Endogenous Land Use and the Ricardian Valuation of Climate Change

by

Christopher Timmins

Yale University Department of Economics
and Economic Growth Center

Abstract

The Ricardian technique uses cross-sectional variation in the capitalized value of climate in land to infer the costs or benefits of dynamic climate change. While an extremely practical approach for predicting the agricultural consequences of global warming, it may yield biased results when land within locations (e.g., US counties) is heterogeneous and land owners behave optimally. This paper illustrates the conditions under which such a bias will occur, outlines an empirical model that controls for it, and identifies that model with readily available aggregate data from Brazil. Results suggest that this source of bias is important and that the agricultural implications of global climate change for Brazil may not as favorable as those implied by a traditional Ricardian regression. The results also imply that climate change may increase deforestation rates with consequent feedback effects on global climate dynamics.

Department of Economics, Yale University, PO Box 208264, New Haven, CT 06520-8264. christopher.timmins@yale.edu, http://pantheon.yale.edu/~cdt5. I would like to thank Patrick Bayer, Steven Berry, Robert Evenson, Robert Mendelsohn, and Bill Nordhaus for their useful insights and helpful comments. All remaining errors and omissions are my own. Fabiana Tito provided excellent research assistance, and Denisard Alves and Robert Evenson generously supplied the data.

1. Introduction

The Ricardian technique [Mendelsohn, Nordhaus, and Shaw (1994, 1996), Mendelsohn, Dinar, and Sanghi (2001)], with its reliance on cross-sectional variation in the capitalized value of climate in land, has proven to be one of the most practical approaches for predicting the agricultural consequences of global climate change. The model's use of readily available data eliminates the need for costly field studies or the collection of expensive panel data over long periods of time. These advantages prove particularly valuable for estimating the consequences of global climate change in developing countries, where much of the focus of international organizations has now turned [IPCC (1995)], and where issues of data availability and reliability are of particular concern.[1]

This paper identifies and addresses an important shortcoming in the Ricardian methodology that may be of particular concern in developing country applications, given limitations on what can be observed (even in good cross-sectional data sets) and how much is, by default, left in the Ricardian error term. Specifically, when plots within locations differ in unobservable ways and when the owners of those plots decide optimally how to employ their land, the error term in a Ricardian regression becomes a weighted average of the unobservable determinants of the value of land in a variety of different uses. A problem arises in that those weights are themselves functions of the same climate variables that the Ricardian regression seeks to value, leading to an endogeneity problem that biases parameter estimates.[2] Ignoring the endogeneity in the way in which heterogeneous plots of land are allocated to alternative uses, moreover, leads to the mis-specification of the marginal effect of climate on land value. These two effects combine to produce erroneous predictions of the agricultural impacts of global warming. This point is illustrated with a stylized example in Section 2. In Section 3, we introduce an alternative methodology that controls for these problems. Using data described in Section 4, the model's climate change implications are demonstrated for Brazilian agriculture, pasture, and forestry activities in Section 5. While not the primary focus of the current application, our model also yields explicit predictions about long-run changes in land-use patterns, which can be used to draw conclusions about the consequences of climate change for Brazilian deforestation and global warming feedback effects.

---

[1] See Sanghi et al (1997) for an application of the Ricardian model to Brazil and Kumar and Parikh (1998) for an application to India.

[2] Ultimately, this is a problem of data aggregation and could be solved if value data were available for every plot of land, reflecting its particular use. Because of confidentiality issues, however, such data are not available even from the most complete sources (e.g., US Agricultural Census). Requiring such data, especially in developing country contexts, would make the Ricardian technique extremely impractical.

2. The Role of Endogenous Land Use Decisions in the Ricardian Model

The Ricardian model exploits cross-sectional covariation in agricultural land values and climate in order to predict how an intertemporal change in climate (e.g., a 2.5°C temperature increase over the next 100 years) would change the value of land in a particular location, holding constant all other non-climate local attributes. Practically, this involves estimating an equation of the form:[3]

$$\overline{V}_j = \beta_0 + \beta_1 C_j + \beta_2 C_j^2 + \beta_3 X_j + \beta_4 X_j^2 + \beta_5 C_j X_j + \varepsilon_j \tag{1}$$

where $\overline{V}_j$ represents the average land value per hectare in location j (e.g., a US county or Brazilian municipio), C_j represents a vector of climate attributes, X_j represents a vector of non-climate attributes, and ε_j is an unobservable determinant of the average value of land. With the estimated parameters from this regression, the effect on land value of a marginal climate change in location j is given by:

$$\frac{\partial \overline{V}_j}{\partial C_j} = \alpha_1 + 2\alpha_2 C_j + \alpha_5 X_j \tag{2}$$

while the impacts of larger shifts in climate can be predicted by comparing fitted values for $\overline{V}_j$ under alternative climate scenarios.

An important strength of this approach is its ability to predict a cost or benefit from a change in climate without ever observing how the value of land in a particular location actually adjusts in response to such a change. It does so by assuming that, if one location were made to look like another because of a change in climate, its land owners would behave like those in the second location. The remainder of this section demonstrates how this assumption can be a source of biased predictions when land within a location is heterogeneous and employed in different uses at the same time.

Consider the following stylized example of a Ricardian valuation exercise. The simplifications we make relative to equation (1) will facilitate our simulations later in this section.

---

[3] For illustrative purposes, we use a quadratic functional form in this section, following MNS (1994) and most of the subsequent papers in this literature. For our model and application in Sections 3 through 5, we employ a more flexible logarithmic functional form. The arguments made in this section are fully generalizable to that logarithmic specification.

Suppose that there are only two uses to which land can be put ($i = A, B$), and that there is only a single observable attribute (T = temperature), which impacts the value of land in each use in locations indexed by $j = 1, 2, ..., J$.

$$\begin{aligned} V_{A,j,k} &= \beta_{0,A} + \beta_{1,A} T_j + \beta_{2,A} T_j^2 + \xi_{A,j} + \eta_{A,j,k} \\ V_{B,j,k} &= \beta_{0,B} + \beta_{1,B} T_j + \beta_{2,B} T_j^2 + \xi_{B,j} + \eta_{B,j,k} \end{aligned} \tag{3}$$

where $\xi_{i,j}$ represents an unobserved determinant of value that is common to all land in location j dedicated to use i, and $\eta_{i,j,k}$ is an idiosyncratic component of value that is specific to plot k in location j employed in use i. In reality, land in any particular Brazilian municipio is typically employed in a variety of different uses at the same time – $\eta_{i,j,k}$ helps to explain this sort of heterogeneity. The remainder of these expressions represent deterministic relationships between land use and temperature. Figure 1 portrays specific cases of each relationship, which approximate the sorts of relationships described in MNS (1994) and which will be used in our simulation exercises below.

Given these use-and-plot-specific values, the average value of land in each location is determined by a weighted average of the average value of land employed in each use:

$$\overline{V}_j = \sum_{i=A,B} s_{i,j} V_{i,j} \tag{4}$$

where[4]

$$\begin{aligned} V_{i,j} &= \beta_{0,i} + \beta_{1,i} T_j + \beta_{2,i} T_j^2 + \xi_{i,j} \\ s_{A,j} &= P(V_{A,j,k} \geq V_{B,j,k}) \\ s_{B,j} &= P(V_{B,j,k} \geq V_{A,j,k}) \end{aligned} \tag{5}$$

[4] At this point we make a simplification in that we ignore the plot-specific idiosyncratic component of value in the calculation of a location's average value. While it would be logical to include this term if we thought that average land value represented, for example, the land-area-weighted average of values reported by individual land owners in a survey, including it would significantly complicate the estimation model outlined in the following section by introducing a conditional expectation, $E[\eta_{i,j,k} \mid V_{i,j,k} > V_{\ell,j,k} \;\; \forall\, \ell \neq i]$, into the solution of a simultaneous system of equations. Moreover, by including this term, we would do nothing to correct the biases that we intend to illustrate in the Ricardian model. As the goal of this paper is to provide an empirical technique with a computational burden similar to that of the Ricardian approach, but which avoids most of that approach's biases from ignoring endogenously determined land-use, we therefore omit this term.

