Known and Unknown: Uncertainty in Estimating Land use Change from Satellite Data

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Abstract

Increasing crop prices may lead to an expansion of cropland, raising significant concerns about the effects of policy interventions such as biofuel mandates on land use change (LUC). The recent explosion in the availability of satellite imagery provides an opportunity to track the land use change at the field level. However, assessments of LUC from satellite products are only as good as the data and assumptions upon which they are based. In this study, we provide the first systematic comparison of the accuracies of three dominant satellite-based land cover data and examine the extent to which measurement errors can lead to uncertainty in estimating price-induced LUC in empirical analysis. we find that crop prices have a positive and statistically significant effect on total cropland acreage, regardless of the data source. However, the magnitudes of estimates are substantially different across data sources. Specifically, the price-acreage elasticity estimated by CDL is at least two times larger than those from MODIS and LCMAP. This difference is statistically significant and persists even after controlling for the variations in the definition of land categories. In addition, we also find that LUC estimates on noncropland are highly sensitive to data sources and the methods used for land category aggregations. This study contributes to the literature by underlining the importance of constructing and comparing inferences from different satellite land cover datasets. It also provides a practical approach to understanding and quantifying the uncertainty in LUC estimates and useful policy insights.

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Introduction

The increase in corn-ethanol production in the past decade has led to substantial concerns about the land use change (LUC), i.e., expansion of cropland to natural land, in response to higher crop prices induced by policy interventions such as biofuel mandates (Fargione et al., 2008; Searchinger et al., 2008). LUC has the potential to reduce soil carbon stock, to increase greenhouse gas emissions (Lark et al., 2022; Khanna et al., 2021), as well as to degrade water quality and biodiversity (Chen et al., 2021; Ferin et al., 2021; Lark et al., 2020a). Therefore, accurately quantifying LUC and accounting for its implied environmental implications are critical for informing biofuel and environmental policies.

Estimating LUC requires precise measurements of the types, amounts, and locations of land conversions at a fine-scale spatial resolution over time, which are extremely difficult to obtain from ground surveys. The recent explosion in the availability of satellite imagery provides an opportunity to track changes in land use at the field level, and such measures are increasingly used in recent empirical studies (Chen and Khanna, 2022; Lark et al., 2022, 2020a; Pates and Hendricks, 2021; Jiang et al., 2021b).

However, measurement errors seem inevitable in using satellite products to track land use change. First, the difference in the raw spectral signature, classification techniques, and protocols often lead to large discrepancies in land labels reported across different satellite land cover products (Li et al., 2018). Second, many satellite-based land cover products are produced with a purpose of mapping annual land cover ("snap-shot") rather than for tracking changes in land cover over time (Lark et al., 2017; Wehmann and Liu, 2015; Cai et al., 2014). Such a discrepancy could lead to temporal inconsistency in classification models and unrealistically high level of year-to-year changes in land classification labels (Abercrombie and Friedl, 2016; Emery et al., 2017; Li et al., 2018). Third, even for the same satellite product in any particular year, the validity and reliability of land classifications may vary substantially across land types and regions. For example, the previous LUC studies have relied exclusively on the CDL, which provides detailed land use classification for crops, but that may be at the expense of accuracy of land categories, especially for the noncropland (Kline et al., 2013a; Wright et al., 2017; Lark et al., 2015).

To mitigate these concerns, recent studies have developed several approaches to correct for measurement errors in satellite-based products. One such solution is to incorporate postprocessing algorithms in the data generating process to remove spurious land use change over time. For example, Abercrombie and Friedl (2016) develop a Hidden Markov Model (HMM)-based approach to estimate the likelihood of land use change at each pixel; this method has been implemented in the latest version of the MODIS land cover product. Yet, the effectiveness of this ad hoc adjustment and the extent to which this method can be applied to other land cover products are unclear. An alternative solution is to correct the estimators based on econometric techniques. For instance, Torchiana et al. (2022) propose a bias-corrected estimator of transition rates, which links the HMM- based correction to formal identification results.[2] Alix-Garcia and Millimet (2022) and Sandler and Rashford (2018) extend the maximum likelihood estimators in Hausman et al. (1998) and develop consistent estimators for binary choice models with mismeasured dependent variable. While these estimators are attractive and bring transparency to the correction of measurement errors in nonlinear models, they are complex and computationally burdensome for large regions with diverse land cover types and frequent transitions.[3]

In this paper we offer a different approach. We apply a unified reduced-form empirical

[2] For example, the probability of switching from cropland to forestland in the following year.

[3] Sandler and Rashford (2018) use a relatively simple specification with two types of land use and one transition period. They acknowledge that the likelihood function in a more complex model (such as multiple uses and many transition periods) may not converge. To ease the computation burden, Torchiana et al. (2022) have to split the entire sample and randomly select 1% observation within each subsample (approximately 10,000 observations) to estimate their model. Related studies such as Pates and Hendricks (2021) also note that many empirical studies that used the mixed or nested logit models typically have a small sample (less than 100, 000 observations) to reduce the computation burden.

framework to three dominant satellite-based land cover product used in the literature: Cropland Data Layer (CDL), Moderate Resolution Imaging Spectroradiometer Terra + Aqua Combined Land Cover Product (MODIS), and Land Change Monitoring, Assessment, and Projection (LCMAP). We examine the extent to which measurement errors could lead to uncertainty in ILUC estimates across these satellite data. In light of the limited comparison of classification accuracy across these data, we first introduce two benchmark land use data at both the pixel level and county level. By taking these benchmark data as "ground truth", we demonstrate the structure of measurement errors and potential causes of misclassification bias in CDL, MODIS, and LCMAP. This comparison helps us evaluate the practical importance of addressing measurement errors in these three data and also provides a general guidance in the choice and application of the empirical framework used to estimate LUC effects. We then estimate the LUC effects of crop prices on different types of land and regions across these satellite data using a uniform reduced-form model. Our empirical strategy addresses the endogeneity of crop prices by using the instrumental variable approach, following Chen and Khanna (2022). We also control for weather conditions, population density, unobserved local heterogeneity, idiosyncratic temporal shocks, and potential improvement in agricultural productivity over time. To construct comparable LUC estimates, we restrict our sample to the period of 2009-2019 when all satellite-based data are available.

We find that the crop price has a positive and statistically significant effect on total cropland acreage, regardless of the data source. However, the magnitudes of estimates are substantially different across data sources. The LUC estimates obtained from CDL are at least two times larger than those from MODIS and LCMAP. This difference is statistically significant and persists even after controlling for the discrepancies in definitions of land categories across these data.

