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Converting Croplands to Grassland: A Spatial Analysis of the Economic Feasibility of Soil Greenhouse Gas Mitigation in Midwest, United States

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Cover Page Footnote

I would like to thank Rattan Lal of Ohio State and Sahan Dissanayake for their help and guidance through the long and arduous process of research data, making sense of it, analyzing the data, and then writing and discussing the significance of these results at length.

1- Introduction

2015 has been declared the International Year of the Soils (IYS) by the United Nations at its 68th general assembly meeting in December 2013. As a global community, we are approaching a time of coupled economic growth and agricultural innovation and expansion throughout the developing world. Increased population growth and economic pressure is pushing already degrading soils and associated agricultural ecosystems and processes up to--or past--their ecological thresho support to their limit of functional capability. Through IYS the UN hopes to bring awareness to the global community of important research and applications that can be utilized to promote better soil health for the sake of conservation, the environment as well as building resilient communities and improving food security and the local and global level (FAO, 2013).

Global climate change has taken a central role on politician's agendas across the world. The recent dramatic rise in anthropogenic CO2 emissions have already increased to nearly global atmospheric CO2 concentration to nearly 400 parts per million (ppm) from a pre-industrial (pre-1750 AD) average concentration of 280ppm (Marland et al, 2001). This increase of over 100ppm CO_2 represents a total of ~270 gigatons (Gt) of elemental carbon (C) that has worked its way to the atmosphere from land use change or because of the burning of previously sequestered fossil fuels (Lal, 2004).

Land use change has long been a significant source of CO_2 due in part to the rise in agriculture. Many agricultural lands in temperate, humid regions (such as New England, or most of Europe) were previously rich, productive forest before they were stripped of vegetation and prepared for agricultural practices. The clearing of forests becomes a significant carbon emission source, but more importantly with the absence of perennial vegetation cover, forest's soil is no longer able to hold as much carbon (soil organic carbon content, or SOC). Under annual agriculture practices the crop residue left in the field is quickly decomposed and respired (cellulosic material is turned back into CO_2 by bacteria), leaving not enough time to accumulate the rates of SOC experienced in healthy grassland ecosystems (Lal, 2003)

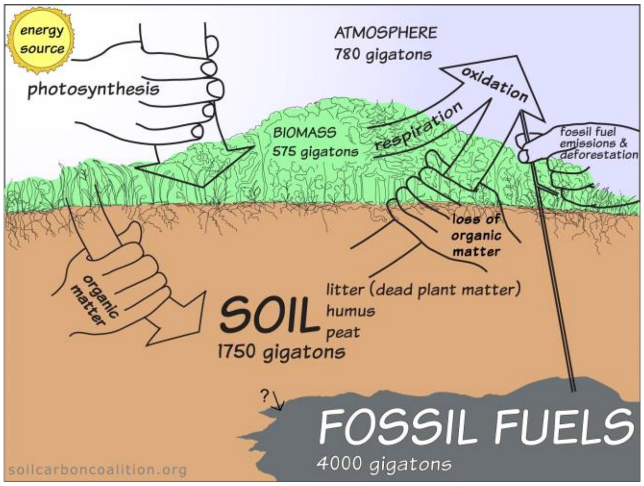

Figure-0: Simplified schematic of the soil carbon cycle, values are in gigatons (Gt) of carbon

CO_2 is considered to be a harmful greenhouse gas (GHG) and is blamed for raising the global average temperature by about 2ºF over the last century (Lal, 2004). GHG's trap what would otherwise leave as radiant heat in the earth's atmosphere and instead deflect this thermal energy back to the earth's surface. There are other potent and serious greenhouse gasses such as methane (CH_4) and nitrous oxide (NO_2) but in this paper we will stay focused on CO_2 and ways to mitigate and slow the rate of increase of atmospheric concentration.

<u>1.1 – Background, Previous Literature and Soil Science 101</u>

As mentioned above, anthropogenic processes that have elevated greenhouse gasses (mainly CO_2) are considered to have impacted the globe's current climate and are expected to warm the climate much more over the next hundred years if efforts are taken to significantly reduce GHG emissions (Stocker et al, 2013). Efforts can be taken to limit CO_2 emissions, but curbing emissions is not enough to mitigate the change humans have already made in terms of atmospheric gas composition and associated climate implications. The problem of rising GHG emissions must also be mitigated through the sequestration of carbon in a chemically stable form (such that it does not oxidize and return to the atmosphere as CO_2 gas). Carbon sequestration is any method that is promoted by humans (though usually a natural process) that takes on CO_2 gas out of the atmosphere, and 'stores' it within the earth. Other examples of carbon sequestration include afforestation, marine carbonate growth (ie, coral and seashells) and the promotion of algae growth via ocean fertilization (Stocker et al, 2013).

