IMPACT OF CLIMATE CHANGES ON FARMLAND CONVERSION IN CALIFORNIA

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Abstract

To model the impact of climate change on farmland conversion, I propose using climate extreme variables instead of climate normals. I particularly look at the number of extreme heating days, or days which recorded temperature reaches 90^{o}F. I construct a 25-year climate extreme surface using real time observations from the weather station network in California. Initial result confirms the proposition that farmland conversion is affected by climate condition, although the effect is minimal, but present and remains highly significant across a number of specifications. Extreme variables are better predictors of climate change impact than using mean condition. Farmland conversion is nonlinearly affected by climate changes: an increase in heat and precipitation is beneficial, but excessive increase is harmful and will accelerate farmland conversion.

[1] Frankie is a doctoral candidate at Department of Agriculture and Resource Economics. I am motivated by the work on the impact of climate changes on farmland values and discussions with Professor Anthony Fisher. I would like to thank Dan Cayan and Mary Tyree at California Climate Change Center, Scripps Institution of Oceanography, UCSD for their permission to use the downscaled dataset. This is a preliminary work and subject to changes and additional materials. For any suggestion please contact the author at phule2311@gmail.com.

INTRODUCTION

There is a growing consensus that climate changes[2] will bring harmful consequences. The impacts of climate changes have already occurred and will likely exacerbate in the future. According to IPCC WGII Fourth Assessment Report (WGII-AR4), Chapter 14, “North America has experienced substantial social, cultural, economic and ecological disruption from recent climate related extremes, especially storms, heatwaves and wildfires” and that “North American people, economies and ecosystems tend to be much more sensitive to extremes than to average conditions. Incomplete understanding of the relationship between changes on the average climate and extremes limits our ability to connect future impacts and the options for adaptation.”

There have been many researches on the possible impacts of climate changes in economic impacts, public health, urban growth and the environment. However, there is a challenge in the study of climate change impacts, since modeling the impacts of extreme events are more difficult than shifting in average condition (WGII, Chapter 5). For the agriculture, there is no agreement on how crops respond in various conditions, although it is generally understood that the increasing frequency of extreme events may lower crop yield beyond marginal gains from longer growing seasons and more precipitation. It is important to note that the there is still some doubt over the impacts on agricultural production. North America agriculture, especially in mid and high latitude region, may benefit from moderate increase in local temperature, but further warming would be harmful (with medium to low confidence, WGII, chapter 5). But the lower latitude regions including California would likely suffer.

In this study I will look at the impacts of climate changes, particularly the extreme events, on farmland conversion in California. I will use comprehensive state-wide farmland tracking data from 1984 to 2006 to map out the location of the conversion at each county, then model the conversion on a set of climate condition and extreme events, controlling for other potential factors such as soil or socio-economic characteristics.

[2]Climate change is defined as a long run trend in weather fluctuations, versus short run deviation of weather variables from average daily values. IPCC WGII emphasizes that “detection of climate change is the process of demonstrating that an observed change is significantly different (in statistical sense) from what can be explained by natural variability.”

CURRENT LITERATURE ON CLIMATE CHANGE IMPACTS AND FARMLAND CONVERSION: REVIEW AND SHORTCOMINGS

Although there have been many studies on the conversion of agriculture land to urban usage (often known as land use-land use change or urbanization model[3]), very limited efforts have been spent on studying the impacts of climate changes on land conversion.

Multiple difficulties are encountered in this issue. Firstly, climate changes occur over a long time horizon, so to reliably study the impacts of climate changes there need very good time series data. Secondly, there are many factors behind farmland conversion, among which most often cited urban-driven factors such as rapid population growth, increasing income and expansion of urban infrastructure are easy to model in many studies as the exclusive causes of urbanization.

Another reason as often perceived in public opinion is that climate changes happen gradually rather than sudden changes, thus adaptive capability can be introduced on time to weather out the possible impacts from global warming. This is not the case, unfortunately. Climate changes, while defined as the long term trend in mean climate variables such as temperature and precipitation, the increasing fluctuations in climate and the extreme events have the most serious consequence, given short-run adjustment may not be feasible or the adaptive capability to extreme events is "uneven and not adequate" (IPCC, WGII).

In most studies involving climate change impacts, temperature and precipitation is used as the indicators and the most easily observed variables. Mean temperature and seasonal cycle in temperature over relatively large spatial areas show these clearest signals of changes in the observed climate (WGII, Chapter 1). However, this comes with a cost: no extreme events may be used to determine the effect at local level. This would result in significant underestimation of the effect of climate changes, since the extreme events have more significant impacts than projected gradual changes. Climate models using mean temperature and precipitation often aggregate data over a large spatial scale and pooled time series, thus unable to estimate the effect of localized events such as heavy precipitation or local droughts.

This leads to questionable results in many existing models using only trend in mean variables, which isn't enough to capture the full variations, to predict the impacts of climate changes. Without accounting for climate extremes, the impacts would be vastly underestimated. While anticipated changes were often well adapted to (such as future heating, so houses were built to be

[3] There is some difference in the term "urbanization" in general literature from "farmland conversion" or "farmland loss" used in this study since the former specifically refers to the conversion of agriculture land to urban usage, but the latter not necessarily. This view is also reflected in California Department of Conservation's Farmland Monitoring and Management Program (FMMP) report that farmland loss is not due to urbanization alone (FMMP 2002-2004 report, page 2). FMMP classifies farmlands into 8 categories (see appendix), and in this paper I am looking at the conversion away from prime farmland to any other usage, urban or non-urban wise. Attention is paid to the conversion of prime farmland, the most productive land, for the very economic reason that climate changes and agricultural production is related. Inclusion of unproductive land would divert the attention away from impacts on agricultural production. Although climate changes may affect land conversion in many different channels, nonagricultural conversion has more to do with urban-driven factors rather than through agricultural production.

more heat efficient, require less cooling, or redundant capacity is built in new irrigation system to store more water for anticipated longer droughts), but extreme events were often surprised and thus unprepared for.

The next section will briefly review two relevant branches of literature in climate change impacts on US agriculture and California specifically, and land use change models.

Climate Change Impacts on California Agriculture

Most reviewed studies seem to agree that future California is adversely affected by climate changes, although for the whole US it may be different. Schlenker, Hanemann and Fisher (2005) show that there is a significant relationship between precipitation, temperature measured at selected months for primarily non-irrigated farmland in US and farmland values. Further work by Schlenker et al (2006) with spatial model using a more sophisticated modeling of climate variables such as degree days and precipitation over growing season also confirms the effect of harmful high temperature or precipitation. That is precipitation and degree days positively related with farm values, but too much will be harmful. Extreme temperature (degree days over $34^{o}C$) is also negative and significant. Schlenker et al (2007) applies the model to California using water availability (access to irrigation water) also predicts damages from climate changes from potentially large increase in growing-season temperatures and less water for irrigation.

California agricultural landscapes mean climate change impacts are further exacerbated by multiple vulnerabilities. California agriculture is more dependent on irrigated water unlike the rest of the country and won't benefit from increased precipitation. Higher temperature, more evaporation and less precipitation would mean more demand for water from agriculture and urban uses. Future water shortage is also expected due to rapid population growth, which is predicted to almost triple by the end of the century (Cavagnaro, Jackson, and Scow, 2006).

Among very few studies of the impacts of climate extremes on agriculture, Lobell, Torney and Field (2009), by measuring insurance and disaster payment, concludes that excess moisture, cold spells and heat waves are the most significant causes of damage, "major damages to crop and livestock industries are possible with extreme events, with costs of insurance claims from specific extreme events reaching into the hundreds of millions" (Lobell, Torney and Field, 2009). However, this is only a descriptive summary linking payout and proportion of each type of extreme events, not an empirical model.

In contrast, Deschenes and Greenstone (2007) predict the opposite result that US agriculture may benefits from climate changes. In their study, they define climate changes as the difference between observed weather realization and historical mean (1970-2000) at county level, then model farmers' profit as a function of weather fluctuations and find that "predicted changes in climate will have a statistically and economically small effect on crop yields of the most important crops". However, treatment of climate variation in Deschenes and Greenstone study might cause a significant underestimation of the impact. The use of climate extremes must be properly handled so as to preserve the variation of the local events from averaging over time and space. Deschenes and Greenstone, by "simple average maximum and minimum temperature from each station" and "simple average of the mean temperature across all stations within a county"[4], will dampen any fluctuations in the measured temperature. In the presence of high fluctuation between observations and spatial dependence, averaging those extreme observations is misleading. However, it is worth to note that they reach the same conclusion that significant negative effect of climate changes is expected in California.