Our results also indicate that LUC estimates on noncropland are highly sensitive to data sources and the methods used for land category aggregations. The LUC estimates for grassland from

CDL are at least five times larger than those from MODIS and LCMAP. However, the LUC estimates on aggregated category such as natural land, defined as the sum of grass, forests, and wetland, from CDL is much smaller and close to corresponding estimates from MODIS and LCMAP. In addition, we find the acreage effect of crop prices on fallow/idle land obtained from CDL is substantially higher than the corresponding effect on natural land, indicating that a majority of the price-induced cropland expansion occurs on fallow/idle land rather than natural land. These results contradict findings in previous studies that suggest price-induced cropland expansions are mostly happening on natural vegetation areas (Lark et al., 2015, 2022; Wright et al., 2017).

The large discrepancy in LUC estimates using different datasets and land categories lead to reliability concerns about previous studies which only leverage one single satellite data such as CDL and/or focuses on individual land category such as grassland. Given the difficulty to directly correct the measurement errors, it is important to construct inference from different datasets and both the individual and aggregated land categories. Accordingly, we suggest that robust conclusions can only be drawn if all these estimates are consistent and aligned.

Our paper is close to Lark et al. (2022), Sandler and Rashford (2018), Chen and Khanna (2022) and Scott (2014). One major difference between our work and the existing studies is that we separately estimate the LUC effects of crop prices on land use measures constructed from multiple satellite data under a uniform empirical framework. We also contribute to the literature by presenting two novel datasets—MODIS and LCMAP—that is comparable to CDL in terms of the reliability and covers longer time period, which enables the quantification of LUC in unprecedented detail. Due to data limitation and modelling complexity, existing studies often focus only on a limited set of land transition types. For example, Lark et al. (2022) estimate the probability of transitions between cropland and pastureland as well as transitions between cropland and Conservation Reserve Program (CRP) land, while other important land types, such as the cropland pasture, are ignored since there are very few observations in their sample to support any valid statistical inference. Sandler and Rashford (2018) restrict their analysis to land conversions between cropland and grassland in Northern Great Plains from 2009 to 2010. Chen and Khanna (2022) mainly focus on the land conversion between cropland and grassland, though their study covers the entire rainfed region and the period of 2001-2019. Other related studies such as Scott (2014) aggregate hay acreage, pastureland, and unmanaged natural land in CDL into a one single category labelled as "others". While restricting land transition types or constructing aggregated category might have reduced the computation burden in empirical analysis, these practices might also limit the understanding of heterogeneity in the responses to crop prices across different types of land, which is the key to the making environmental and biofuel policies.

Our reduced-form approach thus contributes a flexible framework and allows us to directly estimate and compare acreage effects across different types of land, as well as across space and over time. Moreover, by applying a uniform reduced-form model to all these data, we can isolate the uncertainty in LUC estimates due to the discrepancy in definitions of land categories, misclassification errors, and heterogeneity in study periods or regions. This comparison provides an informal but practical approach to understanding and quantifying the uncertainty in LUC estimates and offer useful policy insights.

In addition, our study also provides the first large-scale and systematic comparison of the accuracy in three dominant satellite land cover data used in the literature and the extent to which measurement errors could lead to uncertainty in LUC estimates across different datasets, types of land and locations. While some recent studies have acknowledged the importance of addressing such measurement errors, their methods either rely on extremely strong assumptions or are limited to one single dataset (Lark et al., 2022; Chen and Khanna, 2022). For instance, Lark et al. (2022) propose a hybrid approach that transfer LUC estimates obtained from survey data, which are accurate but restricted to sampling periods and spatial coverage, to high-resolution satellite data to map possible locations and characteristics of converted land.4 However, the inconsistency in study periods between survey-based and satellite-based land use measures, the discrepancy in the definition of land categories, and the measurement errors in both land use measures jointly make reliable inferences from this kind of hybrid approach difficult (Taheripour et al., 2022). Chen and Khanna (2022) extract the quality assurance information from MODIS and perform a set of robustness exercises to understand the extent to which their estimates would be biased due to potential measurement errors in land classification that correlate with explanatory variables.5 However, the conclusions drawn from these robustness exercises are highly context specific and could not be directly applied to other datasets6, or even the same satellite data with different temporal or spatial coverage. In contrast, this study develops a consistent comparison across satellite data by utilizing the pixel-level "ground truth" benchmark data, which allows us to demonstrate the structure of measurement errors and potential causes of misclassification in data in a comparable way.

This paper is organized as follows: Section 2 discusses the source and consequences of measurement errors in satellite-based land use data and lays out the empirical framework; Section 3 discusses the use of validation data to evaluate the accuracy of each satellite data and provides

[4] Lark et al. (2022) use National Resources Inventory (NRI), which provides annual land use information at sampling points across CONUS from 2000-2012, to obtain the LUC estimates and then apply these estimates to cropland data layers (CDL) in 2008-2016 to identify possible locations and characteristics of converted land. The motivation behind this method is that the survey data from NRI only indicate county in which a point is located but not its exact geographic location. In addition, NRI data contains very few transitions between cropland and non-cropland types except the pasture and CRP categories, while CDL covers a wide range of non-cropland categories. However, Taheripour et al. (2022) criticized this practice by pointing out two important observations. First, land categories such as "pastureland" and "CRP" in NRI data are substantially different from non-cropland categories (such as "grassland/pasture") in CDL. Thus, simply applying the estimates from NRI to CDL is very likely to overestimate the LUC effects. Second, land use pattern in NRI data is tremendously different across years, i.e., the discrepancy in land transitions between cropland and pastureland in 2012 and 2015 NRI data. This kind of inconsistency could lead to severely biased LUC estimates and questionable conclusions.

[5] They find that weather shocks could significantly reduce the quality assessment scores and reduces the probability of a pixel being classified as cropland, but the magnitudes of biasness are small and negligible in their study period and region.

[6] In practice, one additional challenge is that the quality assessment information in different satellite data is typically constructed on demonstrably different protocols and cannot directly compare with each other

guidance for empirical analysis; Section 4 examines the extent to which measurement errors could lead to uncertainty in ILUC estimates across data, types of land, as well as regional locations; Section 5 concludes.

