***	0.006	0.01	0.008	0.008
			(1.78)	(2.53)	(2.82)	(3.00)	(0.35)	(0.60)	(0.40)	(0.39)
		PrecLong — Long	−0.025*	−0.027*	−0.009	−0.015	0.01	0.008	0.025	0.017
			(−1.72)	(−1.90)	(−0.38)	(−0.63)	(0.55)	(0.40)	(0.34)	(0.23)
		GDD — Short	−0.001	−0.01	−0.067**	−0.064**	0.094**	0.087**	0.026	0.023
			(−0.05)	(−0.60)	(−2.50)	(−2.32)	(2.50)	(2.27)	(0.71)	(0.64)
		GDD — Long	−0.043	−0.028	−0.042	−0.024	−0.058	−0.052	−0.088	−0.033
			(−1.63)	(−1.11)	(−0.66)	(−0.33)	(−1.30)	(−1.01)	(−1.21)	(−0.43)
		GDDHigh — Short	−0.021*	−0.02	0.001	−0.005	0.003	0.006	−0.015	0.006
			(−1.90)	(−1.53)	(0.09)	(−0.28)	(0.22)	(0.37)	(−0.54)	(0.21)
		GDDHigh — Long	0.032**	0.032**	0.08***	0.076***	−0.01	−0.01	−0.061	−0.035
			(2.46)	(2.26)	(3.90)	(3.50)	(−0.44)	(−0.35)	(−1.30)	(−0.71)
	Ellsworth	*Prec* — Short	0.007***	0.007*	−0.013**	−0.021***	0.006	0.009	−0.026***	−0.024**
			(2.58)	(1.78)	(−2.52)	(−3.22)	(0.73)	(1.06)	(−2.76)	(−2.29)
		Prec — Long	0.033***	0.03***	−0.033***	−0.042***	0.043***	0.053***	−0.081*	−0.074
			(6.37)	(5.44)	(−2.84)	(−3.51)	(4.49)	(4.92)	(−1.87)	(−1.61)
		PrecLow — Short	−0.053*	−0.054*	−0.001	0.006	−0.056*	−0.039	−0.035	−0.042
			(−1.86)	(−1.87)	(−0.02)	(0.12)	(−1.69)	(−1.05)	(−0.71)	(−0.79)
		PrecLong — Long	0.121***	0.114***	0.25***	0.213***	0.147***	0.155***	0	0.045
			(3.37)	(3.13)	(3.78)	(3.15)	(4.63)	(4.62)	(0.00)	(0.26)
		GDD — Short	−0.168***	−0.171***	0.152	0.266**	0.029	−0.017	−0.102	−0.091
			(−3.14)	(−3.05)	(1.63)	(2.51)	(0.24)	(−0.13)	(−0.70)	(−0.59)
		GDD — Long	−0.105**	−0.067	−1.296***	−0.854***	−0.14*	−0.134*	−2.073***	−2.026***
			(−2.02)	(−1.12)	(−6.16)	(−3.35)	(−1.85)	(−1.71)	(−7.06)	(−6.78)
		GDDHigh — Short	0.007	0.005	−0.301***	−0.343***	0.052	0.091*	−0.256***	−0.255***
			(0.17)	(0.12)	(−5.24)	(−5.34)	(1.13)	(1.83)	(−4.44)	(−3.91)
		GDDHigh — Long	0.187***	0.152***	−0.121*	−0.258***	0.063	0.124***	−0.539***	−0.535***
			(4.28)	(3.40)	(−1.69)	(−3.02)	(1.58)	(2.61)	(−5.67)	(−5.12)

Note: Values in parentheses are z-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A13 continued

			Lag Structure							
			Short = 1 to 3, Long = 4 to 10				Short = 1 to 5, Long = 6 to 20			
			Models							
Land Use	**County**	**Variable**	**LIN-DML-RE**	**NL-DML-RE**	**LIN-OLS-FE**	**NL-OLS-FE**	**LIN-DML-RE**	**NL-DML-RE**	**LIN-OLS-FE**	**NL-OLS-FE**
Alfalfa	Gove	*Prec* — Short	−0.004	−0.004	−0.003	−0.001	−0.004	−0.006	0.003	0.003
			(−1.00)	(−0.98)	(−1.02)	(−0.18)	(−0.70)	(−0.87)	(0.56)	(0.59)
		Prec — Long	0.002	0	−0.001	0.013**	0.003	0	0.019	0.025
			(0.70)	(0.10)	(−0.24)	(2.05)	(0.74)	(−0.03)	(1.36)	(1.53)
		PrecLow — Short	0.001	−0.009	−0.022	−0.03*	−0.055**	−0.053*	−0.071***	−0.068***
			(0.07)	(−0.50)	(−1.34)	(−1.74)	(−1.98)	(−1.95)	(−2.99)	(−2.64)
		PrecLong — Long	−0.001	0.005	−0.039	−0.039*	0.069*	0.063*	0.027	0.03
			(−0.03)	(0.22)	(−1.64)	(−1.65)	(1.85)	(1.71)	(0.49)	(0.53)
		GDD — Short	0.006	0.014	−0.028	−0.081***	0.127***	0.128***	0.155***	0.149***
			(0.19)	(0.38)	(−1.11)	(−2.84)	(2.85)	(2.72)	(3.73)	(3.55)
		GDD — Long	−0.022	−0.004	−0.063	−0.103	−0.093	0.001	0.028	0.003
			(−0.51)	(−0.09)	(−0.94)	(−1.22)	(−1.38)	(0.01)	(0.29)	(0.03)
		GDDHigh — Short	0.006	0.005	0.019	0.026	0.019	−0.011	0.102***	0.101***
			(0.29)	(0.22)	(1.02)	(1.36)	(1.07)	(−0.27)	(3.76)	(3.63)
		GDDHigh — Long	−0.011	−0.013	0.037	0.13***	−0.053	−0.086	0.146***	0.144***
			(−0.39)	(−0.38)	(1.37)	(3.68)	(−1.30)	(−1.49)	(3.04)	(2.77)
	Lincoln	*Prec* — Short	−0.005	−0.016***	0.013*	0.013	−0.011	−0.009	0.013	0.02*
			(−1.05)	(−3.01)	(1.73)	(1.58)	(−1.63)	(−1.13)	(1.32)	(1.75)
		Prec — Long	−0.019***	−0.005	−0.005	−0.008	−0.027***	−0.055***	−0.086**	−0.08**
			(−4.47)	(−1.05)	(−0.48)	(−0.67)	(−5.03)	(−8.92)	(−2.26)	(−2.07)
		PrecLow — Short	0.194***	0.219***	−0.033	−0.04	0.114**	0.117**	−0.214**	−0.176*
			(4.61)	(4.29)	(−0.52)	(−0.62)	(2.42)	(2.00)	(−2.15)	(−1.68)
		PrecLong — Long	−0.292***	−0.308***	−0.346***	−0.375***	−0.327***	−0.403***	−0.581**	−0.639**
			(−6.60)	(−5.89)	(−3.03)	(−3.03)	(−5.63)	(−6.08)	(−2.56)	(−2.48)
		GDD — Short	0.094*	0.095	−0.25***	−0.237***	0.123	0.158*	−0.485***	−0.502***
			(1.91)	(1.64)	(−4.08)	(−3.67)	(1.61)	(1.80)	(−4.89)	(−4.99)
		GDD — Long	0.297***	0.733***	−0.36*	−0.301	0.368***	0.9***	−1.239***	−1.586***
			(4.67)	(11.30)	(−1.73)	(−1.17)	(4.21)	(9.34)	(−3.66)	(−3.82)
		GDDHigh — Short	0.061***	0.102***	0.119***	0.113***	0.031	0.043**	0.2***	0.208***
			(3.52)	(5.16)	(3.95)	(3.56)	(1.63)	(2.09)	(5.54)	(5.68)
		GDDHigh — Long	0.055***	0.08***	0.182***	0.166***	0.133***	0.199***	0.065	0.05
			(3.29)	(4.86)	(3.68)	(3.01)	(5.37)	(7.91)	(0.75)	(0.57)
	Ness	*Prec* — Short	−0.001	−0.003	0	−0.003	−0.002	−0.003	−0.003	−0.004
			(−0.28)	(−0.45)	(−0.21)	(−1.15)	(−0.31)	(−0.42)	(−1.22)	(−1.38)
		Prec — Long	−0.006*	−0.008	0.002	0.002	−0.009	−0.009	−0.014*	−0.016**
			(−1.84)	(−1.54)	(0.55)	(0.59)	(−1.03)	(−0.90)	(−1.70)	(−1.97)
		PrecLow — Short	0.006	0.004	−0.006	0.002	0.018	0.017	0	0.002
			(0.22)	(0.15)	(−0.39)	(0.09)	(0.40)	(0.39)	(0.01)	(0.10)
		PrecLong — Long	−0.035	−0.035	−0.041	−0.035	−0.055	−0.057	0.03	0.03
			(−1.13)	(−1.01)	(−1.43)	(−1.17)	(−0.90)	(−0.92)	(0.58)	(0.58)
		GDD — Short	−0.009	−0.014	−0.037	−0.016	−0.016	−0.011	−0.019	−0.021
			(−0.32)	(−0.43)	(−1.43)	(−0.58)	(−0.21)	(−0.15)	(−0.47)	(−0.51)
		GDD — Long	−0.001	0.013	0.015	0.079	−0.017	−0.02	−0.116*	−0.114*
			(−0.03)	(0.39)	(0.33)	(1.54)	(−0.28)	(−0.32)	(−1.71)	(−1.68)
		GDDHigh — Short	0.01	0.011	0.011	0.005	0.003	0.004	0.012	0.012
			(0.38)	(0.37)	(0.91)	(0.38)	(0.19)	(0.20)	(0.85)	(0.85)
		GDDHigh — Long	0.017	0.014	0.054***	0.043**	0.022	0.022	0.018	0.013
			(0.91)	(0.71)	(2.81)	(2.15)	(1.22)	(1.27)	(0.71)	(0.51)

Note: Values in parentheses are z-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A13 continued

			Lag Structure							
			Short = 1 to 3, Long = 4 to 10				Short = 1 to 5, Long = 6 to 20			
			Models							
Land Use	**County**	**Variable**	**LIN-DML-RE**	**NL-DML-RE**	**LIN-OLS-FE**	**NL-OLS-FE**	**LIN-DML-RE**	**NL-DML-RE**	**LIN-OLS-FE**	**NL-OLS-FE**
Alfalfa	Ottawa	*Prec* — Short	−0.004	−0.002	0.006	0.008	−0.022*	−0.014	−0.013	−0.038*
			(−0.38)	(−0.21)	(0.51)	(0.59)	(−1.76)	(−0.99)	(−0.63)	(−1.71)
		Prec — Long	−0.01	−0.023**	−0.014	−0.013	0.02**	0.005	−0.023	−0.071
			(−1.26)	(−2.52)	(−0.88)	(−0.66)	(2.32)	(0.49)	(−0.48)	(−1.30)
		PrecLow — Short	−0.022	−0.006	0.205**	0.206**	−0.173***	−0.128**	0.148	0.232*
			(−0.35)	(−0.09)	(2.39)	(2.38)	(−2.85)	(−2.00)	(1.22)	(1.86)
		PrecLong — Long	−0.085	−0.092	0.244	0.243	0.044	−0.051	0.189	0.414*
			(−1.15)	(−1.22)	(1.27)	(1.25)	(0.57)	(−0.60)	(0.97)	(1.93)
		GDD — Short	−0.028	−0.037	−0.283***	−0.307**	0.143	0.095	−0.149	−0.148
			(−0.43)	(−0.56)	(−2.84)	(−2.39)	(1.58)	(1.04)	(−1.07)	(−1.02)
		GDD — Long	−0.342***	−0.297***	−0.627**	−0.737	−0.608***	−0.541***	−0.864***	−0.607*
			(−4.93)	(−4.16)	(−2.12)	(−1.57)	(−5.75)	(−5.06)	(−2.64)	(−1.78)
		GDDHigh — Short	0.079***	0.102***	0.263***	0.273***	0.068**	0.064*	0.31***	0.283***
			(2.93)	(3.29)	(5.71)	(4.77)	(2.34)	(1.95)	(4.57)	(4.10)
		GDDHigh — Long	0.141***	0.113***	0.309***	0.335***	0.22***	0.226***	0.688***	0.775***
			(5.06)	(3.69)	(4.69)	(3.02)	(6.22)	(5.86)	(4.34)	(4.75)
	Rush	*Prec* — Short	−0.007**	−0.009**	−0.021***	−0.02***	0.028	0.003	−0.015**	−0.007
			(−2.16)	(−2.45)	(−3.80)	(−3.56)	(1.08)	(0.67)	(−2.24)	(−0.93)
		Prec — Long	0.014***	0.014***	−0.01	−0.015	−0.027	0.015*	−0.031	−0.038*
			(4.51)	(4.47)	(−1.01)	(−1.35)	(−1.33)	(1.87)	(−1.58)	(−1.88)
		PrecLow — Short	0.024	0.034	−0.028	−0.048	0.474***	0.092*	0.03	−0.019
			(0.64)	(0.89)	(−0.81)	(−1.32)	(3.86)	(1.80)	(0.74)	(−0.45)
		PrecLong — Long	−0.089***	−0.097***	0.071	0.085*	−0.213	−0.249***	−0.146	−0.175
			(−3.00)	(−3.22)	(1.45)	(1.69)	(−1.37)	(−5.34)	(−1.11)	(−1.32)
		GDD — Short	0.139***	0.169***	0.098*	0.074	0.465**	0.284***	0.455***	0.325***
			(4.19)	(3.51)	(1.69)	(1.27)	(2.37)	(3.16)	(4.24)	(2.83)
		GDD — Long	−0.026	−0.039	−0.399***	−0.533***	0.476**	−0.076	−0.832***	−0.951***
			(−0.96)	(−1.07)	(−5.74)	(−7.08)	(2.18)	(−0.75)	(−5.71)	(−6.34)
		GDDHigh — Short	−0.064*	−0.073*	−0.021	−0.062*	−0.019	−0.006	−0.032	0.005
			(−1.73)	(−1.94)	(−0.59)	(−1.68)	(−0.34)	(−0.18)	(−0.63)	(0.10)
		GDDHigh — Long	0.08***	0.106***	0.105***	0.071*	−0.27***	0.053*	−0.086	−0.088
			(2.91)	(3.40)	(3.07)	(1.83)	(−3.96)	(1.83)	(−1.19)	(−1.20)
	Russell	*Prec* — Short	0	0	−0.012***	−0.011***	−0.142***	0	−0.004	−0.002
			(0.00)	(−0.05)	(−3.18)	(−2.89)	(−7.03)	(−0.03)	(−0.70)	(−0.33)
		Prec — Long	0.016***	0.015***	−0.024***	−0.023***	−0.198***	0.017	−0.007	0.004
			(3.52)	(2.83)	(−3.01)	(−2.90)	(−7.98)	(1.51)	(−0.28)	(0.15)
		PrecLow — Short	0.031	0.027	−0.01	−0.017	−1.148***	0.014	−0.07	−0.064
			(1.22)	(0.91)	(−0.31)	(−0.55)	(−8.91)	(0.37)	(−1.18)	(−1.07)
		PrecLong — Long	0.017	0.015	−0.012	−0.013	0.41***	0.054*	−0.094	−0.071
			(1.26)	(1.11)	(−1.17)	(−1.22)	(3.80)	(1.89)	(−0.51)	(−0.38)
		GDD — Short	0.042	0.039	0.118**	0.105**	−3.241***	0.307***	0.205**	0.196**
			(1.31)	(0.95)	(2.33)	(2.03)	(−12.87)	(3.82)	(2.15)	(2.03)
		GDD — Long	−0.112**	−0.114**	−0.406***	−0.475***	2.822***	−0.183***	−0.497**	−0.587**
			(−2.32)	(−2.40)	(−4.20)	(−4.41)	(11.40)	(−2.74)	(−2.25)	(−2.52)
		GDDHigh — Short	−0.002	0	−0.076**	−0.065	−0.136	0.034	−0.008	−0.007
			(−0.06)	(−0.01)	(−1.98)	(−1.64)	(−1.28)	(1.18)	(−0.13)	(−0.11)
		GDDHigh — Long	0.068***	0.068***	−0.038	−0.019	0.583***	−0.002	−0.137*	−0.127*
			(2.58)	(2.59)	(−1.03)	(−0.48)	(6.39)	(−0.05)	(−1.78)	(−1.65)

Note: Values in parentheses are z-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A13 continued

