Perception Biases and Land Use Decisions

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Abstract

A large literature has shown that perceptions are not always consistent with reality and can have significant impacts on behaviors. Perception biases documented in the literature often pertain to subject matters that are difficult to observe or measure. In this paper, we study perception biases with respect to an indicator that is very concrete and can be objectively measured—land use changes in a local area. Despite its potential significance, how perceptions about land use changes compare to objective measurements has received little attention. In this paper, we start to fill this gap with a farmer survey and satellite land use data. We found systematic biases in farmers' perceived land use changes. Furthermore, the biases are associated with decisions made in the past. Farmers who had converted grassland to cropland had over-perception, on average; they perceived larger cropland increases than there actually were. Farmers who had converted from cropland to grassland did not exhibit such biases, on average. We also found evidence on a linkage between perception biases and intended future land conversions. Our findings suggest that any communication strategies that are intended to guide resource allocations through addressing perception biases have to recognize these linkages.

Keywords: behavioral economics; grassland conversions; human dimensions; land use changes; perception biases

JEL codes: D03, D83, R14

1. Introduction

An individual's decisions are shaped by her perceptions and these perceptions are not always consistent with the reality. Heterogeneous perceptions about qualitative measures are ubiquitous, e.g., people have different opinions on how beautiful a landscape is. But large heterogeneity can also exist on perceptions about common quantifiable objective measures. Perception biases have been documented in complex measures such as income distribution and inflation rate as well as in more concrete and observable measures such as average height and weight of a specific population (Cruces et al., 2013; Proto and Sgroi, 2015; Matsumoto and Spence, 2016). For sound policy making it is important that we understand whether perception biases exist and, if so, what factors contribute to bias formation. In this paper, we study perception bias in the context of land use changes which are critical for the health of ecosystems as well as the human communities who own these lands, and consume the land's outputs. As Brown et al. (2014) assert, it is increasingly recognized that "Land-use decision processes are influenced not only by the biophysical environment, but also by markets, laws, technology, politics, perceptions, and culture." We aim to examine how perceptions regarding land use changes compare with the reality and how perceptions relate to actual land use decisions.

Our study contribute to the decision making literature regarding perception biases by identifying and assessing different measures of perception biases in the context of land use changes. People with the same available information can have systematically different beliefs (Akerlof and Dickens 1982; Bénabou 2015). Understanding the driving factors behind perception biases is a necessary step for any public policies that are likely to be affected by such biases. Perception biases arise due to many different context-dependent factors. Some biases are related to our past experience, our limited information as in the case of "law of small numbers" (Rabin 2002) or our psychology tendency to perceive ourselves as being smart and nice. The latter is manifested in so-called confirmation bias. For a representative sample of German residents aged

16 and above, Dohmen et al. (2009) found that almost a third of the respondents exhibit systematically biased perceptions of probability and the perceptions biases are related to individual economic outcomes. Botzen et al. (2015) found that homeowners' perception of the probability of flood risk and the magnitude of damages could be biased and that homeowners who have experienced a flood are likely to overestimate the probability of a future flood while those who do not have such experience will underestimate the probability. Proto and Sgroi (2015) showed evidence of a powerful and ubiquitous bias in perceptions that are "self-centered" in the sense that those at extremes tend to perceive themselves as closer to the middle of the distribution than is actually the case. The self-centered perception biases are likely to be "self-serving" due to some form of subconscious "strategic ignorance" to meet individuals' psychological needs.

While perception biases have been found in many contexts and measures, the underlying reasons for biases may differ in different circumstances. It is important that we understand perception biases within the conceptual context in which it arises. In this analysis, we identify two measures of perception bias that can be defined in the context of confirmation biases. First, we can measure average perception bias as the difference between the average of a perceived outcome and the average actual outcome in a population. The premise is that if people do not have systematic biases, then individual biases will cancel out on average. Another measure of perception bias is identified based on how perception is linked with one's past behavior. If one takes an action (e.g., to grow more corn or switch to energy-efficient appliances), then confirmation biases can imply that one thinks that many other people have also taken the same action. If so, perception biases about the action's general outcome can be introduced. Thus, we can compare perception biases among action takers with the perception biases among the inactive.

The main objective of our study is to examine perception biases as applied to land use changes. Even though a large body of literature has examined the drivers and consequences of land use changes, few studies have focused on how perceptions are related to land use decisions. For example, Claassen et al. (2011) and Wright and Wimberly (2013) identified the eastern Dakotas as an area of intensive land conversion from grass to crop production. Such conversions are of increasing concern due to their implications for regional ecosystems. Several studies have examined the drivers behind the rapid land use changes in the region (e.g., Rashford et al. 2010; Claassen et al. 2011; Feng et al. 2013). High commodity prices, weather cycles, and government commodity market supports have been identified as the main drivers of land use changes in the region. To our best knowledge, our study is the first to focus on behavioral aspects of farmers' land use decisions, which can be a critical factor that contributes to land use changes. Understanding the extent and impacts of perception biases in the context of land use changes will provide new insights into drivers of land use changes and may in turn help policymakers better target limited conservation resources.

In this paper, we form and test three hypotheses. We first examine whether there are perception biases in land use changes in our study region. Next we conjecture that, if a farmer made a conversion from one land use to another in the past then her current perceptions on land use changes is likely to be biased toward the new converted land use. Finally, we posit that farmers who currently perceive excessive changes in one land use are more likely to express intention for similar future land use changes. Whether perceptions about land uses is consistent with reality may have important policy implications if farmers' land use perceptions directly affect their land use change decisions. For example, land use changes in an area often imply other changes. If the perception about land use changes are related to perceptions about other factors (e.g., infrastructure support system related to a particular type of production), then perceptions about land use changes can have larger impacts. Also, perceived land use changes may be a driving force behind policy positions of interest groups. Therefore, it is imperative that we understand the extent, if any, and the implications of biases in these perceptions.

2. Conceptual framework of perceptions and land use decisions

Suppose there are N farmers in a geographical area where land is used for crops, grasses, and other uses such as forest and urban development. We focus on land use changes between crops and grasses because they are the main land uses in our study region (described in detail later), and these uses have very different ecological outcomes. Grass cover is usually more beneficial in terms of water quality, wildlife habitat, and carbon sequestration while the main crops, and especially corn, are more input intensive with higher adverse impacts on the environment. To represent our study region, we assume that all farmers have cropland while some farmers have both grassland and cropland.

To model changes over time, we assume that there are three time periods: past, present, and future, denoted as $t=0$, $t=1$, and $t=2$, respectively. Denote $q_i^{k,1}$ as the actual land use changes that has occurred between time $t=0$ and $t=1$ in farmer i's local area, which is defined as an area within a given distance (say, five mile radius) of the farmer's location. Superscript k represents the new converted land use, which could be either crop or grass, i.e., $k \in \{c, g\}$ with c for crop and g for grass. Similarly, $y_i^{k,1}$ represents farmer i's perceived land use change towards land use k that has occurred between time $t=0$ and $t=1$ in her local area. Our focus is on the difference between perceived and actual land use changes, which we refer to as perception bias $z_i^{k,1}$, i.e., $z_i^{k,1} \equiv y_i^{k,1} - q_i^{k,1}$.

In a world with complete information and perfect observation, there would be no perception bias, i.e., $z_i^{k,1} = 0$. In a large population, we can assume that perception has some idiosyncratic errors within the population but $\mathbb{E}[z_i^{k,1}] = 0$ where $\mathbb{E}[\cdot]$ represents statistical expectation. When systematic factors affect perception errors in a given population, we will have $\mathbb{E}[z_i^{k,1}] \neq 0$. For example, as we discussed in the introduction, perception might be systematically affected by farmers' past experiences but the magnitude and direction of perception biases still need to be tested.