Results

Regression estimates of land use change, as measured with errors by satellite-based land use data, are subject to misclassification bias. In practice, how much do the measurement errors matter for LUC estimates, and if so, under what circumstances? In this section, we examine the extent to which measurement errors could lead to uncertainty in LUC estimates across data sources, types of land, as well as regional locations. Based on the recommendations from the accuracy analysis above, we control for the unobserved time-invariant and idiosyncratic temporal shock in our empirical framework and compare LUC estimates obtained from aggregated and individual categories of noncropland.

LUC Effects on Cropland Acreage. Table 2 reports the average effects of the crop price index on county-level aggregated cropland acreage, using the lagged crop stocks as the instruments. Panel A reports the estimates for all the counties in the CONUS using equation (1). Panel B reports the estimates for counties in the major agricultural production region (area that had planted any of the ten major crops over the period of 1996-2000) and non-agricultural region (area that had never planted any of the ten major crops from 1996 to 2000), respectively. The Kp F statistics reported in Table 2, which are significantly larger than 10, suggest that lagged crop stocks are valid instruments. The details of the first-stage results can be found in Appendix Table C.5. Column 1–4 in each panel report the estimated effect of the crop price index on four satellite-based measures of cropland acreage: acreage for all crops in MODIS, CDL, and LCMAP, as well as acreage for major crops in

CDL.

We find that the increase in crop price leads to significant expansion in aggregated cropland acreage (hereafter, “price-induced LUC effect”). The estimated coefficients for counties in CONUS (panel A) or major agricultural regions (panel B) are both positive for all cropland measures. All else being equal, a half-unit increase in the price index, which is approximately one standard deviation of the price index, increases the net cropland acreage by 3-14 thousand acres for all CONUS counties and by 4-22 thousand acres for counties located in the major agricultural region. These coefficients imply a price effect of 3.5-30.7%, or a price-acreage elasticity of 0.06-0.22. In addition, we find the average LUC effects of counties in the major agricultural region are at least 15% larger than those of CONUS counties, while the average LUC effects of the non-agricultural region are either small in magnitude or insignificant, indicating that the price-induced cropland expansion is mostly happening in the region that was historically under agricultural production. To simplify the discussions in the following sections, we then use the models in Panel B of Table 2 as our preferred specification and focus on discussing the LUC effects in the major agricultural regions. Table 2 allows us to quantify how much difference it would make if we use different satellite data to estimate LUC effects. Ideally, if all satellite data are accurately classifying landscape in the same way, we would obtain similar and statistically indistinguishable estimates across Columns 1–4 of Table 2 since they are all estimated based on the exact same model specification. However, we find that CDL leads to substantially larger estimates than those from MODIS and LCMAP. 19In appendix Table S4, we also report estimated effects of crop prices on total crop acreage obtained from alternative survey-based data such as FSA and NASS. Our findings remain robust and consistent. Specifically, the price-induced LUC effects estimated by CDL are almost two times larger than that of MODIS and five times larger than that of LCMAP.

To further investigate whether these point estimates are statistically distinguishable from each other, we conduct a formal test by bootstrapping our sample 1,000 times with replacement and calculating the differences in point estimates from these three specifications for each iteration.21 Appendix Figure C.6 confirms that there are statistically significant differences in LUC estimates across these three satellite-based data. Using the effect estimated from MODIS as the reference group, we find that the average difference between CDL (LCMAP) estimates and MODIS estimates is 20.8 (-15.7), with 979 (999) of 1000 estimates being larger (smaller) than zero. In almost all cases, we can conclude that CDL suggests a significantly larger ILUC effect than MODIS and LCMAP. In addition, all confidence intervals, represented by the distributions of difference in estimated coefficients, suggest that we can reject the null hypothesis that there has been no difference in point estimates from these three satellite-based products (one-sided p-value on the test of null against the alternative hypothesis is p=0.03 or smaller).

Heterogeneity in LUC Effects across Noncropland Acreage. Panel A-C of Table 3 report the LUC effects on different noncropland classes in CDL, LCMAP, and MODIS, respectively. Overall, the LUC estimates on fallow/idle land and some categories of natural land, such as grassland and wetland, are significant and substantial in magnitudes. The estimates from LCMAP have the same signs as those from MODIS and CDL, but generally an order of magnitude smaller; this is possibly due to its relatively broad definition of cropland that masks the land use change between activate cropland and pastureland under livestock operation, which indicate that cropland expansion is occurring on both land that used to be under agricultural production but had been set aside or abandoned, as well as land under natural vegetation coverage. Within the natural land, we find that the LUC estimates on grassland and wetland are significant and substantial, while those on forestland are either small in magnitudes or statistically insignificant, indicating newly cropland expansion on natural land mostly occurs on grassland and wetland rather than forestland.

Additionally, we find that the magnitudes of coefficients differ substantially across these satellite- based noncropland measures. For instance, a one-unit increase in crop price could reduce the grassland acreage in the major agricultural region in CDL by 69.4, which can be translated into a percentage change of 54.3%(=69.4/127.9), while the corresponding change in price can only reduce the grassland acreage in MODIS by 16.2 thousand acres (or a reduction of 8.2%(=16.2/198.2)). The corresponding effect on LCMAP grassland acreage is even insignificant with a small magnitude.

This substantial difference in the estimated LUC effects on noncropland categories can be explained by two possible reasons: inconsistency in definitions and misclassification errors. First, the same land pixel can be classified under different noncropland categories due to the inconsistency in the definition across satellite-based data, leading to a large variation in the estimated coefficients. For example, the grassland categories in CDL and MODIS include managed and unmanaged grassland as well as pastureland under livestock operation (Appendix Table C.2), while the grassland category in LCMAP only includes unmanaged grassland (Appendix Table C.3). Thus, the insignificance of LUC effect on grassland acreage in LCMAP should be interpreted as the increase of crop price index does not affect the unmanaged grassland. It is possible that higher crop prices could lead to conversions between cropland and crop pasture, or rangeland that are under active livestock operation. Second, even under the same definition, misclassification errors in these satellite-based data, as we noted in Section 3, could also substantially affect the magnitude of LUC estimates or even reverse the signs. In fact, the positive and significant coefficients of shrubland and developed land from CDL also imply there might exists substantial misclassification errors between grassland and these two land categories.

Given the uncertainty in estimating LUC effects for these individual noncropland categories, we then aggregate grass, forest and wetland into one single category —natural land— and estimate the LUC effects on this super category instead. The estimated coefficient from CDL on natural land shrinks significantly. Specifically, one unit increase in crop price only leads to a reduction of 4.2% (=9.2/218.5), a magnitude that is much closer to corresponding estimates from LCMAP (2.2% (=6.7/335.2)) and MODIS (4.8% (=19.3/398.6)). These results suggest a substantially smaller effect of crop prices on land under natural vegetation coverage, The price-acreage elasticity on natural land ranges between 0.03-0.07, with magnitudes close to the effects of prices on cropland estimated in the above section.