Cropland (cultivated land that is used to grow annual rowcrops, such as corn and soybeans) is known to have much lower levels of SOC when compared to grassland (Lal, 2004; Rees et al, 2005). Grasslands have much more biomass in their ecosystems (long roots, perennial covered with living vegetation) and additionally provide mulch over the soil, hindering the ability of decaying biomass to oxidize (ie, releases CO_2 back into atmosphere). Intuitively, transforming barren, cultivated croplands into perennial grasslands will have a positive impact on sequestration. Burke et al (1987) address this difference in their model for estimating SOC rates in both grassland and cropland soils, which was used to predict the spatial distribution of SOC across counties in this paper (see *Methods*).

The current importance and significance of food security and greenhouse gas mitigation amongst policy makers and NGOs has led many researchers to try to piece together role soil organic carbon (SOC) has on soil health, ecosystem resilience (ie, draughts, toxic herbicides, etc) and global climate (Parton et al., 1987; Lal, 2004; West and Post, 2002). These researchers have attempted to look at the biological, geologic and atmospheric systems that control the dynamic processes of the carbon cycle in dynamic agricultural and non-agricultural (forest) soils. Researchers have estimated that the global "pool" of all biological carbon (this

includes SOC, decayed plant matter, living and dead peat and soil inorganic carbon) to be at 2500 gigatons (Gt), which is 3.3x larger than the atmospheric (CO_2) carbon pool (Lal, 2004). This represents both a risk if more soil carbon is oxidized through land use change, but also an opportunity as a potential source for a carbon-sequestering sink and restore degraded soils in the process.

In the late-90's and 2000's during heightened global awareness of greenhouse gasses and international pressure to study these issues rooted from the Kyoto Protocol led many economists to embark on assessing the financial feasibility of storing carbon in the soil. Furthermore, this temporally coincided with the proliferation in awareness of the "No-Till" methods for commodity agriculture. In no-till agriculture the farmer does not till his fields in before cropping nor after the seasons harvest. This allows vast amounts of crop reside (dead biomass) to accumulate on the surface of agricultural fields. The benefits of no-till include hypothetically higher rates of SOC (Lal, 2004) and an organic mulch that that will keep the soil more moist during times of drought stress. During the late-90's environmental economists began to evaluate the feasibility of letting No-Till farmers sell carbon-credits from soil carbon sequestration, leading to many studies reporting various results throughout the globe (Manley et al, 2005). Results were variable and mixed, with wide difference in higher costs-of-production with No-Till and varying degrees of success at improving SOC. Data from many studies were compiled by Manley et al., in 2005 who wrote a meta-analysis using hundreds of data points from researchers across the globe. Manley concluded that there is too much spatial variability between the results of cost-benefit analyses that address No-Till farming, and overall across all studies there was little evidence of increased SOC rates in soils under No-Till and as such it would be erroneous to let No-Till farmers sell carbon credits (Manley et al., 2005).

Without research that finds conclusive evidence No-Till agriculture practices significantly sequestering more carbon, I hope to instead understand and address the economic and atmospheric implications associated with converting croplands to grasslands. It is possible that well managed grasslands are capable of holding significantly more soil carbon than cultivated soils (West and Post, 2002). My goal is to develop of a cost-benefit framework that analyzes the effect converting croplands into grasslands would have on the economy and the climate using spatially distributed data in the upper Midwest region of the United States.

Stavins (1999) evaluates landowners' willingness to sequester carbon through afforestation by estimating the opportunity costs they will incur if they chose to take their land out of whatever form it may currently be in. This analysis provides a useful revealed preference model, but the model was designed at the micro, per-landowner level; it does not address any problems and solutions involving the implementation of afforestation on a broader scale. To successfully mitigate climate change, policy makers must better understand the variations in cost

of implement such carbon sequestration initiatives with more of a broadened view. The model presented in this paper—while simplifying the problem—uses spatial attributes to provide better insight and accuracy of a possible carbon sequestration framework and its associated costs.

1.2 Gaps in the Previous Literature

In summary, the previous literature in this field has mostly centered on estimating costs (Manley et al, 2005) and hypothesizing incentives to promote carbon sequestration (Stavins, 1999; Kosoy and Guigen, 2012). The initial portion of this paper, the spatial cost-benefit analysis framework, provides the same idea in a different light. More significant is Part II of this report where I assess the relationship potential carbon sequestration has agricultural land price trends across counties. The control carbon sequestration potential may have on land prices can be used as a proxy to see whether investors' behaviors reflects optimization of carbon sequestration potential when buying land.