Land Use	County	Variable	Short = 1 to 3, Long = 4 to 10: LIN-DML-RE	Short = 1 to 3, Long = 4 to 10: NL-DML-RE	Short = 1 to 3, Long = 4 to 10: LIN-OLS-FE	Short = 1 to 3, Long = 4 to 10: NL-OLS-FE	Short = 1 to 5, Long = 6 to 20: LIN-DML-RE	Short = 1 to 5, Long = 6 to 20: NL-DML-RE	Short = 1 to 5, Long = 6 to 20: LIN-OLS-FE	Short = 1 to 5, Long = 6 to 20: NL-OLS-FE
Alfalfa	Saline	*Prec* — Short	−0.004	−0.004	0.003	0.01	−0.02	−0.024**	−0.035**	−0.046**
			(−0.80)	(−0.67)	(0.29)	(0.85)	(−1.38)	(−2.52)	(−1.98)	(−2.44)
		Prec — Long	0.033***	0.022***	0.003	−0.004	−0.432***	0.045***	0.084	0.03
			(5.42)	(3.17)	(0.15)	(−0.19)	(−17.04)	(3.16)	(1.62)	(0.52)
		PrecLow — Short	−0.052	−0.011	0.172*	0.114	0	−0.02	0.665***	0.632***
			(−1.27)	(−0.26)	(1.80)	(1.17)	(0.00)	(−0.36)	(4.62)	(4.39)
		PrecLong — Long	0.053	0.03	0.358***	0.19	−0.762***	0.085	1.255***	1.105***
			(1.18)	(0.66)	(3.32)	(1.49)	(−12.58)	(1.19)	(3.87)	(3.34)
		GDD — Short	−0.035	0.028	−0.278***	−0.428***	−1.435***	0.46***	0.265*	0.104
			(−0.43)	(0.34)	(−2.65)	(−2.98)	(−6.26)	(3.75)	(1.85)	(0.57)
		GDD — Long	−0.38***	−0.267***	−1.89***	−2.244***	1.434***	−0.613***	−3.21***	−3.336***
			(−5.12)	(−3.09)	(−6.46)	(−4.73)	(7.41)	(−4.53)	(−7.99)	(−8.11)
		GDDHigh — Short	0.006	−0.031	0.098**	0.175**	−0.165	−0.04	−0.358***	−0.33***
			(0.14)	(−0.70)	(2.05)	(2.56)	(−1.56)	(−0.87)	(−3.86)	(−3.44)
		GDDHigh — Long	0.225***	0.152***	0.376***	0.48***	−0.091	0.106*	−0.106	−0.143
			(4.53)	(2.96)	(5.22)	(4.30)	(−0.60)	(1.86)	(−0.62)	(−0.84)
	Trego	*Prec* — Short	−0.001	−0.002	0.001	−0.001	0.001	0.001	0.012***	0.011**
			(−0.34)	(−0.99)	(0.43)	(−0.52)	(0.36)	(0.35)	(2.79)	(2.45)
		Prec — Long	0.002	0.002	0.013***	0.009**	0.003	0.003	0.049***	0.045***
			(0.64)	(0.57)	(3.23)	(2.02)	(0.48)	(0.51)	(3.48)	(3.02)
		PrecLow — Short	−0.002	−0.014	−0.019	−0.021	−0.013	−0.005	−0.005	0.007
			(−0.12)	(−0.68)	(−1.34)	(−1.44)	(−0.65)	(−0.23)	(−0.22)	(0.28)
		PrecLong — Long	0.007	0.021	0.032	0.038*	0.034	0.027	−0.114**	−0.084
			(0.31)	(0.76)	(1.63)	(1.85)	(1.26)	(0.92)	(−2.13)	(−1.53)
		GDD — Short	0.003	0.022	−0.025	0.015	0.168***	0.187***	0.15***	0.187***
			(0.11)	(0.69)	(−1.17)	(0.56)	(3.86)	(2.94)	(5.06)	(5.72)
		GDD — Long	−0.178***	−0.074	−0.001	0.121	−0.097	−0.088	0.061	0.132**
			(−3.07)	(−0.84)	(−0.01)	(1.36)	(−1.38)	(−1.12)	(1.00)	(1.98)
		GDDHigh — Short	0.013	−0.007	0.03*	0.001	0.009	0.004	0.003	−0.024
			(0.36)	(−0.18)	(1.81)	(0.04)	(0.39)	(0.16)	(0.15)	(−0.98)
		GDDHigh — Long	0.046**	0.018	0.055***	0.007	−0.043	−0.045	−0.04	−0.076
			(2.08)	(0.56)	(2.96)	(0.29)	(−1.16)	(−1.04)	(−0.86)	(−1.57)
Corn, Sorghum	Barton	*Prec* — Short	−0.009	−0.037***	0.032***	0.02	−0.142***	−0.177***	0.013	−0.019
			(−1.26)	(−3.92)	(2.80)	(1.22)	(−9.74)	(−11.57)	(0.71)	(−0.90)
		Prec — Long	−0.092***	−0.131***	0.018	0.013	0.134***	0.008	0.282***	0.15
			(−6.11)	(−6.48)	(0.81)	(0.44)	(4.83)	(0.26)	(3.09)	(1.57)
		PrecLow — Short	−0.251***	−0.277***	−0.217*	−0.206*	−0.285***	−0.467***	−0.104	−0.149
			(−3.09)	(−3.39)	(−1.77)	(−1.66)	(−2.72)	(−4.38)	(−0.62)	(−0.88)
		PrecLong — Long	0.298***	0.378***	−0.028	0.042	0.622***	0.615***	1.017*	1.361**
			(3.28)	(4.02)	(−0.17)	(0.24)	(6.39)	(6.04)	(1.72)	(2.26)
		GDD — Short	−0.883***	−0.758***	−1.153***	−1.041***	−0.117	−0.28	−2.655***	−2.397***
			(−6.63)	(−5.55)	(−6.00)	(−4.77)	(−0.56)	(−1.34)	(−7.23)	(−5.99)
		GDD — Long	0.348***	0.465***	0.38	0.432	−0.252	0.339	−2.375***	−1.759**
			(3.46)	(3.77)	(0.95)	(1.03)	(−1.13)	(1.43)	(−3.05)	(−2.19)
		GDDHigh — Short	−0.099	−0.225**	−0.182	−0.248	−0.599***	−0.811***	−0.301**	−0.316**
			(−1.13)	(−2.42)	(−1.32)	(−1.63)	(−6.30)	(−8.21)	(−2.22)	(−2.20)
		GDDHigh — Long	0.571***	0.379***	0.71***	0.686***	1.297***	1.026***	0.496*	0.45*
			(5.92)	(3.30)	(4.87)	(3.62)	(15.22)	(11.63)	(1.93)	(1.74)

Note: Values in parentheses are z-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A13 continued

			Lag Structure							
			Short = 1 to 3, Long = 4 to 10				Short = 1 to 5, Long = 6 to 20			
			Models							
Land Use	**County**	**Variable**	**LIN-DML-RE**	**NL-DML-RE**	**LIN-OLS-FE**	**NL-OLS-FE**	**LIN-DML-RE**	**NL-DML-RE**	**LIN-OLS-FE**	**NL-OLS-FE**
Corn, Sorghum	Ellis	*Prec* — Short	0.129***	0.056***	0.164***	0.147***	−0.148***	−0.126***	−0.179***	−0.216***
			(9.04)	(3.53)	(6.59)	(5.57)	(−8.25)	(−5.44)	(−4.22)	(−4.96)
		Prec — Long	−0.112***	−0.168***	−0.076*	−0.119***	0.304***	0.179***	−0.228	−0.487***
			(−6.81)	(−10.12)	(−1.87)	(−2.92)	(9.67)	(4.33)	(−1.61)	(−3.21)
		PrecLow — Short	0.937***	0.697***	0.852***	0.673***	0.028	0.027	−0.264	−0.293*
			(8.43)	(6.07)	(5.98)	(4.69)	(0.24)	(0.23)	(−1.52)	(−1.67)
		PrecLong — Long	−0.991***	−0.821***	−1.224***	−0.89***	−0.411***	−0.365***	−1.954***	−2.008***
			(−9.48)	(−7.59)	(−5.71)	(−4.09)	(−3.67)	(−3.01)	(−3.03)	(−3.09)
		GDD — Short	−0.962***	−0.597***	−0.975***	−1.336***	−2.085***	−2.411***	−2.846***	−2.87***
			(−8.69)	(−5.06)	(−4.09)	(−5.42)	(−7.87)	(−6.50)	(−8.84)	(−8.90)
		GDD — Long	−0.602***	−0.825***	−1.814***	−3.79***	−1.478***	−1.018***	−6.994***	−6.095***
			(−4.33)	(−5.61)	(−3.17)	(−5.86)	(−7.14)	(−4.20)	(−10.84)	(−8.93)
		GDDHigh — Short	−0.347***	−0.249***	−0.454***	0.012	−1.068***	−0.913***	−0.39	−0.03
			(−4.69)	(−3.31)	(−3.23)	(0.08)	(−13.58)	(−7.09)	(−1.62)	(−0.12)
		GDDHigh — Long	0.603***	0.456***	0.613***	1.032***	2.147***	2.003***	2.435***	2.863***
			(6.85)	(5.06)	(3.35)	(5.31)	(18.41)	(8.08)	(5.79)	(6.59)
	Ellsworth	*Prec* — Short	0.013	0.024*	0.047***	0.052**	0.003	0.006	0.069**	0.086**
			(1.15)	(1.85)	(2.62)	(2.35)	(0.13)	(0.24)	(2.15)	(2.38)
		Prec — Long	−0.115***	−0.172***	−0.13***	−0.151***	0.033	0.039	0.262*	0.303*
			(−5.57)	(−6.78)	(−3.25)	(−3.67)	(1.04)	(1.11)	(1.75)	(1.91)
		PrecLow — Short	0.099	0.087	−0.117	−0.03	−0.031	−0.031	−0.419**	−0.307*
			(1.05)	(0.91)	(−0.72)	(−0.18)	(−0.28)	(−0.26)	(−2.46)	(−1.70)
		PrecLong — Long	−0.051	−0.135	0.01	−0.036	0.235*	0.241*	−0.03	0.011
			(−0.45)	(−1.18)	(0.05)	(−0.16)	(1.70)	(1.69)	(−0.05)	(0.02)
		GDD — Short	−0.28	−0.397*	−0.587*	−0.567	−1.76***	−1.8***	−1.776***	−2.067***
			(−1.28)	(−1.76)	(−1.82)	(−1.56)	(−4.39)	(−4.02)	(−3.52)	(−3.88)
		GDD — Long	1.203***	1.652***	−2.742***	−1.735**	1.735***	1.742***	−0.582	−0.621
			(6.31)	(7.23)	(−3.78)	(−1.98)	(5.99)	(5.93)	(−0.58)	(−0.60)
		GDDHigh — Short	0.132	0.274	−0.239	−0.125	−0.182	−0.158	−0.364*	−0.215
			(0.80)	(1.51)	(−1.21)	(−0.56)	(−1.29)	(−0.94)	(−1.84)	(−0.96)
		GDDHigh — Long	−0.206	−0.592***	−0.777***	−1.027***	0.701***	0.726***	−0.172	0.02
			(−1.22)	(−3.01)	(−3.14)	(−3.49)	(4.51)	(4.14)	(−0.53)	(0.06)
	Gove	*Prec* — Short	−0.04**	−0.047***	−0.117***	−0.112***	−0.128***	−0.128***	−0.001	−0.096*
			(−2.24)	(−2.58)	(−4.18)	(−3.89)	(−4.85)	(−4.77)	(−0.02)	(−1.85)
		Prec — Long	0.004	−0.027	−0.364***	−0.301***	0.179***	0.175***	−0.003	−0.364**
			(0.23)	(−1.20)	(−8.50)	(−5.02)	(8.01)	(7.34)	(−0.03)	(−2.47)
		PrecLow — Short	0.497***	0.235**	0.247*	0.133	−0.248*	−0.387***	0.75***	0.182
			(5.04)	(2.15)	(1.65)	(0.86)	(−1.73)	(−2.61)	(3.45)	(0.78)
		PrecLong — Long	−0.805***	−0.573***	−0.226	−0.232	0.26	0.339*	−0.406	−1.188**
			(−7.05)	(−4.63)	(−1.05)	(−1.08)	(1.52)	(1.93)	(−0.81)	(−2.31)
		GDD — Short	0.421***	0.626***	−0.647***	−0.373	1.185***	1.121***	−0.374	−0.782**
			(2.85)	(3.96)	(−2.82)	(−1.43)	(4.13)	(3.90)	(−0.99)	(−2.04)
		GDD — Long	0.01	0.594***	−3.487***	−1.696**	−1.993***	−1.791***	−8.741***	−8.457***
			(0.05)	(2.81)	(−5.66)	(−2.21)	(−4.83)	(−4.13)	(−9.78)	(−9.27)
		GDDHigh — Short	−1.034***	−1.042***	−0.564***	−0.543***	−0.108	−0.254**	−0.557**	−0.179
			(−10.38)	(−9.67)	(−3.28)	(−3.15)	(−1.02)	(−2.05)	(−2.26)	(−0.71)
		GDDHigh — Long	0.093	−0.035	0.56**	0.475	0.369**	0.512***	−1.266***	−0.029
			(0.74)	(−0.23)	(2.30)	(1.47)	(2.11)	(2.81)	(−2.89)	(−0.06)

Note: Values in parentheses are z-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A13 continued

			Lag Structure							
			Short = 1 to 3, Long = 4 to 10				Short = 1 to 5, Long = 6 to 20			
			Models							
Land Use	**County**	**Variable**	**LIN-DML-RE**	**NL-DML-RE**	**LIN-OLS-FE**	**NL-OLS-FE**	**LIN-DML-RE**	**NL-DML-RE**	**LIN-OLS-FE**	**NL-OLS-FE**
Corn, Sorghum	Lincoln	*Prec* — Short	0.012 (1.09)	0.024** (1.96)	0.009 (0.41)	0.013 (0.59)	−0.036** (−2.25)	−0.029* (−1.70)	0.018 (0.63)	0.027 (0.86)
		Prec — Long	−0.07*** (−5.49)	−0.082*** (−5.40)	−0.037 (−1.38)	−0.03 (−0.98)	−0.038** (−2.03)	−0.03 (−1.37)	0.501*** (4.77)	0.507*** (4.77)
		PrecLow — Short	−0.985*** (−9.26)	−0.879*** (−7.82)	−0.448** (−2.54)	−0.423** (−2.38)	−0.893*** (−6.80)	−0.614*** (−3.92)	−0.879*** (−3.20)	−0.79*** (−2.72)
		PrecLong — Long	0.327*** (2.91)	0.19 (1.60)	1.475*** (4.68)	1.553*** (4.55)	0.194 (1.11)	−0.14 (−0.72)	0.744 (1.19)	0.746 (1.05)
		GDD — Short	−0.842*** (−7.91)	−0.81*** (−7.46)	−0.859*** (−5.06)	−0.909*** (−5.11)	−1.479*** (−6.95)	−1.47*** (−6.75)	−0.842*** (−3.08)	−0.862*** (−3.10)
		GDD — Long	−0.035 (−0.20)	0.011 (0.06)	−0.416 (−0.72)	−0.745 (−1.05)	0.346 (1.40)	0.295 (1.13)	4.661*** (4.98)	4.052*** (3.53)
		GDDHigh — Short	0.327*** (5.51)	0.299*** (4.94)	0.537*** (6.44)	0.553*** (6.30)	0.064 (1.18)	0.066 (1.22)	0.229** (2.29)	0.24** (2.38)
		GDDHigh — Long	−0.074* (−1.66)	−0.065 (−1.45)	0.225* (1.65)	0.291* (1.90)	0.102 (1.63)	0.129** (2.02)	1.333*** (5.54)	1.311*** (5.40)
	Ness	*Prec* — Short	−0.013 (−0.95)	−0.007 (−0.47)	0.006 (0.30)	−0.006 (−0.25)	−0.087*** (−4.72)	−0.092*** (−4.90)	0.005 (0.20)	0 (−0.01)
		Prec — Long	0 (−0.02)	−0.019 (−1.16)	−0.151*** (−5.11)	−0.128*** (−4.12)	0.133*** (6.44)	0.134*** (6.09)	0.047 (0.63)	0.033 (0.44)
		PrecLow — Short	−0.402*** (−4.55)	−0.374*** (−4.15)	0.255* (1.67)	0.295* (1.88)	−0.176 (−1.37)	−0.162 (−1.26)	−0.495** (−2.40)	−0.47** (−2.26)
		PrecLong — Long	0.076 (0.87)	0.053 (0.60)	1.077*** (4.04)	1.271*** (4.54)	−0.311** (−2.38)	−0.339** (−2.57)	0.263 (0.55)	0.291 (0.60)
		GDD — Short	−0.905*** (−8.92)	−0.915*** (−8.83)	−1.065*** (−4.36)	−1.099*** (−4.27)	−0.033 (−0.12)	0.013 (0.04)	−1.87*** (−4.92)	−1.849*** (−4.78)
		GDD — Long	−1.142*** (−9.42)	−1.047*** (−8.00)	−2.942*** (−7.11)	−3.109*** (−6.44)	−2.11*** (−7.49)	−2.15*** (−7.49)	−5.243*** (−8.24)	−5.21*** (−8.16)
		GDDHigh — Short	0.032 (0.41)	0.015 (0.19)	0.17 (1.48)	0.224* (1.90)	−0.088 (−1.18)	−0.087 (−1.15)	0.453*** (3.44)	0.45*** (3.42)
		GDDHigh — Long	0.858*** (13.00)	0.829*** (12.43)	0.358** (2.00)	0.464** (2.48)	1.095*** (14.27)	1.102*** (14.25)	1.01*** (4.35)	0.995*** (4.23)
	Ottawa	*Prec* — Short	−0.044*** (−2.63)	−0.049*** (−2.88)	−0.041* (−1.84)	−0.032 (−1.29)	0.007 (0.25)	−0.021 (−0.73)	−0.064 (−1.58)	−0.048 (−1.10)
		Prec — Long	−0.117*** (−5.86)	−0.094*** (−3.88)	−0.056* (−1.81)	−0.087** (−2.32)	−0.08*** (−3.96)	−0.062*** (−2.76)	−0.126 (−1.35)	−0.086 (−0.80)
		PrecLow — Short	−0.117 (−0.93)	−0.121 (−0.97)	0.151 (0.89)	0.187 (1.10)	0.067 (0.48)	−0.033 (−0.24)	0.194 (0.82)	0.141 (0.58)
		PrecLong — Long	0.183 (1.39)	0.173 (1.31)	0.755** (1.99)	0.793** (2.09)	−0.331* (−1.90)	−0.12 (−0.67)	−0.586 (−1.54)	−0.7* (−1.66)
		GDD — Short	0.056 (0.41)	0.085 (0.61)	0.459** (2.35)	0.474* (1.88)	−0.297 (−1.41)	−0.155 (−0.73)	−0.226 (−0.83)	−0.203 (−0.71)
		GDD — Long	0.341** (2.15)	0.245 (1.46)	1.12* (1.93)	0.654 (0.71)	0.103 (0.43)	0.029 (0.12)	1.435** (2.23)	1.277* (1.91)
		GDDHigh — Short	−0.153** (−2.41)	−0.18*** (−2.60)	−0.164* (−1.81)	−0.137 (−1.22)	−0.256*** (−4.07)	−0.33*** (−4.68)	0.002 (0.02)	0.023 (0.17)
		GDDHigh — Long	−0.165*** (−2.65)	−0.128* (−1.86)	−0.302** (−2.34)	−0.356 (−1.64)	0.055 (0.76)	0.096 (1.23)	0.73** (2.35)	0.689** (2.15)

Note: Values in parentheses are z-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A13 continued