The large discrepancy in LUC estimates between grassland and natural land category in CDL leads to questions on reliability of using individual noncropland categories from satellite data, especially CDL on LUC estimation. Since misclassifications between these noncropland categories are difficult to address in the absence of a large-scale, reliable validation data, we suggest that any LUC estimates on individual noncropland categories should be interpreted with caution. Inference from one single satellite data should not be directly used for informing policy without proactively address potential misclassification bias.

Regional Heterogeneity. Considering that there is vast spatial heterogeneity in environmental and resource endowments across the CONUS, it is possible that the LUC effects could vary across space. We therefore explore the regional heterogeneity by allowing regional heterogeneous coefficients in our main specification. Appendix Table C.8 presents the estimated coefficients on interaction terms between crop price index and indicators of nine regions across CONUS on acreage of different land categories, using the states in the Corn Belt region as the reference group.

To facilitate the narrative, we convert the estimated coefficients into price-acreage elasticities, evaluated at the sample mean of crop price index and corresponding land acreage

(Table C.6).

We find that price elasticities from CDL are generally higher and suggest a significant regional difference in price-induced LUC effects. Column 1 of Table C.6 suggest that, comparing to Corn Belt states (e.g., Illinois and Iowa), states in the Northern Plains region (e.g., North and South Dakota), Lake states (e.g., Minnesota, Wisconsin), South Atlantic (e.g., North and South Carolina), and West Pacific (e.g., California) are more sensitive to the increase in crop price index. The estimated price-acreage elasticities in these regions are at least 44% larger than that of corn belt states. In contrast, states in the northeast (e.g., New York state) and South Central region (e.g., Mississippi, Alabama) are relatively inelastic to the price change. These results echoes findings of several related studies that suggest the corn acreage in North and South Dakota are much more sensitive than that in central corn belt (Pates and Hendricks, 2021), although our study mainly focus on the aggregated cropland rather than corn acreage. However, we also find that the spatial patterns of LUC effects obtained from MODIS and LCMAP are substantially different from those from CDL. Columns 2-3 reports the regional-specific price elasticities estimated based on LCMAP and MODIS data. These elasticities are similar in magnitudes and suggest no evidence of significant difference in LUC effects across regions.

As for the price-acreage elasticities for noncropland categories, we find that estimates are substantially different between individual and aggregated categories of noncropland. For instance, the price-acreage elasticities estimated based on individual categories of noncropland in CDL, such as grassland and wetland (Columns 6-7 of Table C.6), are significantly larger than those obtained from aggregated category, such as the total acreage of grassland, wetland, and forestland (Column 9 of Table C.6). In addition, the magnitudes of price elasticities of aggregated category, such as natural land, are similar and statistically indistinguishable across regions, especially for states in the corn belt states, lake region, and northern plain region. This discrepancy suggests that the estimates on individual categories of noncropland could be severely biased due to measurement errors in these land categories. Overall, these results are highly sensitive to data source and the methods used for measurement and reporting land categories. which implies weak evidence of spatial heterogeneity in LUC effects across CONUS.

Conclusion.

The increasing availability of satellite-based land use data offers new opportunities for empirically estimating land use change induced indirectly by higher crop prices and understanding the heterogeneity in LUC effects across different types of land and regional locations. However, this new type of information also poses new challenges for empirical analysis due to the discrepancy in definition and protocols across satellite datasets and the non-classical nature of its error structure.

In this paper, we assess the accuracies of land use measures from three dominant satellite data used in the literature – CDL, MODIS, and LCMAP – and demonstrate the structure of measurement errors and potential causes of misclassifications in these data. We then examine the extent to which measurement errors in these satellite data could lead to uncertainty in LUC estimates across different land types and regions and across datasets. By applying a uniform reduced-form model to all these data, our approach allows us to isolate the uncertainty in IUC estimates due to the discrepancy in definitions of land categories, misclassification errors, and heterogeneity in study regions.

We find that the crop price has a positive and statistically significant effect on total cropland acreage, regardless of the data source. However, the magnitudes of estimates are substantially different across data sources. This difference is statistically significant and persists even after controlling for the discrepancy in the definition of land categories. Our results also indicate that LUC estimates on noncropland are highly sensitive to data sources and the methods used for land category aggregations. The large discrepancy in LUC estimates using different datasets and land categories lead to reliability concerns about previous studies which only leverage one single satellite data such as CDL and/or focuses on individual land category such as grassland. It also underlines the importance of constructing and comparing inference from different datasets and both the individual and aggregated noncropland categories. In addition, we find that there is weak evidence of cropland expansion on natural land in the lake states and northern plain region.

While “better data” is always desirable, these remote sensing products are the only long-term continuous high-resolution detailed land cover data for empirical analysis. We acknowledge that, to this end, there is effectively no way to accurately map land use change without any error, and one must inevitably rely on reasonable but imperfect proxies and assumptions. The estimates of LUC from satellite-based products are only as good as the data and assumptions upon which they are based. Accordingly, empirical results from studies using satellite-based products should be interpreted with caution, and it is advisable to compare estimates from alternative satellite-based products to increase the reliability of the conclusion drawn from these estimates. We acknowledge that our approach does not provide any direct correction for misclassification or uncertainty in inference from temporal land use change in satellite-based data. Although there is a growing literature on developing efficient methods applying full maximum likelihood in joint estimation with correction for misclassification, these have not yet been ready to implement in a complicated problem such as LUC. Therefore, for the time being, our approach can be treated as an informal but practical approach to understand and quantify the uncertainty in LUC estimates and provide useful policy insights. We leave it for future research to develop more sophisticated econometric methods to address the misclassification issue formally.