1.3 Roadmap of Methods, Results, Analysis and Applications

This paper is comprised of two parts which build on top of each other while still having their own significance and importance. This paper will first develop the spatial distribution of expected potential for carbon sequestration after cropland-grassland conversion of agricultural soils. Land costs of the counties analyzed (measured in cultivated cropland rental fees) will also be addressed and incorporated into the final results to provide a spatial distribution of the cost-benefit of sequestering soil carbon through agricultural land conversion.

The latter half of this paper involves using the spatial distribution data, and assessing whether carbon sequestration potential positively reflects the land price (as opposed to rental rates) of agricultural lands in the counties looked at. This would be test the hypothesis that investors may be seeking out lands of high carbon-storage potential with the expectations they may later be able to convert these agricultural lands into grasslands and sell carbon credits. The paper then concludes with the caveats and limitations of this study, as well as future applications that can be use these results to address problems and concerns in conservation economics.

2- DATA

The initial analysis of the spatial distribution of predicted changes to the total tons of carbon sequestered per acre after cropland-grassland conversion. The spatial distribution analysis of the cost-benefits need empirical data on the environmental (for evaluation of ΔSOC) conditions and cost parameters to achieve results.

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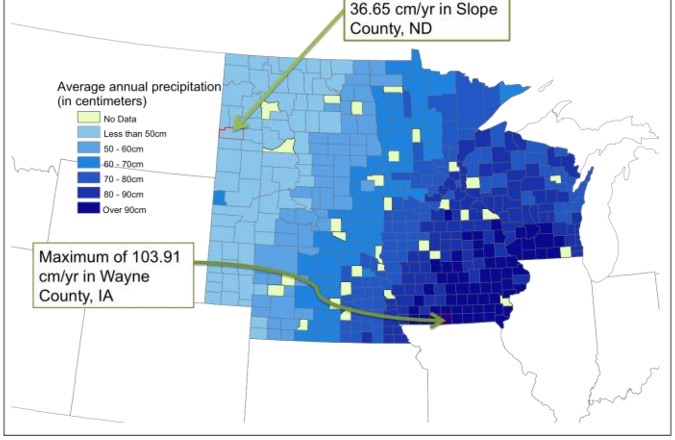
2.1 - Climatic Data

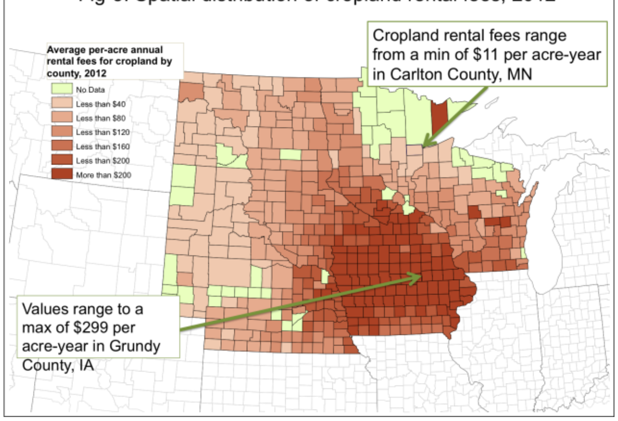
Climatic data in the form of mean annual temperature and precipitation was obtained from the National Oceanographic and Atmospheric Administration's (NOAA) National Climatic Data Center (NCDC). A data set was compiled that included all of NOAA's official affiliate weather stations located in the six state study area of the upper Midwest/great plains region. Each data point (a NOAA weather station) includes the attributes of spatial location (latitudinal-longitudinal coordinates), the mean annual temperature (MAT, in degrees Celsius) and mean annual precipitation (APPT, in centimeters per year). The two climatic means are the annual average readings at the weather station from 1980 to 2010 (Arguez, 2010).

Fig-1: Average annual precipitation using1980 to 2010 means[1]



This data (originally in the lat/long coordinates) needed to be interpolated to the county level so it could be used to explain the expected average SOC at the county level per Burke et al's (1987) soil carbon model. The geographic coordinates were interpolated via ArcGIS spatial analysis software, which linked the attributes of the latitude-longitude data points to each county's attribute vector.