Following the literature (Bénabou 2015; Tirole 2002), we model utility as a weighted average of return and psychological adjustment. Suppose landowner *i* has the following utility function at $t = 1$:

$$U_i^1 = f\left[\alpha * \Pi(\mathrm{a}_i^{k,0}, W_i^{k,0}) + (1-\alpha) * \Omega(q_i^{k,1}, y_i^{k,1}, \mathrm{a}_i^{k,0})\right] \tag{1}$$

where $0 \leq \alpha \leq 1$, $\Pi(\cdot,\cdot)$ and $\Omega(\cdot,\cdot,\cdot)$ are functions of return from land use and psychological adjustment, respectively. Note that $q_i^{k,1}$ represents actual land use changes; $\mathrm{a}_i^{k,0}$ represents changes farmer i made for land use k; and W_i include farmer *i*'s characteristics (such as years in farming), her farm's attributes (such as total acreage), and some other control variables to be explained in the empirical part of the paper. Psychological adjustment ($\Omega(\cdot,\cdot,\cdot)$) could come from self-validation: if a past decision brings additional positive utility to a landowner, then self-validation will cause $\Omega(\cdot,\cdot,\cdot)$ to exceed zero. In our context, one form of self-validation is that a landowner perceives the land use change in a locality to be consistent with her past decisions. In other words, if a landowner made a conversion from grassland to cropland, she would perceive an increase in cropland area in the locality. Similarly, if a conversion from cropland to grassland is made, there could be a perceived increase in grassland area, which can be expressed by the following equations:

$$\Omega(\cdot,\cdot,\cdot) = \begin{cases} > 0 & \text{if either } \{(q_i^{k,1} > 0) \cap (\mathrm{a}_i^{k,0} = 1)\}, \text{ or } \{(q_i^{k,1} \leq 0) \cap (\mathrm{a}_i^{k,1} = 0)\}; \\ = 0 & \text{otherwise.} \end{cases} \tag{2}$$

The magnitude of $\Omega(\cdot,\cdot,\cdot)$ and the weight on $\Omega(\cdot,\cdot,\cdot)$ are determined by psychological needs. A landowner will try to maximize U_i^1 in determining her perception about land use changes, and what weight to assign to the actual realized net return. Note that $a_i^{k,0}$ is a decision made in the past so it is not a decision variable here. Also, $y_i^{k,1}$ is perceived land use change and so is also not a decision variable.

$$\max_{\alpha, y_i^{k,1}} \left\{ U_i^1 \mid a_i^{k,0} = 1,\ q_i^{k,1} \right\} \tag{3}$$

We conjecture that the utility from self-validation decreases as perception bias (i.e., the difference between perception and reality) increases. Thus, the two key hypotheses for our analyses concern about the existence of perceptions biases and how the biases are linked with past decisions. The first hypothesis that we test is as follows,

Hypothesis I: There is significant perception bias in land use changes in our study region, that is, $\mathbb{E}[z_i^{k,1}] \neq 0$.

Our perceptions are related to our experience and who we are. Perceptions are affected by objective happenings, the way we process such happenings, and our (subconscious) psychological needs (e.g., Rabin 1998, Bénabou 2016). For example, there is evidence that supports motivated visual perception, i.e, “we see what we want to see” (e.g., Balcetis and Dunning 2006). In our context, we posit that farmers’ perceptions of land use changes in their locality will on average differ from the actual land use changes. In addition, farmers’ perceptions may be affected by past land use decisions they made. Perhaps those who have converted grassland to cropland would like to think what they did was normal in that most others in their locality have made similar decisions. Additionally, we posit that farmers’ perceptions are affected by their own characteristics and situations. Writing perceptions as a function, $f(.)$, of all these factors, we have

$$y_i^{k,1} = f(q_i^{k,1}, a_i^{k,0}, W_i) + \nu_i^{k,1} \quad (4)$$

We model $a_i^{k,0}$ as an indicator variable, representing whether farmer *i* made a conversion to land use k at $t=0$ with $a_i^{k,0}=1$ and $a_i^{k,0}=0$ denoting, respectively, that there was and was not a conversion. In this paper, we are mostly interested in assessing whether and how past land use decisions have affected perceptions of land use changes in a local area. One hypothesis regarding this issue can be stated as follows,

Hypothesis II: If a farmer made a conversion to land use k, then her perception of land use changes is likely to bias toward land use k. In other words, conversion to land use k is likely to lead to higher perception of land use k in the local area, i.e., $y_i^{k,1}|_{a_i^{k,0}=1} > y_i^{k,1}|_{a_i^{k,0}=0}$.

Perception feeds back to decision making as has been shown in Arbuckle and Roesch-McNally (2015). In our context, this means that current perceptions about local land use changes may also affect a farmer's intention for future land use changes. Let $\hat{a}_i^{k,2}$ be the land use intention for $t=2$ that is expressed by farmer *i* at $t=1$. In particular, we model the intention to convert to land use k from another land use. If $k=c$, it means conversion from grass to crop and if $k=g$ it means conversion from crop to grass. In canonical economic modeling, conversion decision is determined by economic returns: if a crop is expected to bring higher returns than grass, then conversion from grass to crop will be preferred; and vice versa (Claassen et al. 2011). In our analysis, we examine to what extent, if any, perception of local land use changes plays a role in land conversion intentions. In particular, we posit the probability of $\hat{a}_i^{k,2}=1$ is determined by a function of $g(.)$ with,

$$\Pr(\hat{a}_i^{k,2}=1) = g(a_i^{k,0}, y_i^{k,1}, W_i) + \psi_i^{k,1}.\ . \quad (5)$$

Here, $\Pr(\hat{a}_i^{k,2}=1)$ is affected not only by factors considered in traditional analyses such as land quality indicators and farmers' characteristics (W_i), (Claassen et al., 2011), but also by the farmer's perception of land use changes in local areas ($y_i^{k,1}$) and her past decisions ($a_i^{k,0}$). The hypothesis regarding the role of perceptions on future conversions can be expressed as follows,

Hypothesis III: Farmers who currently perceive more land conversion to k is more likely to express intention of future conversion to k, i.e.,

$$\frac{\partial \Pr(\hat{a}_i^{k,2}=1)}{\partial y_i^{k,1}} > 0 \tag{6}$$

3. Data

3.1. Survey of farmers' land use decisions and perceptions

A survey was conducted in 2015 that asked farmer three types of questions regarding: (i) their land use changes in the preceding 10 years (2004-2014) and intended land use changes in the subsequent 10 years (2015-2025), (ii) perception on land use changes in their local area, and (iii) the ranking of factors that influence land use changes on their individual farms and in their local area. Our analysis combines these survey data with satellite land use data and land quality indicators to assess to what extent farmers' perceptions on land use changes are consistent with satellite data and the linkage between farmers past land use decisions, their current land use perceptions, and their stated future land use intentions.

The survey was conducted with farmers in the eastern region (the Prairie Pothole Region) of the Dakotas which, as mentioned in the introduction, is a region that have experienced dramatic land use changes in recent years and is therefore ideal for our study. Fig. 1 shows a map of our study region.

A sample of 3,000 farms in the eastern Dakotas was purchased from Survey Sample International, a large company specializing in survey services. We only included farms with at least 100 acres of cropland because our focus was on farmers who make decisions on a substantial amount of land area. A stratified sampling strategy was used so that counties with proportionally more farms overall had proportionally more farms included in our sample. Iowa State University's Survey Research Center was contracted to implement the survey and data entry from returned surveys. Respondent mailing addresses are available to researchers. The survey distribution and collection occurred from early March to early May of 2015 through a Dillman Protocol that involves an advance letter, an initial mailing, a postcard reminder, and a second mailing to non-respondents. A two dollar incentive was included in the initial mailing that also contained a cover letter, the 8-page questionnaire, and the return envelope. A total of 1,050 completed surveys were received, giving a survey response rate of 36.2% in the eligible sample (i.e., the original sample excluding non-deliverable addresses).