Tables and Figures

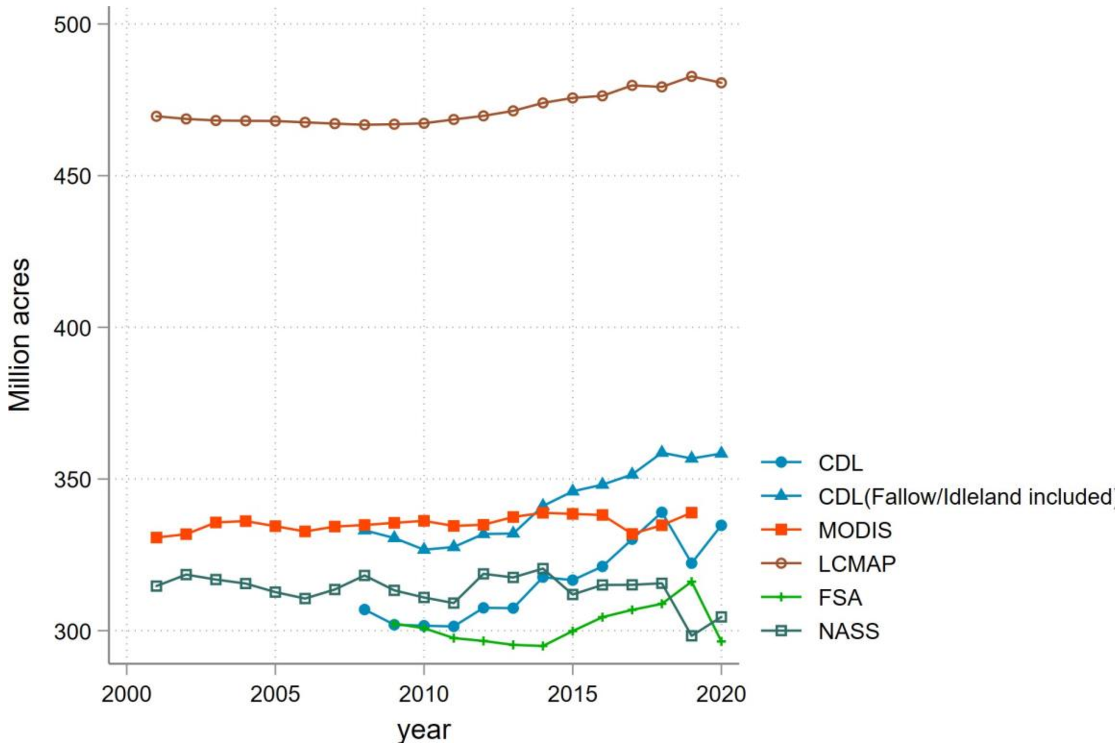

Figure 1: Aggregated Cropland Acreage for CONUS in 2001-2019 (Million acres)

Notes: Total cropland acreage were calculated by aggregating cropland area for each pixel (or county) in satellite-based data (or survey-based data). The legend labels are defined as follows: (1) "CDL"– total acreage for all conventional crops in CDL, including Alfalfa and hay acreage); (2) "CDL (Fallow/Idle land included)" – total acreage for all conventional crops and fallow/idle land acreage in CDL; (3) "MODIS" – total acreage for all cropland categories in MODIS; (4) "LCMAP" – total acreage for all cropland categories in LCMAP; (5) "FSA" – total acreage for all conventional crops, including acreage under fallow and prevented planting program; (6) "NASS" – total acreage for all conventional crops. More details on land categories and the aggregating procedure can be found in Appendix Table C.1-C.3.

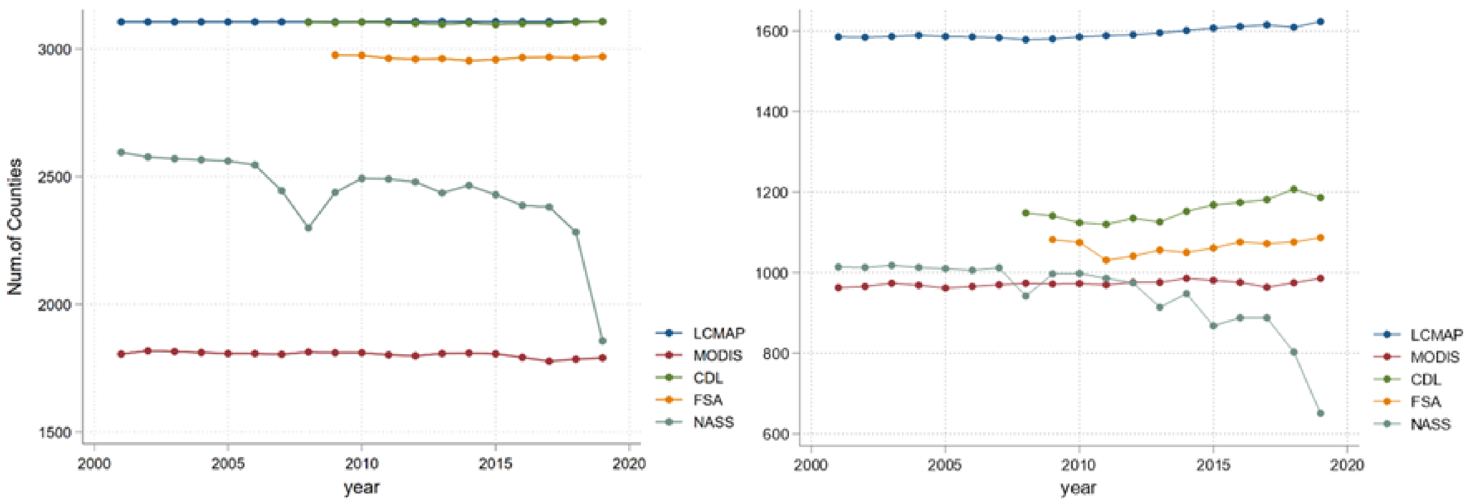

Figure 2: Number of Counties with any Cropland Acreage (left) and Cropland Acreage lager than 100 thousand acres (right).

Notes: Number of counties were counted based on the total cropland acreage for each county, which were defined as follows: “CDL”– total acreage for all conventional crops in CDL, including Alfalfa and hay acreage); (2) “MODIS” – total acreage for all cropland categories in MODIS; (3) “LCMAP” – total acreage for all cropland categories in LCMAP; (4) “FSA” – total acreage for all conventional crops, including acreage under fallow and prevented planting program; (5) “NASS” – total acreage for all conventional crops. More details on land categories and the aggregating procedure can be found in Appendix Table C.1-C.3.