Fig-3: Spatial distribution of cropland rental fees, 2012



2.2 - Cost

After analyzing the effect the above data has on SOC, there is a need to estimate the opportunity cost of taking an acre of land out of row crop production and putting it to use as pasture instead. Fig-3 shows the USDA-NASS cash-rental data from the six states (Nebraska, the Dakotas, Minnesota, Wisconsin and Iowa)

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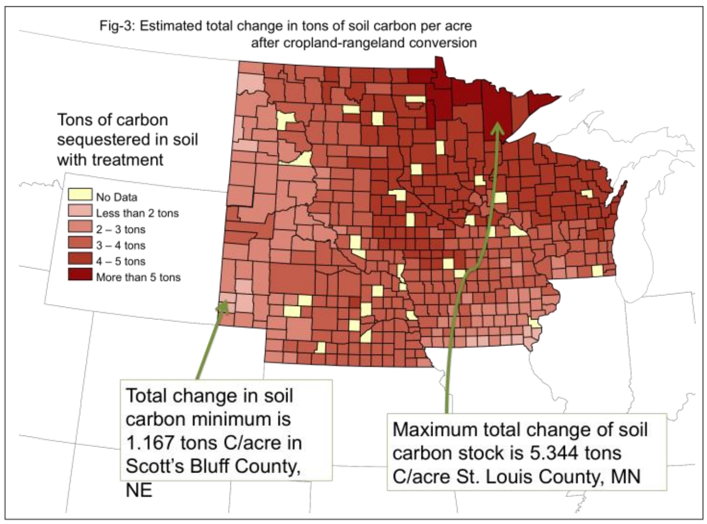
for annual rates imposed by renting an acre of land to use for agricultural production. This data was procured at the county level for each state and depicts average price paid to a landowner in that county for renting either an acre of cropland (tillable) or pasture (perennial grass for grazing or hay) during the 2012 growing season. I then subtracted the rental rate of pasture from cropland to enumerate the discount associated with renting out pasture. The discount then becomes the per-acre cost used in this model since the model's foundation analyzes turning cropland into perennial grassland.

3 – Methods



Burke et al. (1987) published a model that describes the impact precipitation (APT, cm/yr), mean annual temperature (MAT, ºC) and soil composition (fraction made up of silt and clay) have on soil organic carbon content (SOC). Burke developed an OLS-based model that used a population of 945 samples of agricultural soils throughout the great plains region, and models SOC content for two groups: grassland (perennial grass) soils and cultivated (cropland, tilled) soils. The coefficients for this model can be seen in Table-1.

Variables	Grassland Soils	Cropland Soils
MAT	-0.827	-0.750
(MAT)^2	0.0224	0.0210
APT	0.127	0.0581
(APT)^2	-0.000938	-0.000458
APT x Silt (silt = 0.6)	0.000899	0.000494
APT x Clay (clay = 0.2)	0.000600	0.000582
Constant (SOC intercept)	4.09	5.15

Table-1: Two models that describe predicted SOC of a soil based on mean annual temperature (MAT) and precipitation (APT) developed by Burke et al., 1987.

Eq-1: SOC (kg m^{-2}) = $\alpha_0 + \alpha_1(\text{MAT}) + \alpha_2(\text{MAT}^2) + \alpha_3(\text{APT}) + \alpha_4(\text{APT})^2 + \alpha_5(\text{APTxSilt}) + \alpha_6(\text{APTxClay})$

Spatially distributed data for the soil's clastic composition (% silt, clay and sand) remained challenging to find and was found to be randomly distributed throughout the study area and not controlled by climate or geographic position (Amelung et al, 1999). Instead of a variable, the dominant benchmark soil found throughout the great plains and upper Midwest was used in all iterations of this model. The benchmark soil would be a silt-loam soil, which is composed of 20% clay, 60% silt and 20% sand (these classes refer to the size of each of the siliclastic soil particles, with clay being the smallest and sand the largest). This resulted in the absence of interaction variables in my analysis and the silt fraction (0.6) was then multiplied by the APT x Silt coefficient, that along with the fixed clay fraction (0.2) multiplied by the its respective coefficients, were added to the coefficient in front of the linear APT variable, with the whole aggregate value multiplied by APT to find the predicted SOC content (eg, the product of ((0.00060*.2)+(0.000899*0.6)+1.27)*APT was used as the linear APT term to find the SOC of a rangeland). Burke et al (1987) reveal that the silt and clay composition showed much less of a relationship with SOC than the relationships precipitation and temperature have on SOC.
Each county used the average value of the predicted SOC rates of the data points that were located with said county. Some of the very rural counties of Nebraska and the

Fig-4: Spatial distribution of predicted annual costs of sequestering one ton of carbon through grassland conversion