The most important result of Schlenker, Hanemann and Fisher studies is that farmland value is adversely affected by decreasing water availability or warming condition in California: degree day (or precipitation) is significant, but too much heat (quadratic degree days) (Schlenker et al, 2007), and extreme heat (greater than 34^{o}C) will harm the crops, thus decrease farmland values (Schlenker et al, 2006). This will lead to an immediate question about to which extent farmland conversion is affected by changing climate conditions. As we assume farm owners maximize economic profit from the value of the land, adverse weather reduces farm productivity, thus adversely affect the value of the land on which crops are grown. Therefore, it is expected that climate changes would depreciate farmland values and accelerate the conversion to other usage in the presence of increasing threats of urbanization.

I attempt to answer this question using a more comprehensive set of weather and climate extreme variables in addition to the usual treatment of control variables including all relevant soil and socioeconomic characteristics. The paper specifically addresses to the effects of climate extremes particularly heatwaves and heavy precipitations. This would be the first model to map farmlands vulnerable to climate extreme events in California. This approach will extend land use change model with an extra dimension to accommodate for the impact of climate changes. Another advantage is the application of GIS which allows tracking every piece of farmland converted from 1984 to 2006 in most counties in California, thus avoiding the issue of aggregation and possible aggregation bias in the result.

Review of Land Use Change and Urbanization Models

Many researches are done on the modeling of land use/land use changes and urbanization in city planning and transportation studies. Most common approaches are to model the equilibrium of land supply and demand using a monocentric city model (von Thünen) or the bid-rent approach (Alonso), more complicated models used in city planning often integrate GIS data to provide more real-time results.

According to Veldkamp and Fresco (1996), land use "is determined by the interaction in space and time of biophysical factors such as soils, climate, topography, etc., and human factors like population, technology, economic conditions" Kuminoff and Sumner (2002) restate that economists agree that farmland conversions is driven by income growth, population growth and

[4] Details explained in the interpolation of climate extremes section

farm return, but there is no consensus on how these factors interact to shift farmland out of farming, and how important is each factor, and how to model the process.

Among most models reviewed, urban-driven factors such as population and income growth are often modeled as the exclusive causes of land use changes, constrained by development policy. Some models extend to include interactions with vegetations and the habitat. In the presence of overwhelming population growth and migration toward urban areas, it is comprehensible that climate change impacts were often ignored.

The Kuminoff and Sumner (2002) model offers the simplest approach to farmland conversion using aggregate county level data and reports that urban-rural proximity and population growth is the main driver, while change in farm income and housing price not significant. However, their model uses the average converted acreage over county-wide for all types of farmland, effectively destroying all extremely useful spatial information which could be derived from using GIS data, as well as lacking a treatment for soil and local attributes which could be significant factors beyond urbanization effects alone. By pooling all counties and farmland types together, their result is based on the estimation of only 84 observations for two pooled time periods 1988-1992 and 1992-1998. Such a small sample size raises a question over the reliability of aggregating over huge spatial space and temporal scale while a disaggregate model of land use changes on the same data often have to process million of cells. This model also suffers from a serious endogeneity problem, as farm income can't be treated as an explanatory variable for conversion[5].

Lavia, Clarke and Page (2000) have a more rigorous approach to modeling farmlands prone to residential development by only considering variables which have influence on land values such as farm size, slope and distance to nearest city center, distance to nearest highway.

Only the more complex models such as CURBA (California Urban and Biodiversity Analysis Model) (Landis et al. 1998), which is the next generation of California Urban Futures (CUF) model with an additional module on habitat simulation, can take advantage of GIS to simulate the pattern of future land use changes under different development policies. These models use a random utility framework to predict the probability of conversion at every cell using multinomial logistic regression. Newburn et al (2005) utilized this framework to explore problem of vineyard conversion and residential development in Sonoma County, California to conclude that conversion is more likely in areas with flat slopes and warmer microclimate or growing degree days.

[5] Farm income or rent is dependent on farm attributes. High quality soil can be more productive, thus rent is higher. This is the concept of Ricardian rent. Farmland conversion and farmland income are both a function of farm and other attributes. The analog is to estimate supply (or quantity demanded) on price, yet price at equilibrium is endogenous because it changes on supply and demand. Customer preferences (or farm attributes) are exogenous to both price and quantity. Treating farm income as an exogenous variable will result in biased coefficients using ordinary least square method in Kuminoff and Sumner (2002).

Other land use models that have been used in California such as SLEUTH (Slope, Land Use, Exclusion, Transportation, Hillshading) (Clarke, 1997) or UPLAN (Johnston, 2002) are also exclusively urban driven.

Several land use models have incorporated interaction with the vegetation such as MEDALUS (Mediterranean Desertification and Land Use Project) (Openshaw and Turner, 2000) and CLUE (Conversion of Land Use and Its Effects) (Veldkamp and Fresco, 1996) by including climate variables to model the biophysical process. However, they stop at using mean temperature and precipitation only.

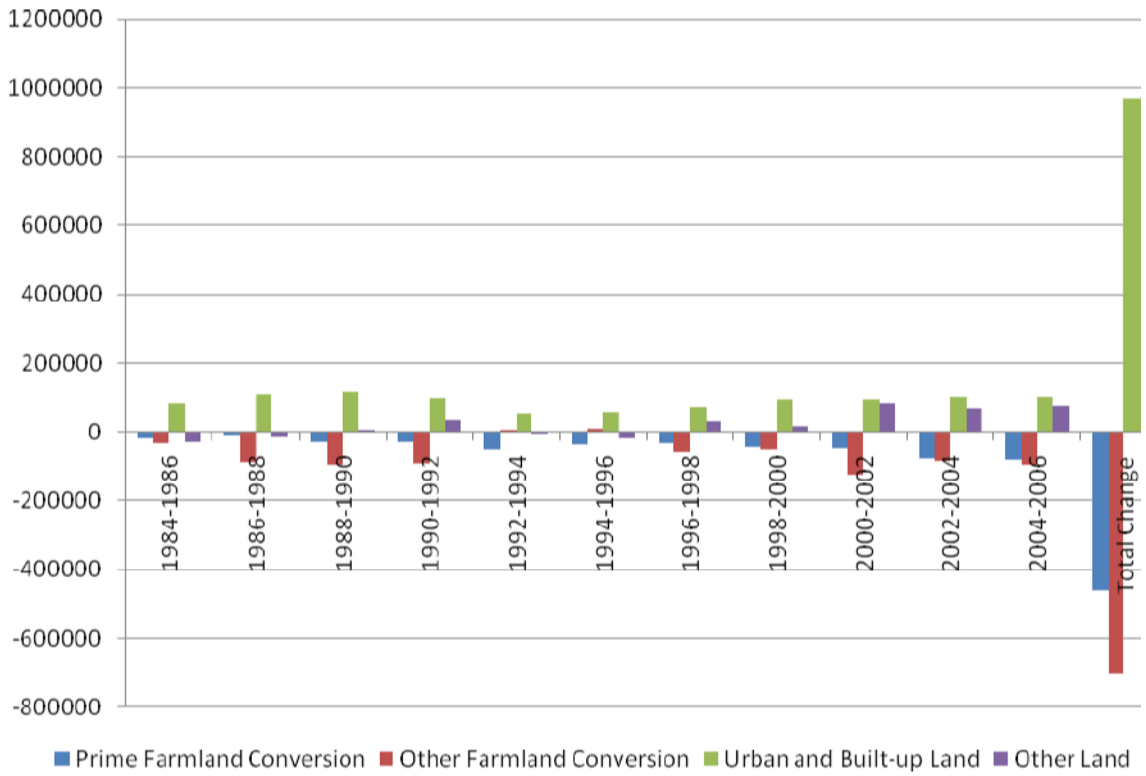
More recent work by Howitt, Azuana and MacEwan (2009) specifically links potential agricultural yields to land use using SWAP model (Statewide Agricultural Production Model), a mathematical optimization model, to conclude that "while the effect of climate change is manifest through yield changes, after economic adaptation, the results on irrigated crop production are predominately shown in economic terms and changes in aggregate land and water use." Their model predicts acreage loss from 16 to 24 percent of irrigated land in various regions, while revenues would fall from 9 to 16 percent due to partial offsets from price and crop changes.

No existing land use model has used climate extremes, which have more substantial impacts and more detectable than using climate normals. Areas vulnerable to adverse weathers are likely to get affected first, and with the increasing trend and severity of adverse weather, we probably see an acceleration of farmland conversion as separately from urban driving factors. Ignoring climate factors would likely result in overestimating the effects of urban-driven factors in place where there are other potential harmful factors, climate changes or otherwise, that negatively affect farm production. As lands expectedly become less arable in the future, the increasing pressure of population and income may drive more farmland out of less profitable agriculture production.

FARMLAND CONVERSION STATUS IN CALIFORNIA

The conversion of agricultural lands poses a serious threat to California agriculture. California's Department of Conservation reported a consistent trend of increasing urbanization and movement of agriculture land to other uses in most counties in California during the past two decades. According to the last report, during the period 2002-2004 there was a loss of 170,982 acres of farmland of all types, among which the highest quality farmland (prime farmland) accounts for 46% of the total. Translating to acreage, prime farmland loss in 2002-2004 period is 78,575 acres, a big surge from 47,172 acres in 2000-2002. Figure 1 shows that the trend of prime farmland conversion is particularly damaging in the past decade with almost half of total conversion in almost periods except 2000-2002. Total prime farmland loss during the period of study is 461,272 acres, approximately 9 percent of total prime farmland stock available by the end of 2004 (5,076,207 acres).