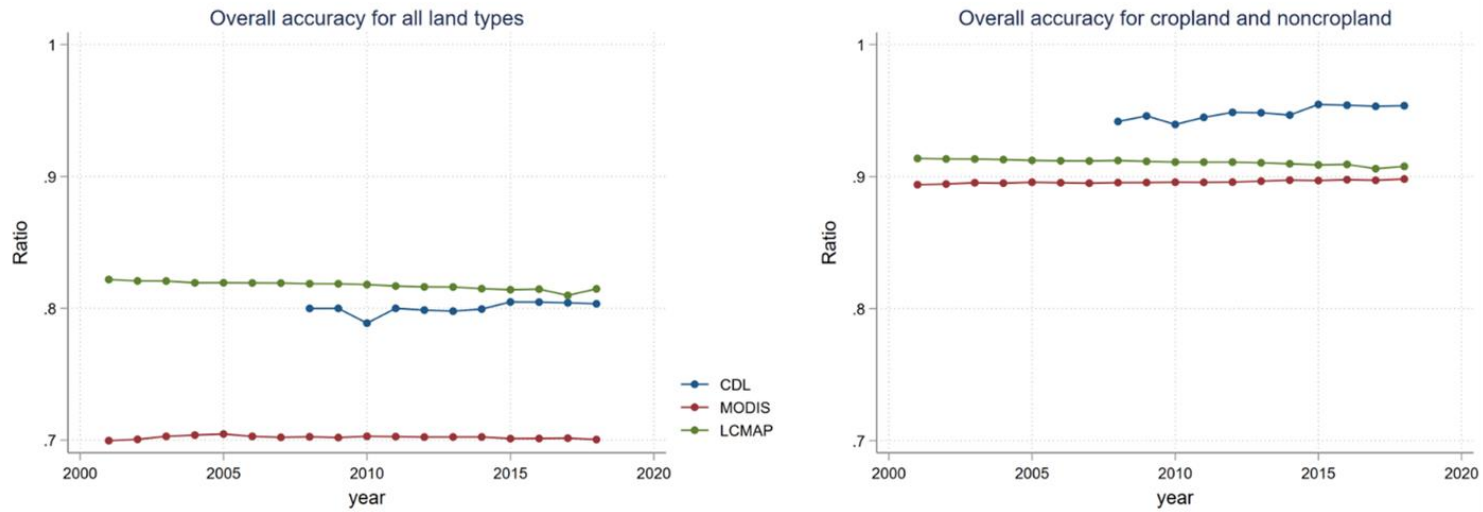

Figure 3: Overall Accuracy of Land Classification between Satellite Data and Pixel-level Reference Data.

Notes: Left panel of the figure shows the average accuracy of all land categories in each year for CDL, MODIS, and LCMAP, comparing to the pixel-level reference data. Right panel of the figure shows the average accuracy of cropland and aggregated noncropland categories in each year for these satellite data, comparing to the reference data. The average accuracy is computed based on the fraction of correct land classification for each category in the data.

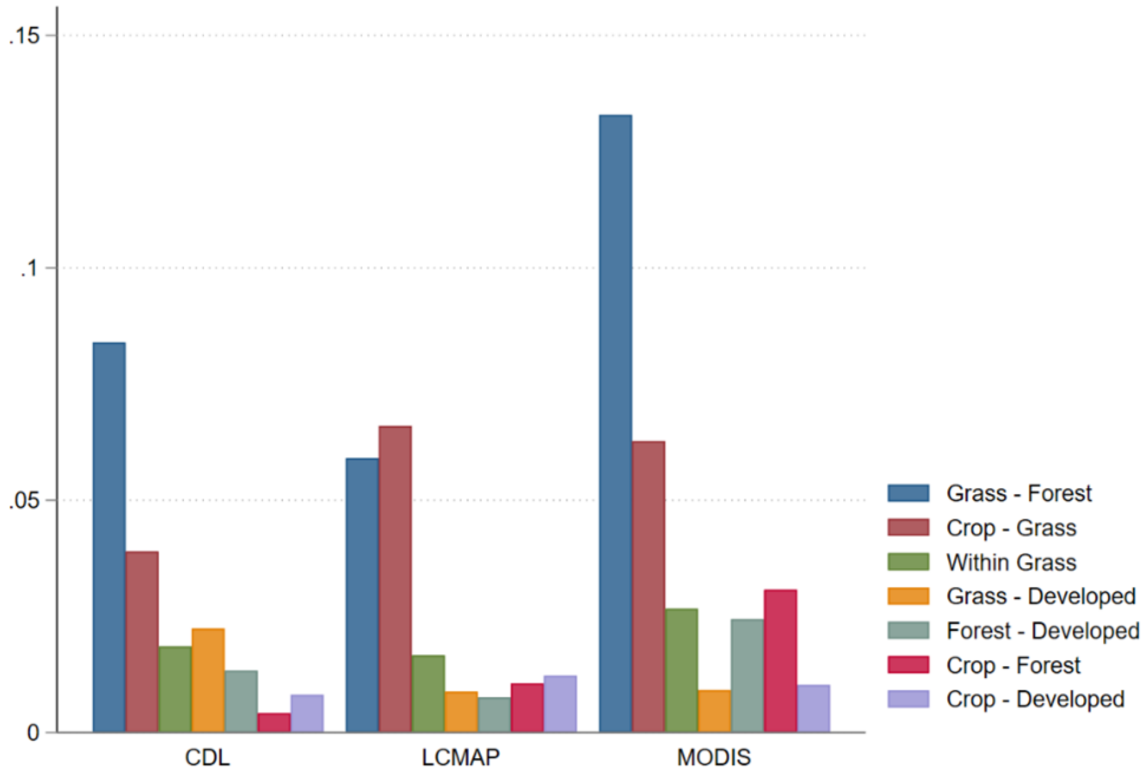

Figure 4: Source of Misclassification in Satellite Land Use Data.

Notes: This figure is compiled based on category-by-year comparison between each satellite-based data and the reference data at the 30-meter by 30-meter pixel level over the period of 2009-2019. The y-axis of the figure reports the ratio of misclassification errors in each land category.