3.2 Land use data based on satellite images

We obtained actual land use data from the Cropland Data Layer (CDL) of USDA National Agricultural Statistics Service (USDA-NASS). The CDL data is a geospatial, crop-specific data product publicly available for use and free for download through *CropScape* (USDA-NASS, 2017). The CDL is assembled annually for the continental United States using satellite imagery and extensive agricultural ground truthing. The first year when CDL became available varies by state. For South Dakota, CDL data are available commencing 2006 while for North Dakota the data are available commencing 1997. Because it is based on high-resolution satellite images, the CDL data has high spatial resolutions. There is a growing literature that uses the CDL data to analyze crop and land use trend (e.g., Wright and Wimberly 2013). These data are most reliable for corn and soybeans and less so for grass cover, see Kline et al. (2013), Laingen (2015) and Reitsma et al. (2016) for discussions on reliability.[1]

[1] By convention, user accuracy is used to project reliability of these data. User accuracy was over 95% for corn and soybeans for 2014 in the Dakotas (USDA-NASS 2016b). For grass, the CDL basically takes the National Land Cover Database (NLCD) grass-data and overlays its agricultural classes on it. So accuracy number is not available for grass and is considered to be lower than the number for corn and soybean. It is very important to note that these accuracy

The CDL data are used to measure land use changes in a respondent's locality. Besides questions regarding own land use changes, our survey asks questions about land use changes in the local area in the preceding 10 years and intentions for the subsequent 10 years. The local area is defined as a 5-mile radius centered on the respondent's location. Changes in corn, soybean, and grassland areas are measured as the changes from 2004 to 2014 for North Dakota, and from 2006 to 2014 for South Dakota given that 2006 was the first year that CDL data were available.

3.3 A summary of survey data and Land use data based on satellite images

Key variables from survey and *CropScape* data are provided in Table 1, which includes summary statistics on three categories: 1) farmer and farm characteristics; 2) land use and infrastructure changes in surrounding areas; and 3) farmer conversion histories and conversion decisions in the future. Categorical data descriptions are provided as follows: For farmer's age, we have '1'='19 to 34'; '2'='35 to 49'; '3'='50 to 59'; '4'='60 to 69'; and '5'='70 or over'; For land tenure status, we have '1' = 'owning all operated acres', '2' = 'owning most operated acres', '3'= 'owning about half of operated acres', '4' = 'renting most operated acres', and '5' = 'renting all operated acres.'; For farmers' principal occupation (off-farm employment), we have '1' = 'farming or ranching, '2' = 'employment in off-farm job, '3'= 'own/operate a non-farm business', '4' = 'retired, and '5' = 'other.'

Of the first category, the average cropland acres is 1,226, accounting for more than 70% of the total farm acre, which averaged 1,686 acres. This is consistent with typical land use patterns in the Eastern Dakotas, where crop production is the major component of the regional economy. Farmer's age, land tenure and off-farm employment are discrete choice variables.[2] Average farm

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numbers are at the pixel-level (30 m X 30 m). The statistics used in our analysis pertains to land cover for a 5-mile radius that is made up of over 200,000 pixels. At this scale of spatial averaging, errors tend to wash out, especially for areas like ours that are mostly composed of corn, soybeans and grass as major land uses.

age is 3.30, which implies the average farmer age is somewhere between 50-59 years old. Land tenure averaged 2.75, indicating most of the farmers own more than half of his/her operated acres. Off-farm employment has average 1.24, implying that most survey respondents have farming or ranching as their principal occupation. The farm location variable indicates that the survey area spans 4.93 degrees in latitude and 4.32 degrees in longitude. Soil quality is measured by the land capability classification (LCC) system (Helms, D., 1992; Wang et al., 2017). Classes I and II soils have few limitations for crop production, where limitations might include slope, soil depth and composition and disposition to erosion. Class III soils have moderate limitations for crop production. Class IV soils are very marginal for crop production although the may be cropped if convenient for farm operations. Class V–VIII soils are seldom cropped. On average, 92.7 percent of land of our surveyed farm has soil quality under class III, which is far from ideal but is generally suitable for crop production.

Of the second category, perceived infrastructure change, perceived change in cropland and grassland acres are discrete choice variables described as follows: for perceived infrastructure change, we have ‘1’ = ‘much worse, ‘2’ = ‘somewhat worse, ‘3’= ‘stayed about the same’, ‘4’ = ‘somewhat better’, and ‘5’ = ‘much better’; for perceived cropland and grassland change, we have ‘1’=’decreased markedly (over 10%)’; ‘2’=’decreased somewhat (5-10%)’; ‘3’=’stayed about the same (less than 5%)’; ‘4’=’increased somewhat (5-10%)’; and ‘5’=’increased markedly (over 10%)’. These three perceived change variables captured the change between the survey year (2014) and 10 years earlier. The perceived infrastructure for corn is 3.83, which means for most farmers the external environment for corn production somehow improved. Noteworthy is that during this time several ethanol plants moved into the area (Gaurav et al., 2015). Soybean processing facilities have also moved into the area. The perceived change in cropland acres averaged 4.31, which means on average a respondent perceives a more than 5% increase in corn and soybean acres. For grassland acres, the perceived change averaged only 1.994, which means a perceived decrease of between 5% and 10%. As to actual changes, *CropScape* data indicates that within 5 mile radius of the farm cropland acres shows a 5.76% increase, while the grassland acres shows a 6.97% decrease from year 2006 to 2014. Grassland accounted for a quarter of the total land in 2006, while the land of class no worse than III was over 90% and land slope of no larger than 3 also accounted for nearly 50%, which demonstrated the potential for land use conversion in the studied region.

Of the third category, a quarter of farmers have converted some portion of grassland to cropland in the 10 years prior to 2015, a decade in which Chicago Board of Trade corn futures prices shifted from just over $2 per bushel during 1999-2006 to beyond $5 per bushel during 2011-2012 and back to about $3.50 per bushel by 2013-2015. Looking into the future 10 years, the percentage of farmers who plan to convert more grassland to cropland dropped to 15.8%, while 9.5% of farmers expressed an interest in converting cropland to grassland. The contrast between historical actions and future plans implies that the aggregate grassland to cropland conversion rate would slowing down in eastern Dakota region.

4. Empirical methods

4.1 Existence of perceptions biases in the studied region

To formally test Hypothesis I that there is no perception biases in land use changes, we calculated the average biases by taking the difference between land use changes as measured by CDL data and land use changes as perceived by farmers. As we noted earlier, the perceived land use changes are measured as discrete variables in five categories whereas land use changes based on CDL data are continuous variables. To calculate the difference between perceived and measured land use changes, we chose the middle point of each perception category as the perceived land use changes. For example, a positive 7.5% is chosen for the category “increased by 5-10%”, and a 0% is chosen for “stayed about the same (-5% to 5%)”. For the category "decrease (increase) by more than 10%," we used 15% in our analysis.

Besides overall average, we will next characterize perception biases in: (a) (mis)matched categories of actual and perceived land use changes; and (b) the number of respondents falling into each category.

4.2 Relationship between current perceptions and past land use decisions

Modeling perception of land use change as a probability will allow us to make use of the categorical nature of our survey data. In the survey, farmers' responses regarding their perceptions about land use changes in their own locality take values that have an intrinsic order and enable us to apply the ordinal logistic regression model: over 10% decrease, 5-10% decrease, stayed within 5%, 5-10% increase, and over 10% increase. We label these responses, in the order given, as 1, 2, 3, 4, and 5. Let m be the highest category number, then in our case, $m=5$. Let $\tau_{i,j} = \Pr(Y_i = j)$ for $j \in \{1, 2, \ldots, m\}$ be the probability that respondent i will choose land use change category j. We define the cumulative probability ($\varphi_{i,j}$), the probability of choosing a higher degree of impact, as $\varphi_{i,j} = \Pr(Y_i \geq j) = \tau_{i,j} + \tau_{i,j+1} + \ldots + \tau_{i,m}$, $\varphi_{i,m} = \Pr(Y_i \geq m) = \tau_{i,m}$, and $\varphi_{i,1} = \Pr(Y_i \geq 1) = 1$. Clearly the cumulative probability function, $\varphi_{i,j}$, (weakly) increases as response value j decreases.