In order to more easily compare this expression to the Ricardian regression equation, we separate use-specific shares for each location into a use-specific average share, $\bar{s}_i$ (i.e., averaged across locations), and a location-and-use-specific deviation from that average, $\Delta_{i,j}$:

$$s_{i,j} = \bar{s}_i + \Delta_{i,j} \tag{6}$$

Grouping together the average share terms in equation (4):

$$\begin{aligned} \overline{V_j} = (\bar{s}_A\beta_{0,A} + \bar{s}_B\beta_{0,B}) + (\bar{s}_A\beta_{1,A} + \bar{s}_B\beta_{1,B})T_j + \\ (\bar{s}_A\beta_{2,A} + \bar{s}_B\beta_{2,B})T_j^2 + (\bar{s}_A\xi_{A,j} + \bar{s}_B\xi_{B,j}) + (\Delta_{A,j}V_{A,j} + \Delta_{B,j}V_{B,j}) \end{aligned} \tag{7}$$

we are now able to write this equation in a form that approximates the traditional Ricardian regression:

$$\overline{V_j} = \alpha_0 + \alpha_1 T_j + \alpha_2 T_j^2 + \omega_j \tag{8}$$

where

$$\begin{aligned} \alpha_q &= \bar{s}_A\beta_{q,A} + \bar{s}_B\beta_{q,B} \\ \omega_j &= \bar{s}_A\xi_{A,j} + \bar{s}_B\xi_{B,j} + \Delta_{A,j}V_{A,j} + \Delta_{B,j}V_{B,j} \end{aligned} \tag{9}$$

Two sets of problems arise when estimating equation (8) and using the resulting parameters to calculate the effects of a marginal increase in temperature with the expression:

$$m_j = \alpha_1 + 2\alpha_2 T_j = \sum_{i=A,B} \bar{s}_i \frac{\partial V_{i,j}}{\partial T_j} \tag{10}$$

First, ignoring the estimation problems associated with the error term, ω_j, equation (10) overlooks an important component of the cost or benefit of a marginal climate change. Going back to equation (4), the marginal effect of T_j on $\overline{V_j}$ is given by:

$$\frac{\partial \overline{V}_j}{\partial T_j} = \sum_{i=A,B} \left(\frac{\partial s_{i,j}}{\partial T_j} V_{i,j} + s_{i,j} \frac{\partial V_{i,j}}{\partial T_j} \right) \tag{11}$$

The first term in (11) does not appear in any form in the marginal effect described in (10). Complicating matters further, the second term in equation (11) is not properly incorporated in equation (10) either, as $\sum_{i=A,B} s_{i,j} \frac{\partial V_{i,j}}{\partial T_j} \neq \sum_{i=A,B} \overline{s}_i \frac{\partial V_{i,j}}{\partial T_j}$. Even considering the average of marginal effects over locations does not solve this problem, as $\frac{1}{J}\sum_{j=1}^{J} \sum_{i=A,B} s_{i,j} \frac{\partial V_{i,j}}{\partial T_j} \neq \frac{1}{J}\sum_{j=1}^{J} \sum_{i=A,B} \overline{s}_i \frac{\partial V_{i,j}}{\partial T_j}$; i.e., the average of the products of two terms is not equal to the product of their averages. Similar arguments carry over to measuring the impacts on value of non-marginal changes in T_j.

The second source of bias comes from the error term, ω_j, the specification of which arose naturally out of the underlying model of optimal land owner behavior. In particular, T_j enters that error term through both $V_{i,j}$ and $\Delta_{i,j}$ (which is itself a function of $V_{i,j}$ as well as $V_{\ell,j}$, $\ell \neq j$), so that a positive effect of temperature on the value of a particular use would induce a positive correlation between T_j and ω_j. Note that temperature enters into ω_j through its effect on both land uses A and B – these effects can either work together to create even stronger correlations, or they can be offsetting.

We next illustrate the effects of these biases on the outcomes of a Ricardian analysis with a simple set of simulations. We first take the expressions for use-and-plot specific land values per hectare described in equation (3), employing the particular parameter values portrayed in Figure 1:

$$\begin{aligned} V_{A,j,k}(T_j) &= 215 + 6T_j - 0.2T_j^2 + \xi_{A,j} + \eta_{A,j,k} \\ V_{B,j,k}(T_j) &= 150 + 4T_j - 0.05T_j^2 + \xi_{B,j} + \eta_{B,j,k} \end{aligned} \tag{12}$$

and simulate temperatures for $J = 1000$ locations with random draws from a distribution ascribing equal probability to every integer between 1 and 50. Assuming that $\xi_{i,j}$ ~ i.i.d. N(0, 25)[5] and $\eta_{i,j,k}$ ~ i.i.d., N(0, 2500), we then take a random draw for $\xi_{A,j}$ and $\xi_{B,j}$ in each location, along with $K = 4000$

[5] Taking larger variances for $\xi_{i,j}$ has the effect of reducing the precision of our simulated Ricardian estimation results, but has no effect on their bias.

random draws of $\eta_{i,j,k}$ for each (i, j) combination. With these random draws and simulated temperatures, values can be constructed for each potential land use for each of the K simulated plots in each location. With these values in hand, it is straightforward to determine the optimal use of land on each plot, with which we can calculate land-use shares and average land values per hectare by location according to equation (4).

After having simulated average land values from the underlying model of optimal land use, we use them to illustrate the conditions under which the traditional Ricardian approach will yield biased estimates of the cost or benefit of climate change. In particular, we first estimate a Ricardian regression with the simulated data. With the estimated coefficients from that regression, we then predict the change in value in each location from a 5° increase in temperature. Since we are working with simulated data and are not confined to a cross-sectional analysis, we are next able to check the accuracy of these Ricardian predictions by simulating the dynamic responses of average land values to the same 5° increase in temperature in each location, allowing land owners to re-optimize over the uses in which they employ their land in response to that change. Indeed, the Ricardian approach was originally motivated by the fact that, given the slow evolution of climate variables over time and the relatively short period over which good data on economic variables like land value have been maintained, this sort of intertemporal experiment (i.e., actually observing how land values in a location change with rising temperature) is not possible. If the Ricardian predictions are unbiased, however, they should replicate the results of the simulated dynamics.

We consider two alternative simulation specifications that are designed to illustrate the source of bias in the Ricardian formulation. In the first, we restrict land-use shares to be constant and equal ($s_{A,j} = s_{B,j} = ½\ \forall j$). This is clearly not a model of optimizing behavior on the part of land owners. However, under this assumption, (i) $\partial s_{i,j} / \partial T_j = 0$ and $s_{i,j} = \bar{s}_i\ \ \forall\ i, j$, so that the marginal effect (m_j) derived from the Ricardian regression is the same as the true marginal effect of T_j on average land value in equation (11), and (ii) $\Delta_{A,j} = \Delta_{B,j} = 0$, so that ω_j in equation (8) is no longer correlated with T_j. In this highly constrained setting, our theory would predict that the traditional Ricardian model would yield unbiased predictions of the effects of a climate change. In our second specification, we relax this constraint, and allow $s_{i,j}$ to be determined by the optimizing decisions of land owners. Now with $\Delta_{i,j} \neq 0$, we would expect the parameter estimates from our Ricardian regression to be biased, and with $\partial s_{i,j} / \partial T_j \neq 0$, we would expect the fitted marginal effect of a temperature increase derived from the Ricardian model to be incorrect as well.

Table 1 reports the results of a single simulation run of these two specifications. In order to verify that the biases we find are not specific to a particular set of data and unobservables, we repeat the simulation process 1000 times, and report in Figures 2 and 3 (for Specifications 1 and 2, respectively) the distributions of the differences between the mean effect (i.e., averaged over all 1000 locations in each simulation run) of a 5° temperature increase measured with the Ricardian approach and the mean effect arising from the simulated dynamics. In the case in which land-use shares are constant and equal in Table 1, the average Ricardian cost understates the true cost by only 2.7%. Based on repeated simulations, Figure 2 reinforces the unbiasedness of these predictions, with a tight distribution centered around zero (mean = 0.002, variance = 0.002). On the other hand, when we allow land-use shares to be endogenously determined by optimizing behavior, the Ricardian model misses the sign of the average effect of a 5° temperature increase in Table 1. This result is replicated by the repeated simulations in Figure 3, where the distribution of prediction errors under endogenously determined shares is clearly centered below zero (mean = -2.28, variance = 0.07).

In order to control for these sorts of biases, the Ricardian framework must be adapted to control for endogenously determined land-use shares.[6] The model presented in the next section does just that, with a straightforward algorithm that imposes little additional computational burden relative to the standard Ricardian approach. The empirical significance of that model is then illustrated with an application to Brazil in the following sections.