Figure 1



Source: Author calculates from FMMP reports. Other farmland conversion includes all nonprime farmland conversions. Farmland classification is in the appendix.

However, urbanization is not the only cause of conversion, as nearly 40% of the conversions out of agriculture land were to other uses. There are also other conversions from productive farmland to idling land, non-irrigated cropping, wildlife areas, low density residential uses, mining, or confined animal agriculture facilities, which need explanations more than just conversion to urban uses. This shows that the dynamics of farmland conversion in California is more complex than urbanization alone (FMMP 2002-2004 report). As a consequence, any study modeling farmland conversion must consider factors beyond urban driving forces.

MODELING THE IMPACT OF CLIMATE CHANGES ON FARMLAND CONVERSION

The aim of this paper is to model the impact of climate changes on farmland conversion, paying attention particularly to extreme events such as high temperature, frosts and heavy precipitation, while controlling for other factors such as urban influence and soil characteristics.

It is assumed that farmland owners maximize profit, either as a net discounted rent from future farming (or the Ricardian rent), or sell the land and convert it to another usage. This is the traditional approach to urbanization. Facing possible adverse climate impacts which would reduce future farming profit, more farmland conversion is expected. There are a couple of notes here. Firstly, I assume that the conversion is purely based on economic decision. Farmlands that have been planned for other usage will be excluded from the data. Unlike urbanization model which requires the land to be converted to urban usage, in this model farmland can be converted to urban or other usage, or even left idling.

Secondly, is there any market mechanism which may benefit farm owners from harmful climate extreme events? If farm supply was disrupted by local climate events, but not replenished from other places, then price was expected to increase. If price increases by too much it may offset the losses of damaged crops and farm owners may actually benefit. In this case probably we can see a conversion from idle lands or other lands back to prime farmland! However, it is reasonable to assume such events, if had, is not strong enough to interfere with the conversion trend since short term gain would not outweigh expected future cost of maintaining the farm. Similarly, if demand for some crops increases, we may see idle land move back to cultivated lands. (FMMP 2002-2004 period reports irrigated acreage gains in Antelope Valley of Los Angeles County due to strong market demand of baby carrots and potatoes, although two thirds of those lands didn't meet prime farmland criteria). That will partly offset the effects of climate changes on conversion. The easiest way to deal with this is to assume price constant, thus no external market intervention. Existing study (Deschenes and Greenstone, 2007) also holds price constant. Including a time fixed effects may also solve this problem.

Thirdly, there is a legislative issue which may limit the option of farm owners from conversion. California initiated Williamson Act from 1965 to protect the state's farmland from conversion by giving financial incentive to farm owners. Farm owners will get property tax credit by entering a 10 year rolling contract with the government. Up to a half of the state's farmland is under protection of the act now. Only farms of 100 acres up are eligible. Farm owners must pay cancellation fee if want to drop out of the program before contract is due. Thus, a downward bias of the impacts of climate events will be expected.

The next section will describe the data sources, followed by the methodology and estimation strategy.

DATA SOURCE AND DATA PREPARATION

Much data used in this paper come from public GIS database, which often need extensive processing for analytical modeling. There are several occasions in which the use of GIS operations is explained in details to provide insight of the raw data and the data format used in the econometric modeling.

Data Sources and Description

Farmland data

California Department of Conservation initiated the Farmland Mapping and Monitoring Program (FMMP) in response to "a critical need for assessing the location, quality, and quantity of agricultural lands and conversion of these lands over time. FMMP is a nonregulatory program and provides a consistent and impartial analysis of agricultural land use and land use changes throughout California" (California Department of Conservation).

The first biennial report on farmland landscape was available in 1984. Since then there have been 10 published reports and 12 GIS database made available to the public with the latest report in 2006 (by the time of this writing, the 2006 report is classified as unofficial). Over time, there are more counties and land area mapped and published, up from 38 counties in 1984 report to 46 counties in 2006. The database now maps nearly 96% of state's privately held agricultural and urban land use covering 47.9 million acres in 49 counties.

There are 8 types of important land use in FMMP classification: prime farmland, farmland of statewide importance, unique farmland, farmland of local importance, grazing land, urban and built-up land, other land and water (farmland list in appendix). FMMP team uses remote sensing satellite images, aerial orthophotos and soil survey data from the US Department of Agriculture in the classification process and verifies by ground survey, as well as inputs from other parties.

Climate data

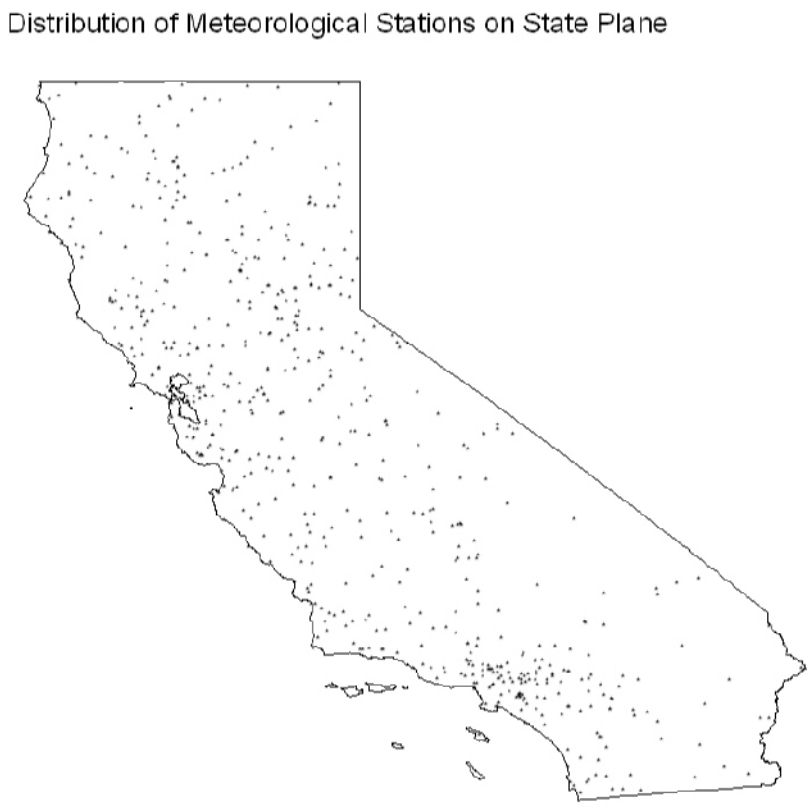
Mean weather variables from the PRISM dataset (Parameter-elevation Regressions on Independent Slopes Model of the Oregon State University PRISM group) are used. I am using 30-year average max, min and mean temperature, precipitation for the period 1971-2000. PRISM data is available in grid cells at a resolution of 30 arcsecond (roughly 800mx800m). Within each cell it is assumed that weather variables are homogenous. Figure 2 in the appendix shows the pattern of PRISM climate normal 30-year max and min temperature.

The reason we need to consider both max and min temperature separately, according to Lobell et al. (2006), is that “because they are often not correlated from year to year with each other, particularly in winter and often one but not the other is highly correlated with yields. Combining the two into average temperature would therefore degrade model performance. Also square term is included to capture non linear relationships, as crops often possess an optimal temperature where yields are maximized relative to both cooler and warmer temperature”.

Historical weather records

Another set of weather variables are real time observations at the National Climatic Data Center (NCDC) weather station networks. I only extract observations from those stations having reports for any the studied period from 1980 to 2006. There are data on daily maximum and minimum temperature and precipitation. There were 628 stations listed as active during at least some or the full period from 1980 to 2006. The station positions are matched onto state plane by longitude and latitude address, from which weather data on the whole state surface can be obtained by interpolation method. Figure 3 shows the locations of the station network on the state plane.

Figure 3. Location of the weather stations on state plane



Soil characteristics

Since the classification of the farmland was done on USDA's SSURGO soil survey database, this paper will use the same dataset to make it consistent with the classification[6]. Following literature, I will also use a set of variables representative of farmland quality like average water capacity, permeability, erodibility, percent clay, irrigation class and depth to water table. Complete explanation of the soil characteristics is included in the appendix. Soil characteristics are assumed unchanged overtime.

Demographic and socioeconomic data

To control for urban pressure which drives the conversion from the demand side, population density and median income will be used. These come from two US censuses in 1990 and 2000. The urban influence is weighted by distance from urban areas to the farm location. Since there is no hard edge between urban-rural areas, many studies use the distance by centroid between the farm location and the nearest census tract or the central business district as in mono-centric urban growth model. US census database provides a useful urban area designation[7], which could be more informative than using census tract.