Define the cumulative logit link as $\text{logit}(\varphi_{i,j}) = \log[\varphi_{i,j} / (\tau_{i,1} + \tau_{i,2} + \ldots + \tau_{i,j-1})] =$ $\log[\Pr(Y_i \geq j) / \Pr(Y_i < j)]$. Using the control variables in **Error! Reference source not found.**, the proportional odds model can be specified as:

$$\text{logit}(\varphi_{i,j}) = \alpha_j + \beta_1 q^{k,1} + \beta_2 \text{a}_i^{k,0} + \gamma W_i, \quad j \in \{2, 3, \ldots, m\}. \tag{7}$$

If other variables are fixed at 0, then α_j represents the log odds of choosing $Y_i \in \{j, \ldots, m\}$ instead of $Y_i \in \{1, \ldots, j-1\}$. The model assumes that categorization does not affect the impacts of the explanatory variables on the odds. An implication is that coefficients for different functions are held to be the same across regressions in system (7) and only the intercept term differs. These cross-equation restrictions have been imposed in system (7). When compared with the multinomial logit regression model, the proportional odds model is more parsimonious in that fewer coefficients are estimated. Capuano et al. (2007) has an extensive discussion on the strengths and weaknesses of the proportional odds model.

We consider two groups of variables for inclusion in W_i: (a) farm and farmer attributes which include farmers age, farm size and farm tenure status; and (b) land and land use characteristics in a respondent's locality, which include land class and percent of land in particular classes within 5-mile radius of the respondents' addresses. How these control variables affect a respondent's perception is not apparent and, to our best knowledge, there is no theory that deals with these issues. We conjecture that farmers' perceptions could be affected by these control variables. Operators' years in farming can account for inertia in the sense that farm operators have already invested in establishing the farm operation that they are comfortable with. A tenancy index is also considered that measures what fraction of the land operated is rented in. We expect that tenancy should increase the desire to convert but also reduces the ability to convert, so we are not sure what sign the variable should have. We also consider the respondents operated acreage, our prior regarding which is that larger operations might lead to perceptions closer to the actual land use changes because the operators may devote more attention to land use related issues. Finally, we consider a group of variables that reflect land characteristics in a respondent's locality: the fraction of land within 5 miles Euclidian radius that was under grass in 2006, directional variables representing, respectively, degrees latitude north and degrees longitude west; and the fraction within land capability class 3 or better and the fraction that has slope three or lower of land within 5 mile radius.

4.3 Relationship between current perceptions and future land use intentions

We use a logistic regression to capture the relationship between the probability of intended land conversion in the future and current perceptions of land use changes along with other control variables,

$$\Pr(\hat{a}_i^{k,2} = 1) = \alpha_0 + \delta_1 \mathrm{a}_i^{k,0} + h(y_i^{k,1}) + \lambda W_i + \varepsilon_i, \quad (8)$$

with ε_i as the error term, $\mathrm{a}_i^{k,0}$ representing past land use decisions, and W_i representing a vector of control variables including farm and farmer characteristics, natural endowments and/or the lay of the land. Coefficients α_0, δ_1 and λ are regression coefficients.

Several alternative forms will be estimated regarding the perceptions component, $h(y_i^{k,1})$, which is our primary variable of interest. We can model how perceptions bias affects land conversion decisions, i.e.,

$$h(y_i^{k,1}) = \gamma_1 (y_i^{k,1} - q_i^{k,1}). \quad (9)$$

A positive response would suggest that, operators are more likely to convert to a certain land use if she has positive perception bias towards that type of land use, which may in turn create a positive feedback loop.

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5. Results

5.1 The extent and characteristics of perception biases in land use changes

Table 2 indicate that the actual change in cropland area, as measured by *CropScape* data, is 5.76%. The perceived cropland change averaged at 9.80%, which is 4.05 percentage points higher than the actual *CropScape* data and is statistically significant. This indicates that regarding percentage increase in the cropland area, on average producers' perception rate is much higher than the actual rate. For the extent of grassland area changes, the perceived changing rate is -7.55%, which is slightly below the actual change of -6.97%. This time the perception bias is only 0.53 percentage points and is not statistically significant. These perception patterns seem to suggest that people tend to overemphasize the changes that directly relate to their own benefits while underestimate the changes associated with indirect social benefits. In our context, more cropland acreage means increased profits to the farmers, while less grassland acreage implies compromised ecosystem service to the overall society.

5.2 Mismatched categories of actual and perceived land use changes.

Fig. 2 provides a box-and-whiskers plot of CropScape assessed cropland changes in a five-mile radius of a respondent's location during 2006-2014, conditioned on the respondent perception categories. With the exception of the 'over 10% decrease' perception category, the 25%, 50% and 75% percentiles[3] of CropScape-assessed cropland change, hereafter referred to as the actual percentage change, increased with perception categories. For the two lowest perception categories, 'over 10% decrease' and '5-10% decrease,' the perceived cropland change was much lower than the actual percentage change. For the two highest perception categories, '5-10% increase' and 'over 10% increase', the perceived changes were higher than the median value of actual change. Perceived change is most aligned with actual change for the median perception category, 'stayed within 5%'. Similar to Fig. 2, Fig. 3 compares grassland change perceptions with the *Cropscape* assessment over the same period. On grassland change, the median of actual value was below 0 for each perception category. However, there is no clear trend in how actual grassland change relates to perceived grassland change categories. Fig. 3 suggests that more than 75% of those in the two highest perception categories had over-perceived grassland change.

Figures 2 and 3 do not contain information on the number of respondents in each category. It turns out that respondents are very unevenly distributed across the perception categories. In

[3] The 50% percentile is denoted by the middle bar of the box, the arithmetic mean is denoted by diamond shape, while the 25% and 75% percentile are denoted by the lower bar and upper bar of the box, respectively, in the box-and-whiskers plot.

particular, the two lowest categories regarding cropland area change and the two highest categories regarding grassland change had very few respondents. According to panel A in Table 3A, only 14 producers, or 1.4% of all respondents, perceived more than 5 percent reduction in cropland area. Similarly, Table 4B shows that only 31 producers (3.1% of total) perceived grassland area had increased by more than 5%. The majority of producers, 33% and 50% of the total respondents perceived ‘5-10% increase’ and ‘over 10% increase’ in cropland area, respectively. As Fig. 2 illustrates, for about 50% of the producers responding ‘5-10% increase’, and over 75% of the producers responding ‘over 10% increase’, the actual changes were below perceived changes. This suggests more than half of all producers over-perceived the increase in cropland area (33% x 50% + 50% x 75%=54%). For changes in grassland area, Table 3B shows that the majority of respondents, 34% and 37% respectively, belong to the ‘over 10% decrease’ and ‘5-10% decrease categories. The rest 26% of respondents chose the ‘stayed within 5%’ category. Whether there is under-perception or over-perception concerning grassland area changes is not clear from Fig. 2.

To determine whether the distributions of actual land use change remain the same when perceived land use changes differ, A Chi-square test was conducted using information in Table 3. Note that Chi-square is not a valid test for Table 3A and 3B since 55% of the cells have expected counts less than 5. Therefore, for cropland changes, we will drop the two decreasing categories, which has very few counts based on both perception and CropScape criteria as indicated by Table 3A. Similarly, the two increasing categories will be dropped for grassland changes. The Chi-square value for the remaining 3 x 3 tables are significant at 1% with a value of 22.85 for the cropland and 14.25 for the grassland, both with degree of freedom of 4. This indicates that actual land use distributions are not the same when perceived land use changes differ. From the frequency table (3C and 3D) we can also see that if respondents perceive a higher percentage of land use change surrounding their farm, the actual percentage of land use change is more likely to be high as well. In other words, the perceived changes shows a certain degree of consistency with the actual changes.

5.3 Characteristics of over-perception and under-perception groups.

To better understand the nature of discrepancies between perceived and actual land use change, we divide the respondents into three groups depending on the extent of the discrepancies (Table 3A, B). Group I refers to the 5 diagonal yellow shaded boxes, on which the respondents' responses are consistent with CropScape data. Group II refers to the 8 blue cross-shaded boxes, which are only 1 cell off the diagonal, implying the responses only have slight discrepancies from the *CropScape* values. The remaining 12 non-shaded boxes belong to Group III, which are at least two cells away from the corresponding *Cropscape* values, i.e., the category of perception is at least two categories away from CropScape values.

Table 4A and 4B report Duncan's Multiple Range tests of the three groups described above on variables such as age, years operating the land, education level, employment off-farm or not, acres operated, and land locations. The tables reveal no clear trend on how perception accuracy changes with most of these variables. On off-farm employment status, the trend is apparent from crop side, which shows that farmers more involved in on-farm jobs are more likely to make the right prediction. This is probably because those who are more involved in farming should have a better sense of what is happening in their neighborhood. In addition, location may play a role in prediction error too. On the cropland side, it seems that producers are more likely to make accurate predictions when they are located further south; while on grassland side, producers located further west generally make more accurate predictions.