3. Endogenous Land Use in the Ricardian Valuation of Climate

The previous section demonstrated that deducing the value of climate change from cross-sectional variation in the capitalized value of climate in land could lead to biased predictions if land-use shares within locations were endogenously determined by the optimizing decisions of owners of heterogeneous plots. Our model addresses this problem by directly modeling the land-use decisions of these owners and aggregating them to a level comparable with available data. From such a comparison, we are able to recover the determinants of land value per hectare by use, from which we can derive unbiased estimates of the agricultural value of climate change from a counterfactual experiment of land owner decision-making. An added benefit of this approach is that

[6] Note that including land-use shares directly in the traditional Ricardian regression does not correct the bias, but rather introduces a new, equally problematic source of endogeneity. These shares are themselves functions of use-specific land values, which are combined to determine the observed average land value (i.e., the dependent variable). In order to obtain unbiased estimates from a traditional Ricardian regression that includes land-use shares, a set of instruments that determine those shares, while not also affecting land value, is required. We see no obvious candidates for such instruments in our application.

it also yields predictions about long-run changes in land-use patterns accompanying global warming, which will be useful for drawing conclusions about issues like deforestation.

Our model begins with the specification of a reduced-form profit function for land-use i (i = forest, pasture, temporary crops, and permanent crops in our application)[7] on a plot of land k in location j:

$$\pi_{i,j,k} = A_{0,i} X_j^{\beta_{X,i}} C_j^{\beta_{C,i,j}} e^{u_{i,j}} e^{\eta_{i,j,k}} \tag{13}$$

$\pi_{i,j,k}$ measures the best annual return that can be achieved given climate (C_j), non-climate (X_j), and unobservable ($u_{i,j}$) attributes of that location. Flexibility is added in that $\beta_{C,i,j}$, the parameters associated with the vector of climate attributes, are allowed to vary with Cj:

$$\beta_{C,i,j} = \beta_{C0,i} + \beta_{C1,i} C_j \tag{14}$$

so that the marginal effect of the climate attribute C_j on profits from use i can be positive for some values of C_j and negative for others.[8] Finally, in conjunction with our previous discussion, the unobservable location-specific attribute is allowed to differ with land-use, as are the marginal effects of each observed attribute ($\beta_{X,i}$, $\beta_{C0,i}$, $\beta_{C1,i}$). $\eta_{i,j,k}$ represents an idiosyncratic attribute of plot k in location j being employed in use i, and is used to introduce within-location heterogeneity into the model in order to account for land being employed in a variety of different uses within a single location at a particular point in time.

---

[7] In Brazil, where we apply this model in Section 5, most land outside urban areas is contained in private farms, including land in forests. Its value is therefore incorporated into municipio-level average agricultural land values along with pasture, temporary and permanent crops. In an application of this model to the United States, forestry would not likely be included as most US forest land is owned by the government. Instead, important differences would exist between pasture, temporary and permanent crops, and even between agricultural uses within a crop category.

[8] There has been a great deal of debate about the ability of the Ricardian model to produce "inverted-U" shaped relationships between climate attributes and land value, so as to suggest an interior optimal climate value. Such a "bliss point" is desirable when predicting land value at climates well outside of those observed in the data (e.g., an upright U-shaped relationship would predict very high land values at temperatures of -100°C and +100°C). Given the categories of land uses that we consider, however, it would be unrealistic to expect the model to always fit inverted-U shaped relationships – there are many varieties of forest, pasture, temporary and permanent crops, some of which may flourish at lower temperatures while others would do better at higher temperatures. There is therefore no reason to expect a temperature in the middle of the range to always be optimal. As a result, one should be cautious in using our results (and those from most Ricardian analyses) to predict land value effects for very large climate changes that go well outside of the observed data.

Given an interest rate $r_{i,j}$ (which we allow to differ both with land use and location), the capitalized value of land in use i in location j on plot k is:

$$V_{i,j,k} = \frac{A_{0,i} X_j^{\beta_{X,i}} C_j^{\beta_{C,i,j}} e^{u_{i,j}} e^{\eta_{i,j,k}}}{r_{i,j}} \tag{15}$$

so that the natural logarithm of the value of plot k in location j employed in use i is given by:

$$lnV_{i,j,k} = \beta_{0,i} + \beta_{X,i} \, ln\, X_j + \beta_{C0,i} \, ln\, C_j + \beta_{C1,i} C_j \, ln\, C_j + \xi_{i,j} + \eta_{i,j,k} \tag{16}$$

where $\xi_{i,j} = u_{i,j}$ - $\ln r_{i,j}$ and $\beta_{0,i} = \ln A_{0,i}$. Assuming that $\eta_{i,j,k}$ is independently and identically distributed Type I Extreme Value across all plots, uses, and locations, the probability that any particular land owner will choose use i is given by:[9]

$$s_{i,j} = P(\ln V_{i,j,k} \geq \ln V_{l,j,k} \forall\, l \neq i) = \frac{e^{\beta_{0,i} + \beta_{X,i} \ln X_j + \beta_{C0,i} \ln C_j + \beta_{C1,i} C_j \ln C_j + \xi_{i,j}}}{\sum_{l=1}^{N} e^{\beta_{0,l} + \beta_{X,l} \ln X_j + \beta_{C0,l} \ln C_j + \beta_{C1,l} C_j \ln C_j + \xi_{l,j}}} \tag{17}$$

Since the only source of heterogeneity amongst land owners within a location appears in the term $\eta_{i,j,k}$, this probability also determines the share of hectares in each location in each use, $s_{i,j}$.

Without the presence of the unobservable attribute $\xi_{i,j}$ as a determinant of ln $V_{i,j,k}$, data and a vector of parameters would yield a prediction of the share of land in each use in each location. These predictions could be compared to the data on land-use shares, and the difference could be minimized in order to estimate [$\beta_{0,i}$, $\beta_{X,i}$, $\beta_{C0,i}$, $\beta_{C1,i}$]. Assuming, however, that all of the relevant determinants of land value are summarized by [X_j, C_j] is heroic (especially given the scope of the data that are available for most developing countries) and ignores the concerns arising from the

[9] Note that the entire methodology is generalizable to other distributions for within- location heterogeneity in land values (e.g., $\eta_{i,j,k}$ might be distributed normal, as in our numerical example in Section 2). The logit distributional assumption, however, offers tremendous computational benefits and is therefore adopted for the remainder of this paper.

stylized model in Section 2. Instead, we use $\xi_{i,j}$ as a single-dimensional index to control for all those location- and use-specific determinants of land value not included in $[X_j, C_j]$. This adds an additional degree of freedom to the model, however, so that data and a vector of parameters are no longer sufficient to predict land-use shares for each location. Instead, given data and a vector of parameters, one could match the predictions of the model to observed land-use shares ($\hat{s}_{i,j}$) for each location, and invert the resulting simultaneous system of equations to obtain the vector of use- and location-specific unobservables, $\xi_{i,j}$, which could then be used in an econometric procedure to choose new parameter values that minimize some criterion function. [Berry (1994)]

Practically, the structure of the problem allows us to use an even simpler algorithm. First, for each location *j,* solve a system of equations described by:

$$\hat{s}_{i,j} = \frac{e^{\ln V_{i,j}}}{\sum_{l=1}^{N} e^{\ln V_{l,j}}} \tag{18}$$

$\forall\, i = 1, 2, ..., N$, for the vector of $\ln V_{i,j}$, which represents the natural logarithm of the value of land in location *j* in use *i* (less the plot specific idiosyncratic component, $\eta_{i,j,k}$, but inclusive of the sources of value attributable to $\beta_{X,i} \ln X_j$, $\beta_{C0,i} \ln C_j$, $\beta_{C1,i}\, C_j \ln C_j$, and $\xi_{i,j}$). Practically, this can be done by taking the ratio of observed land-use shares relative to the share in some particular use (e.g., use *N*):

$$\frac{\hat{s}_{i,j}}{\hat{s}_{N,j}} = \frac{e^{ln V_{i,j}}}{e^{ln V_{N,j}}} \tag{19}$$

$\forall\, i = 1, 2, ..., N$-1. This represents a system of *N*-1 equations and *N* unknowns. Data on the average value of agricultural land by location and an assumption that the average value is a geometric share-weighted mean of use-specific land values, however, introduces an additional equation:

$$ln \overline{V}_j = \sum_{i=1}^{N} \hat{s}_{i,j}\, ln V_{i,j} \tag{20}$$

which allows us to recover a unique set of values for $\ln V_{i,j}$, $i = 1, 2, ..., N$ for each location.