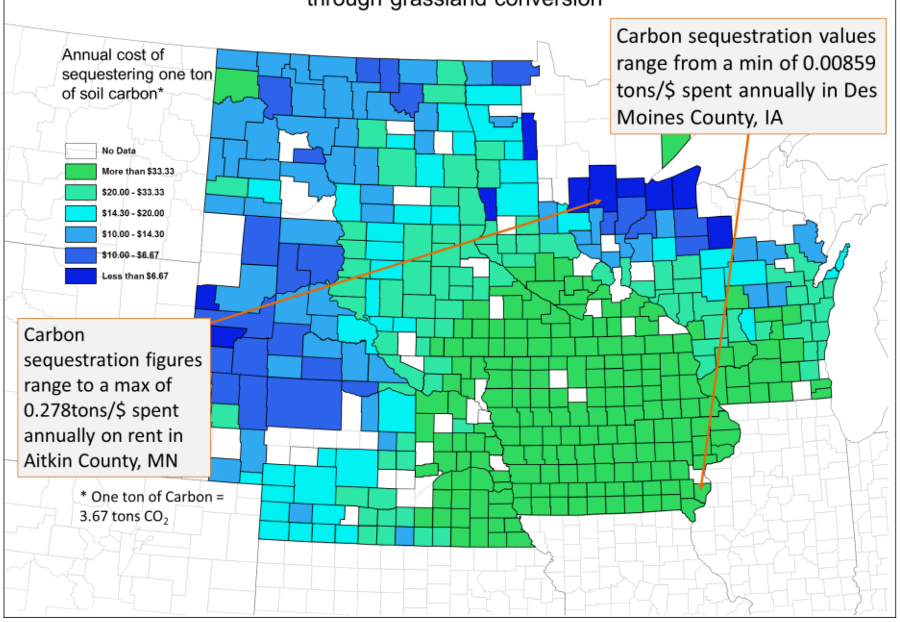


Fig-4: Cost-benefit of cropland-grassland conversion in terms of carbon sequestration

Dakotas did not have any weather stations located in them, and a resulting cost-effectiveness value could not be found for these counties. This is reflected in the absence of data points in fig-1. The predicted SOC was then divided by the average cropland rental price for every county (that there was data for), resulting in the cost-benefit value for each county (fig-4).

The above map (fig-4) depicts the spatial-distribution of the cost-benefit of cropland-grassland conversion at the county level. There is a generally a trend of highly cost-effective land in the west and northwest to poorly cost-effective land to the southeast.

The entire state of Iowa is in the highest cost per ton-C-acre^{-1} sequestered category, of costing more that $33.33 per ton carbon sequestered per acre per year. There are many counties where just one variable was missing, and had to be omitted from the analysis, but overall the results shown in fig-4 provide a strong representation of geographic trend of the cost of the sequestering carbon.

4.2 – Implications, uses and caveats

This study provides a result for the predicted spatial distribution of carbon sequestration (and relative costs) in the Upper Midwest, United States. A more accurate cost-benefit analysis would be able to compare the results found in this model with carbon sequestration costs found in other studies. The main caveat with the results found in this model (in terms of cost($) per ton-C sequestered) is that the cost is incurred annually as an upkeep cost, where as other researchers who also assess the costs of different methods carbon sequestration look at the cost as a per-ton cost, not an annual upkeep. For this reason, the results in this study can not be compared relative to the results from other studies, since this study reflects the cost in terms of annual cropland rental fees. Furthermore, the benefit of grazing has not yet been applied to this model but is obviously a strong benefit that is currently contributing to upwards bias in the per county cost estimates. The grazing of ruminants provides a further provisioning ES (in addition to the regulating ES of carbon sequestration) that will reduce the overall cost of converting cropland to grasslands, but this remains unaccounted for in the above model.

4.2.1- Applications – Site selection and carbon sequestration optimization

The spatial distribution of this model still marks the relative differences of predicted costs of carbon sequestration across Upper Midwestern counties. The relative costs between counties in this region could have several significant and important applications. At first they provide a general framework for cost-effectiveness of sequestering carbon through change in agriculture. The most notable aspect of this study is that it controls for spatially-varying attributes of each county. The ability to see how cost-effectiveness of agricultural soil carbon-sequestering initiative varies through space is unprecedented in literature.

In addition these results suggest that when accounting for cost in a soil carbon-sequestering initiative it is best to make the most out of abundant cheaper land, rather than attempting to use highly-sought after land priced at premium. This is seen in Fig-2 where nearly the entire state of Iowa--a state of world-renowned and unparalleled agricultural productivity--is in the least cost-effective category, while the fringes of the Dakotas and western and central Nebraska have many counties in the dark blue category, sequestering at least five times more marginal carbon per dollar spent on land. This phenomenon is better explored when the data derived from my analysis is used to solve a site-selection problem.