5.2. Current perception biases and past land use decisions

Table 5 breaks down respondents in each perception categories by past land use decisions. The left and right panel are perceived changes in cropland and grassland area, respectively. For example, the table indicates that among 500 respondents who perceived cropland area “increased by >10%”, 126 converted grassland to cropland and 374 did not make such changes. Conversely, among the 16 who perceived grassland “Increased by >10%”, only 2 respondents converted grassland to crop and 14 did not make such a conversion.

Table 6A and 6B present the test results for Hypo II., that is the relationship between perceptions and past land use decisions based on the ordinal logit model explained earlier in equation (4). As indicated by Table 3, for changes in cropland area, very few respondents chose the two decreasing categories, so we combined ‘decreased by >10%’, ‘decreased by 5-10%’ and ‘within 5%’ into a single category, referred to as the ‘non-increase of cropland’ category and labeled as ‘1’ in the model. Consequently, ‘increased by 5-10%’ and ‘increased by >10%’, are labeled as ‘2’ and ‘3’ respectively. For similar reasons, ‘increased by >10%’, ‘increased by 5-10%’ were combined with ‘within 5%’ when it comes to changes in grassland area, referred to as the ‘ non-decrease of grassland’ category. Regarding perceived grassland change, ‘decreased by >10%’, ‘decreased by 5-10%’, and ‘non-decrease of grassland’ are labeled as 1, 2 and 3 respectively. Therefore moving to a higher category means either a larger increase in cropland acres, or a smaller decrease in grassland acres.

Three different models, from the most concise to the most complex, were estimated for both perceptions on cropland change and grassland change, with the results summarized in Tables 6A and 6B. The number of control variables increases from Model I to III. While Model I only includes the previous conversion variable, Model II includes the previous conversion action, perception on crop price importance and farmer/farm characteristics. Model III includes all the variables in Model II and further extends to the variables related to farm surrounding areas. Table 6A indicates that previous conversion decisions from grass to crop has a significantly positive impact on perceived cropland area changes in all three models. Even after control variables such as characteristics of the farm and farm surrounding areas are included, the odds of higher perception from producers who converted grassland to cropland is still 1.30 higher than producers who did not convert. Therefore, in terms of cropland change, Hypothesis II is confirmed and producers made grassland to cropland conversion in the past 10 years are more likely to have a higher perception on cropland area change.

Perceived impact of changing crop prices and tenure index are two variables in Model III that significantly increase the odds of higher perception on cropland area change. If changing crop prices on land use change is perceived to have a higher impact, e.g., “5: great impact” vs. “4: quite a bit of impact”, then the odds of higher perception increases by 1.241. In addition, if the producer rent a higher proportion of the farmed land, then the odds of higher perception increases by 1.150. These two variables remain significant in Model III.

Five other control variables on farm surrounding areas are significant in Model III, and all increase the odds of perceiving more conversion to cropland. Those include *CropScape* recorded cropland change, percent of grassland area in 2006, percent of land of class I to III, change in infrastructure for corn and latitude. This indicates that respondent’s perception of cropland are generally consistent with *CropScape* records. When the proportion of grassland area within 5 mile radius in 2006 increased by 1%, then the odds ratio of higher perception increased by 1.025, given other factors fixed. This shows that people generally perceived higher grassland to cropland conversion rate when there were originally higher proportion of grassland available for conversion. Consistent with our intuition, there were also higher perceptions of cropland area change when a higher percentage of land was suitable for crop production and when greater improvements in corn infrastructure were reported. Latitude remains significant even after accounting for the other control variables, which shows some regional perception biases. Producers in the North are more likely to perceive a higher cropland change, as indicated by the 1.676 odds ratio increase when latitude increase by 1 degree.

Regarding perception on changes of grassland area, since the question on previous cropland to grassland conversion decisions was not included in the questionnaire, Hypothesis II cannot be tested as we did for cropland area change perception. However, similar to Model I in Table 6A, Model I in Table 6B indicates that for those farmers who made grassland to cropland conversion are less likely to have a higher perception of grassland change, which means less decrease of grassland acres. In other words, this simply means the cropland converters are more likely to perceive more decrease in grassland acres. Interestingly, education and principal occupation, though not significant in cropland area change perception, play significant roles here. It indicates that people with more education and more involvement with the farm are more likely to perceive less decrease in grassland acres than their counterparts. Intuitively, the variables that increases the odds of higher cropland change perception, such as percentage of grassland within 5 miles radius in 2006, and percentage of land in class III or better, decrease the odds of higher grassland change perception. It also makes sense that the perceived improvement in cattle infrastructure goes hand in hand with the perception of grassland area increase. The increase in latitude, however, also increases the perception of grassland area change, but the odds ratio of such increase here is 1.188, lower than the odds ratio of 1.676 in Table 6A. This means producers live further north are likely to overestimate cropland and grassland change, especially on the cropland land change.

5.3. Future land use intentions, current perceptions and land use decisions

Results in Table 7 support Hypohesis III regarding cropland area perception and future conversion intention from grass to crop. If we disregard the two decreasing categories (or we may combine those two with the within 5%), among the rest 3 categories, those who perceived a higher increase in cropland area are also more likely to intend grass to cropland conversion in the next 10 years. However, Table 7 shows no positive relationship between perceived change in grassland area and intention to convert to grassland in the future, thus lending no support to

Hypothesis III regarding grassland change perception. On the contrary, those who perceived a decrease in grassland area are more likely to express a willingness to convert to grassland in the future. This indicates that most respondent's desire to convert to grassland arise from the concern of further grassland loss, rather than following others producers' conversion pattern as in cropland case.

Table 8A and 8B provide test for Hypothesis III using 3 different models, from most parsimonious to the most complex, which resembles the layouts of Table 6A and 6B. On the cropland side, Model I shows that perception bias significantly increases the odds for future conversion intention. However, as more control variables are included this is no longer the case. Therefore Hypothesis III is not supported. Previous conversion experience, instead, has most significant impact on future conversion experience, as it increases the odds of future conversion by 2.58. Principal occupation also plays a significant role, as those who are less involved with farming are more likely to make future conversions to cropland. Not surprisingly, land quality (land class I to III) increases the odds of future conversion to cropland. In addition, we found that in areas where *CropScape* predicted higher percentage increase in cropland, future conversion is not likely to occur. A likely explanation is that landowners' expectation about the future profitability of cropland has dropped, as this survey took place in Spring 2015, a time when commodity prices already started to decline. Longitude, too, has a significant positive impact on future conversion to cropland. It seems the focus of land use conversion will gradually shift to the west as most of the land in the east has already been converted.

On grassland side, similar to the conclusion in Table 7, Model III found the perception bias decreases the odds for future conversion, which is contrary to Hypothesis III. Besides the impact of perception bias, only two factors that are significant in Model III and both improves the odds of future conversion to grassland. These factors are percentage of grassland in 2006 and percentage of high quality land (Table 8B). A plausible explanation is that in areas where most grassland prevails in 2006, producers who learned the conversion consequences may try to resume the previous grassland and cropland balance in the future.

5.4. Perceptions biases and land use choice motives

There is some interesting connection between perception biases about local land use changes and the perceived main drivers of land use changes. In our study, we asked respondents about factors that motivated land use change over the prior ten years within 5 miles of their operation base. With the exception of land units at issue, the queries were structured exactly as with those for own-farm land use with the summary statistics provided in Table 9. Four items stand out. One is that the response rate was lower for questions about their neighborhood, likely because growers were less sure of information beyond their operation or because the question was asked later in the survey. Secondly, the mean values are generally larger than corresponding own responses. A student's *t* test confirms the difference at significance level of 1% for all variables except that for changing climate patterns, for which the difference between one's own land and local area is not significant.

We can conceive of two possible, related, reasons why these differences exist. Growers may only ascribe economic motives to their neighbors' actions but see more complexity and nuance in their own motives. For example, they may have weighed land stewardship, family circumstances and legacy concerns in their own response but not in those of other landowners. The other possible reason is that own response is likely to be more variable than the average response of others. If non-economic motives are idiosyncratic then they are likely to average out over growers, leaving economic motives with a stronger response on average.