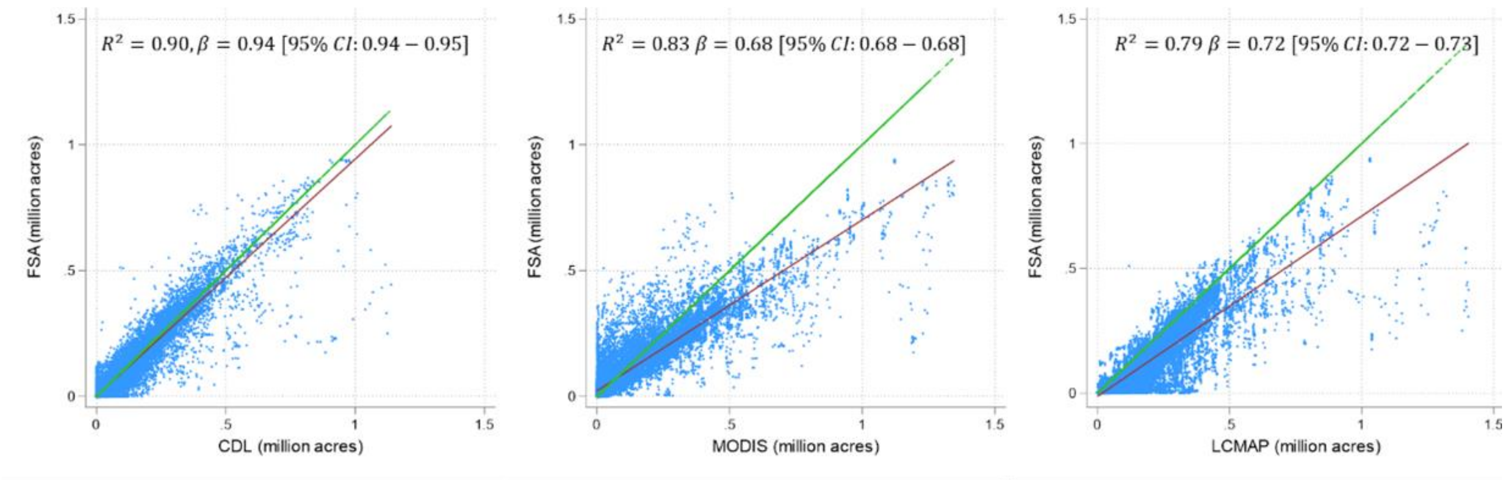

Figure 5: Accuracy of Total Cropland Acreage. Left to right: CDL, MODIS, LCMAP.

Notes: This figure shows the "county-by-year" agreement between total cropland acreage from satellite products and that from FSA land use report over the period of 2009-2019. Blue dots represent "county-by-year" observations; green line represents the 45-degree line; red line in each subplot represents a fitted regression line by regressing FSA cropland acreage on satellite-based cropland acreage. The overall fitness and estimated coefficient are reported on the left top of each subplot.

Table 1: Summary of Land Use Data

Dataset	Resolution	Time Period	Definition for Major Land Categories	Major Classification Inputs	Validation	Source
CDL	30m	2008-2021 for all states; 1999-2006 for major cropping area	(1) Cropland category includes active cropland by crop types, including Alfalfa and other hay. Planted Acres in the growing season (2) Fallow/Idle cropland (3) Grass/Pasture (both managed and unmanaged grassland)	At least one cloud-free usable image every two weeks throughout the growing season from Landsat 8 OLI/TIES	FSA Common Land Unit Reports by crop type; NLCD is also used as the reference dataset for non-agricultural land classification.	USDA
LCMAP	30m	1985-2021	(1)Cropland includes cultivated and uncultivated croplands, hay lands, orchards, vineyards, and confined livestock operations. Land in either a vegetated or unvegetated state used in production of food, fiber, and fuels. (2)Grass/Shrub (unmanaged grassland)	All available cloud- and shadow-free pixels in the USGS Landsat Analysis Ready Data (ideally every two weeks)	25,000 pixel-level plots land use reports from U.S. Forest Service.	USGS
MODIS	500m	2001-2021	(1)Cropland category includes areas dominated by herbaceous annuals (¡2m). At least 60% cultivated cereal/broadleaf crops. (2)Grass/Shrub/Pasture (both managed and unmanaged grassland)	A full-year of 8-day MODIS Reflectance imagery Database.	Post-processed by a Hidden Markov Model to reduce inter-annual variability.	NASA/USGS
FSA	County	2008-2021; Data before 2007 are not publicly available.	(1)Cropland category includes planted acres reported by Insured farmers; (2)Grass/Conservation/Pasture (managed grassland but with vague definitions)	-	-	USDA
NASS Survey	County	1990-2021;	Cropland category includes active planted/harvested cropland by crop types, including Alfalfa and other hay. The annually survey data provide both planted and harvested acres while the census data only provides harvested acres for every 5 year.	June Area Survey (Annually): personal interview during the first two weeks of June. Typically includes a sample of nearly 11,000 segments selected from each land use stratum.	-	USDA

Table 2: Effect of Crop Prices on Aggregated Cropland Acreage

	MODIS All Crops (1)	CDL All Crops (2)	CDL Major Crops (3)	LCMAP All Crops (4)
	Panel A: CONUS			
Lagged Crop Price Index	16.9***	28.2**	22.7***	6.9***
	(4.2)	(11.1)	(6.0)	(1.9)
Obs	33346	33346	33346	33346
F-test (Kp statistics)	126.7	126.7	126.7	126.7
	Panel B: Major Agricultural Regions			
Lagged Crop Price Index	23.5***	43.6***	33.6***	7.9***
	(7.3)	(16.1)	(9.0)	(2.54)
Obs	22417	22417	22417	22417
F-test (Kp statistics)	101.8	101.8	101.8	101.8
	Panel C: Non-agriculture Regions			
Lagged Crop Price Index	3.6**	7.0	-1.2	6.6***
	(1.5)	(7.7)	(1.1)	(2.6)
Obs	10573	10573	10573	10573
F-test (Kp statistics)	46.22	46.22	46.22	46.22

Note: Panel A of Table 2 presents the regression results using all counties in the CONUS while Panel B and C show the results using subsamples which covers the major agricultural production region and non-agricultural production regions. The major agriculture region is defined as counties that had planted any of the ten major crops in 1996-2000. The minor agriculture region is defined as counties that had never planted any of the ten major crops in 1996-2000. The description of ten major crops is documented in the Data Section. All regressions include flexible weather controls, including 9 temperature bins (<0, 0-5, 5-10, 10-15, 15-20, 20-25, 25-30, 30-35, >35°C), and indicators for extreme precipitation events. We also control for a set of location-specific and temporal fixed effects, including county, year, and linear time trends at the agricultural statistics district level. All the regressions are estimated by clustering the standard errors at the county and year-by-district level. $* \ p < 0.10$, $** \ p < 0.05$, $*** p < 0.01$.