Consider briefly the role of $\overline{V}_j$ in this estimation procedure. Without data describing the average value of land in agricultural and forestry uses, the typical approach to a discrete-choice problem of this sort would be to include an additional category of land use (e.g., non-agricultural – including urban, residential, commercial, and industrial land), and model the division of all land in the location into five activities. If we were only considering land in a single location, that could be done easily by normalizing the natural log of the per hectare value of non-agricultural land to zero, and measuring the value of the other uses relative to it. Because we are considering land in many locations with many different values for non-agricultural use, however, such a simple normalization will not suffice. Instead, we would need actual data on the value of non-agricultural land in every location, which are not available for Brazil and most other countries (developed and developing). Data describing average agricultural land values and an implicit assumption of constant returns to scale in our four land uses (i.e., use-specific land value is modeled per hectare) overcome this problem and allow us to decompose use-specific land values into their determinants. Note, however, where this data constraint will limit our analysis. In our counterfactual simulations of climate change, from which we deduce the cost or benefit to landowners from a change in rainfall and/or temperature, we are forced to assume that the total quantity of land in forestry, pasture, temporary and permanent crops does not change; i.e., an increase in one implies a reduction in another. Given the alternative uses included in the ignored non-agricultural category, this may not be a bad approximation, but should be kept in mind when interpreting our predicted percentage changes in average land value. Note that, because our predicted changes in use-specific land values are done on a per-hectare basis, they are immune to the assumption about the overall scale of agricultural activity as long as the constant returns to scale assumption is valid. The use-specific percentage changes in land value would be particularly relevant if one were concerned about the relative impact of global climate change across sectors.

With these use-specific measures of the natural log of land value in each location, it becomes a simple application of OLS to decompose ln $V_{i,j}$ into its component parts:[10]

[10] The regression equations in (21) could alternatively be estimated by a Seemingly Unrelated Regressions procedure with an increase in efficiency. In the current application, we estimate the equations separately with OLS because the practical implications for the parameter estimates were found to be negligible, and because separately estimating the equations allows for the easy application of weighted-least-squares procedures along with heteroskedastic-consistent standard errors in most statistical packages.

$$
\begin{aligned}
&lnV_{1,j} = \beta_{0,1} + \beta_{X,1}\, ln\, X_j + \beta_{C0,1}\, ln\, C_j + \beta_{C1,1} C_j\, ln\, C_j + \xi_{1,j} \\
&lnV_{2,j} = \beta_{0,2} + \beta_{X,2}\, ln\, X_j + \beta_{C0,2}\, ln\, C_j + \beta_{C1,2} C_j\, ln\, C_j + \xi_{2,j} \\
&. \\
&. \\
&. \\
&lnV_{N,j} = \beta_{0,N} + \beta_{X,N}\, ln\, X_j + \beta_{C0,N}\, ln\, C_j + \beta_{C1,N} C_j\, ln\, C_j + \xi_{N,j}
\end{aligned}
\tag{21}
$$

with each equation in the system akin to a traditional Ricardian regression, and ($\xi_{1,j}$, $\xi_{2,j}$, ..., $\xi_{N,j}$) serving as regression errors. Unbiasedness therefore requires that these errors be uncorrelated with [$X_{j,}$, C_j], but this assumption is no different from the assumption that ε_j is uncorrelated with the regressors in a traditional Ricardian regression analysis.

At this point, it is important to point out that the only additional assumption we made in this model (in comparison with a traditional Ricardian analysis) was to specify a distribution for the plot-specific component of unobservable heterogeneity.[11] This allows us to determine use-specific land values up to a vector of parameters with data on use-specific shares, and to predict new shares under a counterfactual climate scenario. As was demonstrated in Section 2, ignoring the determination of land-use shares lies at the heart of the bias that can occur in a traditional Ricardian analysis with unobserved heterogeneity amongst plots, and a model predicting how those shares would change with a change in climate is therefore essential to eliminating that bias. As evidence that our model succeeds in this respect, we use it to predict changes in the average value of agricultural land arising from the same simulation runs conducted at the end of Section 2 (replacing logistic with normal error terms in our model where appropriate). Figure 4 describes the distribution of prediction errors (i.e., predicted changes in value, averaged across locations, from our model, less those predicted by simulated dynamics) from each of the 1000 simulation runs. The results of these simulations indicate that our predictions are unbiased (distribution mean = 0.01 and variance = 0.01), especially in comparison with the results of the Ricardian model (see Figure 3). In the remainder of this paper, we apply our estimation algorithm to actual data from Brazil in order to predict the agricultural consequences of global warming for that country.

[11] Initial tests confirm that our results are not sensitive to the exact distributional assumption (e.g., normally distributed idiosyncratic unobservables and a multivariate probit model underlying the determination of land-use shares yield similar results, but with a far greater computational cost).

4. Data

In our empirical application, we use readily available data from the Brazilian agricultural census describing the share of farm land in forest, pasture, temporary crops, and permanent crops, along with the average value of land in farms, in each of 3177 municipios (i.e., political entities similar to US counties). In the current application, we use only data from the 1985 census, but similar data from 1970, 1975, and 1980 exist and will be incorporated in future work. A richer analysis would exploit the information in the changes in land use and values observed across these years in order to recover the structural parameters underlying the land owner's dynamic decision process. Our previous attempts to do so have proven unsuccessful, however, owing to inadequacies in the data describing the changes in returns to various uses of land over time.[12] By eschewing the dynamic approach in favor of a static model, we avoid these difficulties. Moreover, given the long-run nature of the counterfactual climate scenarios we will consider, it is not a bad approximation to simply compare two alternative static outcomes – that observed today and that which will be attained after one-hundred years of climate change.

The remaining variables in our analysis, which are not obtained from agricultural census data, describe climatic, geological, geographical, and population attributes of each Brazilian municipio. Climate data, which report thirty year norms for temperature (°C) and rainfall (cm) in December, March, June, and September, were obtained from Sanghi et al (1997). We use the average climate measures for the winter (June and September) and summer (December and March) months. Latitude (which proxies for solar flux), altitude, population density, and road density (i.e., km of federal, state, and municipal roads divided by km^2 in the municipio) were obtained from the IBGE *(Instituto Brasileiro de Geografia e Estatiística*), which collects these data as part of its population census. Finally, data describing the erosion potential of the terrain (moderate, strong, very strong, and extreme) were obtained from Sanghi et al (1997) along with a vector of soil type indicators.[13] Table 2 describes the (unweighted) averages of each of the variables used in our analysis by region. [See Figure 5 for regional definitions]

---

[12] Recall that use-specific land values (i.e., the capitalized values of the use-specific annual returns) are imputed in our model from use-specific share data. Imputing these values in a model with explicit dynamics introduces a variety of complications that are left for future work.

[13] Soil type indicators are defined so as to describe the dominant soil type or collection of soil types in each municipio. Certain soil types may overlap. The eight types used in our analysis are (1) Latossolo Amarelo, Bruna, Vermelho-Escuro, Roxo, Vermelho-Amarelo, (2) Podzolico Amarelo, Vermelho-Escuro, Vermelho-Amarelo, (3) Solos Litolicor, Afloramento Rochoso, Mangue, (4) Areias Quartzosas, Areias Quartzosas Hidromorficas, (5) Plintossolo, Plintossolo Petrico, (6)Regossolo, (7) Planosolo, Planosolo Solodico, and (8) Cambissolo, Cambissolo Bruno, Gleissolos.

5. Results

Tables 3 and 4 report estimation results for the system of equations described in equation (21) and for a traditional Ricardian regression (i.e., the natural log of average land value regressed on the natural log of local attributes).[14] Table 3 reports unweighted regression results, while the results in Table 4 use weights based on total land area in the four use categories we consider. In general, the statistical significance of the results is good, but estimates are weakest for forestry.[15] Focusing on the non-climate results (impacts of climate on land value will be discussed in the following sub-section), increasing latitude (i.e., moving closer to the equator) is generally worse for the value of land in every use, especially forestry and pasture. Higher altitudes, on the other hand, are generally desirable for pasture and temporary crops, but are detrimental to forestry and the planting of permanent crops. Higher levels of population density are beneficial to the value of land in every use, especially permanent and temporary agriculture (which relies more than the other uses on a pool of inexpensive labor), while higher levels of road density are advantageous in every land use except forestry – a result that corresponds to the received wisdom from the deforestation literature which says that the removal of forested lands tends to follow the construction of roads.