Data Preparation

Since the farmland polygon isn't parceled, and most often come with irregular shapes of various size (Figure 4 and 5), as in any spatial modeling of conversion, we need a standardized measurement unit.

To do this, I create a grid layer of .25x.25 arcmin (roughly 4x4 km) on the state plane to be used as the geo-referencing layer. As in any spatial modeling, the choice of cell size is arbitrary, thus a valid result should remain using different cell sizes. Validation using different cell size is tempted. However, the choice of size is induced by computing resource and at the same time preserves some local attributes. Too coarse resolution would facilitate computation at a loss of local information, thus prone to aggregation bias. This is particularly true when we have very irregularly shaped, elongated farm polygons spreading over a wide area, thus different parts may have exposed to very different condition (urban stress, soil, weather etc).

[6] Soil Survey Geographic Database from the U.S. Department of Agriculture, Natural Resources Conservation Service. SSURGO version 2.1 (2006) is used.

[7] Urban areas are designated as places where "Core census block groups or blocks that have a population density of at least 1,000 people per square mile (386 per square kilometer) and surrounding census blocks that have an overall density of at least 500 people per square mile (193 per square kilometer)." (http://en.wikipedia.org/wiki/Urban_area)

Then I use this layer to join and clip with other data layers to extract all interested variables. The products will be layers with each cell complete of spatial reference and attributes.

Figure 4 : Location of Prime Farmlands

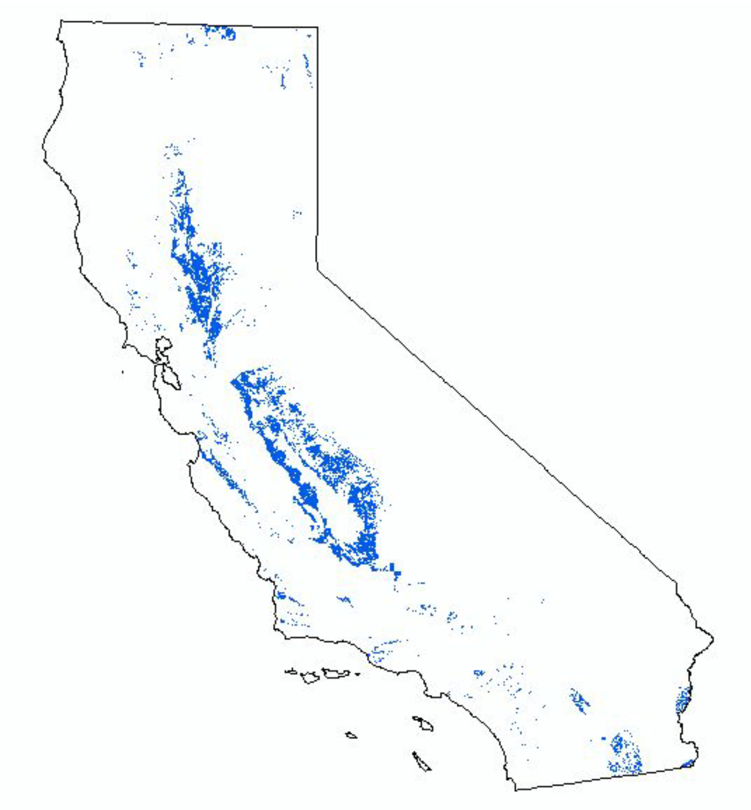
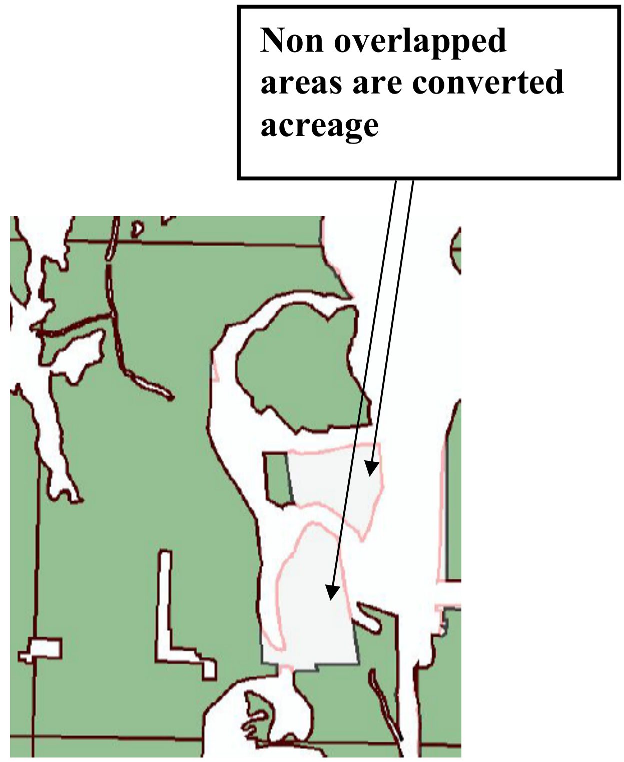


Figure 5 : Extracting Converted Land Demo



Extracting converted farmland polygons from state farmland layers

Each type of farmland is classified as farm polygon in FMMP data. To extract the converted area during each biennial report, firstly each layer was successively overlaid onto another to detect where a conversion had taken place between two report periods. The dependent variable will be derived as the amount of prime farmland converted between two biennial reports in each cell (Figure 5). The edge length (perimeter) will be calculated for each cell, since more fragmented or close proximity to the edge farmlands are prone to conversion than contiguous farms.

According to FMMP report, the minimum mapping unit used in FMMP data is 10 acres. Farmland of smaller size will be attached to the next neighbor land. The minimum unit of measurement within GIS database is 0.3 acre. This has an implication on the number of the converted farmlands found. Due to mapping inconsistency, or human errors, there are occasions which the polygons or lines do not perfectly line up. The result is that there are some areas which didn't experience a conversion but incorrectly determined, and some converted areas appear very small compared to the minimum unit of measurement of 0.3 acre. So these areas resulting from mapping errors will be excluded from our analysis.

Some extra caution is taken with regard to farmland conversion due to administrative issues. Due to the reclassification of the farmland in some areas, the farmland loss due to being reclassified won't be used in the analysis. Farmland loss due to government plans will be excluded too. Report on big conversions was often available at county level and published by FMMP, and those plots would be removed from the data.

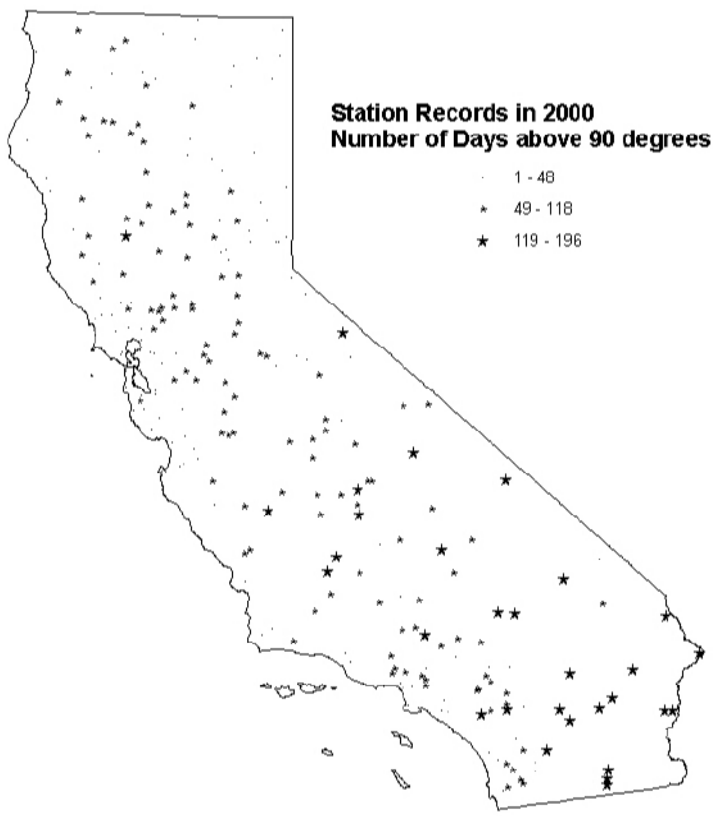
Deriving climate extreme surface – choice of interpolation methods

This section will explain the method behind weather interpolation from weather station dataset to the whole state plane. This is a crucial part of predicting the effects of climate changes and weather extremes, especially because the nature of extreme events is rare, thus generalization and interpolation must be very cautious. I focus on the use of extreme temperature, i.e. temperature supposed to be damaging to crops. According to agronomic literature, this threshold is set at 90^{o}F for maximum temperature. The number of days with maximum temperature recorded above 90^{o}F at every location were interpolated from a series of nearby stations, thus avoid the issue of aggregating and averaging over space.