			Lag Structure							
			Short = 1 to 3, Long = 4 to 10				Short = 1 to 5, Long = 6 to 20			
			Models							
Land Use	**County**	**Variable**	**LIN-DML-RE**	**NL-DML-RE**	**LIN-OLS-FE**	**NL-OLS-FE**	**LIN-DML-RE**	**NL-DML-RE**	**LIN-OLS-FE**	**NL-OLS-FE**
Corn, Sorghum	Rush	*Prec* — Short	0.058***	0.066***	0.038	0.032	0.003	−0.213***	−0.057*	−0.089**
			(3.33)	(3.72)	(1.46)	(1.20)	(0.68)	(−8.80)	(−1.73)	(−2.53)
		Prec — Long	−0.027**	−0.047***	−0.076	−0.068	0.016*	0.248***	−0.178*	−0.154
			(−1.96)	(−3.19)	(−1.52)	(−1.24)	(1.95)	(8.34)	(−1.89)	(−1.60)
		PrecLow — Short	−0.132	−0.129	−0.214	−0.165	0.082**	0.599***	0.136	0.318
			(−1.01)	(−0.96)	(−1.30)	(−0.94)	(2.19)	(3.56)	(0.70)	(1.54)
		PrecLong — Long	−1.218***	−1.22***	−0.745***	−0.824***	−0.232***	−1.044***	−0.699	−0.593
			(−11.65)	(−10.81)	(−3.13)	(−3.38)	(−6.21)	(−8.04)	(−1.10)	(−0.93)
		GDD — Short	−0.975***	−1.145***	−1.15***	−1.059***	0.296***	1.235***	−1.556***	−1.071*
			(−8.17)	(−8.31)	(−4.10)	(−3.76)	(3.41)	(4.01)	(−3.01)	(−1.94)
		GDD — Long	−0.176	−0.037	−1.735***	−1.185***	−0.106	−0.881***	−5.192***	−4.753***
			(−1.20)	(−0.24)	(−5.18)	(−3.26)	(−1.22)	(−2.90)	(−7.41)	(−6.58)
		GDDHigh — Short	−0.434***	−0.318**	−0.276	−0.123	0.001	−1.369***	0.123	−0.017
			(−3.00)	(−2.18)	(−1.58)	(−0.69)	(0.02)	(−10.77)	(0.50)	(−0.07)
		GDDHigh — Long	0.823***	0.792***	0.914***	1.001***	0.056**	0.689***	1.793***	1.801***
			(7.38)	(6.56)	(5.57)	(5.38)	(2.02)	(6.44)	(5.17)	(5.08)
	Russell	*Prec* — Short	−0.007	−0.003	0.129***	0.134***	0	−0.135***	0.062*	0.031
			(−0.54)	(−0.24)	(5.28)	(5.35)	(0.00)	(−6.57)	(1.85)	(0.89)
		Prec — Long	−0.241***	−0.245***	0.088*	0.066	0.021**	0.069	−0.122	−0.287*
			(−9.98)	(−9.16)	(1.76)	(1.29)	(2.11)	(1.56)	(−0.77)	(−1.68)
		PrecLow — Short	0.02	0.065	0.358*	0.365*	0.024	−0.179	−0.381	−0.488
			(0.13)	(0.43)	(1.81)	(1.82)	(0.72)	(−0.99)	(−1.01)	(−1.29)
		PrecLong — Long	−0.115**	−0.111**	0.132**	0.147**	0.061**	0.266***	−1.307	−1.595
			(−2.33)	(−2.24)	(1.97)	(2.19)	(2.01)	(2.76)	(−1.11)	(−1.35)
		GDD — Short	−0.522***	−0.459***	−1.992***	−1.995***	0.321***	−0.372	−2.734***	−2.663***
			(−3.78)	(−3.08)	(−6.16)	(−6.07)	(4.39)	(−1.11)	(−4.48)	(−4.33)
		GDD — Long	0.028	0.028	2.107***	2.423***	−0.174***	−1.934***	−2.198	−0.906
			(0.10)	(0.10)	(3.41)	(3.51)	(−2.66)	(−7.18)	(−1.56)	(−0.61)
		GDDHigh — Short	0.304**	0.252*	1.813***	1.79***	0.031	−0.723***	1.585***	1.576***
			(2.13)	(1.75)	(7.36)	(7.12)	(1.10)	(−4.99)	(4.05)	(4.03)
		GDDHigh — Long	0.523***	0.503***	1.935***	1.812***	0.003	0.974***	4.214***	4.061***
			(4.22)	(4.02)	(8.32)	(7.27)	(0.06)	(4.73)	(8.59)	(8.23)
	Saline	*Prec* — Short	0	−0.003	−0.014	−0.014	−0.03***	−0.021	0.061*	0.054
			(−0.05)	(−0.31)	(−0.82)	(−0.70)	(−3.10)	(−1.08)	(1.92)	(1.62)
		Prec — Long	−0.036***	−0.02	−0.032	−0.038	0.057***	−0.013	0.006	0.034
			(−3.22)	(−1.42)	(−0.96)	(−1.10)	(4.34)	(−0.46)	(0.07)	(0.33)
		PrecLow — Short	−0.207***	−0.25***	−0.206	−0.224	−0.036	−0.206**	−0.476*	−0.485*
			(−2.82)	(−3.30)	(−1.21)	(−1.29)	(−0.65)	(−2.04)	(−1.86)	(−1.91)
		PrecLong — Long	−0.039	−0.044	−0.44**	−0.52**	0.106	−0.103	−1.119*	−1.438**
			(−0.51)	(−0.57)	(−2.30)	(−2.30)	(1.46)	(−0.80)	(−1.94)	(−2.47)
		GDD — Short	0.799***	0.691***	0.574***	0.582**	0.473***	0.8***	0.696***	0.883***
			(5.64)	(4.68)	(3.09)	(2.29)	(4.32)	(3.68)	(2.74)	(2.73)
		GDD — Long	0.485***	0.186	1.819***	1.93**	−0.682***	0.346	0.592	0.496
			(3.76)	(1.28)	(3.50)	(2.30)	(−5.36)	(1.53)	(0.83)	(0.68)
		GDDHigh — Short	−0.3***	−0.2**	−0.011	−0.011	−0.056	−0.463***	−0.265	−0.268
			(−3.83)	(−2.29)	(−0.14)	(−0.09)	(−1.24)	(−5.52)	(−1.61)	(−1.58)
		GDDHigh — Long	−0.549***	−0.438***	−0.337***	−0.339*	0.135**	−0.497***	−0.488	−0.379
			(−6.82)	(−5.16)	(−2.64)	(−1.71)	(2.35)	(−5.24)	(−1.61)	(−1.26)

Note: Values in parentheses are z-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A13 continued

			Lag Structure							
			Short = 1 to 3, Long = 4 to 10				Short = 1 to 5, Long = 6 to 20			
			Models							
Land Use	**County**	**Variable**	**LIN-DML-RE**	**NL-DML-RE**	**LIN-OLS-FE**	**NL-OLS-FE**	**LIN-DML-RE**	**NL-DML-RE**	**LIN-OLS-FE**	**NL-OLS-FE**
Corn, Sorghum	Trego	*Prec* — Short	0.022 (1.63)	0.028** (1.99)	0.015 (0.62)	0.043* (1.68)	−0.117*** (−6.65)	−0.106*** (−5.95)	0.109** (2.43)	0.115** (2.48)
		Prec — Long	−0.25*** (−17.81)	−0.249*** (−17.10)	−0.187*** (−4.64)	−0.096** (−2.07)	−0.159*** (−5.27)	−0.127*** (−4.13)	0.521*** (3.67)	0.553*** (3.67)
		PrecLow — Short	−0.373*** (−3.60)	−0.359*** (−3.37)	−0.288** (−2.02)	−0.131 (−0.89)	−0.369*** (−3.29)	−0.356*** (−3.09)	−0.276 (−1.14)	−0.224 (−0.91)
		PrecLong — Long	−0.166 (−1.54)	−0.202* (−1.85)	0.275 (1.37)	0.388* (1.88)	−0.764*** (−6.92)	−0.798*** (−7.17)	−0.425 (−0.78)	−0.262 (−0.47)
		GDD — Short	−1.817*** (−12.06)	−1.898*** (−12.21)	−2.309*** (−10.85)	−2.864*** (−10.80)	−2.841*** (−10.37)	−2.322*** (−7.99)	−2.977*** (−9.95)	−2.81*** (−8.52)
		GDD — Long	−4.816*** (−14.83)	−5.245*** (−13.08)	−4.039*** (−5.11)	−5.084*** (−5.64)	−7.959*** (−23.17)	−7.25*** (−20.41)	−8.524*** (−13.88)	−8.231*** (−12.22)
		GDDHigh — Short	0.778*** (7.01)	0.843*** (7.29)	1.085*** (6.45)	1.499*** (7.29)	0.46*** (4.41)	0.262** (2.41)	1.527*** (6.60)	1.359*** (5.41)
		GDDHigh — Long	2.28*** (16.92)	2.412*** (15.76)	2.8*** (14.94)	3.406*** (13.00)	3.999*** (25.44)	3.789*** (23.64)	5.363*** (11.39)	5.081*** (10.34)
Fallow	Barton	*Prec* — Short	0.004 (0.83)	0.022*** (3.63)	−0.019** (−2.43)	−0.026** (−2.34)	−0.021** (−2.44)	−0.045*** (−4.98)	−0.088*** (−6.86)	−0.167*** (−11.20)
		Prec — Long	−0.172*** (−17.39)	−0.134*** (−9.46)	−0.088*** (−5.70)	−0.13*** (−6.46)	−0.3*** (−17.65)	−0.385*** (−18.90)	−0.102 (−1.60)	−0.248*** (−3.75)
		PrecLow — Short	0.046 (0.90)	0.07 (1.36)	−0.118 (−1.39)	−0.083 (−0.96)	0.15** (2.22)	0.075 (1.10)	−0.707*** (−6.03)	−0.78*** (−6.66)
		PrecLong — Long	0.042 (0.70)	−0.022 (−0.35)	−0.701*** (−5.95)	−0.743*** (−6.02)	0.096 (1.58)	−0.002 (−0.03)	−3.153*** (−7.69)	−2.285*** (−5.46)
		GDD — Short	−0.093 (−1.08)	−0.199** (−2.26)	1.057*** (7.93)	1.095*** (7.24)	−1.805*** (−13.87)	−1.953*** (−14.73)	0.347 (1.36)	1.308*** (4.71)
		GDD — Long	0.397*** (5.69)	0.277*** (3.32)	4.542*** (16.39)	4.815*** (16.49)	1.821*** (12.71)	2.239*** (14.55)	7.684*** (14.19)	9.109*** (16.35)
		GDDHigh — Short	0.085 (1.59)	0.159*** (2.88)	0.101 (1.06)	0.057 (0.54)	−0.318*** (−5.30)	−0.417*** (−6.66)	−0.071 (−0.75)	−0.294*** (−2.94)
		GDDHigh — Long	−1.107*** (−18.39)	−0.923*** (−12.51)	−0.979*** (−9.69)	−1.262*** (−9.62)	−0.476*** (−9.12)	−0.587*** (−10.98)	1.537*** (8.60)	1.383*** (7.72)
	Ellis	*Prec* — Short	0.041*** (3.25)	−0.004 (−0.33)	0.028 (1.20)	−0.019 (−0.74)	−0.089*** (−5.72)	−0.092*** (−5.61)	−0.236*** (−5.81)	−0.248*** (−5.95)
		Prec — Long	−0.048*** (−3.13)	−0.114*** (−7.05)	0.1*** (2.60)	0.055 (1.41)	−0.014 (−0.50)	0.012 (0.35)	−0.332** (−2.46)	−0.426*** (−2.94)
		PrecLow — Short	−0.357*** (−3.61)	−0.518*** (−5.13)	−0.383*** (−2.83)	−0.519*** (−3.80)	−0.536*** (−5.13)	−0.544*** (−5.14)	−0.99*** (−5.96)	−0.994*** (−5.93)
		PrecLong — Long	0.616*** (6.62)	0.753*** (7.92)	0.361* (1.77)	0.625*** (3.02)	0.634*** (6.33)	0.632*** (6.07)	−2.209*** (−3.59)	−2.254*** (−3.63)
		GDD — Short	−0.352*** (−3.41)	−0.183* (−1.68)	0.515** (2.27)	0.546** (2.33)	−2.747*** (−12.02)	−2.773*** (−11.52)	−1.961*** (−6.38)	−1.977*** (−6.42)
		GDD — Long	0.492*** (3.95)	0.541*** (4.06)	5.562*** (10.22)	5.486*** (8.92)	1.613*** (8.99)	1.579*** (7.81)	4.754*** (7.72)	5.128*** (7.86)
		GDDHigh — Short	0.099 (1.46)	0.189*** (2.73)	−0.025 (−0.19)	0.14 (0.98)	−0.591*** (−8.15)	−0.609*** (−7.79)	−0.509** (−2.22)	−0.366 (−1.51)
		GDDHigh — Long	−0.55*** (−6.77)	−0.652*** (−7.85)	−1.114*** (−6.40)	−1.107*** (−5.99)	0.477*** (4.46)	0.504*** (3.94)	1.61*** (4.01)	1.789*** (4.31)

Note: Values in parentheses are z-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A13 continued

			Lag Structure							
			Short = 1 to 3, Long = 4 to 10				Short = 1 to 5, Long = 6 to 20			
			Models							
Land Use	**County**	**Variable**	**LIN-DML-RE**	**NL-DML-RE**	**LIN-OLS-FE**	**NL-OLS-FE**	**LIN-DML-RE**	**NL-DML-RE**	**LIN-OLS-FE**	**NL-OLS-FE**
Fallow	Ellsworth	*Prec* — Short	−0.026*** (−3.64)	−0.017** (−2.13)	0.052*** (4.21)	0.068*** (4.46)	0.052*** (4.25)	0.049*** (3.61)	0.034 (1.55)	0.043* (1.72)
		Prec — Long	−0.079*** (−6.34)	−0.027* (−1.87)	0.157*** (5.74)	0.163*** (5.77)	−0.327*** (−15.97)	−0.338*** (−14.84)	−0.095 (−0.92)	−0.063 (−0.58)
		PrecLow — Short	−0.278*** (−5.29)	−0.192*** (−3.51)	−0.16 (−1.42)	−0.129 (−1.13)	0 (0.00)	−0.007 (−0.10)	0.281** (2.41)	0.29** (2.34)
		PrecLong — Long	0.338*** (4.82)	0.409*** (5.79)	0.049 (0.32)	0.093 (0.58)	−0.006 (−0.07)	−0.017 (−0.20)	0.988*** (2.63)	1.134*** (2.81)
		GDD — Short	0.605*** (4.33)	0.497*** (3.34)	0.169 (0.77)	−0.024 (−0.09)	−1.93*** (−8.27)	−1.856*** (−7.48)	−1.304*** (−3.76)	−1.343*** (−3.67)
		GDD — Long	1.061*** (9.70)	0.478*** (3.45)	4.545*** (9.15)	4.247*** (7.05)	1.677*** (9.87)	1.674*** (9.72)	3.143*** (4.52)	3.276*** (4.63)
		GDDHigh — Short	−0.427*** (−4.24)	−0.297*** (−2.64)	−0.273** (−2.01)	−0.141 (−0.93)	−0.129* (−1.68)	−0.174** (−1.98)	−0.398*** (−2.92)	−0.359** (−2.32)
		GDDHigh — Long	−1.116*** (−11.55)	−0.613*** (−5.23)	−0.592*** (−3.49)	−0.47** (−2.33)	−1.142*** (−12.38)	−1.186*** (−11.26)	−0.823*** (−3.65)	−0.759*** (−3.07)
	Gove	*Prec* — Short	0.096*** (5.83)	0.109*** (6.51)	0.138*** (5.49)	0.132*** (5.13)	−0.068*** (−2.91)	−0.068*** (−2.88)	0.03 (0.67)	0.013 (0.27)
		Prec — Long	−0.162*** (−11.83)	−0.116*** (−6.11)	0.081** (2.12)	−0.002 (−0.03)	−0.14*** (−7.30)	−0.146*** (−7.14)	0.616*** (5.32)	0.57*** (4.30)
		PrecLow — Short	−0.151* (−1.76)	0.147 (1.56)	−0.016 (−0.12)	0.147 (1.06)	0.688*** (5.49)	0.62*** (4.81)	0.745*** (3.81)	0.646*** (3.05)
		PrecLong — Long	0.519*** (5.20)	0.246** (2.32)	0.403** (2.09)	0.413** (2.15)	−0.874*** (−5.83)	−0.83*** (−5.42)	0.545 (1.20)	0.401 (0.86)
		GDD — Short	−0.787*** (−5.83)	−1.08*** (−7.61)	−0.199 (−0.97)	−0.645*** (−2.76)	−4.315*** (−16.71)	−4.379*** (−16.96)	−2.793*** (−8.20)	−2.904*** (−8.42)
		GDD — Long	0.729*** (3.97)	0.013 (0.07)	4.448*** (8.04)	1.765** (2.56)	4.869*** (13.18)	5.062*** (13.01)	9.603*** (11.93)	9.537*** (11.60)
		GDDHigh — Short	0.463*** (5.31)	0.503*** (5.32)	0.51*** (3.31)	0.484*** (3.12)	−0.58*** (−6.22)	−0.675*** (−6.29)	−1.859*** (−8.38)	−1.788*** (−7.86)
		GDDHigh — Long	0.372*** (3.48)	0.545*** (4.18)	0.298 (1.36)	0.494* (1.70)	0.677*** (4.58)	0.73*** (4.77)	−0.599 (−1.52)	−0.36 (−0.85)
	Lincoln	*Prec* — Short	0.021*** (5.45)	0.018*** (4.67)	0.003 (0.30)	0.007 (0.69)	0.055*** (9.66)	0.05*** (8.90)	0.014 (1.07)	0.024 (1.64)
		Prec — Long	0.014*** (3.08)	0.025*** (5.11)	0.027** (2.17)	0.043*** (2.95)	−0.063*** (−8.82)	−0.029*** (−3.56)	0.126*** (2.58)	0.134*** (2.70)
		PrecLow — Short	−0.269*** (−6.77)	−0.225*** (−5.29)	−0.302*** (−3.69)	−0.267*** (−3.23)	0.037 (0.79)	0.191*** (3.35)	0.048 (0.38)	0.126 (0.93)
		PrecLong — Long	0.447*** (10.00)	0.342*** (7.25)	−0.003 (−0.02)	0.147 (0.93)	−0.093 (−1.34)	−0.257*** (−3.33)	0.398 (1.36)	0.356 (1.08)
		GDD — Short	−0.069 (−1.64)	0.01 (0.24)	0.354*** (4.49)	0.286*** (3.46)	−0.563*** (−6.47)	−0.395*** (−4.32)	0.175 (1.38)	0.151 (1.17)
		GDD — Long	−0.408*** (−5.15)	−0.604*** (−7.30)	2.336*** (8.72)	2.071*** (6.26)	0.261*** (2.75)	−0.032 (−0.30)	3.62*** (8.32)	3.022*** (5.67)
		GDDHigh — Short	0.052*** (2.60)	0.031 (1.46)	−0.055 (−1.43)	−0.024 (−0.58)	0.014 (0.71)	−0.008 (−0.41)	−0.203*** (−4.37)	−0.191*** (−4.05)
		GDDHigh — Long	−0.182*** (−11.27)	−0.16*** (−9.82)	−0.552*** (−8.68)	−0.472*** (−6.66)	−0.151*** (−6.08)	−0.154*** (−6.13)	−0.001 (−0.01)	−0.025 (−0.22)

Note: Values in parentheses are z-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A13 continued