Turning next to geologic indicator variables, effects become harder to generalize across uses. Focusing on the results of the weighted regressions, land values in forestry are highest under conditions of moderate and extreme erosion, while strong and very strong erosion potential reduces land value. Considering land in pasture and temporary crops, all erosion potentials generally reduce land value, but less so for strong and very strong potential, in comparison with moderate and extreme potential. All erosion potentials yield higher values for land in permanent crops, with strong and extreme potentials showing the largest positive effects. While they might seem difficult to interpret at first, these erosion results make some sense – low levels of erosion potential refer to soil that is not likely to wash away in a strong rain, but might not be that rich for planting purposes, while extreme levels of erosion refer to soil that may be very rich for agriculture, but difficult to keep in one place. Varying strength of these two competing effects could yield the sorts of patterns we observe in our estimates.[16] As for our varied soil type indicators, there are a number of (difficult to

[14] In all specifications in this paper, latitude and, of course, dummy variables, are left in levels. All other variables are converted to natural logarithms.

[15] This is likely a result of the fact that forestry in Brazil is our broadest category of land use, including both temperate forests and tropical rainforests, each of which flourishes under very different climate conditions.

[16] One should also keep in mind that these results could arise simply from the way in which erosion potential data may have been collected. Some researchers familiar with these data have expressed concern that (especially in

summarize) statistically significant effects. Soil types 1, 3, 4, 6, 7, and 8, for example, exhibit statistically significant negative effects on the value of land planted to permanent crops. The same is true (except for soil types 1 and 4) for land used in forestry. Soil types 1, 2, 3, and 8 are detrimental to the value of land planted with temporary crops, while soil type 6 is beneficial. Soil types 6 and 7 have a positive effect on the value of land in pasture while soil type 8 is detrimental to that land use.

The last two columns of Tables 3 and 4 report results of similarly specified Ricardian regressions. In general, the signs of many of the parameters in these regressions correspond to the signs of the dominant use-specific parameters described in the other columns of each table, but even when parameters are the same sign, there are often significant differences in magnitudes. Looking at the effects of non-climate variables on land values in these regressions, we find that increasing latitude is detrimental, while increasing altitude, road and population density are all beneficial. Moderate and extreme erosion potential have negative effects on average land value that are both economically and statistically significant in the weighted Ricardian regression, while strong erosion potential has a positive and significant effect. In the unweighted regression, on the other hand, all erosion potentials yield higher land values than the omitted "light-to-moderate" category. Soil types 3 and 8 are detrimental for average agricultural land value, while soil type 6 is beneficial.

5.1. Measuring the Impacts of Climate Change on Land Values

We next conduct a series of counterfactual experiments in order to recover the cost or benefit to land owners from a small change in climate – e.g., a 1°C increase in temperature and a 1 cm increase in rainfall. Specifically, for each counterfactual climate scenario, we calculate new shares and per-hectare values for each land-use in each municipio and use them to determine the weighted geometric mean value according to equation (20).[17] We then compare that value to the mean value similarly calculated using actual climate data and use shares, and report percent changes from that baseline. Tables 5 - 9 report results (i.e., percent changes in land value by use, changes in land-use

remote regions) erosion potentials may have been inferred by recording the dominant crop patterns and then determining the most common erosion characteristics associated with those crops, rather than by a true geological survey. In recognition of this possibility, we have also estimated our model with an alternative specification that replaces all geologic indicators with a set of regional dummy variables. Because the results are similar, we omit them for the sake of brevity. In any case, our results pertaining particularly to erosion potential and soil type (owing to similar concerns) should be interpreted with caution.

[17] Note that, when dealing with the actual climate scenario, our model is set up so that the predicted land-use shares will equal the observed land use shares exactly. When we consider a counterfactual climate scenario, we control for adjustments in $s_{i,j}$ resulting from the decisions of optimizing land owners.

shares, and percent changes in average land values, from both the weighted and unweighted regressions, averaged within regions with weights determined by each municipio's share of the total land in its region) for increases in summer and winter rainfall, summer and winter temperature, and simultaneous increases in every climate measure, respectively. For the purposes of comparison, each table also reports percent changes in value associated with the our traditional Ricardian results.

In contrast to the traditional Ricardian model, which generally predicts increases in average land value from increasing rainfall (indeed, very large increases in the winter season), our model predicts smaller increases (or even reductions) in every season and location with the exceptions of the Northeast region in the summer and the North region in the winter. In the summer season, this result appears to be driven by the detrimental effects of increasing rainfall on land in pasture and temporary agriculture, particularly in Minas Gerais and the North and Center-West regions. In the winter, it is primarily due to the detrimental effects of increasing rainfall on land in pasture in all but Minas Gerais and the Northeast region. In both seasons, increasing rainfall is beneficial in every use for the Northeast region, which is subject to severe periodic droughts that give it a lower average rainfall [see Table 2]. The same is true in the summer season for the South region, where average rainfall levels are lower than anywhere else in the country except the Northeast. The benefits of increasing summer rainfall seem to fall most consistently on land planted to permanent agriculture. While land in agriculture (temporary and permanent) enjoys particularly large benefits from increasing winter rainfall in Minas Gerais and the Northeast region, benefits are also enjoyed by land in forestry throughout the country.

Turning to temperature, we see a similar sort of bias in the traditional Ricardian results in the winter in Minas Gerais and in the Center-West and Southeast regions. In the remaining regions in the winter, and in all regions (except the North) in the summer, the Ricardian model predicts smaller increases (or bigger reductions) in average land value with a 1 °C increase. In the North, increasing summer temperatures reduce average land values according to our model, owing to a reduction of the value of land in forests, while the Ricardian model predicts a very large percentage increase in value (21%). Increasing summer temperatures generally reduce the value of land in forests in every region (especially in the South), while everywhere increasing the value of land in pasture (except in the South) and in temporary agriculture. The value of land in permanent agriculture is increased in the northern half of the country, and reduced in the southern half. Increasing winter temperature, on the other hand, universally increases the value of land in forests, while nearly everywhere reducing the value of land in pasture and temporary agriculture. The largest percentage increase in use-specific land value from rising winter temperatures is found for permanent agriculture in the South region (55.7%). This makes sense, as the planting of permanent crops is usually prevented in this region by the threat of winter frost.

Table 9 summarizes these results by considering simultaneous marginal increases in every season's rainfall and temperature. The implication derived from both the weighted and unweighted specifications is that global climate change will not be as beneficial for Brazilian land owners as predicted from a traditional Ricardian analysis, once one accounts for endogenous land-use decisions.[18] This results from the reduction in the value of land in all uses in the North, and a reduction of the value of forested land in every region. The implications of the latter result are discussed further in the next sub-section.

5.2. Measuring the Impact of Climate Change on Land Use

Our estimated model allows us to also make explicit predictions about how land-use patterns will adjust in response to a change in climate. Indeed, such predictions underlie the valuation exercises just described. Tables 5 - 9 also report the change in land shares devoted to forestry, pasture, temporary crops, and permanent crops, from the climate changes described above for both the weighted and unweighted specifications. Note that changes in land-use are implicit in the traditional Ricardian approach, so we are unable to present comparative results from that model.

Effects differ by climate variable, season, and region. Increases in summer temperature generally lead to deforestation, with forested land (and some land in permanent crops) being converted to pasture, especially in the North and Northeast regions. Increasing summer rainfall, on the other hand, tends to drive a small number of land owners out of pasture activities and into agriculture and forestry (except in the Northeast and South, where increasing rainfall greatly improves the viability of temporary agriculture relative to forestry). The same is true of increasing winter rainfall (except in the Northeast and Minas Gerais, where land in forestry falls), only on a slightly larger scale. Finally, increasing winter temperature tends to increase the quantity of land devoted to forestry, while also reducing the share of land devoted to pasture and temporary agriculture. Summarizing the impacts of simultaneously increasing temperature and rainfall, the weighted regression results predict a reduction in forested land in every region but the North, along with reductions in pasture in the North, Southeast, and South. Most of this land is predicted to be converted to temporary agriculture. Unweighted regression results yield slightly different conclusions – forested land falls substantially in every region, as does land devoted to permanent agriculture (except in the South). Most of this land is converted to pasture, although some is used

[18] Indeed, if we reported unweighted medians by region, our model would predict net losses from this climate change scenario, while the Ricardian model would yield smaller (but still large) positive predictions.

for temporary agriculture.