Since the records of extreme events are set of point estimates at the weather station locations, to estimate the impacts on a farm location far away from the observatories, we must interpolate the value of extremes to different places. Several interpolation methods are often used such as inverse distance weighting (IDW), nearest neighbor, spline and kriging. The results of Schenker, Hanemann and Fisher (2006) and Deschenes and Greenstone (2007) show how different interpolation methods may lead to very different, sometime even contradictory, results. Pointedly, Deschenes and Greenstone restrict climate variation to average observations from weather stations in the same county. This has a drawback that using mean temperature or precipitation often results in underestimating the impact from extremes. I attempt to use several interpolation methods including IDW and kriging. IDW assumes that the effect fall by linear function of the distance while kriging can accommodate for spatial dependence in the observations, in which nearby stations tend to report similar values than distant ones. Kriging is a geostatistical method, unlike deterministic approaches such as IDW.

The potential problem with deterministic approach is that interpolated value is purely a function of distance between locations. Kriging takes into account the spatial autocorrelation between observations. The difference is evident when the observations are not randomly distributed. By examining Figure 6 we can see how these stations with high and low records cluster at different places: high number of days above 90^o F is concentrated in Southern California, the desert and central valley, in opposite to coastal and Northern areas with very few records. Moran test for spatial dependence rejects the spatial independence of these observations. Averaging the records over space will result in underestimating impact of the high records and overestimating the low records. A sample of interpolated extreme heating surface is presented in figure 7 in the appendix.

Figure 6: Distribution of Number of Days above 90^{o}F (Real-time Observations) in 2000



DATA SUMMARY

For the initial result has been completed to date, Table 1 summarizes 4220 cells covering all documented prime farmland acreage from 2000 to 2006.

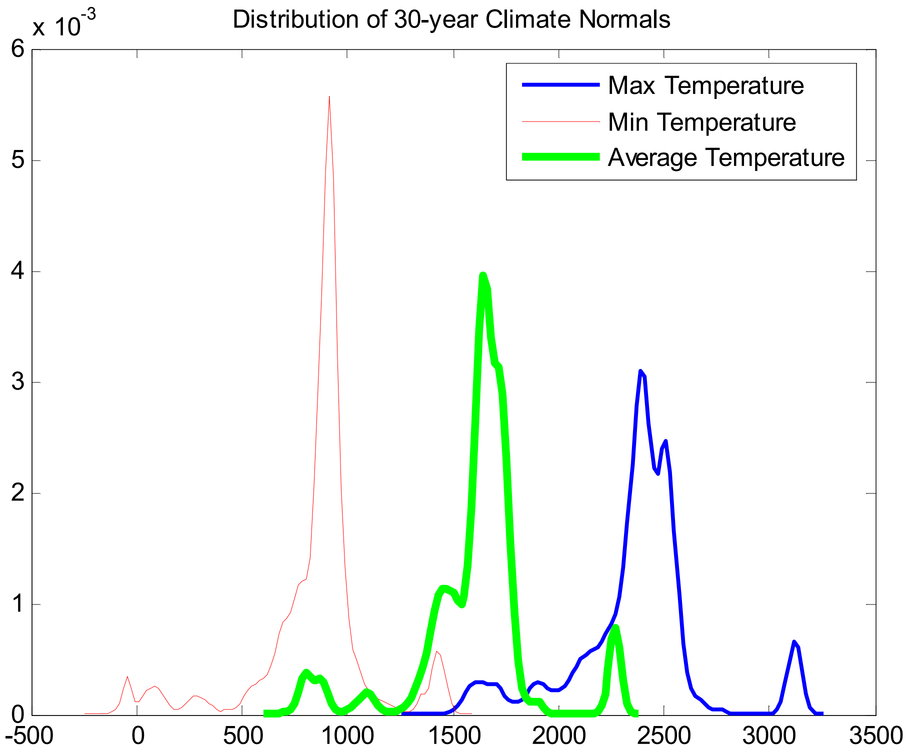
Table 1: Some Descriptive Statistics
(For PRISM data, temperature is in hundredths of a degree Celsius,
precipitation in hundredths of a millimeter; interpolated precipitation is in inches)

Description	Source	Mean	Std. Dev.	Min	Max
Climate Data					
30-year Average Max Temperature	PRISM	2372.78	287.4649	1351	3165
30-year Average Min Temperature	PRISM	854.3367	254.5065	-196	1482
30-year Mean Temperature	Average of max and min temp.	1613.558	260.339	676.5	2293.5
30-year Mean Precipitation	PRISM	41213.75	22925.66	7108	186940
25-year Average Number of Days Above 90F (IDW)	Interpolated from NCDC observations	70.04261	32.61343	4.457164	191.5524
25-year Average Number of Days Above 90F (Kriging)	Interpolated	114.0945	24.94456	52.73724	190.1058
25-year Average Precipitation (IDW)	Interpolated	14.00324	6.89008	1.735603	49.17206
25-year Average Precipitation (Kriging)	Interpolated	14.38143	6.835474	2.43149	50.25348
Soil Data					
Average Water Capacity (AWC)	SSURGO	.1314087	.0431373	0	.4652072
Saturated Hydraulic Conductivity (Ksat)	SSURGO	16.62466	14.84382	1.21	96.6791
Percent Clay	SSURGO	23.5575	8.979848	.7846025	51.3
K-factor, whole soil	SSURGO	.2906025	.0878168	0	.49
Depth to Water Table	SSURGO	190.2441	28.92158	0	201.0012
Irrigation Class	SSURGO	2.263655	.848156	1	7
Socio-economic					
Median Family Income, Weighted by inverse distance (US dollar, 1999)	US Census 2000, SF3, entry P077001	45340.37	10672.72	27331.87	90768
Population Density, Weighted by inverse distance (people per square km)	US Census 2000, SF3, entry P003001	3631.014	1186.466	555.3243	31956.36

There are some anomalies worth mentioning in the values of soil characteristics regarding average water capacity, K-factor and depth to water table, i.e. the reported values are zeros. They aren't necessarily missing or incorrect values, strictly speaking. Since the values are either weighted average or dominant condition at each cell level, it is possible to get such values. However, the impact of such anomaly is minimal. There are only 30 cells with reported zero value of AWC, 7 cells of depth to water table and 37 cells of K-factor less than .02 (the minimum value reported by SSURGO), representing less than 1% total number of cells. Models tested with and without such cells didn't reveal any significant change at all. The largest missing cells come from irrigation class, which only have values for 3064 cells. However, dropping irrigation class also doesn't change the result, especially with regard to the significance of the climate indicators.

To see how separating maximum and minimum temperature from using mean only is significant, Figure 8 shows the distribution of these three climate normals at 4220 cells. We can see that max and min temperature keep the variation much better than the distribution of mean. This would later prove to be important in models using max and min temperature versus model using mean temperature alone.

Figure 8



It's also tempted to see how using extreme conditions, i.e. number of days above 90^{o}F will better keep the variation than separating max and min temperature, Table 2 shows the correlation coefficients of these variables. Although the correlation is high, it is not as high as the correlation between max and min temperature. Figure 1 already shows the spatial variation of these two indices on the state plane. It's easy to see that max and min temperature tends to be correlated with each another, i.e. Southern part is, on average, warmer than other areas. Yet, extreme heating days are quite different from average condition, evidently when we look at the correlation between number of extreme days with max and min temperature, .83 and .65, while the correlation between average max and min temperature is even higher at .85. Some areas may be subject to more fluctuation in temperature, i.e. both more low and high temperature, thus even with a high number of heating days, using annual max and min temperature would just amount to averaging out these fluctuations, therefore underestimating the effect of the extremes.

Table 2: Correlation between Climate Indicators

	Max Temperature, 30-year Average	Min Temperature, 30-year Average	Mean Temperature, 30-year Average	Number of Days above 90F, IDW	Number of Days above 90F, Kriging
Max Temperature, 30-year Average	1				
Min Temperature, 30-year Average	.8454	1			
Mean Temperature, 30-year Average	.9653	.9555	1		
Number of Days above 90F, IDW	.8288	.6474	.7740	1	
Number of Days above 90F, Kriging	.8134	.6901	.7864	.9294	1

In the analytical part, I show results using several combinations of different climate indicators, using mean temperature and precipitation, separating out max and min temperature from mean, using the number of extreme heating days and finally validate the result with Schlenker et al (2006) data using degree days measure.

SPATIAL REGRESSION MODEL

I adopt a reduced-form approach[8] to land use conversion as in Chomitz and Gray (1996), which models the conversion at each cell as a function of biophysical and socioeconomic characteristics:

$$y_i = \beta_o + X_i\beta + Z_i\gamma + \varepsilon_i$$

for each cell i

[8] The mechanism of conversion is through allocating the land to highest-value usage, either as farmland rent or converting to other usage. Yet, farmland rent is endogenous as a function of farm attributes. But we can formulate a model of farm rent on attributes, thus conversion function thereof. The first part is similar Mendelsohn et al (1994) approach to estimating farm value by hedonic regression.

y is the amount of prime farmland converted in each cell over the two report periods. X is vector of weather means and climate extreme variables. Z is vector of control variables including soil and socio-economic characteristics.