Land Use	County	Variable	Short = 1 to 3, Long = 4 to 10: LIN-DML-RE	NL-DML-RE	LIN-OLS-FE	NL-OLS-FE	Short = 1 to 5, Long = 6 to 20: LIN-DML-RE	NL-DML-RE	LIN-OLS-FE	NL-OLS-FE
Fallow	Ness	*Prec* — Short	0.053*** (3.49)	0.019 (1.08)	0.031 (1.44)	−0.031 (−1.25)	−0.105*** (−5.03)	−0.123*** (−5.64)	0.027 (0.90)	0.011 (0.38)
		Prec — Long	−0.188*** (−12.08)	−0.137*** (−7.56)	−0.095*** (−2.92)	0.007 (0.21)	−0.166*** (−7.34)	−0.193*** (−7.94)	0.85*** (10.41)	0.841*** (10.06)
		PrecLow — Short	0.165 (1.53)	0.013 (0.12)	0.156 (0.93)	0.371** (2.15)	−0.722*** (−4.68)	−0.71*** (−4.59)	−0.339 (−1.50)	−0.262 (−1.14)
		PrecLong — Long	0.112 (1.04)	0.245** (2.23)	0.322 (1.10)	1.198*** (3.90)	0.981*** (6.48)	0.989*** (6.43)	0.724 (1.37)	0.867 (1.63)
		GDD — Short	−0.677*** (−5.58)	−0.44*** (−3.52)	0.439 (1.64)	0.4 (1.42)	−2.857*** (−8.95)	−2.865*** (−8.81)	−2.999*** (−7.19)	−2.844*** (−6.70)
		GDD — Long	1.25*** (8.98)	0.831*** (5.57)	3.11*** (6.83)	2.722*** (5.14)	3.154*** (9.84)	3.198*** (9.68)	6.752*** (9.67)	6.883*** (9.82)
		GDDHigh — Short	−0.118 (−1.35)	−0.12 (−1.35)	−0.702*** (−5.59)	−0.497*** (−3.83)	−0.507*** (−5.79)	−0.47*** (−5.27)	−0.367** (−2.54)	−0.378*** (−2.61)
		GDDHigh — Long	−0.674*** (−8.77)	−0.567*** (−7.25)	−1.302*** (−6.61)	−0.897*** (−4.37)	−0.619*** (−6.86)	−0.639*** (−7.00)	1.167*** (4.58)	1.203*** (4.66)
	Rush	*Prec* — Short	0.044*** (2.92)	0.02 (1.28)	0.114*** (4.68)	0.148*** (5.98)	0.009 (1.40)	−0.131*** (−6.36)	−0.13*** (−4.18)	−0.088*** (−2.65)
		Prec — Long	−0.102*** (−8.20)	−0.067*** (−5.14)	0.095** (2.06)	0.285*** (5.57)	0.018* (1.92)	−0.264*** (−9.87)	0.046 (0.52)	−0.047 (−0.52)
		PrecLow — Short	−0.995*** (−9.15)	−0.802*** (−7.14)	−0.587*** (−3.82)	−0.132 (−0.81)	0.067 (1.42)	−1.023*** (−6.96)	−1.252*** (−6.90)	−1.309*** (−6.81)
		PrecLong — Long	0.816*** (9.10)	0.559*** (5.69)	0.899*** (4.05)	1.323*** (5.83)	−0.031 (−0.81)	0.273** (2.44)	0.702 (1.18)	0.494 (0.83)
		GDD — Short	−1.522*** (−14.04)	−0.977*** (−7.83)	−1.626*** (−6.21)	−1.605*** (−6.12)	0.404*** (3.62)	−3.658*** (−13.93)	−3.674*** (−7.61)	−4.456*** (−8.64)
		GDD — Long	0.831*** (6.31)	0.507*** (3.62)	2.275*** (7.28)	1.66*** (4.91)	−0.124 (−1.09)	3.312*** (12.67)	4.479*** (6.84)	4.433*** (6.58)
		GDDHigh — Short	0.608*** (5.00)	0.506*** (4.14)	0.124 (0.76)	0.18 (1.08)	−0.019 (−0.56)	−0.165 (−1.52)	−0.29 (−1.26)	0.027 (0.11)
		GDDHigh — Long	−0.4*** (−4.20)	−0.072 (−0.69)	−0.509*** (−3.32)	0.172 (0.99)	0.02 (0.64)	0.474*** (5.06)	0.827** (2.56)	1.149*** (3.47)
	Russell	*Prec* — Short	−0.06*** (−6.28)	−0.059*** (−6.08)	−0.051*** (−2.63)	−0.024 (−1.21)	0.015 (1.13)	−0.028* (−1.91)	0.119*** (4.47)	0.161*** (5.69)
		Prec — Long	−0.366*** (−21.22)	−0.367*** (−19.02)	−0.254*** (−6.38)	−0.28*** (−6.91)	0.142*** (5.66)	−0.33*** (−10.27)	0.862*** (6.79)	1.095*** (8.05)
		PrecLow — Short	−0.333*** (−3.19)	−0.295*** (−2.79)	−0.105 (−0.67)	−0.267* (−1.67)	0.089 (0.93)	0.173 (1.26)	−0.377 (−1.25)	−0.234 (−0.77)
		PrecLong — Long	−0.123*** (−3.78)	−0.125*** (−3.82)	−0.038 (−0.71)	−0.028 (−0.53)	0.2*** (3.98)	−0.615*** (−9.19)	1.008 (1.07)	1.448 (1.53)
		GDD — Short	0.868*** (8.77)	1.067*** (10.04)	1.646*** (6.39)	1.344*** (5.14)	0.568*** (2.95)	−1.292*** (−5.50)	−0.048 (−0.10)	−0.192 (−0.39)
		GDD — Long	0.485** (2.29)	0.474** (2.24)	3.506*** (7.13)	2.449*** (4.47)	−0.957*** (−6.49)	1.568*** (8.01)	14.409*** (12.81)	12.542*** (10.55)
		GDDHigh — Short	−0.363*** (−3.56)	−0.318*** (−3.10)	−0.659*** (−3.36)	−0.436** (−2.18)	0.053 (0.79)	−0.234** (−2.20)	0.514* (1.65)	0.533* (1.71)
		GDDHigh — Long	−1.566*** (−17.96)	−1.528*** (−17.14)	−2.098*** (−11.34)	−1.868*** (−9.43)	−0.021 (−0.21)	0.083 (0.53)	3.07*** (7.85)	3.282*** (8.34)

Note: Values in parentheses are z-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A13 continued

			Lag Structure							
			Short = 1 to 3, Long = 4 to 10				Short = 1 to 5, Long = 6 to 20			
			Models							
Land Use	**County**	**Variable**	**LIN-DML-RE**	**NL-DML-RE**	**LIN-OLS-FE**	**NL-OLS-FE**	**LIN-DML-RE**	**NL-DML-RE**	**LIN-OLS-FE**	**NL-OLS-FE**
Fallow	Saline	*Prec* — Short		−0.002 (−1.58)		−0.006** (−2.13)		−0.002 (−0.24)		−0.004 (−0.76)
		Prec — Long		0 (−0.34)		−0.003 (−0.62)		−0.002 (−0.25)		−0.019 (−1.23)
		PrecLow — Short		−0.008 (−1.40)		−0.05* (−1.93)		−0.01 (−0.23)		−0.093** (−2.45)
		PrecLong — Long		0.002 (0.31)		−0.01 (−0.30)		0.007 (0.20)		−0.038 (−0.44)
		GDD — Short		0.005 (0.50)		0.056 (1.48)		−0.011 (−0.23)		−0.04 (−0.82)
		GDD — Long		−0.004 (−0.45)		0.164 (1.31)		0.02 (0.23)		0.304*** (2.79)
		GDDHigh — Short		−0.002 (−0.35)		−0.023 (−1.29)		−0.007 (−0.23)		0.013 (0.51)
		GDDHigh — Long		−0.004 (−0.77)		−0.07** (−2.35)		−0.005 (−0.24)		−0.032 (−0.71)
	Trego	*Prec* — Short	−0.01 (−0.74)	−0.01 (−0.74)	0.016 (0.68)	0.009 (0.37)	−0.075*** (−4.34)	−0.073*** (−4.17)	−0.117*** (−2.67)	−0.114** (−2.50)
		Prec — Long	0 (−0.01)	−0.006 (−0.40)	−0.015 (−0.39)	−0.02 (−0.45)	0.003 (0.10)	0.007 (0.23)	−0.097 (−0.70)	−0.081 (−0.55)
		PrecLow — Short	−0.273*** (−2.69)	−0.309*** (−2.96)	−0.792*** (−5.70)	−0.783*** (−5.41)	−0.308*** (−2.86)	−0.348*** (−3.13)	−0.74*** (−3.13)	−0.752*** (−3.12)
		PrecLong — Long	0.116 (1.18)	0.16 (1.60)	0.147 (0.75)	0.185 (0.91)	0.265** (2.51)	0.281*** (2.62)	−0.016 (−0.03)	−0.037 (−0.07)
		GDD — Short	0.633*** (4.45)	0.73*** (4.92)	0.691*** (3.32)	0.796*** (3.07)	−2.086*** (−7.73)	−2.15*** (−7.57)	−3.39*** (−11.55)	−3.423*** (−10.57)
		GDD — Long	4.907*** (16.33)	5.34*** (14.16)	4.881*** (6.31)	5.285*** (5.99)	3.814*** (11.59)	3.826*** (11.11)	4.083*** (6.77)	4.012*** (6.07)
		GDDHigh — Short	−0.545*** (−5.06)	−0.617*** (−5.51)	−0.546*** (−3.32)	−0.624*** (−3.10)	−0.74*** (−7.30)	−0.731*** (−6.89)	0.09 (0.40)	0.104 (0.42)
		GDDHigh — Long	−1.614*** (−12.96)	−1.742*** (−12.02)	−1.853*** (−10.11)	−1.987*** (−7.75)	−0.118 (−0.75)	−0.105 (−0.65)	2.35*** (5.09)	2.353*** (4.88)
Soybeans, Double Crop	Barton	*Prec* — Short	−0.008* (−1.71)	−0.022*** (−4.20)	0.021*** (3.03)	−0.011 (−1.14)	−0.024*** (−2.82)	−0.023*** (−2.68)	0.057*** (4.96)	0.069*** (5.19)
		Prec — Long	0.013 (1.55)	−0.019* (−1.90)	0.057*** (4.11)	0 (0.01)	0.093*** (5.35)	0.123*** (6.30)	−0.096* (−1.68)	−0.117** (−1.97)
		PrecLow — Short	−0.023 (−0.52)	−0.042 (−0.96)	0.169** (2.22)	0.23*** (2.98)	0.245*** (4.41)	0.266*** (4.67)	0.523*** (4.98)	0.526*** (5.00)
		PrecLong — Long	−0.039 (−0.77)	−0.031 (−0.61)	0.777*** (7.34)	0.88*** (7.94)	−0.445*** (−8.12)	−0.411*** (−7.16)	1.302*** (3.54)	1.16*** (3.09)
		GDD — Short	0.158** (2.02)	0.17** (2.08)	−0.515*** (−4.30)	−0.235* (−1.73)	0.811*** (6.78)	0.824*** (6.81)	−1.084*** (−4.74)	−1.316*** (−5.28)
		GDD — Long	0.017 (0.30)	0.173** (2.50)	−0.532** (−2.14)	−0.126 (−0.48)	−0.466*** (−3.64)	−0.56*** (−4.16)	−2.666*** (−5.49)	−2.868*** (−5.73)
		GDDHigh — Short	−0.032 (−0.63)	−0.067 (−1.24)	0.273*** (3.18)	0.087 (0.91)	−0.22*** (−4.14)	−0.197*** (−3.67)	0.321*** (3.81)	0.402*** (4.49)
		GDDHigh — Long	0.33*** (5.90)	0.165*** (2.61)	0.441*** (4.86)	0.084 (0.71)	0.374*** (7.41)	0.415*** (7.89)	0.157 (0.98)	0.191 (1.19)

Note: Values in parentheses are z-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A13 continued

			Lag Structure							
			Short = 1 to 3, Long = 4 to 10				Short = 1 to 5, Long = 6 to 20			
			Models							
Land Use	**County**	**Variable**	**LIN-DML-RE**	**NL-DML-RE**	**LIN-OLS-FE**	**NL-OLS-FE**	**LIN-DML-RE**	**NL-DML-RE**	**LIN-OLS-FE**	**NL-OLS-FE**
Soybeans, Double, Crop	Ellis	*Prec* — Short	0.007 (1.26)	0.012** (2.16)	−0.095*** (−10.48)	−0.097*** (−10.07)	0.017** (2.44)	0.017** (2.49)	−0.058*** (−3.68)	−0.052*** (−3.26)
		Prec — Long	0.017** (2.24)	0.03*** (3.21)	−0.097*** (−6.58)	−0.1*** (−6.71)	0.025** (2.19)	0.031*** (2.71)	−0.166*** (−3.20)	−0.113** (−2.03)
		PrecLow — Short	−0.123*** (−2.91)	−0.117*** (−2.72)	−0.335*** (−6.43)	−0.346*** (−6.59)	−0.07 (−1.57)	−0.058 (−1.28)	0.104 (1.62)	0.098 (1.52)
		PrecLong — Long	0.037 (1.02)	0.027 (0.73)	0.406*** (5.17)	0.428*** (5.37)	0.057 (1.36)	0.039 (0.91)	1.312*** (5.53)	1.368*** (5.72)
		GDD — Short	0.236*** (4.18)	0.221*** (3.84)	0.265*** (3.04)	0.248*** (2.75)	0.534*** (4.45)	0.631*** (4.81)	1.227*** (10.36)	1.244*** (10.48)
		GDD — Long	−0.183*** (−3.51)	−0.193*** (−3.49)	−1.934*** (−9.23)	−2.033*** (−8.58)	−0.275*** (−2.82)	−0.369*** (−3.43)	−1.681*** (−7.08)	−1.948*** (−7.75)
		GDDHigh — Short	0.093*** (3.37)	0.068** (2.39)	−0.016 (−0.32)	0.01 (0.18)	0.108*** (4.55)	0.085*** (3.32)	0.038 (0.43)	−0.057 (−0.61)
		GDDHigh — Long	−0.156*** (−4.01)	−0.142*** (−3.61)	0.036 (0.53)	0.056 (0.79)	−0.235*** (−5.72)	−0.219*** (−5.19)	−1.193*** (−7.71)	−1.323*** (−8.27)
	Ellsworth	*Prec* — Short	0.052*** (8.67)	0.046*** (6.62)	0.068*** (5.68)	0.044*** (2.98)	0.005 (0.37)	0.014 (1.00)	0.066*** (3.13)	0.03 (1.24)
		Prec — Long	0.082*** (7.52)	0.07*** (5.56)	0.134*** (5.02)	0.123*** (4.49)	0.145*** (7.99)	0.164*** (8.43)	0.222** (2.23)	0.121 (1.15)
		PrecLow — Short	0.24*** (4.05)	0.211*** (3.46)	−0.012 (−0.11)	−0.054 (−0.49)	0.46*** (7.84)	0.427*** (6.42)	0.485*** (4.29)	0.314*** (2.61)
		PrecLong — Long	−0.132** (−1.98)	−0.143** (−2.12)	0.223 (1.47)	0.152 (0.98)	−0.218*** (−3.24)	−0.159** (−2.26)	−0.852** (−2.34)	−1.1*** (−2.81)
		GDD — Short	−0.625*** (−5.12)	−0.582*** (−4.64)	−1.528*** (−7.13)	−1.225*** (−5.06)	0.968*** (4.35)	0.848*** (3.58)	0.007 (0.02)	0.473 (1.33)
		GDD — Long	−0.01 (−0.09)	0.143 (1.19)	−0.082 (−0.17)	0.455 (0.78)	−0.711*** (−4.42)	−0.699*** (−4.30)	0.043 (0.06)	−0.074 (−0.11)
		GDDHigh — Short	0.324*** (4.14)	0.251*** (2.87)	0.621*** (4.72)	0.424*** (2.87)	0.014 (0.19)	0.087 (0.98)	0.18 (1.36)	−0.085 (−0.57)
		GDDHigh — Long	0.464*** (5.21)	0.336*** (3.31)	0.988*** (6.00)	0.779*** (3.98)	0.559*** (6.73)	0.642*** (6.85)	0.603*** (2.76)	0.245 (1.02)
	Gove	*Prec* — Short	−0.026*** (−6.09)	−0.031*** (−6.31)	−0.062*** (−8.20)	−0.055*** (−7.02)	−0.012 (−1.15)	−0.008 (−0.77)	0.009 (0.63)	0.025* (1.73)
		Prec — Long	0.026*** (7.71)	0.036*** (8.79)	0.041*** (3.54)	0.092*** (5.66)	0.026*** (3.11)	0.02** (2.30)	0.055 (1.57)	0.099** (2.46)
		PrecLow — Short	−0.048** (−2.10)	−0.08*** (−3.25)	−0.137*** (−3.36)	−0.182*** (−4.34)	−0.033 (−1.05)	−0.011 (−0.34)	−0.21*** (−3.54)	−0.12* (−1.87)
		PrecLong — Long	0.056* (1.84)	0.096*** (2.98)	0.193*** (3.30)	0.191*** (3.27)	0.064* (1.65)	0.045 (1.11)	0.268* (1.95)	0.398*** (2.82)
		GDD — Short	−0.074 (−1.20)	−0.129** (−2.01)	−0.534*** (−8.57)	−0.597*** (−8.42)	−0.084 (−0.63)	−0.015 (−0.11)	0.055 (0.53)	0.151 (1.44)
		GDD — Long	0.105 (1.58)	0.119* (1.77)	−0.304* (−1.82)	0.035 (0.17)	0.23 (1.20)	0.15 (0.76)	−0.498** (−2.04)	−0.453* (−1.81)
		GDDHigh — Short	0.03 (1.09)	−0.033 (−1.05)	−0.041 (−0.89)	−0.02 (−0.44)	0.145*** (4.94)	0.172*** (5.20)	0.573*** (8.51)	0.509*** (7.37)
		GDDHigh — Long	−0.01 (−0.24)	0.115** (2.35)	0.086 (1.29)	0.292*** (3.33)	−0.15** (−1.99)	−0.199*** (−2.59)	0.131 (1.09)	−0.084 (−0.65)

Note: Values in parentheses are z-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A13 continued