Especially the results of the unweighted regression (although, to a certain extent, the results of the weighted regression as well) suggest the presence of global warming feedback effects along with trends in land-use that could lead to increased soil erosion and land degradation. Scientists estimate that between 23 and 30% of global annual CO_2 emissions can be attributed to anthropogenic deforestation, with Brazil being the biggest contributor. [Rainforest Action Network (2002)] If the warming that occurs because of the previous build-up of greenhouse gasses leads to further deforestation, as our model predicts, the effect would be to cause more severe warming, further extending the feedback cycle.

Turning to national environmental issues, a list of well-documented problems resulting from tropical deforestation includes increased erosion, run-off contaminating fresh water supplies, flooding, and general land degradation as rich soils become depleted and made useless for agriculture. The planting of permanent crops in place of forests has been recognized as one possible option to prevent these problems.[19] Our results predict, however, that it is either pasture (in the unweighted regression) or temporary agriculture (in the weighted regression) that will replace much of the forest depleted because of global climate change. Neither of these land uses are especially protective of the soil, particularly if the temporary agriculture is of the "slash-and-burn" variety that is often practiced by squatters with unsecure tenure rights to the land.

6. Conclusions

Properly predicting the economic consequences of global climate change has clear policy implications as countries continue to bargain in the wake of the Kyoto agreement over greenhouse gas emission reduction targets. Aside from building an elaborate computer simulation model of agricultural activity, turning up the temperature, and seeing what the model predicts, however, there are few available alternatives for making such predictions. Accurately measured data describing rainfall and temperature have not generally been maintained for a sufficiently long period to describe long-run movements in climate, making it difficult to predict how the sorts of climate changes predicted for the next century would affect the value of human activities like agriculture. This is

[19] For example, the Brazilian government in the 1980's, as part of its program to settle the northwestern states, extended subsidized lines of credit to new land owners in an attempt to help them establish permanent crop (e.g., coffee) plantations, in part so as to offset the detrimental effects of deforestation. Macroeconomic difficulties and fiscal austerity measures, however, ended these programs before the plantations could become viable, and most were abandoned or converted to temporary agriculture or pasture.

what makes the Ricardian method such a practical tool – by conditioning on the set of observable things that differ between locations with different climates, it predicts how a magnitude like the value of agricultural land will change over time by looking at how it changes across space. Potential problems arise, however, because of what can be conditioned upon and what is left unobservable. We demonstrate in this paper that, without imposing an unrealistic and non-optimizing restriction on the way in which unobservably heterogeneous plots of land are allocated to different uses, Ricardian predictions of the costs or benefits of a climate change will be biased.

This paper provides an algorithm for controlling for this sort of bias, which is based on a model of the optimizing land-use decisions of the owners of unobservably heterogeneous plots of land. The results derived from this algorithm exhibit differences in magnitude (and often in sign) when compared with values derived from a traditional Ricardian regression, suggesting that this sort of bias may be significant. Although the direction of the bias differs with season, region, and climate variable, our results generally suggest that the traditional Ricardian model overstates the value of greenhouse warming for Brazilian agriculture. Moreover, because our approach models the aggregate land-use decisions of individual owners of heterogeneous plots of land, it allows us to also make explicit predictions of how land-use shares will change under a stylized global warming scenario. Results suggest that climate change will lead to deforestation in Brazil, generating a feedback effect that could possibly cause more severe global warming than that predicted by many general circulation models.

Our model (along with the traditional Ricardian model) is built upon the assumption that landowners are observed exploiting land in its optimal use given its observable and unobservable attributes. It is possible, however, that we are actually observing a snapshot of landowners in the process of adjusting toward a different long-run equilibrium. This is a particular concern in Brazil in light of the programs undertaken by the government in the 1980's to promote settlement in the Center-West and North regions.[20] Our first extension to this research will therefore be to compile comparable data for 1970, 1975, an 1980 (i.e., the other years for which comparable IBGE Agricultural Census data are available) and verify that our predictions are relatively stable over time.

[20] For example, the POLONOERESTE program , which was intended to provide "peopleless land for landless people" is viewed by many as a safety-valve program to cut down on the size of the politically unstable unemployed urban masses, while also avoiding the need for real agrarian land reform. The program allowed frontier land to be acquired for a nominal fee and provided access to agricultural credit at subsidized rates. Also important to the settlement of these regions were road-building programs such as the Belém - Brasilia and Transamôzonica Highways.

References

Berry, Steven. 1994. "Estimating Discrete Choice Models of Product Differentiation." *RAND Journal of Economics.* 25:242-262.

Intergovernmental Panel on Climate Change. 1995. "Summary for Policymakers: The Economic and Social Dimension of Climate Change – IPCC Working Group III." Internet. Available 11/1/98. http://www.ipcc.ch/.

Kumar, K.S. Kavi and Jyoti Parikh. 1998. "Climate Change Impacts on Indian Agriculture: The Ricardian Approach." World Bank Technical Paper no 402. Washington, DC.

Mendelsohn, Robert, Ariel Dinar, and Apurva Sanghi. 2001. "The Effect of Development on the Climate Sensitivity of Agriculture." *Environment and Development Economics*. 6(1):85-101.

Mendelsohn, Robert, William Nordhaus, and Daigee Shaw. 1994. "The Impact of Global Warming on Agriculture: A Ricardian Analysis." *American Economic Review*. 84(4):753-71.

________. 1996. "Climate Impacts on Aggregate Farm Values: Accounting for Adaptation." *Journal of Agricultural and Forest Meteorology.* 80(1): 55-66.

Rainforest Action Network. 2002. "Rainforests and Global Warming." *Rainforest Fact Sheets*. Internet. Available 2/6/2002. http://www.ran.org/info_center/factsheets/04a.html.

Sanghi, Apurva, Denisard Alves, Robert Evenson, and Robert Mendelsohn. 1997. "Global Warming Impacts on Brazilian Agriculture: Estimates of the Ricardian Model." *Economia Aplicada*. 1(1):7-33.

Figure 1

Deterministic Relationships Between Temperature and Land Value
for Simulation Exercises

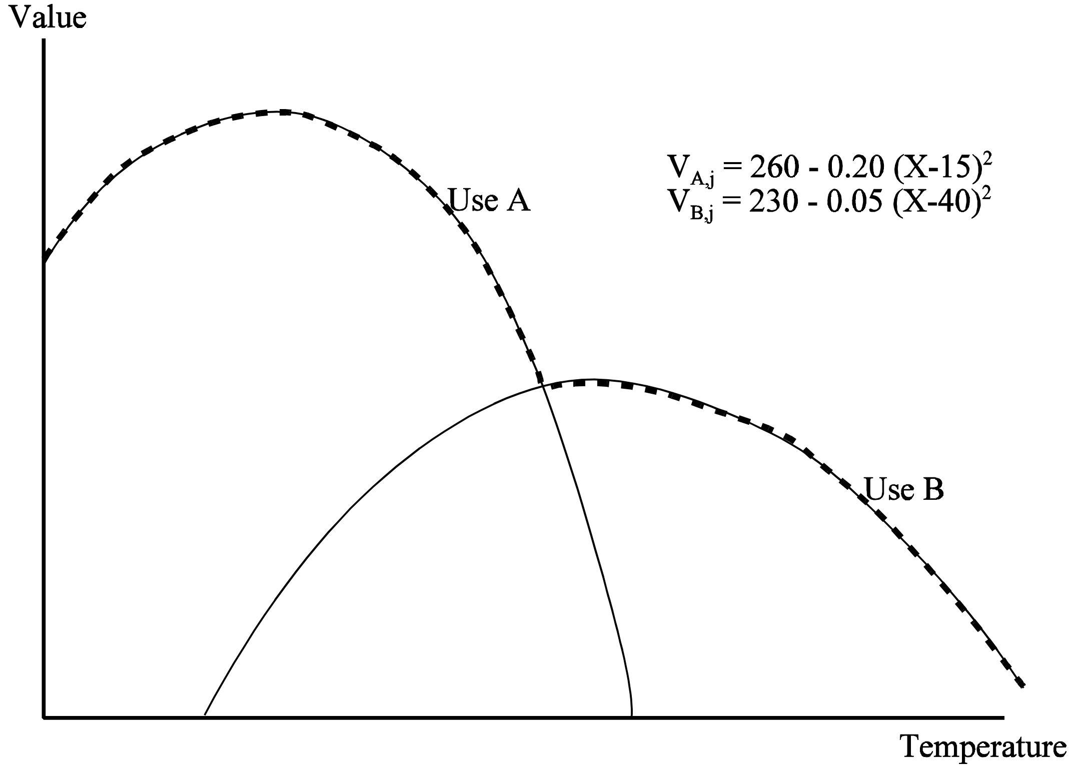

Figure 2

Prediction Error Histogram: (Ricardian Prediction - Simulated Dynamics)
1000 Simulation Runs, $s_{A,j} = s_{B,j} = ½ \quad \forall\, j$