To control for the nonlinear effects of climate condition, I am using the squared maximum temperature, squared precipitation and squared maximum number of days above 90^{o} F. I am going to use three different combinations of climate indicators: by using mean temperature and precipitation only, separating max and min temperature from mean, then my favorite specification using number of days above 90^{o} F.

There is an issue of spatial dependency between observations, as said in the first law of geography that near things are more related than distant units, spatial autocorrelation need to be accounted for. For instance, farm owners may be affected by his neighbor's conversion decision, or the process of clipping and extracting converted areas may have inadvertently created nearby observations which share attributes.

There are two approaches to spatial dependency problem, either by using a spatial autoregressive (SAR) or spatial errors modeling (SEM).

Spatial autoregressive model (SAR):

$$Y_i = \delta WY + X_i\beta + \varepsilon_i$$

Spatial errors model (SEM):

$$Y_i = X_i\beta + \varepsilon_i$$
$$\varepsilon_i = \rho W\varepsilon + \upsilon_i$$

where W is the spatial weighing matrix, δ and ρ is spatial autocorrelation coefficient. The presence of spatial dependence violates the condition that the error terms are uncorrelated, thus ordinary least square regression on spatial data is still unbiased, but inefficient in SEM model. In case of SAR model, it is both biased and inconsistent (Elhorst, 2003).

In this paper I will show models estimated with robust standard errors, model with county fixed effects to control for county difference, then models with spatial errors using popular treatment to cross-sectional spatial dependence such as Conley's GMM approach (1999) and Elhorst's MLE estimator (2003). Test for spatial autocorrelation on robust standard errors shows that there is significant spatial dependence in the residuals, necessitating the spatial approach. I will use two weighting schemes to allow for the spatial spillover effects to extend from 0.1 degree in distance (roughly 10km) to 0.5 degree (~50 km). Extending the influence distance can correct for more spatial dependence, but at a cost, as spatial standard errors will be significantly higher, thus reducing the significance of the interested variables.

Panel data approach is possible, but substantially more data needed, which isn't possible at this time. The initial result presented here comes from cross sectional data for 2002-2006 conversion period. The results here are also confirmed using MLE estimator[9].

EMPIRICAL RESULTS

Results on 2002-2006 conversion are reported in Table 3, 4 and 5 for three different combinations of climate variables: max and min temperature, extreme conditions and mean temperature. Robust standard errors without spatial dependence are shown in column 1. Column 2 and 3 are models with spatial standard errors using inverse distance weighting schemes at two different cutoff ranges. Column 4 is model with robust standard errors and county fixed effects included. Dependent variable is the difference in prime farmland acreage in each cell from 2004-2006 and 2000-2002 reports, so effectively it is the *negative amount* of converted areas. This arrangement is deliberated to generate an inverted U-shaped conversion function much as agricultural production function in agronomics.

The first column in a three table shows all climate variables are highly significant and with the expected sign: 30-year mean maximum temperature and minimum temperature have positive effects on the *negative* farmland loss, or an increase in these variables will counter farmland loss. Yet, squared maximum temperature is negative, or it will accelerate farmland loss. The same holds for precipitation. This result is exactly as expected for the impact of climate on farm production: an increase in average temperature means prolonged growing seasons, thus farm values and helps keep farm in production. Look at Table 1 we see the average max and min temperature is at 23.7 and 8.5 degree Celsius, well below threshold for which crops may be harmed. The squared terms both have negative sign, showing that excessive increase in temperature and precipitation is harmful and will accelerate conversion.

Table 5 reports the same conclusion as using max and min temperature separately: an increase in mean condition can help reduce farm conversion, yet to a certain extent the negative coefficient of the squared term will shadow the benefit of change in mean condition and harmful feedback will set in. What makes Table 3 and Table 5 different is the magnitude of the coefficients: separating max and min temperature both impacts are higher than averaging: for max temperature 2202, 30% higher compared to 1566 using mean temperature, and for squared term -0.50 vs. -0.48. Coefficients using the number of days above 90^{o}F aren't directly comparable with temperature.

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[9] Data and program code are available upon request

Result using the number of days above $90^{o}F$ (Table 4) is interesting: an increase in the number of days above $90^{o}F$ will be beneficial, but it is also harmful if increases by too much.

With regard to the soil coefficients, higher water capacity and higher permeability (K-saturation) are both positive as expected: farm with higher AWC can better support crop growth, thus farm values and less conversion. Higher permeability means that it is less prone to heavy precipitation events. Clay is positive and significant. Higher value of clay in soil content means more capability to keep water, in opposite to having more sand. Irrigation capability class is the suitability of farmland for most kinds of field crops. Higher values indicate the greater is the limitations and narrower choices for practical usage, thus less convertibility. So a positive and highly significant coefficient for irrigation class is well predicted. Two soil variables with negative estimates are K-factor and depth to water table. K-factor indicates the susceptibility of a soil to sheet and rill erosion by water, higher value of K-factor means more erodible soils, other things equal. So the results for K-factor and water table depth are both very intuitive. However, depth to water table variable isn't significant in all models.

For other control variables, the perimeter is negative and significant in all models as expected. This comes from the fact that conversion often took place near the border rather than deep inside farm polygons. Further, more fragmented or close proximity to the edge is likely more influenced by urban factors, planning or other factors than contiguous farms.

Median family income is highly significant and also intuitive. Higher income indicates more pressure from urban demand, either through higher demand for land or implicitly driving up land price, thus inducing conversion. Population density coefficient is unexpectedly positive, however insignificant in all models.

Column 2 and 3 are models with spatial correlation in error terms. Moran's test of spatial correlation in the error terms report a value of 14.65, indicating the need to correct for spatial autocorrelation. Spatial standard errors are higher than those from least squared estimation, thus many explanatory will become less or insignificant. Increasing cutoff ranges will allow for the error terms to be more correlated with one another, thus increasing spatial errors' standard deviation. Most variables remain significant with cutoff range of .1 degree. At cutoff range of .5 degree, only maximum temperature and its squared term is significant. Perhaps the most interesting finding is that the number of days above $90^{o}F$ remains significant, while using mean temperature isn't after all.

Column 4 is model with county fixed effects. There are reasons to think that county difference may be an input to permitting conversion such as difference in policy, existing farmland supply, or any unobserved county difference. The result is still very encouraging that max temperature and max temperature squared are significant with expected sign, same as the squared number of extreme heating days. Using mean temperature won't be able to detect any effect of temperature changes on conversion. Soil and other socio-economic variables are still significant as expected with the exception of precipitation and K-factor now insignificant in all models.

To validate this result, instead of using max temperature or extreme heating days, I use a more agrarian approach to climate, degree days, to see how the conversion may be affected. Degree days is defined as the sum of degrees above a lower baseline and below an upper threshold during the growing season (Schlenker et al, 2006). With the lower bound set at 8^{o}C and upper bound at 32^{o}C, a day can contribute maximum up to 24 degree days unit. Crop growth needs certain amount of degree days, yet too much degree days may mean too warm condition and harmful effects expected. For temperature above 34^{o}C, the effect is always harmful. Harmful degree days is the total number of degrees for any day which maximum temperature passed 34^{o}C threshold.

Table 6
Precipitation, Degree Days and Harmful Degree Days in California
County Average, 50 Counties

Variable	Mean	Std. Dev.	Min	Max
Precipitation (cm)	68.0088	4.8512	62.1884	87.1772
Degree Days (8-32^{o}C)	2738.44	170.45	2421.77	3072.05
Harmful Degree Days (34^{o}C)	2.3594	.2863	1.8008	2.9927

Source: Schlenker et al (2006)[10]

I replace my proposed climate variables with Schlenker et al (2006) data on precipitation, squared precipitation, degree days, squared degree days and the square root of harmful degree days, at every cell for each county using county fips code. Table 6 is a summary of Schlenker et al (2006) data, in county average over 50 counties in California. Validation result is shown in Table 7. It's interesting that the result agrees perfectly with other models, and remains significant across all three specification checks. Since normal degree days has been shown to be positively related to farmland value, so it will help keep farm from converting. Yet too much degree days is bad and harmful degree days (34^{o}C) too. Precipitation follows the same pattern. Note that the sign of population density is counterintuitive in the first two columns (robust standard errors and cutoff range of .1 degree), but no longer an issue at the cutoff range of .5 degree. At cutoff range of .5 degree, the result still holds for degree days and squared degree days. One reason to suspect harmful degree days isn't significant is that there are very few observations and little variation of this variable, as acknowledged by Schlenker et al (2006).

[10] Available at http://www.columbia.edu/~ws2162/agClimateChange.html

These results confirm the proposition that maximum temperature or extreme heating days will accelerate farmland conversion. Although the models only explain a fraction of conversion pattern (R square is low, about 6% for models without fixed effects or roughly 25% for models with fixed effects), the most important result is that the effect is present and significant.