Now that space-dependent variables have been taken into consideration, the next step will be to use a more highly parameterized model to address how management practices and potentially other space-dependent variables can be used to further increase carbon sequestration per acre. The updated CENTURY 4.0 model incorporates a fire parameter to evaluate grassland burning (Parton et al., 2001). This assesses the effect that periodic burning of a grassland has on the health and aggregates of the soil as well as the effect on the soil's total SOC. It may seem counterintuitive, but research has shown that quick, high-temperature managed burning converts the cellulosic plant material into charcoal, which is a longer-lived and more stable form of carbon than organic carbon, since microbes have a much harder time respiring the particles (Schuman et al., 2001). Future research concerning the spatial distribution of cost-benefits of carbon sequestration should incorporated models like CENTURY 4.0 that take management practices into consideration. A cost-benefit analysis should then be applied to these results in a similar framework that I have presented above, exploring how the relationship between opportunity costs of management practices and carbon sequestration vary through space in the Upper Midwest.

Part II – Assessing the impact carbon sequestration potential has on land price

The results found in Part-I of this paper will be used to assess the impact that the potential for carbon sequestration may have of farmland demand, as measured in the land's price. A market for sequestered carbon does not yet exist, but the expectations that such a market will develop may drive investors to seek out cost-effective methods for sequestering carbon, putting increased pressure on the demand for agricultural lands in counties that are predicted to yield a high return in terms of carbon sequestration. A hypothesis is presumed that, after controlling for the dominant controls that affect land price, the amount of carbon expected to become stored in soil after a cropland-grassland conversion will relate to a positive change in land price, which would represent a shift in the quantity of farmland demanded.

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5- Data

Land Price is the dependent used in regression table-5. This is the county average price for an acre of agricultural land in 2010.
Change20102014 is the dependent variable used for the regression model shown in table-4. This is the percent change in each county's agricultural land prices between 2010 and 2014.
Independent Explanatory Variables- All measurements were taken at the county level.
saleacre Agricultural Sales of agricultural products per acre of cultivated cropland, proxie for productivity and expected earning potential for farmland in a given county.
Growth_sales Agricultural product sales growth percent, between 2007 and 2012.
Pop_growth population growth percent, 2000 to 2010.
POP10_SQMI The county's population density from the 2010 census.
farmssqmi the number of farms per square mile.
AVG_SIZE07 is the average size, in acres, of farms.
tonCacre is the predicted change in tons of soil carbon sequestered per acre after cropland-grassland conversion, modeled using Burke et al's (1987) function.

Table 1: Summary Statistics for regressing IA and MN farmland prices

Variables	Min	Max	Mean	STD
	Minnesota			
Land Price	605	64,414	4,225	7,186
Change20102014	-0.2941	1.406	0.5385	0.4695
Saleacre	1.273	62.13	6.766	6.483
Growth_sales	-1.025	2.556	-0.002304	0.5515
Pop_growth	-1.592	3.407	0.1917	1.057
POP10_SQMI	1.7	3005	122.4	392.9
farmssqmi	0.003892	2.896	1.279	0.6479
AVG_SIZE07	31	993	340.2	174.1
tonCacre	3.257	5.343	4.379	0.4213
	Iowa			
Land Price	2085	7,148	5,049	1,199
Change20102014	0.4433	0.7781	0.5809	0.0851
Saleacre	21.29	463.5	175.48	79.688
Growth_sales	-0.6729	0.6934	-0.1486	0.2986
Pop_growth	-1.2934	3.531	-0.1530	0.6860
POP10_SQMI	9.600	740.1	53.0510	89.64
farmssqmi	0.9286	2.538	1.6525	0.2939
AVG_SIZE07	203.0	606.0	339.1735	74.35
tonCacre	1.411	4.282	3.0546	0.6218

5.1 – RESULTS

The following OLS regression was evaluated to decompose *tonCacre*'s relationship on the change in agricultural land prices (2010 – 2014) across Minnesota and Iowa counties.

VARIABLES	(Minnesota) Δ(Ag Land Price)	(Iowa) Δ(Ag Land Price)
Percent cropland	1.310***	-0.289***
	(0.105)	(0.0417)
tonCacre	-0.00728	-0.0179**
	(0.0164)	(0.00831)
Population growth	-0.0869***	-0.0127
	(0.0281)	(0.00983)
Ag sales growth	0.0713*	0.0343
	(0.0412)	(0.0219)
No. of Farms/sq. mi.	-0.108**	0.106***
	(0.0520)	(0.0218)
Constant	0.0313	0.671***
	(0.0997)	(0.0477)
Observations	86	99
R-squared	0.844	0.547

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table-3 shows a the estimated coefficient and their variables used to explain the change in average per-acre agricultural land prices at the county level in Minnesota and Iowa.