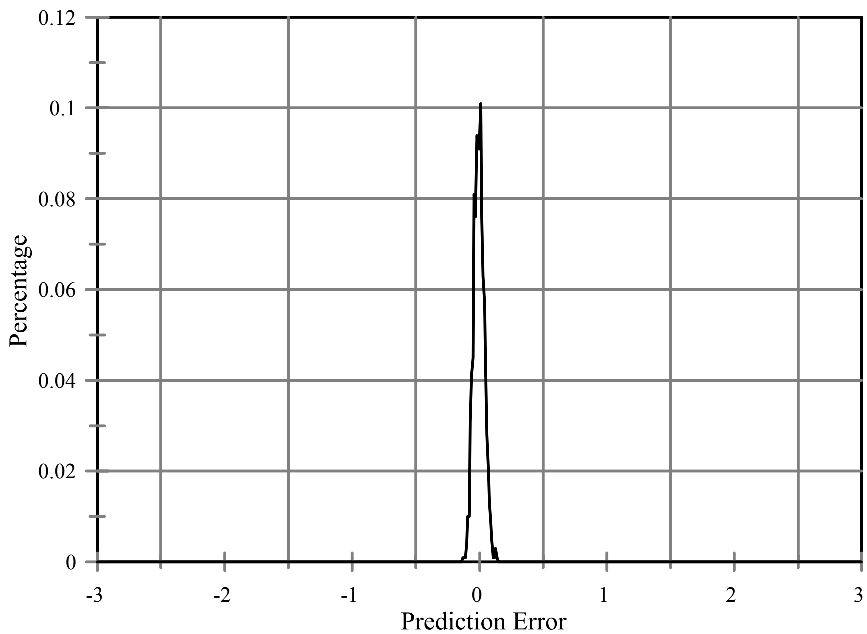

Figure 3

Prediction Error Histogram: (Ricardian Prediction - Simulated Dynamics)
1000 Simulation Runs, $s_{A,j}$ and $s_{B,j}$ Determined by Optimizing Behavior

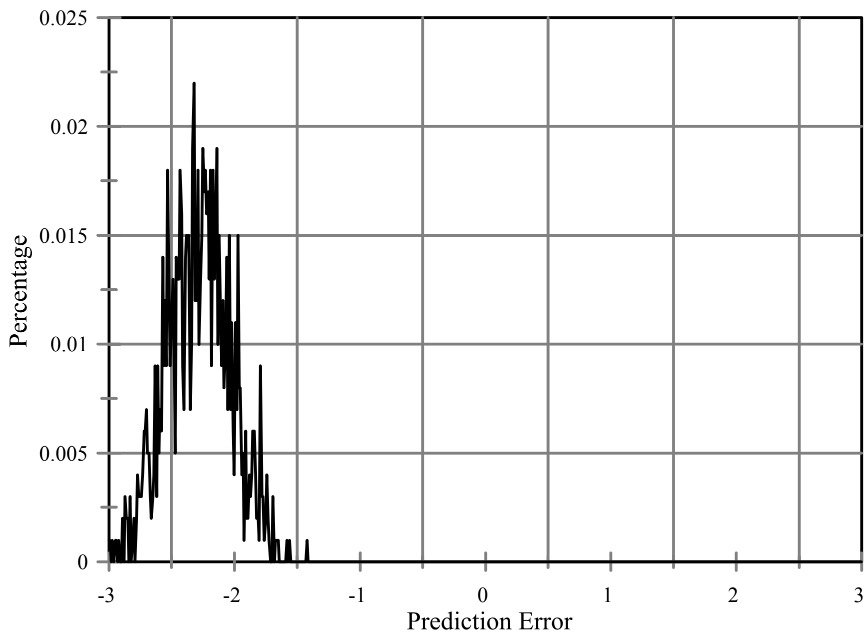

Figure 4

Prediction Error Histogram: (Endogenous Land Use Model Prediction - Simulated Dynamics)
1000 Simulation Runs, $s_{A,j}$ and $s_{B,j}$ Determined by Optimizing Behavior

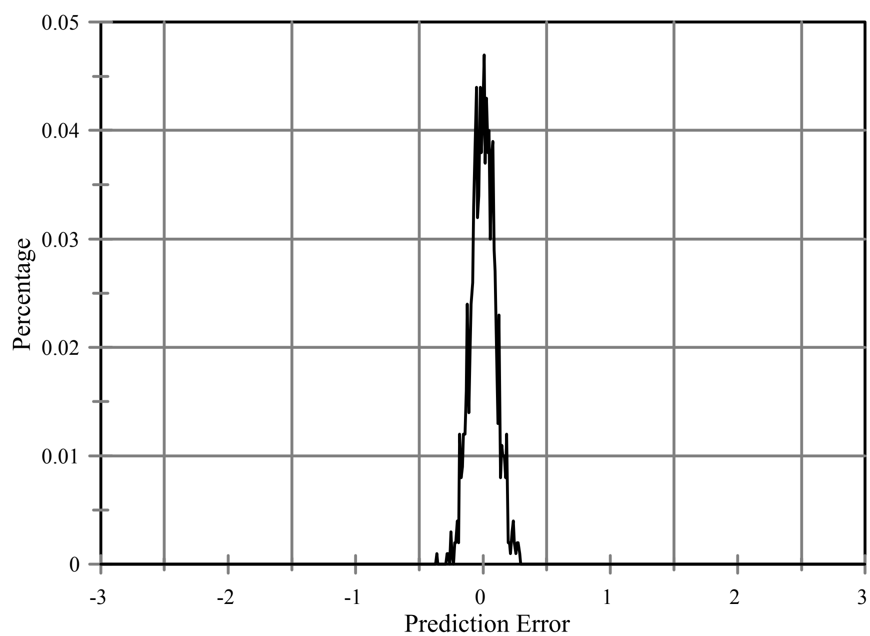

Figure 5 – Map of Brazil[21]

Regional Definitions:

(1) North – Rondonia, Acre, Amazonas, Roraima, Amapa, Para, Tocantins

(2) Northeast – Maranhao, Piaui, Ceara, Rio Grande do Norte, Paraiba, Pernambuco, Alagoas, Sergipe, Bahia

(3) Minas Gerais

(4) Southeast – Espirito Santo, Rio de Janeiro, Sao Paulo

(5) Center – Mato Grosso, Goias, Mato Grosso do Sul

(6) South – Parana, Santa Catarina, Rio Grande do Sul

[21] Maps and boundary data are copyrighted by FOTW Flags Of The World, http://fotw.digibel.be/flags/geo-copy.html. Internet, Available 6/20/99.