CONCLUSION

This paper presents a new approach to study the impact of climate changes on farmland conversion using climate extreme events instead of mean condition. This approach has been proved to better predict the impact of climate changes, especially when considering the impact of heating condition: using the number of days above 90^o F or separating maximum and minimum temperature from average condition are both better predictors of the negative impact of excessive heating on farmland conversion.

A conclusion specific to California agriculture is that there may be benefit, thus less farmland conversion, expected from mild climate changes. But excessive increase will be definitely harmful and drive more conversion away from farm production. This conclusion is also supported by a number of literatures about climate impact in California.

This result is also significant in the sense that shifting the attention to the distribution of the tail, i.e. extreme events, can better estimate climate impact than using average condition. However, there are considerable difficulty in obtaining and analyzing the impact of extremes than changes in predictable mean values.

There are several ways to improve the predictor of impacts to be considered in future study. Firstly, using temperature recorded during growing season only may be more relevant. This is not a problem for California, as growing season (from April to September) comes with most of the observed extreme heating days. However, application to other locations needs to take this into account. Secondly, the number of continuous heating days maybe more harmful than isolated events. Lateral damage (without considering the timing of extreme heating days) can still be mitigated in short term such as pumping more water, but not a solution if climate changes cause severe heating over a prolonged period.

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APPENDIX

FMMP Farmland Classification

Prime Farmland has the best combination of physical and chemical features able to sustain long-term agricultural production. This land has the soil quality, growing season, and moisture supply needed to produce sustained high yields. Land must have been used for irrigated agricultural production at some time during the four years prior to the mapping date.

Farmland of Statewide Importance is similar to Prime Farmland but with minor shortcomings, such as greater slopes or less ability to store soil moisture. Land must have been used for irrigated agricultural production at some time during the four years prior to the mapping date.

Unique Farmland consists of lesser quality soils used for the production of the state's leading agricultural crops. This land is usually irrigated, but may include non irrigated orchards or vineyards as found in some climatic zones in California. Land must have been cropped at some time during the four years prior to the mapping date.

Farmland of Local Importance is land of importance to the local agricultural economy as determined by each county's board of supervisors and a local advisory committee.

Grazing Land is land on which the existing vegetation is suited to the grazing of livestock. This category was developed in cooperation with the California Cattlemen's Association, University of California Cooperative Extension, and other groups interested in the extent of grazing activities.

Urban and Built-up Land is occupied by structures with a building density of at least 1 unit to 1.5 acres, or approximately 6 structures to a 10-acre parcel. Common examples include residential, industrial, commercial, institutional facilities, cemeteries, airports, golf courses, sanitary landfills, sewage treatment, and water control structures.

Other Land is land not included in any other mapping category. Common examples include low density rural developments; vegetative and riparian areas not suitable for livestock grazing; confined animal agriculture facilities; strip mines, borrow pits; and water bodies smaller than 40 acres. Vacant and nonagricultural land surrounded on all sides by urban development and greater than 40 acres is mapped as Other Land.

Water - perennial water bodies with an extent of at least 40 acres.

Soil Characteristics and Implication on Farming Activities (US Soil Data View 2.1)

Available Water Capacity (AWC) refers to the quantity of water that the soil is capable of storing for use by plants. The capacity for water storage is given in centimeters of water per centimeter of soil for each soil layer. The capacity varies, depending on soil properties that affect retention of water. The most important properties are the content of organic matter, soil texture, bulk density, and soil structure, with corrections for salinity and rock fragments. Available water capacity is an important factor in the choice of plants or crops to be grown and in the design and management of irrigation systems. It is not an estimate of the quantity of water actually available to plants at any given time.

Saturated hydraulic conductivity (Ksat) refers to the ease with which pores in a saturated soil transmit water. The estimates are expressed in terms of micrometers per second. They are based on soil characteristics observed in the field, particularly structure, porosity, and texture. Saturated hydraulic conductivity is considered in the design of soil drainage systems and septic tank absorption fields.

Percent Clay: clay as a soil separate consists of mineral soil particles that are less than 0.002 millimeter in diameter. The estimated clay content of each soil layer is given as a percentage, by weight, of the soil material that is less than 2 millimeters in diameter. The amount and kind of clay affect the fertility and physical condition of the soil and the ability of the soil to adsorb cations and to retain moisture. They influence shrink-swell potential, saturated hydraulic conductivity (Ksat), plasticity, the ease of soil dispersion, and other soil properties. The amount and kind of clay in a soil also affect tillage and earth-moving operations.

K-factor, whole soil: Erosion factor K indicates the susceptibility of a soil to sheet and rill erosion by water. Factor K is one of six factors used in the Universal Soil Loss Equation (USLE) and the Revised Universal Soil Loss Equation (RUSLE) to predict the average annual rate of soil loss by sheet and rill erosion in tons per acre per year. The estimates are based primarily on percentage of silt, sand, and organic matter and on soil structure and saturated hydraulic conductivity (Ksat). Values of K range from 0.02 to 0.69. Other factors being equal, the higher the value, the more susceptible the soil is to sheet and rill erosion by water.

Depth to water table: "Water table" refers to a saturated zone in the soil. It occurs during specified months. Estimates of the upper limit are based mainly on observations of the water table at selected sites and on evidence of a saturated zone, namely grayish colors (redoximorphic features) in the soil. A saturated zone that lasts for less than a month is not considered a water table.

Irrigation class: Land capability classification shows, in a general way, the suitability of soils for most kinds of field crops. Crops that require special management are excluded. The soils are grouped according to their limitations for field crops, the risk of damage if they are used for crops, and the way they respond to management.

In the capability system, soils are generally grouped at three levels-capability class, subclass, and unit. Only class and subclass are included in this data set.

Capability classes, the broadest groups, are designated by the numbers 1 through 8. The numbers indicate progressively greater limitations and narrower choices for practical use.

Table 3. Using 30-year average max, min temperature and precipitation including squared terms for 2002 – 2006 conversion, t-value in bracket

Variable	No Spatial Correlation	t-statistics, Corrected for Spatial Dependence (Conley's Method)		With County Fixed Effects
	Robust Standard Errors (Col 1)	IDW Cutoff Range = .1 (Col 2)	IDW Cutoff Range = .5 (Col 3)	(Col 4)
Max Temperature	2202.01 (3.35)***	(2.40)**	(1.65)*	1582.31 (2.17)**
Max Temperature, squared	-.50 (-3.33)***	(-2.37)**	(-1.63)*	-.30 (-1.84)*
Min Temperature	243.06 (3.03)***	(2.19)**	(1.33)	137.39 (.99)
Precipitation	6.72 (1.96)**	(1.37)	(.85)	4.40 (1.22)
Precipitation, squared	-.0000486 (-2.40)**	(-1.68)*	(-1.04)	-.0000194 (-1.12)
Perimeter, 2002	-9.65 (-8.67)***	(-6.39)***	(-3.41)***	-10.39 (-9.33)***
Median Family Income, 2000	-10.02 (-5.23)***	(-3.67)***	(-2.33)**	-6.60 (-1.65)*
Population Density, 2000	8.52 (.75)	(.52)	(.33)	-20.83 (-1.11)
Water Capacity	3814582 (3.49)***	(2.50)**	(1.66)*	1727221 (2.08)**
K Saturation	11675.32 (3.46)***	(2.47)**	(1.84)*	10508.2 (3.29)***
Percent Clay	10623.35 (2.44)**	(1.73)*	(1.50)	11549.2 (2.23)**
K factor	-927405 (-1.97)**	(-1.44)	(-1.12)	-526346 (-1.30)
Irrigation Class	53252 (5.07)***	(3.71)***	(2.43)**	23969 (2.28)**
Water Depth	-1258.42 (-1.31)	(-1.34)	(-1.21)	-297.81 (-.41)
Constant	-2686994 (-3.21)***	(-2.32)**	(-1.61)	-2295537 (-2.52)**
F-stat	9.10			7.66
Spatial Autocorrelation Coefficient (rho)		.69 (32.28)***	.47 (7.67)***	

***, **, * symbols denote coefficient significant at 1%, 5% and 10% significance level, respectively

Increasing cutoff range or placing less weight to distant observations will produce less spatial autocorrelation as expected in rho values.