5.2.1 – Interpretation

In Minnesota, we find the *tonCacre* (the predicted average increase in sequestered carbon from cropland-grassland conversion for a given county) has no effect or relationship with the dependent variable in the above model, *ΔAg Land Price*, as the parameter's estimated coefficient fails to reject the null hypothesis, H_0: $\beta_{tonCacre} = 0$ and is shown to be statistically insignificant. Alternatively, the coefficient for the parameter representing the same explaining variable in the estimated regression model using data from Iowa counties shows that at the county level increased levels of predicted carbon sequestration (from cropland-grassland conversion) is associated with a negative excursion of average cropland prices, which is statistically significant to the 5% level.

These results from Iowa are somewhat troublesome as they show that

farmland that is predicted to have greater potential for carbon storage relates to a slower rater of growth in price (and demand) in comparison to land with a lesser potential for carbon sequestration, holding all else fixed. Ideally, the data would depict a positive correlation between change in land price and carbon sequestration potential. The above model explains the *change* experience in Iowa land prices from 2010 to 2014 across counties, and thus only reflects the trend seen over the last four years. Considering the temporal trend over the last four years, the results above may support the following hypothesis.

Hypothesis addressing and value and carbon sequestration potential

The demand for lands that are predicted to sequester relatively more tons per acre of carbon through grassland-cropland conversion may have been in higher demand prior to 2010, when there were greater aspirations and expectations for developing a carbon cap-and-trade system in the United States. Thus the sequestration of carbon was then expected to hold future economic value as markets for sequestered carbon would become developed. Unfortunately for many environmentalists and conservationists, such a system was never implemented in this country and the failure of a similar system in the EU (Kossoy and Guigon, 2012) began to lead investors to speculate that their would never be such a private market that puts an economic value on sequestered carbon. Pessimism then began to spread between 2010 and 2014 that greatly decreased the expectation of developing markets for carbon credits. Lands that may have once held a premium price for their expected carbon sequestration potential (through cropland-grassland conversion) may now be receding in value relative to those that are predicted to have less carbon sequestration potential as the expected future value of carbon sequestration erodes.

Unfortunately, this hypothesis is not supported by the modeling of Minnesotan data, which suggests that the carbon sequestration potential of agricultural lands has no effect on the growth in price of these agricultural lands. Thus there is no increased (or decreased) demand for agricultural lands of high carbon-sequestration value. If the direction that carbon sequestration potential effects Iowa land prices is due to nationwide market forces and investors speculations on future markets then the same trend should be reflected in the changes in Minnesota farmland prices based on the ability of carbon sequestration. As mentioned, the trend in Minnesota farmland prices from 2010 to 2014 are not sensitive to the lands predicted carbon sequestration, which does not support the aforementioned hypothesis.

This hypothesis can be tested by looking back and analyzing the controls in 2010 farmland values. Upon controlling for other variables, we can assess whether carbon sequestration had a positive effect on raw land prices. Support of this hypothesis would show that after originally having a positive effect, the relationship has degraded as the markets for sequestered carbon did not develop as expected,

and likewise has since shown a negative correlation with the change in land price over the last four years.

6 - Results II: Explaining raw 2010 land values

	(Iowa)	Minnesota	(Iowa)
VARIABLES	2010 Agricultural Land Price		
percent_cropland	3,926***	1,042	3,985***
	(916.3)	(982.7)	(562.0)
tonCacre	142.9**	-33.48	504.7***
	(68.69)	(96.10)	(116.8)
POP10_SQMI	1.667***	10.06***	1.866***
	(0.623)	(0.626)	(0.569)
AVG_SIZE07	-1.973	-2.850*	-3.709***
	(2.649)	(1.506)	(1.061)
Saleacre	318.2***	519.7***	304.7***
	(54.74)	(37.27)	(51.84)
Avg_LONGIT			-66.48**
			(30.01)
Avg_LATITU			-187.6***
			(69.13)
farmssqmi	-102.2	-398.2	95.60
	(544.5)	(367.9)	(515.1)
Constant	528.2	538.5	1,527***
	(1,347)	(757.8)	(452.9)
Observations	99	87	99
R-squared	0.847	0.978	0.869

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table-4: Assessing the control predicted carbon sequestration has on 2010 land prices

Eq-2: $2010\_AgLandPrice\_IA\_county = \beta_0 + \beta_1(percent\_cropland) + \beta_2(POP10\_SQMI) + \beta_3(AVG\_SIZE07) + \beta_4(Saleacre) + \beta_5(Avg\_LONGIT) + \beta_6(tonCacre) + u$