Land Use	County	Variable	Lag Structure							
			Short = 1 to 3, Long = 4 to 10				Short = 1 to 5, Long = 6 to 20			
			Models							
			LIN-DML-RE	**NL-DML-RE**	**LIN-OLS-FE**	**NL-OLS-FE**	**LIN-DML-RE**	**NL-DML-RE**	**LIN-OLS-FE**	**NL-OLS-FE**
Soybeans, Double Crop	Lincoln	*Prec* — Short	0.008 (1.01)	−0.011 (−1.20)	0 (−0.02)	−0.013 (−0.72)	−0.005 (−0.42)	0.006 (0.46)	0.071*** (3.08)	0.064** (2.50)
		Prec — Long	0.024*** (2.95)	0.053*** (5.12)	−0.037* (−1.69)	0.023 (0.93)	0.085*** (6.56)	0.05*** (3.27)	−0.096 (−1.12)	−0.118 (−1.36)
		PrecLow — Short	0.414*** (5.93)	0.173** (2.16)	0.437*** (3.06)	0.461*** (3.19)	0.039 (0.45)	−0.127 (−1.16)	0.451** (2.02)	0.635*** (2.69)
		PrecLong — Long	−0.936*** (−12.08)	−0.685*** (−7.98)	−1.153*** (−4.50)	−0.74*** (−2.67)	−0.376*** (−3.04)	−0.228 (−1.63)	−1.695*** (−3.32)	−1.084* (−1.88)
		GDD — Short	0.159* (1.95)	−0.027 (−0.32)	0.41*** (2.98)	0.399*** (2.76)	0.638*** (4.19)	0.452*** (2.86)	0.104 (0.47)	0.159 (0.71)
		GDD — Long	−0.167 (−1.29)	0.125 (0.95)	−1.347*** (−2.87)	0.182 (0.31)	−0.719*** (−3.99)	−0.33* (−1.73)	−4.69*** (−6.17)	−5.006*** (−5.37)
		GDDHigh — Short	−0.232*** (−6.04)	−0.18*** (−4.52)	−0.579*** (−8.55)	−0.491*** (−6.89)	−0.033 (−0.87)	−0.016 (−0.42)	−0.213*** (−2.62)	−0.22*** (−2.67)
		GDDHigh — Long	0.45*** (13.48)	0.459*** (13.74)	−0.008 (−0.07)	−0.063 (−0.50)	0.417*** (9.12)	0.456*** (9.76)	−0.6*** (−3.07)	−0.581*** (−2.95)
	Ness	*Prec* — Short	−0.013*** (−2.65)	−0.02** (−2.32)	0.008 (1.48)	0.006 (1.00)	0.012* (1.71)	0.011 (1.36)	−0.02*** (−2.80)	−0.022*** (−3.03)
		Prec — Long	0.006 (1.60)	0.007 (1.39)	0.04*** (5.00)	0.037*** (4.43)	−0.012 (−1.57)	−0.015* (−1.67)	−0.166*** (−8.29)	−0.182*** (−8.90)
		PrecLow — Short	−0.039 (−1.33)	−0.024 (−0.66)	−0.114*** (−2.78)	−0.108** (−2.57)	0.051 (1.39)	0.04 (1.05)	−0.052 (−0.94)	−0.046 (−0.83)
		PrecLong — Long	0.047 (1.42)	0.037 (0.96)	−0.232*** (−3.24)	−0.249*** (−3.32)	−0.051 (−1.32)	−0.038 (−0.84)	−0.254** (−1.96)	−0.269** (−2.07)
		GDD — Short	0.053 (1.04)	0.022 (0.40)	−0.678*** (−10.34)	−0.644*** (−9.32)	0.083 (0.77)	0.089 (0.79)	−0.439*** (−4.30)	−0.469*** (−4.51)
		GDD — Long	0.056 (1.05)	0.117** (1.99)	−0.205* (−1.84)	−0.092 (−0.71)	−0.015 (−0.13)	−0.017 (−0.14)	−1.409*** (−8.25)	−1.412*** (−8.24)
		GDDHigh — Short	−0.018 (−0.61)	−0.017 (−0.52)	0.248*** (8.07)	0.232*** (7.30)	0.05** (2.15)	0.061** (2.47)	0.242*** (6.85)	0.243*** (6.86)
		GDDHigh — Long	−0.009 (−0.24)	−0.022 (−0.55)	0.626*** (13.01)	0.597*** (11.88)	−0.063* (−1.91)	−0.068** (−2.02)	0.207*** (3.32)	0.172*** (2.71)
	Ottawa	*Prec* — Short	−0.034** (−2.10)	−0.045*** (−2.79)	−0.029 (−1.24)	−0.078*** (−2.95)	0.028 (1.08)	−0.012 (−0.45)	0.13*** (3.11)	0.101** (2.20)
		Prec — Long	−0.013 (−0.73)	0.006 (0.25)	−0.135*** (−4.18)	−0.099** (−2.52)	−0.027 (−1.33)	−0.019 (−0.88)	0.536*** (5.48)	0.452*** (4.03)
		PrecLow — Short	0.28** (2.47)	0.253** (2.22)	0.541*** (3.06)	0.459*** (2.58)	0.474*** (3.86)	0.38*** (3.02)	−0.534** (−2.15)	−0.432* (−1.68)
		PrecLong — Long	0.382*** (3.13)	0.363*** (2.97)	0.484 (1.22)	0.448 (1.13)	−0.213 (−1.37)	0.083 (0.50)	−2.477*** (−6.20)	−2.269*** (−5.14)
		GDD — Short	0.423*** (3.21)	0.494*** (3.72)	0.468** (2.28)	0.89*** (3.36)	0.465** (2.37)	0.757*** (3.79)	0.93*** (3.26)	0.873*** (2.93)
		GDD — Long	0.683*** (4.55)	0.707*** (4.46)	−2.575*** (−4.22)	0.291 (0.30)	0.476** (2.18)	0.373* (1.68)	2.021*** (3.00)	2.324*** (3.32)
		GDDHigh — Short	0.027 (0.50)	−0.126** (−2.10)	−0.103 (−1.09)	−0.346*** (−2.93)	−0.019 (−0.34)	−0.208*** (−3.22)	−0.1 (−0.72)	−0.141 (−1.00)
		GDDHigh — Long	−0.32*** (−5.62)	−0.222*** (−3.48)	−0.378*** (−2.79)	−0.752*** (−3.30)	−0.27*** (−3.96)	−0.159** (−2.13)	−0.302 (−0.93)	−0.229 (−0.68)

Note: Values in parentheses are z-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A13 continued

			Lag Structure							
			Short = 1 to 3, Long = 4 to 10				Short = 1 to 5, Long = 6 to 20			
			Models							
Land Use	**County**	**Variable**	**LIN-DML-RE**	**NL-DML-RE**	**LIN-OLS-FE**	**NL-OLS-FE**	**LIN-DML-RE**	**NL-DML-RE**	**LIN-OLS-FE**	**NL-OLS-FE**
Soybeans,	Rush	*Prec* — Short	−0.003	−0.007	0.005	−0.001	0.316***	0.003	0.025*	0.01
			(−0.65)	(−1.40)	(0.53)	(−0.09)	(13.45)	(0.48)	(1.91)	(0.69)
Double		*Prec* — Long	0.024***	0.026***	0.067***	0.029	−0.065**	0.022**	−0.296***	−0.265***
			(6.25)	(6.40)	(3.42)	(1.33)	(−2.14)	(2.31)	(−8.00)	(−7.02)
Crop		*PrecLow* — Short	0.054	0.058	−0.117*	−0.209***	0.597***	0.099*	−0.184**	−0.156*
			(1.37)	(1.45)	(−1.81)	(−3.06)	(3.66)	(1.92)	(−2.41)	(−1.94)
		PrecLong — Long	−0.103***	−0.075**	−0.173*	−0.253***	0.888***	−0.024	−0.517**	−0.444*
			(−3.21)	(−2.26)	(−1.85)	(−2.65)	(6.68)	(−0.61)	(−2.08)	(−1.78)
		GDD — Short	0.158***	0.062	−0.291***	−0.299***	1.557***	0.443***	−0.223	0.055
			(4.38)	(1.44)	(−2.65)	(−2.71)	(5.02)	(3.97)	(−1.10)	(0.25)
		GDD — Long	0.072*	0.157***	−0.257**	−0.16	−1.814***	−0.154	−1.915***	−1.878***
			(1.76)	(3.39)	(−1.96)	(−1.12)	(−6.18)	(−1.34)	(−6.96)	(−6.63)
		GDDHigh — Short	−0.115***	−0.11***	0.122*	0.104	1.428***	−0.031	0.738***	0.628***
			(−2.81)	(−2.67)	(1.79)	(1.49)	(11.60)	(−0.86)	(7.64)	(6.26)
		GDDHigh — Long	0.098***	0.085**	0.542***	0.403***	−1.275***	0.037	0.809***	0.705***
			(3.39)	(2.55)	(8.43)	(5.53)	(−11.71)	(1.19)	(5.95)	(5.07)
	Russell	*Prec* — Short	0.017**	0.015**	−0.025*	−0.028*	0.142***	0.019	−0.047**	−0.053***
			(2.53)	(2.05)	(−1.78)	(−1.93)	(6.66)	(1.43)	(−2.47)	(−2.62)
		Prec — Long	0.075***	0.082***	−0.077***	−0.05*	0.164***	0.101***	−0.166*	−0.207**
			(6.47)	(6.93)	(−2.69)	(−1.71)	(4.19)	(3.51)	(−1.82)	(−2.12)
		PrecLow — Short	0.081	0.087	−0.102	−0.131	0.093	0.068	0.085	0.069
			(1.17)	(1.24)	(−0.90)	(−1.14)	(0.51)	(0.68)	(0.39)	(0.32)
		PrecLong — Long	0.127***	0.123***	0.137***	0.118***	0.186**	0.152***	0.338	0.23
			(4.82)	(4.64)	(3.57)	(3.06)	(1.99)	(2.83)	(0.50)	(0.34)
		GDD — Short	−0.052	−0.031	−0.439**	−0.473**	0.979***	0.595***	0.16	0.228
			(−0.67)	(−0.38)	(−2.36)	(−2.50)	(3.08)	(3.07)	(0.46)	(0.64)
		GDD — Long	−0.929***	−0.937***	−3.627***	−4.183***	1.563***	−1.041***	−5.407***	−5.034***
			(−6.62)	(−6.67)	(−10.22)	(−10.56)	(5.93)	(−6.69)	(−6.68)	(−5.88)
		GDDHigh — Short	−0.079	−0.106	−0.188	−0.129	0.816***	0.081	−0.127	−0.136
			(−1.07)	(−1.40)	(−1.33)	(−0.89)	(5.46)	(1.18)	(−0.57)	(−0.60)
		GDDHigh — Long	0.15**	0.17***	0.222*	0.417***	−0.855***	−0.026	−1.332***	−1.366***
			(2.53)	(2.85)	(1.66)	(2.91)	(−4.29)	(−0.26)	(−4.73)	(−4.82)
	Saline	*Prec* — Short	−0.003	−0.003	−0.074***	−0.065***	−0.008	0.064***	−0.156***	−0.106***
			(−0.26)	(−0.31)	(−3.65)	(−2.82)	(−0.34)	(3.37)	(−4.24)	(−2.76)
		Prec — Long	0.068***	0.062***	−0.082**	−0.046	−0.012	−0.038	−0.217**	−0.167
			(5.62)	(4.47)	(−2.18)	(−1.16)	(−0.35)	(−1.25)	(−2.03)	(−1.40)
		PrecLow — Short	−0.264***	−0.277***	−0.009	0.178	0.645***	−0.408***	0.807***	0.973***
			(−3.06)	(−3.18)	(−0.05)	(0.89)	(4.65)	(−3.63)	(2.73)	(3.32)
		PrecLong — Long	−0.165*	−0.126	0.01	0.542**	−0.2	0.204	0.952	1.796***
			(−1.88)	(−1.43)	(0.05)	(2.08)	(−1.16)	(1.48)	(1.43)	(2.67)
		GDD — Short	−0.109	−0.083	0.51**	0.404	−1.066***	−0.215	−0.794***	−0.874**
			(−0.74)	(−0.56)	(2.37)	(1.38)	(−4.29)	(−0.95)	(−2.70)	(−2.34)
		GDD — Long	0.815***	0.985***	−0.777	−1.646*	−1.043***	1.359***	−0.786	−0.092
			(5.36)	(6.07)	(−1.29)	(−1.70)	(−3.58)	(5.29)	(−0.95)	(−0.11)
		GDDHigh — Short	0.012	−0.057	−0.479***	−0.427***	0.233**	0.255***	−0.196	−0.15
			(0.16)	(−0.70)	(−4.89)	(−3.05)	(2.18)	(3.17)	(−1.03)	(−0.77)
		GDDHigh — Long	0.208**	0.167*	−0.164	0	0.38***	0.002	0.405	0.47
			(2.28)	(1.81)	(−1.11)	(0.00)	(2.90)	(0.02)	(1.16)	(1.36)

Note: Values in parentheses are z-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A13 continued

			Lag Structure							
			Short = 1 to 3, Long = 4 to 10				Short = 1 to 5, Long = 6 to 20			
			Models							
Land Use	**County**	**Variable**	**LIN-DML-RE**	**NL-DML-RE**	**LIN-OLS-FE**	**NL-OLS-FE**	**LIN-DML-RE**	**NL-DML-RE**	**LIN-OLS-FE**	**NL-OLS-FE**
Soybeans, Double Crop	Trego	*Prec* — Short	−0.002	−0.009*	−0.022***	−0.03***	−0.003	−0.004	−0.018	−0.025**
			(−0.51)	(−1.94)	(−3.44)	(−4.35)	(−0.78)	(−0.81)	(−1.50)	(−1.99)
		Prec — Long	0.007**	0.014***	0.041***	0.023*	0.023***	0.027***	0.027	−0.001
			(2.04)	(2.99)	(3.82)	(1.82)	(3.10)	(3.29)	(0.70)	(−0.03)
		PrecLow — Short	0.09***	0.099***	0.13***	0.105***	−0.091***	−0.083**	−0.036	−0.011
			(3.54)	(3.59)	(3.42)	(2.64)	(−2.89)	(−2.49)	(−0.55)	(−0.16)
		PrecLong — Long	−0.08***	−0.086***	−0.126**	−0.134**	0.133***	0.112***	0.279*	0.328**
			(−3.05)	(−3.05)	(−2.34)	(−2.41)	(4.35)	(3.21)	(1.90)	(2.20)
		GDD — Short	−0.124*	−0.133*	−0.188***	−0.047	−0.071	−0.083	1.175***	1.247***
			(−1.94)	(−1.87)	(−3.30)	(−0.67)	(−0.76)	(−0.89)	(14.59)	(14.04)
		GDD — Long	−0.411***	−0.315**	−0.798***	−0.457*	0.337***	0.365***	0.008	0.159
			(−3.29)	(−2.36)	(−3.76)	(−1.89)	(3.56)	(3.55)	(0.05)	(0.87)
		GDDHigh — Short	0.035	0.03	0.099**	−0.006	0.253***	0.264***	−0.171***	−0.208***
			(1.26)	(1.07)	(2.19)	(−0.12)	(5.03)	(4.61)	(−2.75)	(−3.07)
		GDDHigh — Long	0.142**	0.109	0.359***	0.197***	−0.38***	−0.383***	−1.331***	−1.355***
			(2.47)	(1.62)	(7.14)	(2.81)	(−6.79)	(−5.56)	(−10.50)	(−10.24)
Wheat	Barton	*Prec* — Short	0.015*	0.045***	−0.002	0.064***	0.182***	0.234***	0.056***	0.124***
			(1.73)	(4.00)	(−0.19)	(3.49)	(11.03)	(13.71)	(2.66)	(5.07)
		Prec — Long	0.213***	0.262***	0.078***	0.204***	0.01	0.184***	−0.021	0.245**
			(12.54)	(12.04)	(3.07)	(6.16)	(0.33)	(5.12)	(−0.20)	(2.25)
		PrecLow — Short	0.226**	0.243***	0.369***	0.237*	−0.079	0.139	0.162	0.253
			(2.47)	(2.64)	(2.65)	(1.68)	(−0.68)	(1.18)	(0.84)	(1.32)
		PrecLong — Long	−0.413***	−0.424***	−0.172	−0.359*	−0.424***	−0.34***	−0.418	−1.141*
			(−4.08)	(−4.04)	(−0.89)	(−1.77)	(−3.91)	(−3.02)	(−0.62)	(−1.66)
		GDD — Short	0.69***	0.671***	0.715***	0.153	0.598***	0.891***	2.898***	2.337***
			(4.41)	(4.16)	(3.26)	(0.62)	(2.63)	(3.85)	(6.92)	(5.13)
		GDD — Long	−0.702***	−0.98***	−2.329***	−3.225***	−0.618***	−1.492***	0.124	−1.163
			(−6.66)	(−7.33)	(−5.11)	(−6.72)	(−2.60)	(−5.91)	(0.14)	(−1.27)
		GDDHigh — Short	0.059	0.159	−0.163	0.217	1.028***	1.281***	−0.127	−0.083
			(0.56)	(1.41)	(−1.04)	(1.25)	(9.55)	(11.57)	(−0.82)	(−0.51)
		GDDHigh — Long	0.063	0.358***	−0.273	0.532**	−1.236***	−0.92***	−2.283***	−2.183***
			(0.57)	(2.77)	(−1.64)	(2.47)	(−12.63)	(−9.01)	(−7.79)	(−7.42)
	Ellis	*Prec* — Short	−0.177***	−0.066***	−0.103***	−0.038	0.22***	0.199***	0.46***	0.506***
			(−11.80)	(−4.03)	(−3.89)	(−1.34)	(12.14)	(9.30)	(10.19)	(10.93)
		Prec — Long	0.137***	0.246***	0.057	0.148***	−0.321***	−0.228***	0.69***	1.004***
			(7.31)	(12.24)	(1.34)	(3.42)	(−9.94)	(−5.95)	(4.60)	(6.23)
		PrecLow — Short	−0.486***	−0.096	−0.178	0.144	0.572***	0.565***	1.143***	1.181***
			(−4.06)	(−0.79)	(−1.18)	(0.95)	(4.54)	(4.45)	(6.19)	(6.34)
		PrecLong — Long	0.363***	0.068	0.466**	−0.147	−0.29**	−0.314***	2.826***	2.877***
			(3.26)	(0.60)	(2.04)	(−0.64)	(−2.46)	(−2.61)	(4.13)	(4.17)
		GDD — Short	1.079***	0.569***	0.261	0.606**	4.204***	4.466***	3.554***	3.58***
			(9.01)	(4.37)	(1.03)	(2.32)	(16.24)	(12.85)	(10.41)	(10.46)
		GDD — Long	0.336**	0.504***	−1.772***	0.361	0.199	−0.14	4.009***	2.948***
			(2.36)	(3.32)	(−2.91)	(0.53)	(0.96)	(−0.62)	(5.85)	(4.07)
		GDDHigh — Short	0.177**	0.012	0.494***	−0.157	1.548***	1.432***	0.876***	0.446*
			(2.22)	(0.15)	(3.31)	(−0.99)	(20.32)	(12.96)	(3.43)	(1.66)
		GDDHigh — Long	0.072	0.306***	0.386**	−0.058	−2.379***	−2.278***	−2.791***	−3.295***
			(0.76)	(3.20)	(1.98)	(−0.28)	(−20.88)	(−11.57)	(−6.25)	(−7.14)