This brings us to the third noteworthy item, that the standard deviation of responses is lower for questions on local land than on own land, which is consistent with the idea that own-responses contain idiosyncratic motives that respondents assume to average out. Finally, own response to the wildlife motive is, though still low, higher on average than is the respondent's views on that motive among other owners. Perhaps respondents feel that they care more about wildlife than do others, a possibility we cannot preclude because the survey response rate was less than 40% and response might indicate a more civic-minded disposition. In any case, if farmers perceive economic forces to be a stronger motives for land use changes in their locality than in their own land use decisions, and the economic conditions were favorable in the study period for conversion from grassland to cropland, then it is reasonable that we observe over-perception of grassland to cropland conversion.

6. Concluding remarks

The human dimensions of land use changes are a critical aspect in our understanding of the drivers underlying the changes. Landowner characteristics and regional land use patterns are central in the study of human dimensions. In the existing literature, this human dimension is mostly reflected in economic motives, and there is little study with respect to the behavioral and psychological factors underlying land use changes. We provide an analysis on how landowners' perception of land use changes are related to actual land use changes. We found substantial over-perception of the expansion of cropland. In particular, farmers' perceived changes are twice as large as the actual changes. Such over-perception can lead to a snowballing effect when perception of land use changes are also associated the change in regional infrastructural support for crop production.

As our results show that farmer's perception of land use changes are correlated with their perceptions of how infrastructure has evolved. Larger perceived cropland increases are positively correlated with perception of improved infrastructure condition for major crop production. The latter implies lower production costs and more convenient business network that supports crop production. This could eventually lead to additional conversion from other land uses to cropland.

Even though, the extent and nature of a region's agriculture is determined largely by the region's climate and soils. There is much more to an efficient production system. An increasingly sophisticated complex of local services supports all land in a locality that is under a given production system. Thus, the presence of such infrastructure as elevators and machinery services a) is the result of significant cropping presence and b) reduces the costs of cropping due to its very presence.

A farmer's perception of land use changes might be based on complex personal experience and neighborhood context and may not be accurate. Our results indicate that their perception is significantly related to their past land use decisions. This finding indicates that a sound land use management strategy need to recognize the underlying reasons of perception biases and accommodate farmers' insights and intelligence in public policy communications. The formation of perception is a complex process and is beyond this analysis. We are not sure how people form their perceptions, our study is only a beginning in the context of land use changes. More can be done regarding the formation of perceptions in future studies.

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Table 1. Summary statistics of key variables from farmers' survey.

Variable	N	Mean	Std. Dev.	Minimum	Maximum
Farm size	996	1686	1937	18	27000
Cropland acre	972	1226	1448	0	19023
Farmer's age	1017	3.303	1.084	1	5
Land tenure indicator	1001	2.752	1.220	1	5
Off-farm employment	1026	1.235	0.701	1	5
Latitude	1025	45.273	1.288	42.909	47.833
Longitude	1025	98.023	1.043	96.466	100.789
Percent of land in land class III or lower	1025	92.683	13.904	0.020	100
Perceived change in infrastructure for corn	1002	3.827	0.879	1	5
% change in corn and soybean acres, perception	1008	4.307	0.802	1	5
% change in grassland acres, perception	1003	1.994	0.898	1	5
% change in corn and soybean acres, CropScape	1025	5.762	3.037	-2.762	18.094
% change in grassland acres, CropScape	987	-6.970	13.201	-60.150	41.281
% of grassland acres, 5 mi. radius, CropScape	1025	24.48	17.66	0.383	80.96
% of land class I-III, 5 mi. radius, CropScape	1025	92.68	13.90	0.020	100
% of land Slope $\leq$ 3, 5 mi. radius, CropScape	1025	47.80	37.26	0	100
Conversion to cropland, past 10 years	1,026	0.242	0.428	0	1
Conversion to cropland, next 10 years	809	0.158	0.365	0	1
Conversion to grassland, next 10 years	872	0.095	0.294	0	1

Table 2. (Testing of Hypothesis I). Average perception biases (measured as the difference between land use changes according to CropScape and land use changes perceived by respondents)

Land use change variables	N	Mean	Pr > |t|
% change in corn and soybean acres, perception	1008	9.799	<.0001
% change in grassland acres, perception	1003	-7.545	<.0001
% change in corn and soybean acres, CropScape	1025	5.762	<.0001
% change in grassland acres, CropScape	987	-6.970	<.0001
Perceptions biases of change in cropland area	1007	4.045	<.0001
Perceptions biases of change in grassland area	966	-0.525	0.2652

Table 3. Number of respondents in different categories of perceived land use changes and actual grassland changes measured by CropScape data, within five-mile radius of a respondent's address.

A. For changes in cropland area

		CropScape				
		Decreased by > 10%	Decreased by 5-10%	Within 5%	Increased by 5-10%	Increased by > 10%
Survey	Decreased by > 10%	**0**	**0**	**2**	**4**	**0**
	Decreased by 5-10%	**0**	**0**	**5**	**3**	**0**
	Within 5%	**0**	**0**	**80**	**71**	**6**
	Increased by 5-10%	**0**	**0**	**138**	**183**	**16**
	Increased by > 10%	**1**	**0**	**169**	**280**	**50**

B. For changes in grassland area

		CropScape				
		Decreased by > 10%	Decreased by 5-10%	Within 5%	Increased by 5-10%	Increased by > 10%
Survey	Decreased by > 10%	**150**	**56**	**84**	**23**	**31**
	Decreased by 5-10%	**144**	**64**	**112**	**23**	**25**
	Within 5%	**82**	**54**	**95**	**12**	**17**
	Increased by 5-10%	**7**	**1**	**5**	**2**	**0**
	Increased by > 10%	**11**	**0**	**3**	**1**	**1**

C. Row frequency tables for changes in cropland area (reduced to 3 x 3)

		CropScape		
		Within 5%	Increased by 5-10%	Increased by > 10%
Survey	Within 5%	**51.0%**	**45.2%**	**3.8%**
	Increased by 5-10%	**41.0%**	**54.3%**	**4.8%**
	Increased by > 10%	**33.9%**	**56.1%**	**10.0%**

D. Row frequency tables for changes in grassland area (reduced to 3 x 3)

		CropScape		
		Decreased by > 10%	Decreased by 5-10%	Within 5%
Survey	Decreased by > 10%	**51.7%**	**19.3%**	**29.0%**
	Decreased by 5-10%	**45.0%**	**20.0%**	**35.0%**
	Within 5%	**35.5%**	**23.4%**	**41.1%**

Table 4. Duncan's Multiple Range tests of the three groups in Table 3 (cropland).

A. For changes in cropland area (groups defined in Table 3A)

Mean Value	Group I (5 diagonal boxes)	Group II (8 cross-line shaded boxes)	Group III (12 non-shaded boxes)
Age	3.24[ab]	3.37[a]	3.12[b]
Years operating land	4.32[b]	4.49[a]	4.26[b]
Education level	2.95[a]	2.93[a]	3.06[a]
Off-farm employment status	1.16[b]	1.25[ab]	1.28[a]
Acres operated	1,883[a]	1,546[a]	1,734[a]
Longitude	98.02[a]	98.00[a]	98.05[a]
Latitude	45.03[b]	45.25[b]	45.73[a]

B. For changes in grassland area (groups defined in Table 3B)

Mean Value	Group I (5 diagonal boxes)	Group II (8 cross-line shaded boxes)	Group III (12 non-shaded boxes)
Age	3.26[ab]	3.21[a]	3.39[a]
Years operating land	4.38[a]	4.36[a]	4.44[a]
Education level	2.92[b]	3.06[a]	2.87[b]
Off-farm employment status	1.27[a]	1.14[b]	1.27[a]
Acres operated	1,787[a]	1,799[a]	1,463[b]
Longitude	98.10[a]	98.06[ab]	97.90[b]
Latitude	45.29[a]	45.33[a]	45.14[a]

Note: Means with the same letter are not significantly different.