Table 3: Effect of Crop Prices on Aggregated Non-cropland Acreage

	Fallow/Idle	**All vegetation (Grass/Shrub/Forest/Wetland)**	**Grass**	**Shrub**	**Wetland**	**Forest**	Develop/Urban
	(1)	**(2)**	**(3)**	**(4)**	(5)	(6)	(7)
Panel A: CDL							
Lagged Crop Price Index	-32.7***	-9.2	-69.4**	74.7**	-11.4***	-3.2	-4.6***
	(8.32)	(16.9)	(33.7)	(30.0)	(3.8)	(5.6)	(1.8)
Obs	22417	22417	22417	22417	22417	22417	22417
F-test (Kp statistics)	101.8	101.8	101.8	101.8	101.8	101.8	101.8
Panel B: LCMAP							
Lagged Crop Price Index	-	-6.7**	-1.2	-	-5.0**	-0.5**	0.4
	-	(3.3)	(3.7)	-	(2.0)	(0.2)	(0.4)
Obs	-	22417	22417	-	22417	22417	22417
F-test (Kp statistics)	-	101.8	101.8	-	101.8	101.8	101.8
Panel C: MODIS							
Lagged Crop Price Index	-	-19.3***	-16.2**	-4.0	-	0.9	0.0530
	-	(7.2)	(7.0)	(5.1)	-	(3.0)	(.)
Obs	-	22417	22417	22417	-	22417	22417
F-test (Kp statistics)	-	101.8	101.8	101.8	-	101.8	101.8

Note: This table reports the estimated impacts of lagged received crop prices, instrumented by lagged crop stock level, on different non-cropland categories in satellite land use data. Panel A, B, and C of Table 3 presents the results using CDL, LCMAP and MODIS, respectively. Column 1-7 reports the estimates of six non-crop land categories in each data, if available. The aggregated natural land is defined as the sum of grassland, shrubland, forestland, wetland. All regressions include flexible weather controls, including 9 temperature bins (<0, 0-5, 5-10, 10-15, 15-20, 20-25, 25-30, 30-35, >35°C), and indicators for extreme precipitation events. We also control for a set of location-specific and temporal fixed effects, including county, year, and linear time trends at the agricultural statistics district level. All the regressions are estimated by clustering the standard errors at the county and year-by-district level. $*\ p < 0.10$, $**\ p < 0.05$, $***\ p < 0.01$.

Table 4: Price-acreage Elasticities across Regions

	(1) CDL All crops	(3) LCMAP All crops	(4) MODIS All crops	(6) CDL Grassland	(7) CDL Wetland	(8) LCMAP Grass/shrub	(9) LCMAP Wetland	(10) MODIS Grassland	(10) CDL Aggregated Natural Land	(10) LCMAP Aggregated Natural Land	(10) MODIS Aggregated Natural Land
Corn Belt	0.54***	0.08*	0.08**	-0.74*	-0.43**	-0.10**	0.03	0.00	-0.22***	-0.05*	-0.04**
	(0.12)	(0.04)	(0.04)	(0.42)	(0.20)	(0.05)	(0.02)	(0.09)	(0.06)	(0.03)	(0.02)
Lake States	0.73***	0.07*	0.07*	-0.99*	-0.58*	-0.09*	0.03	-0.01	-0.27***	-0.04*	-0.04*
	(0.14)	(0.04)	(0.04)	(0.42)	(0.32)	(0.04)	(0.02)	(0.09)	(0.06)	(0.03)	(0.02)
Northern Plains	0.78***	0.11***	-0.02	-0.72**	-1.11***	-0.08**	-0.05*	0.04	-0.28***	-0.05**	0.00
	(0.14)	(0.03)	(0.05)	(0.31)	(0.22)	(0.04)	(0.03)	(0.07)	(0.06)	(0.02)	(0.02)
Northeast	-0.08	0.15	0.06	0.28	-0.90*	-0.21**	0.07**	-0.05	0.04	-0.10*	-0.04
	(0.30)	(0.09)	(0.09)	(0.91)	(0.51)	(0.10)	(0.04)	(0.20)	(0.14)	(0.06)	(0.04)
South Atlantic	0.79***	0.09	-0.02	-1.65**	0.76	-0.21***	0.06**	0.00	-0.47***	-0.06	0.00
	(0.21)	(0.06)	(0.06)	(0.66)	(0.47)	(0.07)	(0.03)	(0.14)	(0.10)	(0.04)	(0.03)
South East Central	0.32**	0.06	0.04	-0.72*	-0.42**	-0.11**	0.04**	0.04	-0.17***	-0.04*	-0.02
	(0.13)	(0.04)	(0.04)	(0.40)	(0.21)	(0.04)	(0.02)	(0.09)	(0.06)	(0.03)	(0.02)
Southern Plains	0.57***	0.12*	0.12	-0.14	-0.70**	0.09	0.04	-0.29**	-0.34***	-0.05	-0.06
	(0.18)	(0.06)	(0.08)	(0.57)	(0.29)	(0.08)	(0.03)	(0.15)	(0.09)	(0.04)	(0.04)
West Mountain	0.25	0.05	0.06	-0.26	0.04	-0.34**	0.16**	0.45*	-0.17	-0.06	-0.04
	(0.41)	(0.10)	(0.14)	(0.87)	(0.60)	(0.14)	(0.06)	(0.25)	(0.19)	(0.06)	(0.06)
West: Pacific	0.96***	0.16*	-0.19*	-1.96*	-0.49	-0.33**	0.04	0.04	-0.51***	-0.12*	0.07
	(0.26)	(0.09)	(0.11)	(1.17)	(0.32)	(0.12)	(0.04)	(0.20)	(0.14)	(0.07)	(0.05)
Obs	22417	22417	22417	22417	22417	22417	22417	22417	22417	22417	22417

Note: This table reports the price-acreage elasticities across regions for land categories in CDL, LCMAP, and MODIS. The elasticity is calculated based on estimated impacts of lagged received crop prices, interacted with nine regional indicators, on acreage of different land categories (reported in Appendix Table S6). The nine regions are defined as follows: Corn Belt region includes Illinois, Iowa, and Indiana, Ohio, and Missouri; Lake states region include Minnesota, Wisconsin, and Michigan; Northern Plain region includes North Dakota, South Dakota, Nebraska, and Kansas; Southern Plains region includes Oklahoma and Texas; Northeast region includes Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont, New Jersey, New York, and Pennsylvania; Southeast Central region includes Alabama, Louisiana, Mississippi, Tennessee, Arkansas, and Kentucky; South Atlantic region includes Delaware, Florida, Georgia, Maryland, North and South Carolina, Virginia, and West Virginia; West Mountain region includes Arizona, Colorado, Idaho, New Mexico, Montana, Utah, Nevada, and Wyoming; West Pacific region includes California, Oregon, and Washington. Standard errors of elasticities, clustered by county and year-by-district level, are reported in parentheses.