Note: Values in parentheses are z-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A13 continued

			Lag Structure							
			Short = 1 to 3, Long = 4 to 10				Short = 1 to 5, Long = 6 to 20			
			Models							
Land Use	**County**	**Variable**	**LIN-DML-RE**	**NL-DML-RE**	**LIN-OLS-FE**	**NL-OLS-FE**	**LIN-DML-RE**	**NL-DML-RE**	**LIN-OLS-FE**	**NL-OLS-FE**
Wheat	Ellsworth	*Prec* — Short	−0.046***	−0.06***	−0.154***	−0.143***	−0.066**	−0.078***	−0.144***	−0.135***
			(−3.67)	(−4.08)	(−7.36)	(−5.55)	(−2.48)	(−2.72)	(−3.87)	(−3.20)
		Prec — Long	0.079***	0.099***	−0.128***	−0.093*	0.107***	0.082**	−0.308*	−0.287
			(3.49)	(3.66)	(−2.75)	(−1.94)	(3.09)	(2.11)	(−1.77)	(−1.55)
		PrecLow — Short	−0.008	−0.051	0.29	0.207	−0.372***	−0.35**	−0.312	−0.256
			(−0.08)	(−0.50)	(1.52)	(1.07)	(−2.94)	(−2.54)	(−1.58)	(−1.21)
		PrecLong — Long	−0.276**	−0.245*	−0.533**	−0.421	−0.158	−0.22	−0.106	−0.089
			(−2.20)	(−1.92)	(−2.01)	(−1.56)	(−1.05)	(−1.42)	(−0.17)	(−0.13)
		GDD — Short	0.467**	0.654***	1.793***	1.55***	2.693***	2.825***	3.176***	3.028***
			(1.99)	(2.71)	(4.79)	(3.66)	(6.13)	(5.85)	(5.41)	(4.88)
		GDD — Long	−2.15***	−2.207***	−0.424	−2.114**	−2.561***	−2.582***	−0.531	−0.554
			(−10.88)	(−9.29)	(−0.50)	(−2.07)	(−8.22)	(−8.14)	(−0.45)	(−0.46)
		GDDHigh — Short	−0.036	−0.233	0.192	0.186	0.244	0.154	0.839***	0.914***
			(−0.20)	(−1.20)	(0.83)	(0.72)	(1.58)	(0.86)	(3.63)	(3.49)
		GDDHigh — Long	0.67***	0.717***	0.503*	0.975***	−0.181	−0.306	0.932**	1.028**
			(3.62)	(3.34)	(1.75)	(2.85)	(−1.10)	(−1.62)	(2.44)	(2.45)
	Gove	*Prec* — Short	−0.026*	−0.027*	0.044*	0.035	0.212***	0.21***	−0.041	0.056
			(−1.71)	(−1.68)	(1.82)	(1.40)	(9.50)	(9.39)	(−0.93)	(1.22)
		Prec — Long	0.131***	0.107***	0.243***	0.197***	−0.068***	−0.049**	−0.687***	−0.33**
			(10.62)	(6.16)	(6.51)	(3.78)	(−3.79)	(−2.56)	(−6.12)	(−2.57)
		PrecLow — Short	−0.299***	−0.294***	−0.072	−0.068	−0.351***	−0.169	−1.213***	−0.64***
			(−3.79)	(−3.36)	(−0.55)	(−0.50)	(−3.03)	(−1.41)	(−6.40)	(−3.13)
		PrecLong — Long	0.232**	0.226**	−0.332*	−0.333*	0.482***	0.384***	−0.433	0.36
			(2.53)	(2.31)	(−1.78)	(−1.78)	(3.50)	(2.72)	(−0.99)	(0.80)
		GDD — Short	0.435***	0.569***	1.409***	1.696***	3.087***	3.145***	2.957***	3.386***
			(3.58)	(4.32)	(7.06)	(7.47)	(13.32)	(13.60)	(8.95)	(10.14)
		GDD — Long	−0.823***	−0.722***	−0.593	−0.002	−3.014***	−3.422***	−0.392	−0.631
			(−4.68)	(−3.90)	(−1.11)	(0.00)	(−8.81)	(−9.35)	(−0.50)	(−0.79)
		GDDHigh — Short	0.536***	0.567***	0.076	0.054	0.524***	0.769***	1.741***	1.357***
			(6.49)	(6.37)	(0.51)	(0.36)	(5.98)	(7.58)	(8.09)	(6.16)
		GDDHigh — Long	−0.444***	−0.612***	−0.981***	−1.392***	−0.843***	−0.958***	1.589***	0.329
			(−4.04)	(−4.50)	(−4.62)	(−4.95)	(−5.54)	(−6.05)	(4.16)	(0.80)
	Lincoln	*Prec* — Short	−0.037***	−0.015	−0.025	−0.02	−0.003	−0.019	−0.116***	−0.135***
			(−3.02)	(−1.06)	(−1.02)	(−0.79)	(−0.16)	(−0.93)	(−3.62)	(−3.78)
		Prec — Long	0.05***	0.008	0.051*	−0.028	0.043**	0.064***	−0.445***	−0.444***
			(3.77)	(0.52)	(1.69)	(−0.79)	(2.15)	(2.65)	(−3.74)	(−3.67)
		PrecLow — Short	0.647***	0.712***	0.345*	0.27	0.703***	0.434**	0.593*	0.205
			(5.59)	(5.57)	(1.73)	(1.34)	(4.88)	(2.42)	(1.90)	(0.62)
		PrecLong — Long	0.454***	0.461***	0.027	−0.586	0.602***	1.028***	1.133	0.621
			(3.63)	(3.35)	(0.08)	(−1.51)	(3.12)	(4.57)	(1.59)	(0.77)
		GDD — Short	0.657***	0.732***	0.345*	0.461**	1.281***	1.255***	1.047***	1.053***
			(5.53)	(5.78)	(1.79)	(2.28)	(5.45)	(5.11)	(3.37)	(3.34)
		GDD — Long	0.313	−0.265	−0.212	−1.207	−0.255	−0.834***	−2.351**	−0.481
			(1.64)	(−1.31)	(−0.32)	(−1.49)	(−0.95)	(−2.84)	(−2.22)	(−0.37)
		GDDHigh — Short	−0.208***	−0.251***	−0.021	−0.151	−0.075	−0.085	−0.013	−0.038
			(−3.28)	(−3.76)	(−0.23)	(−1.52)	(−1.28)	(−1.40)	(−0.12)	(−0.33)
		GDDHigh — Long	−0.25***	−0.313***	0.153	0.078	−0.501***	−0.629***	−0.796***	−0.755***
			(−4.99)	(−5.97)	(0.98)	(0.45)	(−7.08)	(−8.42)	(−2.92)	(−2.74)

Note: Values in parentheses are z-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A13 continued

Land Use	County	Variable	Lag Structure							
			Short = 1 to 3, Long = 4 to 10				Short = 1 to 5, Long = 6 to 20			
			Models							
			LIN-DML-RE	**NL-DML-RE**	**LIN-OLS-FE**	**NL-OLS-FE**	**LIN-DML-RE**	**NL-DML-RE**	**LIN-OLS-FE**	**NL-OLS-FE**
Wheat	Ness	*Prec* — Short	−0.025*	0.011	−0.044**	0.033	0.181***	0.207***	−0.008	0.015
			(−1.88)	(0.71)	(−2.23)	(1.46)	(10.20)	(11.34)	(−0.30)	(0.56)
		Prec — Long	0.188***	0.156***	0.205***	0.082***	0.054***	0.084***	−0.718***	−0.676***
			(14.36)	(10.46)	(6.86)	(2.62)	(2.76)	(3.96)	(−9.60)	(−8.84)
		PrecLow — Short	0.27***	0.381***	−0.291*	−0.56***	0.829***	0.814***	0.885***	0.776***
			(3.00)	(4.13)	(−1.88)	(−3.54)	(6.61)	(6.47)	(4.27)	(3.71)
		PrecLong — Long	−0.2**	−0.299***	−1.126***	−2.184***	−0.564***	−0.555***	−0.763	−0.918*
			(−2.20)	(−3.22)	(−4.18)	(−7.75)	(−4.48)	(−4.34)	(−1.58)	(−1.88)
		GDD — Short	1.538***	1.347***	1.341***	1.359***	2.823***	2.775***	5.328***	5.183***
			(14.75)	(12.55)	(5.44)	(5.24)	(10.55)	(10.21)	(13.95)	(13.33)
		GDD — Long	−0.162	0.087	0.023	0.399	−1.013***	−1.01***	0.016	−0.146
			(−1.40)	(0.69)	(0.05)	(0.82)	(−3.75)	(−3.66)	(0.03)	(−0.23)
		GDDHigh — Short	0.094	0.111	0.274**	0.036	0.541***	0.492***	−0.34**	−0.327**
			(1.27)	(1.49)	(2.37)	(0.30)	(7.62)	(6.83)	(−2.57)	(−2.47)
		GDDHigh — Long	−0.192***	−0.254***	0.264	−0.207	−0.435***	−0.416***	−2.402***	−2.382***
			(−2.79)	(−3.56)	(1.46)	(−1.10)	(−5.47)	(−5.15)	(−10.30)	(−10.07)
	Ottawa	*Prec* — Short	0.082***	0.096***	0.064**	0.103***	−0.013	0.047	−0.054	−0.015
			(4.02)	(4.62)	(2.35)	(3.32)	(−0.39)	(1.38)	(−1.10)	(−0.27)
		Prec — Long	0.14***	0.111***	0.205***	0.199***	0.087***	0.076***	−0.387***	−0.295**
			(6.07)	(4.08)	(5.40)	(4.32)	(3.46)	(2.81)	(−3.37)	(−2.24)
		PrecLow — Short	−0.142	−0.125	−0.897***	−0.852***	−0.368**	−0.218	0.192	0.059
			(−0.95)	(−0.83)	(−4.33)	(−4.08)	(−2.26)	(−1.31)	(0.66)	(0.20)
		PrecLong — Long	−0.48***	−0.444***	−1.484***	−1.484***	0.499**	0.088	2.874***	2.556***
			(−2.94)	(−2.72)	(−3.19)	(−3.18)	(2.38)	(0.39)	(6.13)	(4.93)
		GDD — Short	−0.451***	−0.542***	−0.644***	−1.057***	−0.311	−0.697***	−0.555*	−0.522
			(−2.70)	(−3.18)	(−2.68)	(−3.41)	(−1.28)	(−2.84)	(−1.66)	(−1.49)
		GDD — Long	−0.682***	−0.656***	2.082***	−0.208	0.029	0.138	−2.591***	−2.994***
			(−3.74)	(−3.39)	(2.91)	(−0.18)	(0.10)	(0.49)	(−3.28)	(−3.65)
		GDDHigh — Short	0.047	0.203**	0.004	0.209	0.207***	0.474***	−0.212	−0.164
			(0.63)	(2.46)	(0.04)	(1.52)	(2.78)	(5.60)	(−1.29)	(−0.99)
		GDDHigh — Long	0.344***	0.237***	0.371**	0.773***	−0.005	−0.163*	−1.116***	−1.235***
			(4.79)	(3.00)	(2.34)	(2.89)	(−0.06)	(−1.71)	(−2.92)	(−3.14)
	Rush	*Prec* — Short	−0.092***	−0.069***	−0.137***	−0.159***	−0.187***	0.338***	0.178***	0.174***
			(−5.20)	(−3.80)	(−4.91)	(−5.63)	(−7.89)	(14.01)	(5.02)	(4.63)
		Prec — Long	0.091***	0.075***	−0.076	−0.23***	0.229***	−0.022	0.459***	0.503***
			(6.50)	(4.95)	(−1.44)	(−3.94)	(8.01)	(−0.68)	(4.58)	(4.91)
		PrecLow — Short	1.049***	0.839***	0.946***	0.554***	0.402***	0.233	1.27***	1.167***
			(7.74)	(6.01)	(5.38)	(2.97)	(2.64)	(1.29)	(6.14)	(5.32)
		PrecLong — Long	0.594***	0.833***	−0.053	−0.332	−1.035***	1.043***	0.661	0.719
			(5.52)	(7.30)	(−0.21)	(−1.28)	(−8.27)	(7.60)	(0.98)	(1.06)
		GDD — Short	2.2***	1.891***	2.969***	2.889***	0.984***	1.697***	4.998***	5.148***
			(18.21)	(12.97)	(9.92)	(9.63)	(3.32)	(5.29)	(9.08)	(8.75)
		GDD — Long	−0.7***	−0.588***	0.116	0.218	−0.778***	−2.2***	3.46***	3.149***
			(−4.71)	(−3.63)	(0.33)	(0.56)	(−2.71)	(−7.04)	(4.63)	(4.10)
		GDDHigh — Short	0.005	−0.005	0.051	−0.099	−1.273***	1.571***	−0.538**	−0.643**
			(0.03)	(−0.04)	(0.28)	(−0.52)	(−10.31)	(12.40)	(−2.05)	(−2.36)
		GDDHigh — Long	−0.601***	−0.911***	−1.052***	−1.647***	0.616***	−1.253***	−3.343***	−3.567***
			(−5.34)	(−7.35)	(−6.01)	(−8.30)	(5.92)	(−11.21)	(−9.06)	(−9.45)

Table A13 continued

			Lag Structure							
			Short = 1 to 3, Long = 4 to 10				Short = 1 to 5, Long = 6 to 20			
			Models							
Land Use	**County**	**Variable**	**LIN-DML-RE**	**NL-DML-RE**	**LIN-OLS-FE**	**NL-OLS-FE**	**LIN-DML-RE**	**NL-DML-RE**	**LIN-OLS-FE**	**NL-OLS-FE**
Wheat	Russell	*Prec* — Short	0.05***	0.048***	−0.041	−0.071***	−0.137***	0.143***	−0.13***	−0.137***
			(3.74)	(3.43)	(−1.58)	(−2.70)	(−6.78)	(6.66)	(−3.70)	(−3.68)
		Prec — Long	0.517***	0.515***	0.266***	0.287***	0.105***	0.143***	−0.567***	−0.604***
			(21.84)	(20.10)	(5.07)	(5.37)	(2.83)	(3.03)	(−3.39)	(−3.37)
		PrecLow — Short	0.201	0.115	−0.141	0.051	−0.206	−0.077	0.742*	0.717*
			(1.37)	(0.76)	(−0.68)	(0.24)	(−1.20)	(−0.41)	(1.87)	(1.80)
		PrecLong — Long	0.094**	0.098**	−0.219***	−0.224***	0.315***	0.142	0.054	−0.011
			(1.98)	(2.06)	(−3.12)	(−3.18)	(3.58)	(1.40)	(0.04)	(−0.01)
		GDD — Short	−0.335**	−0.616***	0.668**	1.019***	−0.433	0.762**	2.417***	2.432***
			(−2.33)	(−3.87)	(1.97)	(2.95)	(−1.31)	(2.37)	(3.77)	(3.76)
		GDD — Long	0.528*	0.549*	−1.581**	−0.213	−1.866***	1.59***	−6.307***	−6.015***
			(1.84)	(1.89)	(−2.44)	(−0.29)	(−7.06)	(5.88)	(−4.25)	(−3.84)
		GDDHigh — Short	0.14	0.172	−0.89***	−1.16***	−0.735***	0.843***	−1.964***	−1.966***
			(0.90)	(1.09)	(−3.44)	(−4.40)	(−5.15)	(5.57)	(−4.77)	(−4.77)
		GDDHigh — Long	0.825***	0.787***	−0.022	−0.342	0.964***	−1.028***	−5.815***	−5.849***
			(6.36)	(6.02)	(−0.09)	(−1.31)	(4.84)	(−5.02)	(−11.27)	(−11.26)
	Saline	*Prec* — Short	0.007	0.012	0.086***	0.076***	−0.004	−0.017	0.131***	0.102**
			(0.59)	(0.90)	(3.62)	(2.81)	(−0.21)	(−0.68)	(3.04)	(2.27)
		Prec — Long	−0.064***	−0.064***	0.111**	0.091**	−0.043*	0.008	0.126	0.122
			(−4.19)	(−3.53)	(2.53)	(1.96)	(−1.77)	(0.21)	(1.01)	(0.87)
		PrecLow — Short	0.523***	0.545***	0.043	−0.018	−0.196**	0.643***	−0.996***	−1.026***
			(5.00)	(5.11)	(0.19)	(−0.08)	(−1.97)	(4.58)	(−2.89)	(−3.00)
		PrecLong — Long	0.151	0.139	0.072	−0.202	−0.07	−0.194	−1.088	−1.424*
			(1.38)	(1.26)	(0.28)	(−0.66)	(−0.57)	(−1.09)	(−1.40)	(−1.81)
		GDD — Short	−0.654***	−0.64***	−0.807***	−0.614*	0.641***	−1.034***	−0.167	−0.073
			(−3.49)	(−3.37)	(−3.22)	(−1.79)	(3.33)	(−3.79)	(−0.49)	(−0.17)
		GDD — Long	−0.92***	−0.9***	0.848	1.797	0.606***	−1.111***	3.404***	2.627***
			(−5.00)	(−4.51)	(1.21)	(1.59)	(3.01)	(−3.54)	(3.54)	(2.68)
		GDDHigh — Short	0.282***	0.29***	0.392***	0.286*	−0.438***	0.255**	0.819***	0.735***
			(2.78)	(2.61)	(3.44)	(1.75)	(−5.35)	(2.31)	(3.69)	(3.22)
		GDDHigh — Long	0.116	0.123	0.126	−0.072	−0.511***	0.393***	0.19	0.084
			(1.01)	(1.06)	(0.73)	(−0.27)	(−5.50)	(2.98)	(0.47)	(0.21)
	Trego	*Prec* — Short	−0.01	−0.006	−0.01	−0.021	0.194***	0.181***	0.014	0.012
			(−0.81)	(−0.47)	(−0.45)	(−0.92)	(12.83)	(11.97)	(0.35)	(0.29)
		Prec — Long	0.241***	0.238***	0.149***	0.084**	0.13***	0.089***	−0.5***	−0.516***
			(19.72)	(19.13)	(4.10)	(2.03)	(4.71)	(3.20)	(−3.92)	(−3.81)
		PrecLow — Short	0.558***	0.583***	0.968***	0.831***	0.782***	0.792***	1.057***	0.979***
			(6.15)	(6.20)	(7.58)	(6.25)	(8.39)	(8.33)	(4.89)	(4.45)
		PrecLong — Long	0.122	0.106	−0.328*	−0.476**	0.332***	0.378***	0.277	0.055
			(1.36)	(1.17)	(−1.82)	(−2.57)	(3.60)	(4.08)	(0.57)	(0.11)
		GDD — Short	1.304***	1.279***	1.831***	2.101***	4.83***	4.367***	5.043***	4.799***
			(10.09)	(9.60)	(9.58)	(8.82)	(21.82)	(18.71)	(18.79)	(16.21)
		GDD — Long	0.499*	0.294	−0.044	0.135	3.904***	3.147***	4.373***	3.929***
			(1.82)	(0.86)	(−0.06)	(0.17)	(13.55)	(10.52)	(7.93)	(6.50)
		GDDHigh — Short	−0.28***	−0.25**	−0.668***	−0.869***	0.018	0.2**	−1.449***	−1.231***
			(−2.93)	(−2.52)	(−4.42)	(−4.70)	(0.21)	(2.23)	(−6.98)	(−5.46)
		GDDHigh — Long	−0.855***	−0.797***	−1.36***	−1.624***	−3.459***	−3.256***	−6.342***	−6.003***
			(−7.55)	(−6.13)	(−8.08)	(−6.90)	(−25.87)	(−24.09)	(−15.01)	(−13.62)