Equation-2 depicts the model used to assess the controls affecting predicted average agricultural land prices in Iowa counties the variable *farmssqmi* has been dropped after the estimated coefficient was found to be insignificant, possibly in part due to multicollinearity issues with *AVG_SIZE07* (the average size in acres of each farm in given county) and *percent_cropland*, which exhibit stronger relationships with land price. Together, these two variables may depict the same

trend that *farmssqmi* was hypothesized to show; the size and abundance of farms in each county. The other estimated coeffecients were all found to be significant of the parameters used in this model are shown in column three of the Table-4. The signs of these estimates all make intuitive sense, with the productivity proxy *percent_cropland* and *salesacre* showing strongly positive and significant relationships. The location variables *Avg_LONGIT* and *Avg_LATITU* depict a trend of increasing land prices from the northwestern to the southeastern regions of the state, which reflects increasing precipitation (see Fig-1) and length of the growing season; attributes that intuitively lead to increasing agricultural production potential. Most importantly, we see a positive and significant relationship between land price and *tonCacre*, the parameter that describes the predicted carbon sequestration from cropland-grassland conversion.

6.1 Assumptions

Global and national scale variables- Many national scale parameters exist that would hypothetically have influence on Iowa agricultural land values. However, such variables would influence all farmland the same way and would not differentiate across individual counties. Such variables would include new federal mandates on the amount of ethanol used in American gasoline, driving up the demand for corn and in turn farmland. Any other type of change in the market for global agricultural commodities will intuitively influence the price and demand of farmland, but such variables are assumed not to change across the counties.

Aesthetic value- This model also omits any cross-county variation in the average aesthetic value of agricultural lands. Other research has found that aesthetic values—proxied by the relative abundance of rivers, wetlands and natural areas with a land area—can play a significant role in controlling southwest Michigan agricultural land prices (Ma and Swinton, 2011). However, in this model we are assuming that such variation in aesthetics either does not occur in Iowa or is not reflected in agricultural land prices. This assumption is backed up by the extremely homogenous nature of the state of Iowa; unlike Michigan, Iowa does not border any Great Lakes and is likely less popular amongst tourists. This idea is supported by the differences between the results of the Iowa and Minnesota models. Minnesota, much like Michigan, is far more topographically diverse. Known as the “Land of 10,000 Lakes”, Minnesota likely has much more variation of aesthetic controls between counties. The omission of aesthetic controls in the above model may lead to omitted variable bias (OVB) in our results, but without scrutinizing research using satellite imagery I can not enumerate accurate attributes that reflect the aesthetics of land within Iowa counties.

7. Conclusion

The positive correlation seen between estimated carbon sequestration (through cropland-grassland conversion) and land price across counties, after accounting for spatial variability that directly effects agricultural production and profits, suggests that investors may have increased prioritized high-carbon sequestration lands versus over similar lands that can not potentially sequester as much carbon. Much of this paper remains speculative and there is potential for omitted variable bias (OVB) in these results, this trend is empirically shown in this analysis and should be addressed.

In comparison Minnesota, where the initial model predicted had the most cost-effective counties in terms of carbon sequestration potential, showed no correlation between carbon sequestration potential and land price (in both the change in land price and raw 2010 value data). This could mark other external factors in Minnesota land prices that our model did not control. As mentioned, there are many more lakes in Minnesota and the relative abundance of lakes varies spatially across the state, and the presence of lakes in a county may effect the aesthetic value imposed on land prices in that county (Ma and Swinton, 2011). Minnesota may not show a significant, positive correlation between carbon sequestration potential and land price because there is OVB from the absence of a control on aesthetic value, while Iowa—being a much more uniform and homogenous state in topography—does not experience the same degree of OVB because there is not as much variation in the relative abundance of lakes across Iowa.

To summarize, the first model of this paper shows a unique framework that can be used to assess the relative differences cost-benefits of soil carbon sequestration across space. This can then be used to help solve site-selection problems when trying to optimize carbon sequestration through cropland-grassland conversion using a method such as the Greedy Algorithm. After these initial results were found, I applied this results to agricultural land price regressions to find out if there was any relationship between carbon sequestration potential and Midwest land price trends. I found that in Iowa, a very homogenous state by nature with few external variables effecting land prices outside agricultural productivity proxies, there is a negative relationship with the *change* in land prices, but a significantly positive relationship in the raw 2010 price data, with all else held fixed. This result suggests that before and up the late-2000's recession investors placed a premium price on carbon sequestration potential. After 2010 however, this price premium began to recede, which temporally correlates with the lowered expectations that the United States would implement a carbon cap-and-trade system, creating an economic market for carbon sequestration products (Kossoy and Guigon, 2012).

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