Table 5. (Testing of Hypothesis II tabulation) The number of respondents by past conversion history and perception categories

	Conversion from grass to crop				Conversion from grass to crop		
Perceived change in cropland area	0 (No)	1 (Yes)	total	Perceived change in grassland area	0 (No)	1 (Yes)	total
Decreased by > 10%	6	0	6	Decreased by > 10%	254	90	344
Decreased by 5-10%	6	2	8	Decreased by 5-10%	263	105	368
Within 5%	130	27	157	Within 5%	216	44	260
Increased by 5-10%	247	90	337	Increased by 5-10%	11	4	15
Increased by > 10%	374	126	500	Increased by > 10%	14	2	16
total	763	245	1,008	total	756	245	1,003

Table 6. (Testing of Hypothesis II) Estimation results of perceptions as a function of past land use decisions and other variables from the ordinal Logit model represented by equation (7). (Dependent variable is the odds of choosing a higher categories of changes. Alternative model results were presented that incorporated increasingly more variables.)

A. Perceptions about changes of cropland area (Odds Ratio Estimates)

Parameters	Model I	Model II	Model III
Conversion from grass to crop	1.650[c]	1.503[c]	1.299[a]
Perceived impact of changing crop prices		1.241[c]	1.145[b]
Farm acre		1.009	0.934[a]
Years operating		0.992	1.041
Tenure index		1.150[b]	1.243[c]
Education		1.120	1.106
Principal Occupation		1.040	1.021
CropScape cropland % change			1.080[c]
% of grassland, 2006, 5 mi. radius			1.025[c]
% of land class I-III, 5 mi. radius			1.017[c]
% of land Slope ≤ 3, 5 mi. radius			1.000
Change in infrastructure for corn			1.604[c]
Latitude			1.676[c]
Longitude			0.912
Percent Concordant	29.1%	61.1%	72.6%

B. Perceptions about changes of grassland area (Odds Ratio Estimates)

Parameters	Model I	Model II	Model III
Conversion from grass to crop	0.770[b]	1.003[a]	0.864
Perceived impact of changing crop prices		1.014[a]	0.840[c]
Farm acre		1.089	1.025
Years operating		1.039	0.879[a]
Tenure index		1.048	0.905
Education		1.381[b]	1.164[a]
Principal Occupation		0.942[b]	0.755[b]
CropScape grassland % change			0.996
% of grassland, 2006, 5 mi. radius			0.980[c]
% of land class I-III, 5 mi. radius			0.987[b]
Slope ≤ 3, 5 mi. radius			1.002
Change in infrastructure for cattle			1.220[b]
Latitude			1.188[c]
Longitude			1.018
Percent Concordant	26.8%	56.9%	62.1%

Note: For all estimation results, superscript “a”, “b”, “c” means statistically significant at 10%, 5%, and 1%, respectively.

Table 7. (Testing of Hypothesis III tabulation) The number of respondents by perception and intention of land use changes in the future

	Intention of conversion from grass to crop					Intention of conversion from crop to grass			
Perceived change in cropland area	0 (No)	1 (Yes)	total	Percent of 'yes'	Perceived change in grassland area	0 (No)	1 (Yes)	total	Percent of 'yes'
Decreased by > 10%	5	0	5	0.0%	Decreased by > 10%	263	35	298	11.7%
Decreased by 5-10%	3	1	4	25.0%	Decreased by 5-10%	269	38	307	12.4%
Within 5%	132	8	140	5.7%	Within 5%	221	7	228	3.1%
Increased by 5-10%	264	24	288	8.3%	Increased by 5-10%	12	1	13	7.7%
Increased by > 10%	376	49	425	11.5%	Increased by > 10%	13	1	14	7.1%
total	780	82	862	9.5%	total	778	82	860	9.5%

Table 8. (Testing of Hypothesis III) Estimation results of intended future land use changes as a function of current perception bias and other variables from the logistic model represented by equation (8).

A. Intention of future conversion from grassland to cropland (Odds Ratio Estimates)

Parameters	Model I	Model II	Model III
Perception bias in cropland area change	1.058[c]	1.057[b]	1.038
Conversion from grass to crop		2.770[b]	2.579[c]
Perceived impact of changing crop prices		1.027[c]	1.095
Farm acre		1.063	1.009
Years operating		0.837	0.884
Tenure index		0.794[a]	0.847
Education		0.992	1.023
Principal Occupation		1.396	1.522[b]
CropScape cropland % change			0.889[b]
% of grassland, 2006, 5 mi. radius			1.008
% of land class I-III, 5 mi. radius			1.027[b]
% of land Slope ≤ 3, 5 mi. radius			0.998
Change in infrastructure for corn			1.053
Latitude			0.842
Longitude			1.866[c]
Percent Concordant	59.0%	70.7%	74.9%

B. Intention of future conversion from cropland to grassland (Odds Ratio Estimates)

Parameters	Model I	Model II	Model III
Perception bias in grassland area change	1.004	1.006	0.983[a]
Conversion from grass to crop		1.491[a]	1.283
Perceived impact of changing crop prices		0.902	0.89
Farm acre		1.022	0.998
Years operating		0.823	0.867
Tenure index		0.867	0.93
Education		0.895	0.921
Principal Occupation		0.889	0.852
CropScape grassland% change			0.987
% of grassland, 2006, 5 mi. radius			1.052[c]
% of land class I-III, 5 mi. radius			1.021[b]
% of land Slope ≤ 3, 5 mi. radius			1.004
Change in infrastructure for cattle			0.823
Latitude			1.03
Longitude			0.823
Percent Concordant	47.1%	57.9%	69.9%

Note: For all estimation results, superscript "a", "b", "c" means statistically significant at 10%, 5%, and 1%, respectively.

Table 9. Summary of the impact ranking of different factors in own land use decisions versus in neighborhood land use changes (The ranking ranges from 1 to 5 with 5 being "Great Impact" and 1 being "no impact".)

	Impact on agricultural land use (own farm)			Impact on agricultural land use (local area)		
Variable	N	Mean	Std Dev	N	Mean	Std Dev
Changing crop prices	1010	2.190	0.839	791	2.747	0.520
Changing input prices	1002	2.079	0.823	785	2.353	0.703
Availability of crop insurance policies	1003	1.788	0.813	784	2.125	0.796
Availability of drought-tolerant seed	1004	1.606	0.763	785	1.781	0.760
Development in pest management practices	1003	1.838	0.800	784	2.052	0.752
Improved crop yields	1006	2.114	0.795	786	2.477	0.664
Development of more efficient cropping equipment	1006	1.941	0.833	783	2.315	0.737
Labor availability problems	1004	1.514	0.748	784	1.658	0.752
Improving wildlife habitat	1002	1.416	0.657	781	1.329	0.578
Changing weather/climate patterns	1007	1.766	0.810	783	1.849	0.790