Note: Values in parentheses are z-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A14. NL-DML-RE Partial Effects,
Price Variables, 1-3 and 4-10 lag structure

		Land Use				
County	**Price**	**Alfalfa**	**Corn/ Sorghum**	**Fallow**	**Soy-beans/ Double Crop**	**Wheat**
Barton	p_A	0.001 (0.03)	0.341^{***} (6.85)	-0.164^{***} (−5.62)	0.024 (0.82)	-0.201^{***} (−3.39)
	p_{Sor}	0.000 (0.01)	0.049^{***} (4.8)	0.075^{***} (11.52)	-0.052^{***} (−8.27)	-0.072^{***} (−5.81)
	p_{Soy}	0.000 (0.03)	0.032^{***} (3.76)	-0.080^{***} (−15.28)	0.046^{***} (8.3)	0.002 (0.2)
	p_W	−0.004 (−0.74)	-0.083^{***} (−9.64)	0.054^{***} (10.72)	-0.028^{***} (−5.32)	0.061^{***} (5.9)
Ellis	p_A	0.013^{*} (1.72)	0.224^{***} (4.74)	-0.145^{***} (−3.27)	-0.067^{***} (−3.43)	−0.025 (−0.48)
	p_{Sor}	0.003 (1.09)	0.043^{***} (3.41)	0.120^{***} (10.39)	-0.094^{***} (−11.15)	-0.072^{***} (−5)
	p_{Soy}	−0.001 (−0.41)	0.010 (1.43)	-0.104^{***} (−17.09)	0.049^{***} (10.15)	0.046^{***} (6.06)
	p_W	0.000 (−0.02)	-0.020^{**} (−2.54)	0.035^{***} (4.68)	0.002 (0.62)	-0.017^{*} (−1.94)
Ellsworth	p_A	0.052^{**} (2.03)	−0.067 (−0.71)	0.017 (0.3)	0.010 (0.22)	−0.011 (−0.11)
	p_{Sor}	0.011 (1.42)	0.123^{***} (5.82)	−0.013 (−1.07)	-0.023^{*} (−1.85)	-0.097^{***} (−4.1)
	p_{Soy}	0.002 (0.38)	-0.067^{***} (−3.85)	−0.012 (−1.14)	0.021^{**} (2.33)	0.057^{***} (2.98)
	p_W	-0.009^{*} (−1.76)	−0.002 (−0.14)	0.024^{**} (2.39)	−0.013 (−1.61)	0.001 (0.05)
Gove	p_A	−0.005 (−0.39)	0.494^{***} (8.67)	0.110^{**} (2.26)	0.004 (0.2)	-0.603^{***} (−12.67)
	p_{Sor}	0.001 (0.47)	−0.017 (−1.41)	−0.013 (−1.32)	-0.022^{***} (−3.13)	0.051^{***} (4.79)
	p_{Soy}	−0.002 (−1.13)	0.052^{***} (5.97)	0.036^{***} (4.85)	0.020^{***} (4.04)	-0.106^{***} (−14.6)
	p_W	0.002 (1.22)	-0.032^{***} (−3)	-0.085^{***} (−9.49)	-0.008^{**} (−2.01)	0.123^{***} (13.56)
Lincoln	p_A	-0.035^{**} (−2.5)	0.045 (1.17)	-0.065^{***} (−4.5)	0.130^{***} (5.46)	-0.074^{*} (−1.76)
	p_{Sor}	−0.014 (−1.51)	0.074^{***} (5.11)	0.010^{*} (1.84)	-0.147^{***} (−11.99)	0.077^{***} (4.11)
	p_{Soy}	0.003 (0.64)	-0.030^{***} (−3.24)	-0.022^{***} (−6.22)	0.115^{***} (15.05)	-0.066^{***} (−5.58)
	p_W	−0.005 (−1.25)	−0.005 (−0.68)	0.024^{***} (7.66)	-0.037^{***} (−6.93)	0.024^{***} (2.72)
Ness	p_A	−0.003 (−0.19)	0.198^{***} (3.93)	0.072 (1.24)	−0.021 (−0.86)	-0.245^{***} (−4.92)
	p_{Sor}	0.001 (0.49)	−0.013 (−1.15)	0.061^{***} (4.72)	-0.014^{**} (−2.06)	-0.035^{***} (−2.86)
	p_{Soy}	−0.001 (−0.37)	0.041^{***} (4.45)	-0.025^{**} (−2.38)	0.013^{***} (2.78)	-0.028^{***} (−2.99)
	p_W	0.000 (−0.14)	-0.038^{***} (−4.37)	−0.010 (−0.98)	−0.005 (−1.15)	0.053^{***} (6.04)

Table A14 continued

County	Price	Land Use: Alfalfa	Corn/ Sorghum	Fallow	Soybeans/ Double Crop	Wheat
Ottawa	p_A	−0.025 (−1.17)	0.094** (2.09)		−0.086** (−2.19)	0.017 (0.33)
	p_{Sor}	−0.001 (−0.08)	−0.005 (−0.35)		−0.137*** (−8.63)	0.143*** (7.12)
	p_{Soy}	0.001 (0.23)	0.019 (1.64)		0.080*** (6.96)	−0.101*** (−6.93)
	p_W	0.002 (0.33)	−0.015* (−1.69)		0.001 (0.09)	0.013 (1.12)
Rush	p_A	0.035 (1.61)	0.475*** (5.62)	−0.146** (−2.06)	0.065*** (2.75)	−0.428*** (−4.93)
	p_{Sor}	−0.007** (−2.26)	0.005 (0.43)	0.076*** (7.64)	−0.033*** (−8.49)	−0.041*** (−3.31)
	p_{Soy}	0.007** (2.45)	0.067*** (7.08)	−0.069*** (−8.15)	0.029*** (8.83)	−0.035*** (−3.41)
	p_W	−0.005 (−1.46)	−0.066*** (−4.46)	0.018 (1.43)	−0.012*** (−3.17)	0.065*** (4.33)
Russell	p_A	−0.003 (−0.21)	0.047 (0.71)	−0.156*** (−3.24)	0.046 (1.3)	0.066 (0.89)
	p_{Sor}	−0.002 (−0.55)	0.053*** (3.64)	0.080*** (7.48)	−0.090*** (−10.89)	−0.041*** (−2.67)
	p_{Soy}	0.001 (0.29)	−0.005 (−0.51)	−0.084*** (−11.47)	0.071*** (10.33)	0.018 (1.55)
	p_W	0.002 (0.52)	−0.041*** (−3.28)	0.028*** (3.24)	−0.026*** (−3.87)	0.036*** (2.74)
Saline	p_A	0.043* (1.75)	−0.035 (−0.81)	−0.003 (−0.9)	0.041 (0.93)	−0.046 (−0.79)
	p_{Sor}	−0.005 (−0.63)	−0.034*** (−2.84)	−0.002** (−2.38)	−0.077*** (−5.9)	0.118*** (6.68)
	p_{Soy}	0.014*** (2.97)	0.012 (1.46)	0.001 (1.46)	0.058*** (7.08)	−0.086*** (−7.65)
	p_W	−0.017*** (−2.89)	0.013 (1.33)	0.001* (1.81)	−0.006 (−0.62)	0.009 (0.63)
Trego	p_A	0.002 (0.12)	−0.006 (−0.11)	0.270*** (4.97)	−0.031* (−1.8)	−0.235*** (−4.87)
	p_{Sor}	0.004 (1.13)	−0.009 (−0.58)	0.102*** (7.36)	−0.028*** (−3.4)	−0.069*** (−5.09)
	p_{Soy}	−0.002 (−0.95)	0.025*** (3.13)	−0.051*** (−6.81)	0.018*** (3.6)	0.010 (1.38)
	p_W	0.000 (0.04)	−0.030*** (−3.08)	−0.016 (−1.64)	0.003 (0.42)	0.042*** (4.95)

Note: Values in parentheses are z-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Figures

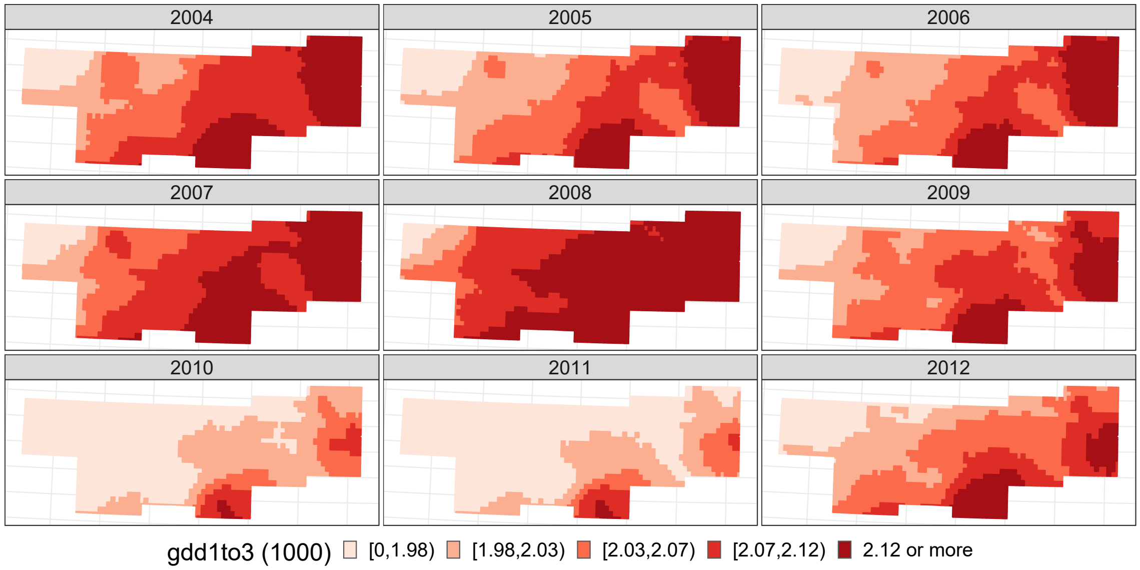

Figure A1. Spatial and temporal variation in $GDD1to3$.

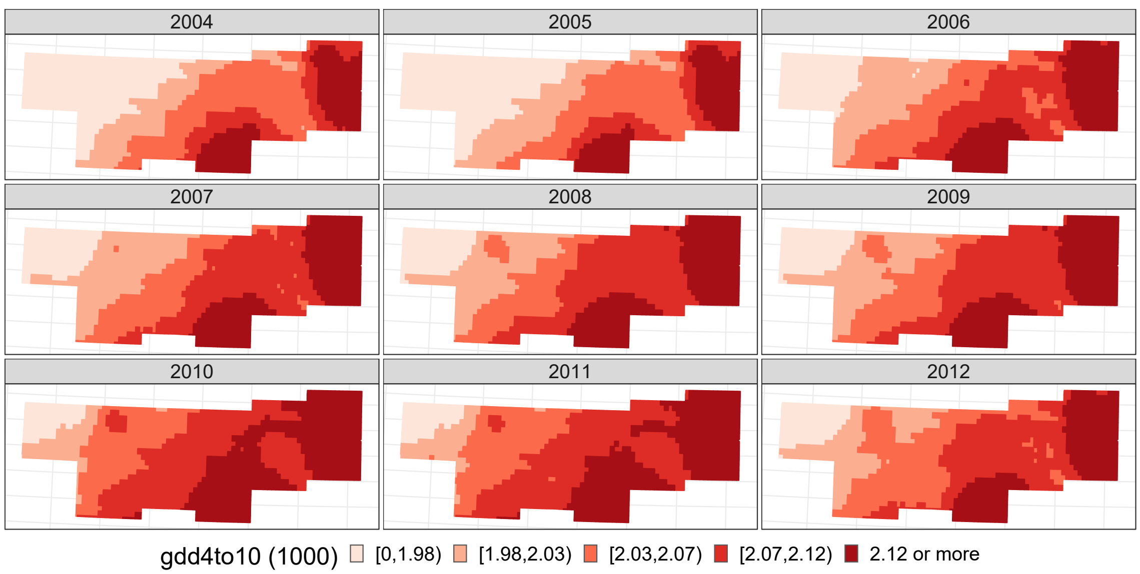

Figure A2. Spatial and temporal variation in $GDD4to10$.

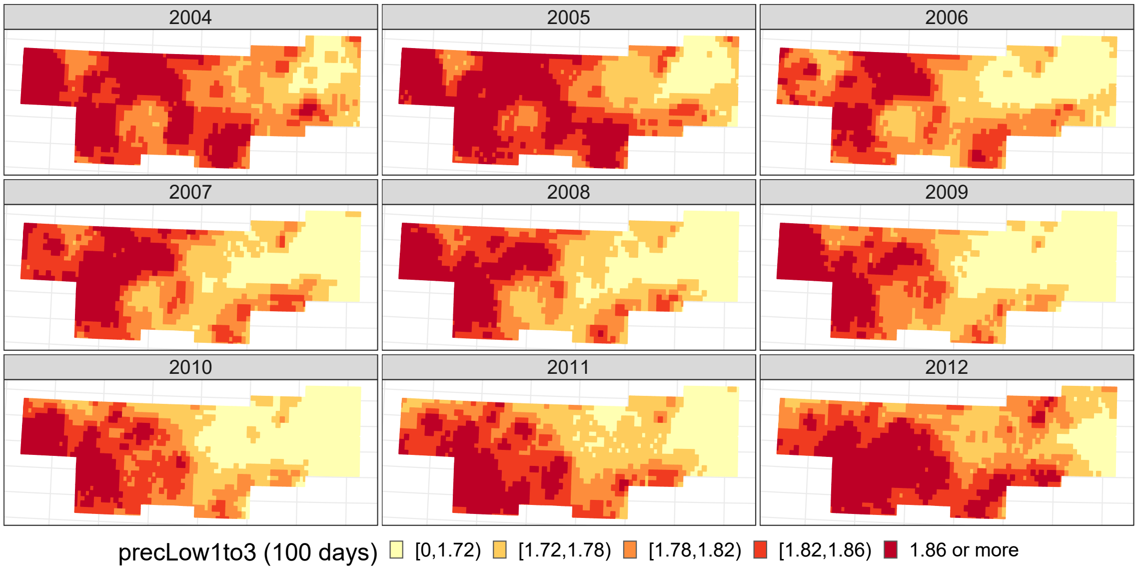

Figure A3. Spatial and temporal variation in $PrecLow1to3$.

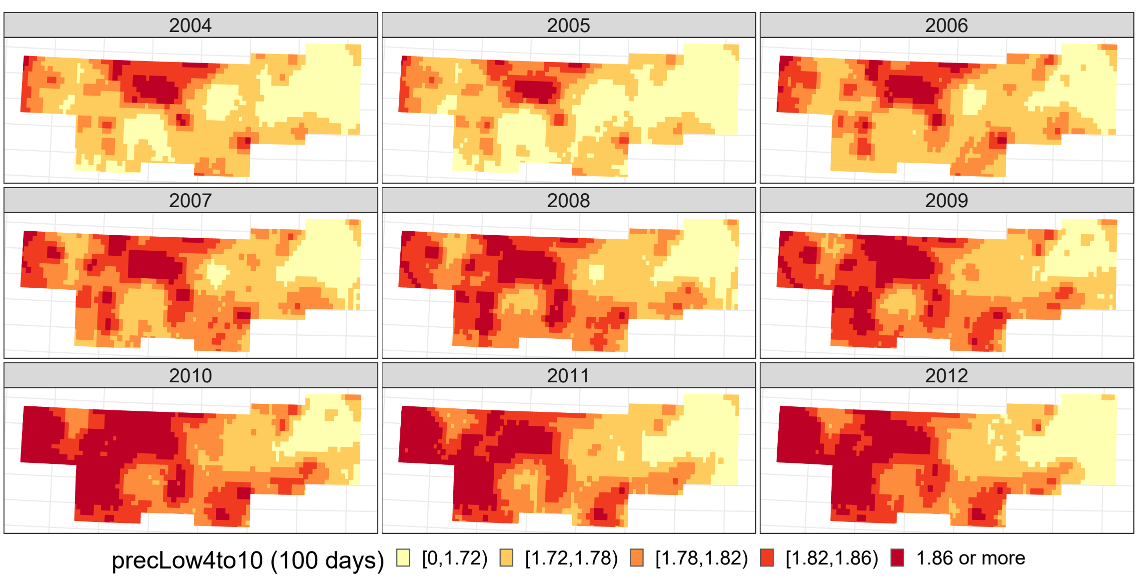

Figure A4. Spatial and temporal variation in $PrecLow4to10$.

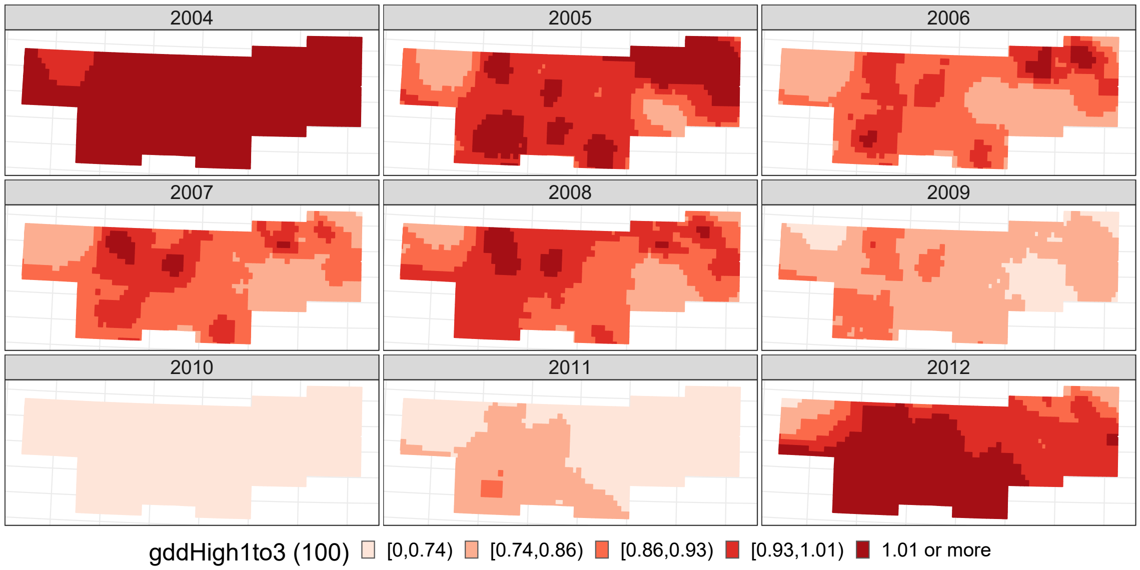

Figure A5. Spatial and temporal variation in $GDDHigh1to3$.