Table 4. Using 25-year average number of days above 90F, min temperature and precipitation including squared terms for 2002 – 2006 conversion, t-statistics in bracket

Variable	No Spatial Correlation	t-statistics, Corrected for Spatial Dependence (Conley's Method)		With County Fixed Effects
	Robust Standard Errors (Col 1)	IDW Cutoff Range = .1 (Col 2)	IDW Cutoff Range = .5 (Col 3)	(Col 4)
Number of Days above 90F	7344.3 (3.50)***	(2.45)**	(1.59)	3007.2 (1.59)
Number of Days above 90F, squared	-52.33 (-3.65)***	(-2.57)**	(-1.69)*	-20.80 (-1.79)*
Min Temperature	225.86 (2.55)**	(1.82)*	(1.10)	208.67 (1.24)
Precipitation	8.46 (2.45)**	(1.71)*	(1.05)	3.88 (1.01)
Precipitation, squared	-.0000582 (-2.77)***	(-1.94)*	(-1.19)	-.0000186 (-.99)
Perimeter, 2002	-9.33 (-8.39)***	(-6.18)***	(-3.37)***	-10.19 (-9.11)***
Median Family Income, 2000	-7.99 (-3.90)***	(-2.75)***	(-1.82)*	-6.94 (-1.71)*
Population Density, 2000	10.77 (.96)	(.66)	(.40)	-21.19 (-1.06)
Water Capacity	3789837 (3.56)***	(2.56)**	(1.69)*	1760094 (2.12)**
K Saturation	11436.6 (3.47)***	(2.49)**	(1.87)*	10394.8 (3.27)***
Percent Clay	10526.3 (2.46)**	(1.76)*	(1.59)	11779 (2.29)**
K factor	-866496 (-1.92)*	(-1.40)	(-1.09)	-467702 (-1.16)
Irrigation Class	49887 (5.00)***	(3.70)***	(2.48)**	23793.6 (2.24)**
Water Depth	-1317.30 (-1.38)	(-1.42)	(-1.29)	-244.75 (-.34)
Constant	-677112 (-2.11)**	(-1.63)*	(-1.18)	-383493.6 (-1.06)
F stat	8.99			7.56
Spatial Autocorrelation Coefficient (rho)			.45 (7.28)***	

Table 5. Using 30- year average temperature and precipitation for 2002 – 2006 conversion, t-value in bracket

Variable	No Spatial Correlation	t-statistics, Corrected for Spatial Dependence (Conley's Method)		With County Fixed Effects
	Robust Standard Errors (Col 1)	IDW Cutoff Range = .1 (Col 2)	IDW Cutoff Range = .5 (Col 3)	(Col 4)
Mean Temperature	1566.23 (3.13)***	(2.24)**	(1.54)	969.94 (1.60)
Mean Temperature, squared	-.48 (-2.89)***	(-2.06)**	(-1.40)	-.20 (-1.06)
Precipitation	8.26 (2.46)**	(1.72)*	(1.07)	4.99 (1.38)
Precipitation, squared	-.0000584 (-2.92)***	(-2.05)**	(-1.27)	-.0000237 (-1.37)
Perimeter, 2002	-9.55 (-8.60)***	(-6.33)***	(-3.40)***	-10.39 (-9.31)***
Median Family Income, 2000	-10.03 (-5.21)***	(-3.66)***	(-2.32)**	-6.50 (-1.63)*
Population Density, 2000	13.56 (1.18)	(.82)	(.51)	-19.02 (-1.02)
Water Capacity	3674447 (3.38)***	(2.43)**	(1.60)	1759850 (2.11)**
K Saturation	11330.9 (3.40)***	(2.43)**	(1.80)*	10323.3 (3.24)***
Percent Clay	10614.3 (2.44)**	(1.73)*	(1.49)	11515.8 (2.24)**
K factor	-880764 (-1.87)*	(-1.37)	(-1.05)	-517007 (-1.27)
Irrigation Class	53029 (5.09)***	(3.72)***	(2.43)**	24250 (2.30)**
Water Depth	-1295.26 (-1.35)	(-1.39)	(-1.26)	-269.30 (-.37)
Constant	-1415466 (-2.81)***	(-2.08)**	(-1.47)	-1171114 (-2.00)**
F stat	9.67			8.02
Spatial Autocorrelation Coefficient (rho)			.49 (7.96)***	

Table 7. Validation with Schlenker at el. (2006) climate data for 2002 – 2006 conversion[1]

Variable	No Spatial Correlation	t-statistics, Corrected for Spatial Dependence (Conley's Method)	
	Robust Standard Errors (Col 1)	IDW Cutoff Range = .1 (Col 2)	IDW Cutoff Range = .5 (Col 3)
Degree Days (8_32)	17141 (3.60)***	(2.61)***	(1.74)*
Degree Days (8_32), squared	-3.17 (-3.61)***	(-2.62)***	(-1.76)*
Degree Days (34), square root	-164748 (-2.44)**	(-1.86)*	(-1.16)
Precipitation	140167 (2.28)**	(1.68)*	(1.21)
Precipitation, squared	-876.78 (-2.09)**	(-1.55)	(-1.16)
Perimeter, 2002	-9.32 (-8.78)***	(-6.64)***	(-3.64)***
Median Family Income, 2000	-6.91 (-4.43)***	(-3.19)***	(-2.20)**
Population Density, 2000	31.82 (2.23)**	(1.71)*	(1.10)
Water Capacity	2908711 (3.12)***	(2.24)**	(1.48)
K Saturation	9562.9 (3.16)***	(2.26)**	(1.71)*
Percent Clay	13173 (2.85)***	(2.01)**	(1.68)*
K factor	-903759 (-2.17)**	(-1.59)	(-1.23)
Irrigation Class	54409 (4.64)***	(3.43)***	(2.16)**
Water Depth	-1431.4 (-1.48)	(-1.51)	(-1.34)
Constant	-2.82e+07 (-4.14)***	(-2.97)***	(-1.88)*
F stat	9.43		
Spatial Autocorrelation Coefficient (rho)			.48 (7.64)***

[1]Note that Schlenker et al (2006) data is county average, so no county fixed effects model could be estimated as the county-level data already capture all other county effects, if had, on conversion.

Figure 2 – PRISM 30-year Climate Normals: Max and Min Temperature

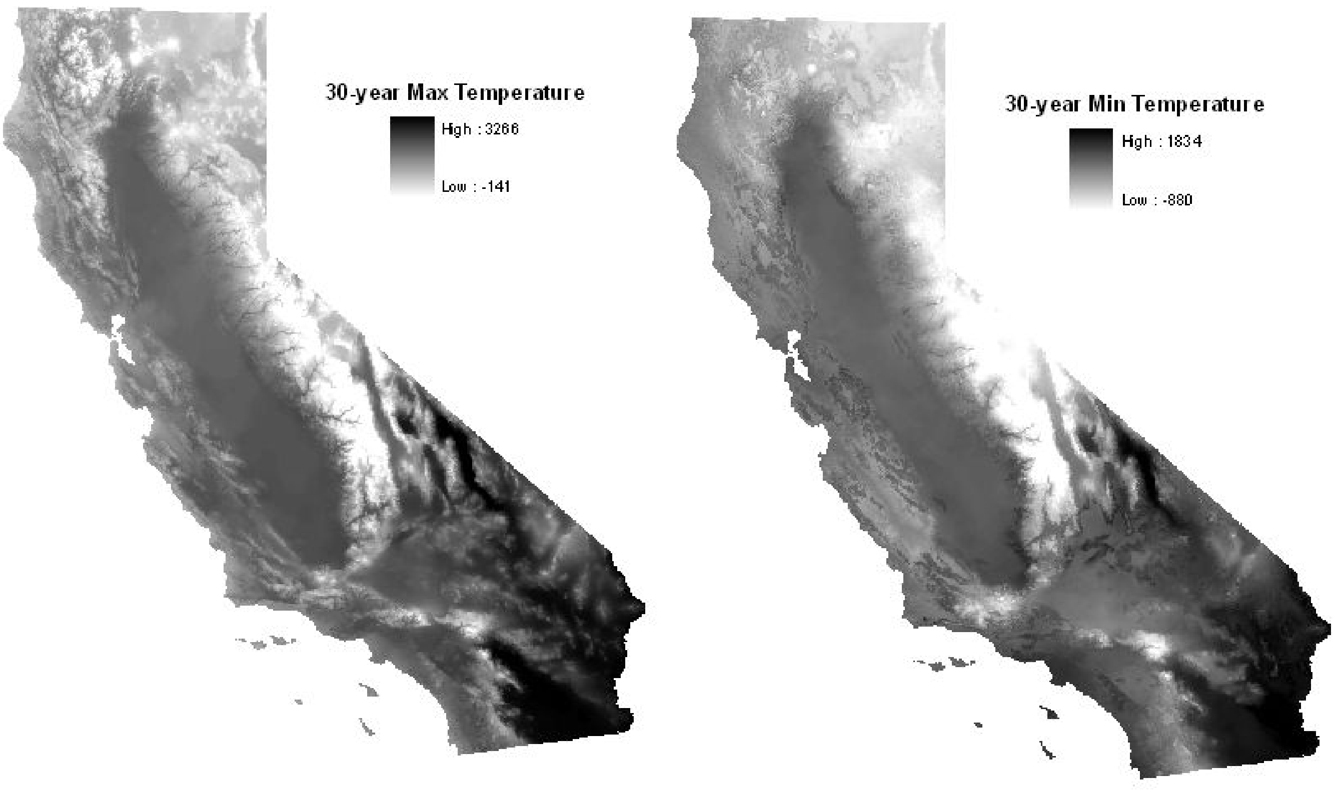

Figure 7: Interpolation of the number of days above 90°F using Kriging and IDW method