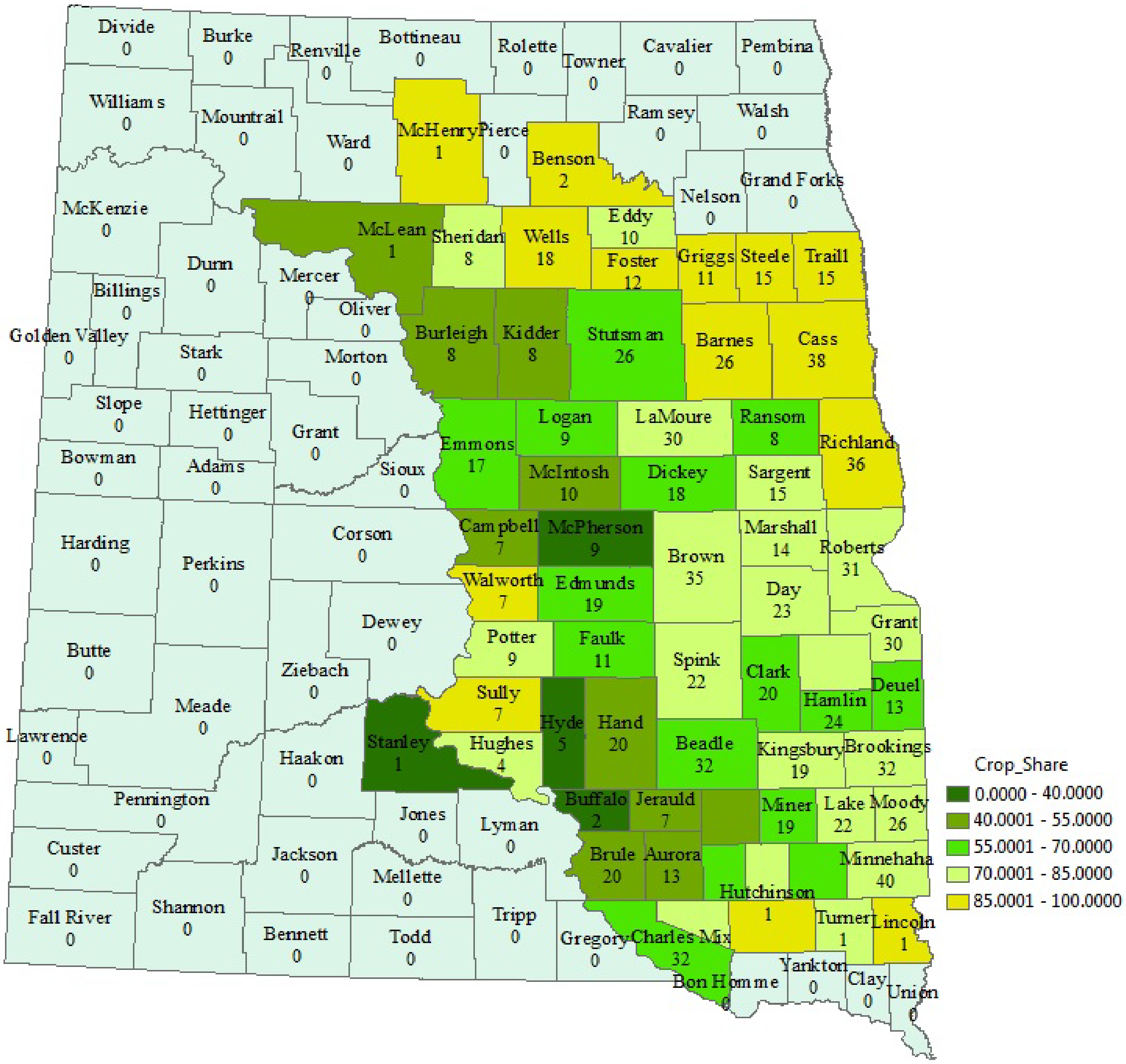

Figure 1. Cropland as a share of respondent acres and the number of survey respondents in each county. (Source: Wang et al., 2017)

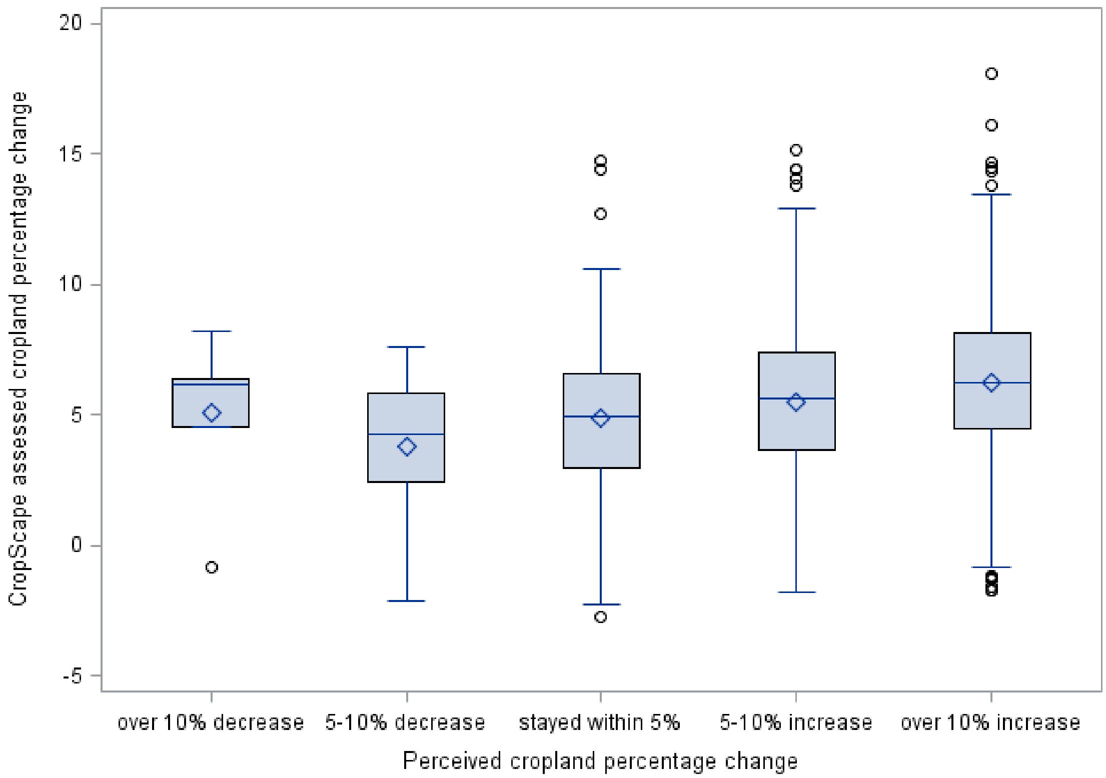

Figure 2: CropScape-assessed vs. Perceived Cropland Percentage Change.

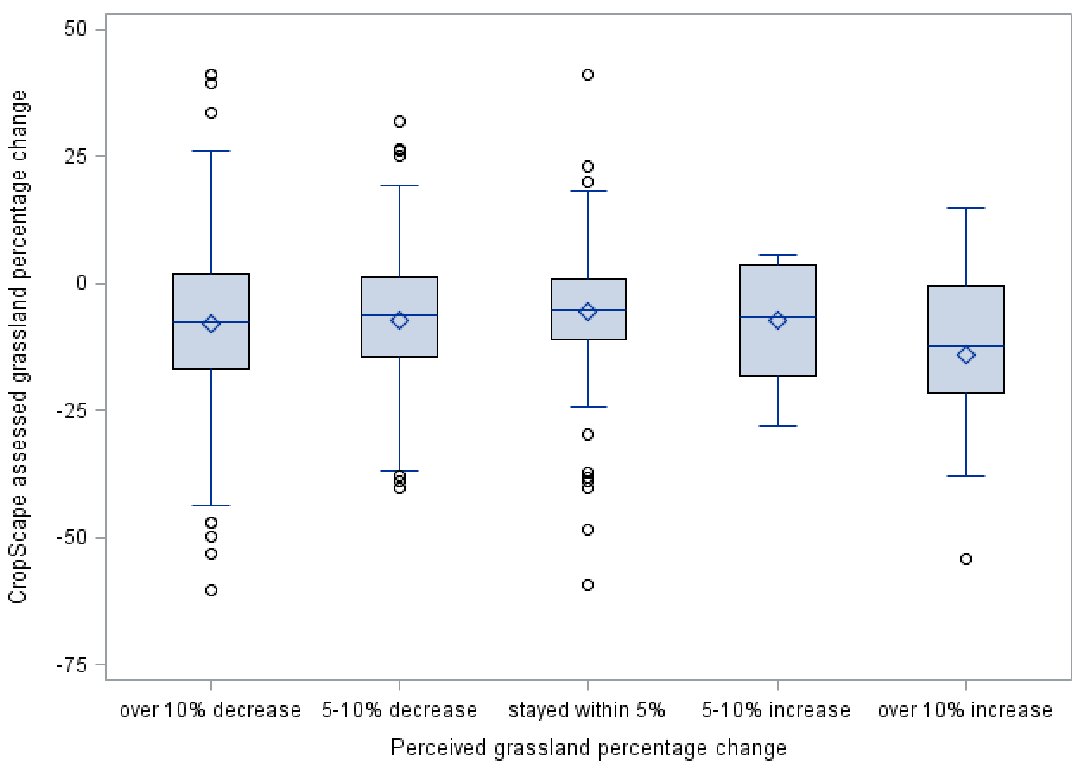

Figure 3: CropScape-assessed vs. Perceived Grassland Percentage Change.