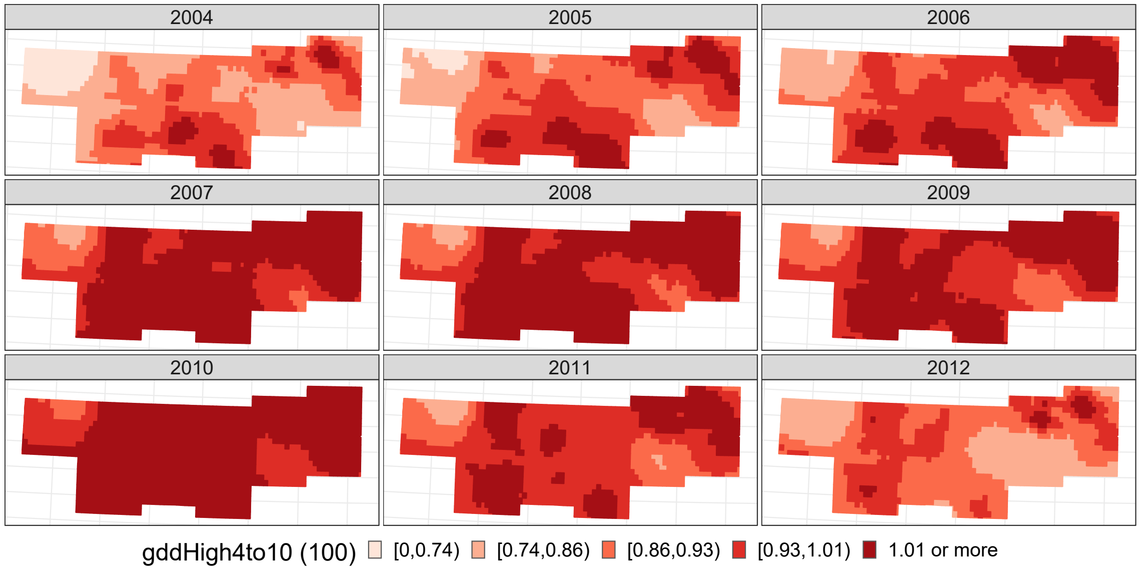

Figure A6. Spatial and temporal variation in $GDDHigh4to10$.

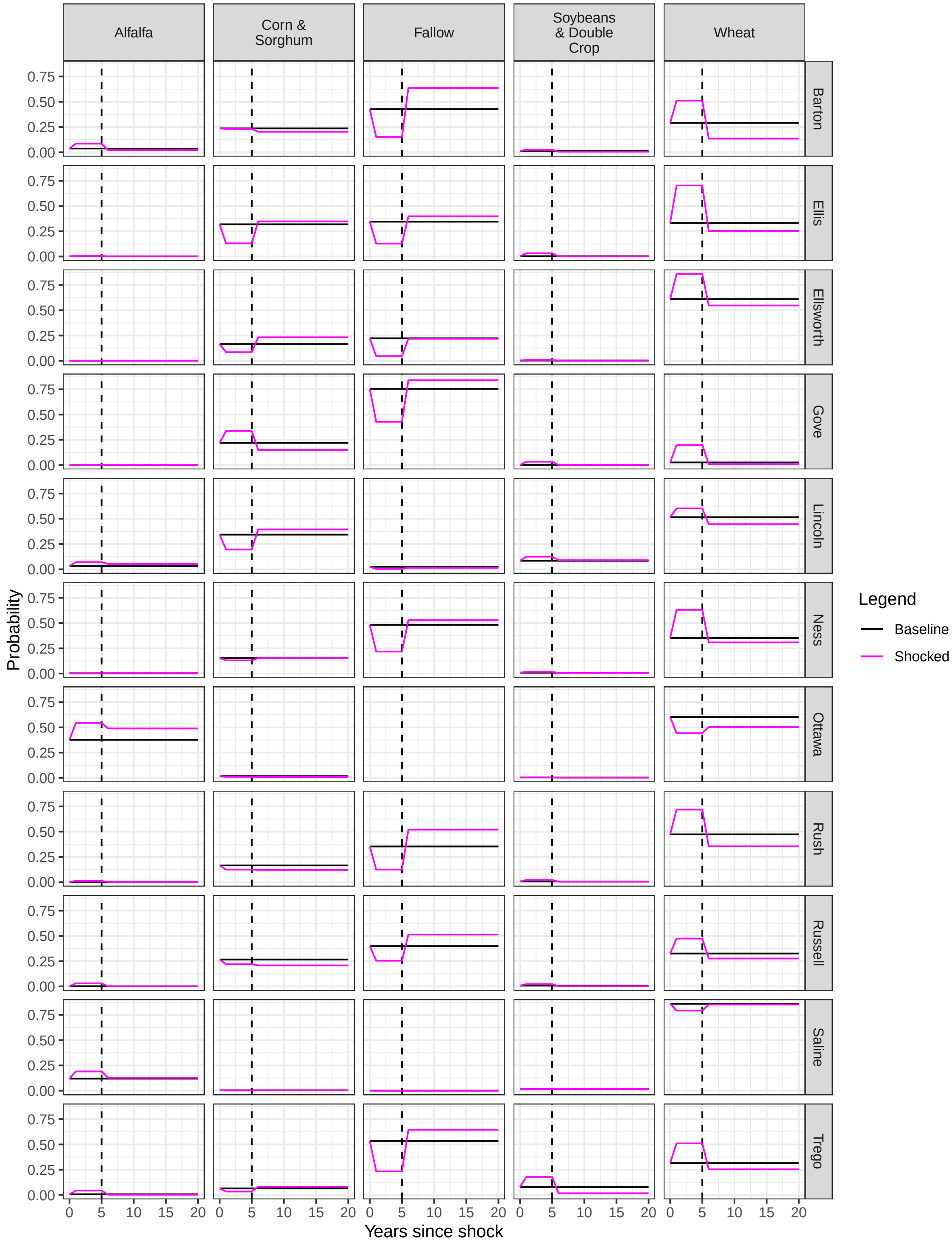

Figure A7. Simulated probabilities from drought lasting one year, NL-DML-RE, 1-5 and 6-20 lag structure

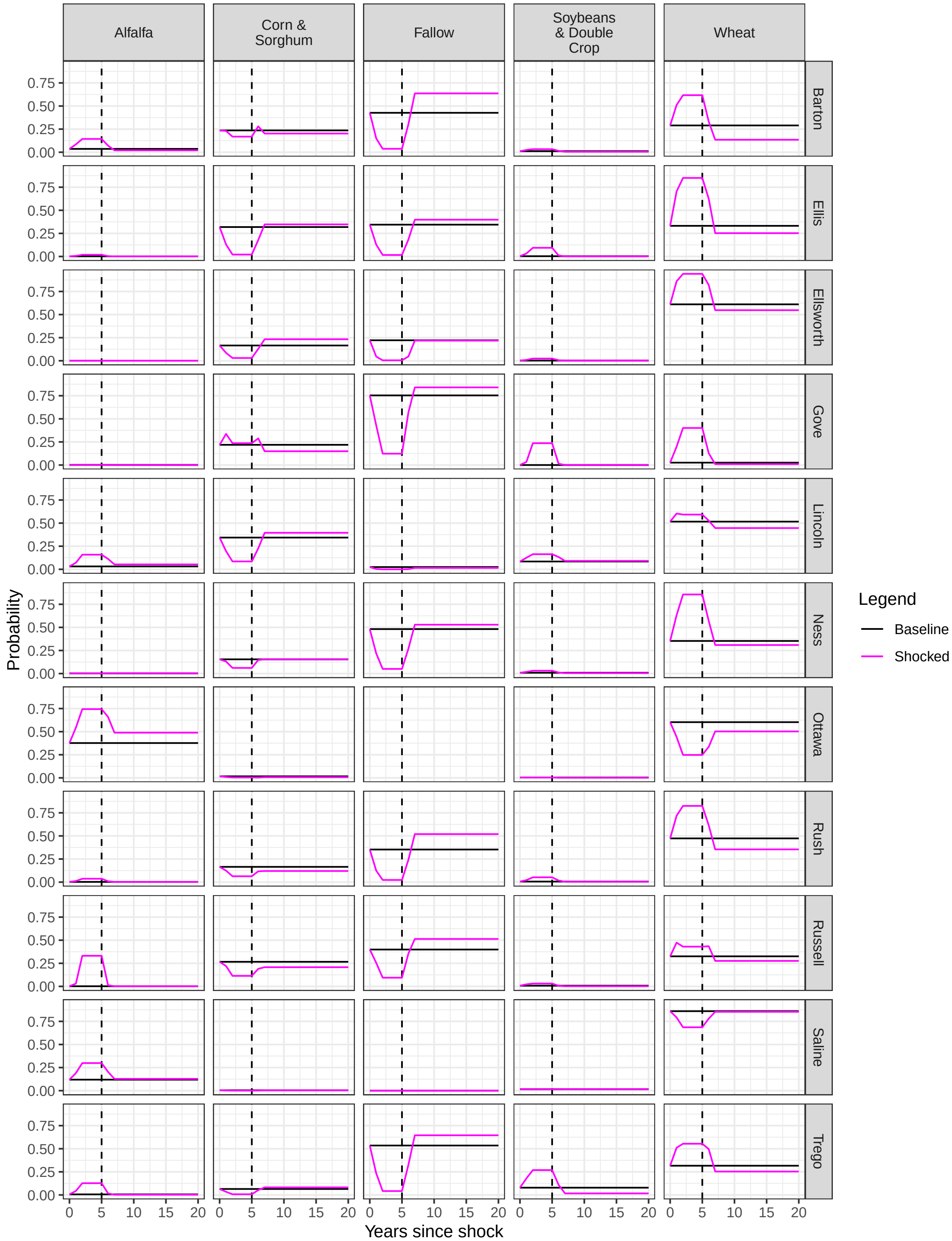

Figure A8. Simulated probabilities from drought lasting two years, NL-DML-RE, 1-5 and 6-20 lag structure

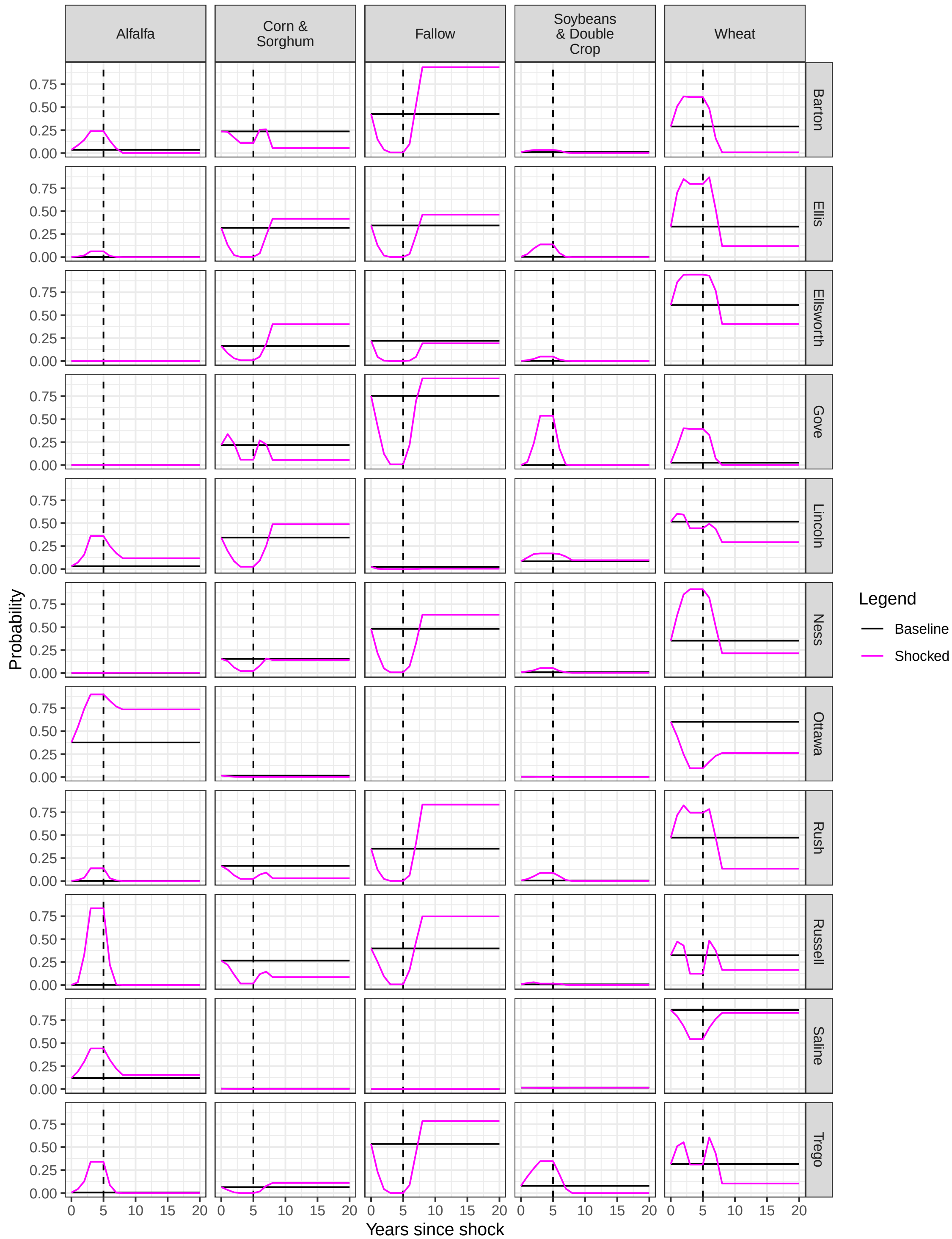

Figure A9. Simulated probabilities from drought lasting three years, NL-DML-RE, 1-5 and 6-20 lag structure

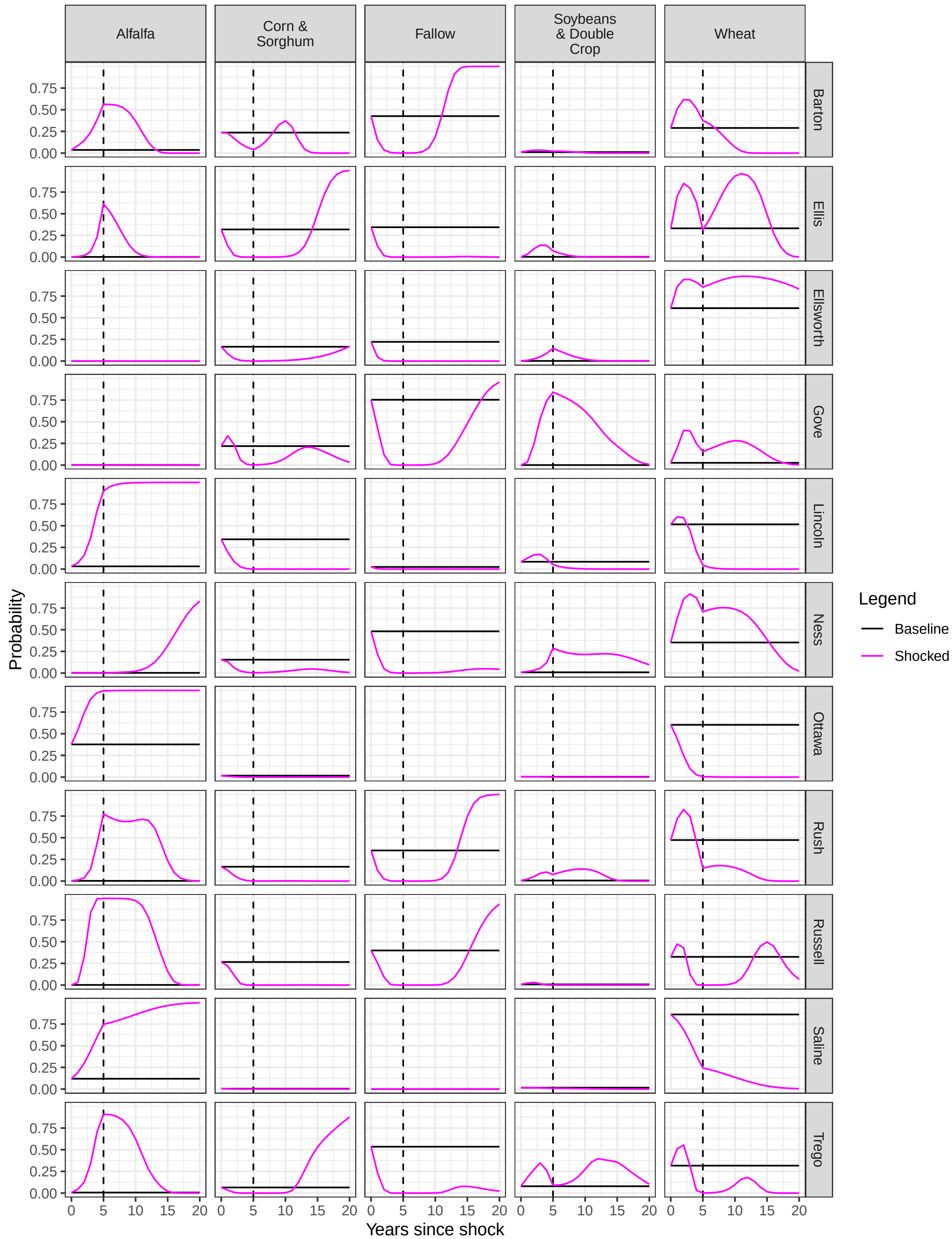

Figure A10. Simulated probabilities from permanent drought, NL-DML-RE, 1-5 and 6-20 lag structure

Figure A11. Average transition probabilities, NL-DML-RE, 1-5 and 6-20 lag structure