Table 1
Simulated Ricardian Valuation and Dynamic

	Specification #1 ($s_{A,j} = s_{B,j} = \frac{1}{2} \quad \forall\, i, j$)		Specification #2 ($s_{i,j}$ determined by optimizing behavior)	
	Estimate	Standard Error	Estimate	Standard Error
α_0	184.5	1.783	232.9	2.511
α_1	4.697	0.159	0.661	0.223
α_2	-0.119	0.003	-0.020	0.004
Ricardian Valuation of 5° Increase in T_j (Averaged Over j = 1, 2, ..., 1000)	-9.987		-2.347	
Simulated Change in Average Land Value From 5° Increase in T_j (Averaged Over j = 1, 2, ..., 1000)	-10.26		0.155	

Table 2
Data Summary

Variable	Region					
	North N = 148	Northeast N = 1151	Center West N = 37	Minas Gerais N = 659	Southeast N = 90	South N = 598
Summer Rainfall (cm)	27.40	12.01	21.30	21.82	17.93	14.76
Winter Rainfall (cm)	11.30	5.92	5.14	3.22	4.52	13.39
Summer Temperature (°C)	26.37	26.21	25.39	22.97	24.27	22.35
Winter Temperature (°C)	26.47	24.39	22.77	19.46	20.32	16.08
Latitude (degrees)	-3.23	-7.95	-17.61	-19.64	-21.02	-26.44
Altitude (m)	67.78	276.55	342.86	692.93	227.17	457.31
Road Density	18.73	297.07	23.79	1427.86	137.70	942.86
Pop Density	30.35	223.13	23.41	134.79	408.85	206.86
Moderate Erosion	0.20	0.28	0.05	0.06	0.16	0.11
Strong Erosion	0.22	0.30	0.35	0.53	0.36	0.44
Very Strong Erosion	0.00	0.19	0.22	0.18	0.01	0.35
Extreme Erosion	0.00	0.00	0.00	0.00	0.30	0.10
Soil Type 1	0.32	0.17	0.41	0.61	0.29	0.22
Soil Type 2	0.51	0.30	0.35	0.19	0.50	0.11
Soil Type 3	0.00	0.11	0.00	0.03	0.00	0.05
Soil Type 4	0.00	0.06	0.14	0.01	0.00	0.01
Soil Type 5	0.00	0.02	0.11	0.00	0.00	0.00
Soil Type 6	0.00	0.05	0.00	0.00	0.00	0.00
Soil Type 7	0.00	0.09	0.00	0.00	0.03	0.04
Soil Type 8	0.16	0.03	0.00	0.17	0.18	0.30
Share: Forest	0.59	0.20	0.21	0.14	0.17	0.17
Share: Pasture	0.21	0.43	0.66	0.67	0.55	0.37
Share: Temporary Crop	0.16	0.28	0.13	0.14	0.13	0.42
Share: Permanent Crop	0.04	0.09	0.00	0.05	0.05	0.03
Average Land Value	0.96	4.32	4.20	8.83	11.17	12.45

Table 3 – Estimation Results (Unweighted)
N = 3177, Heteroskedastic Consistent Standard Errors

Variable	Endogenous Land Use Model								Ricardian Model	
	Forestry		Pasture		Temporary Crops		Permanent Crops			
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Constant	3.377	0.163	85.74	6.443	-39.80	-2.709	-29.69	-0.955	27.40	3.224
ln R_S	1.457	3.674	0.237	1.003	1.450	4.809	2.572	3.835	0.232	1.893
R_S ln R_S	-0.020	-3.388	-0.007	-1.669	-0.018	-3.101	-0.035	-3.281	0.001	0.477
ln R_W	0.102	0.852	0.446	4.935	0.345	5.254	0.424	3.403	0.390	10.16
R_W ln R_W	0.002	0.384	-0.036	-4.914	0.009	2.593	-0.007	-0.998	-0.004	-1.717
ln T_S	-4.288	-0.399	-54.38	-7.645	13.813	1.800	-11.19	-0.695	-27.83	-6.663
T_S ln T_S	-0.001	-0.005	0.557	7.683	-0.110	-1.419	0.051	0.301	0.272	6.269
ln T_W	2.729	0.995	19.12	8.139	-0.677	-0.319	22.49	5.528	16.02	15.12
T_W ln T_W	-0.033	-0.899	-0.247	-8.813	-0.018	-0.667	-0.263	-4.647	-0.183	-12.72
Latitude	-0.033	-2.212	-0.089	-7.729	-0.019	-1.555	0.037	1.665	-0.082	-13.59
ln Altitude	-0.100	-3.145	0.062	1.412	0.184	5.501	-0.223	-4.330	0.071	4.759
ln Road Density	-0.041	-1.194	0.148	4.596	0.127	5.139	0.260	5.434	0.050	4.280
ln Pop Density	0.329	5.672	0.107	1.465	0.576	20.33	0.555	7.245	0.362	24.98
Mod Erosion	0.348	3.785	-0.092	-1.092	0.184	2.083	0.852	5.269	0.013	0.264
Strong Erosion	0.051	0.451	0.210	2.762	0.411	4.714	1.407	9.886	0.293	6.781
V Strong Erosion	-0.233	-2.093	0.302	4.291	0.391	4.648	1.486	9.906	0.216	4.871
Extreme Erosion	0.714	3.456	-0.531	-1.924	0.135	0.965	0.766	2.369	0.177	2.312
Soil Type 1	0.298	2.509	-0.010	-0.154	-0.270	-3.542	-0.255	-1.935	0.010	0.246
Soil Type 2	0.281	2.478	0.224	3.166	-0.163	-2.162	0.107	0.829	0.137	3.487
Soil Type 3	-0.191	-0.960	-0.187	-2.384	-0.423	-4.147	-1.392	-4.502	-0.236	-4.236
Soil Type 4	-0.026	-0.080	0.119	1.098	0.237	1.883	-0.469	-1.769	0.065	0.976
Soil Type 5	0.719	3.037	0.389	1.730	0.412	1.762	-0.428	-1.085	0.131	0.635
Soil Type 6	-0.060	-0.217	0.411	2.340	0.658	3.936	-0.682	-1.990	0.331	3.337
Soil Type 7	-0.506	-2.245	0.410	4.527	-0.162	-1.286	-2.161	-4.765	-0.002	-0.031
Soil Type 8	0.030	0.284	-0.582	-5.850	-0.764	-7.194	-1.309	-7.310	-0.342	-6.798
Adjusted R^2	0.226		0.442		0.538		0.298		0.746	

Table 4 – Estimation Results (Weighted)
N = 3177, Heteroskedastic Consistent Standard Errors

Variable	Endogenous Land Use Model								Ricardian Model	
	Forestry		Pasture		Temporary Crops		Permanent Crops			
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Constant	48.55	3.241	61.01	3.554	-6.343	-0.276	80.68	2.341	33.63	2.307
ln R_S	0.150	0.361	1.160	2.740	1.706	3.148	0.621	0.815	0.100	0.345
R_S ln R_S	0.001	0.105	-0.020	-2.581	-0.022	-2.147	0.000	0.006	0.005	0.934
ln R_W	0.152	2.015	0.525	4.597	0.380	3.255	0.460	2.773	0.405	6.279
R_W ln R_W	0.001	0.092	-0.053	-5.968	-0.014	-1.666	-0.018	-1.672	-0.017	-3.995
ln T_S	-27.42	-3.474	-38.08	-4.347	0.080	0.007	-55.08	-3.059	-27.03	-3.643
T_S ln T_S	0.215	2.645	0.405	4.543	0.036	0.297	0.507	2.789	0.282	3.697
ln T_W	7.956	3.234	11.80	4.346	-1.065	-0.322	20.26	3.891	12.66	6.212
T_W ln T_W	0.067	-1.979	-0.171	-4.623	-0.024	-0.555	-0.224	-3.391	-0.163	-5.786
Latitude	-0.062	-3.742	-0.083	-4.636	-0.042	-2.024	-0.004	-0.129	-0.082	-7.195
ln Altitude	-0.021	-0.642	0.002	0.053	0.086	1.648	-0.114	-1.551	0.018	0.770
ln Road Density	-0.024	-0.877	0.174	5.098	0.168	4.171	0.298	4.793	0.085	4.662
ln Pop Density	0.364	9.412	0.315	7.315	0.750	13.079	0.854	11.00	0.349	12.91
Mod Erosion	0.091	0.583	-0.912	-3.247	-0.485	-1.908	0.152	0.508	-0.267	-2.182
Strong Erosion	-0.194	-2.009	-0.043	-0.325	-0.154	-0.952	0.708	3.323	0.135	1.892
V Strong Erosion	-0.348	-3.530	0.029	0.206	-0.106	-0.644	0.592	2.837	0.044	0.555
Extreme Erosion	0.773	5.298	-0.863	-4.357	-0.560	-2.820	1.238	4.253	-0.346	-3.432
Soil Type 1	-0.024	-0.262	-0.119	-1.130	-0.450	-3.628	-0.506	-2.687	-0.091	-1.254
Soil Type 2	-0.077	-0.732	-0.079	-0.659	-0.506	-3.793	-0.259	-1.293	-0.009	-0.121
Soil Type 3	-0.462	-3.630	-0.099	-0.878	-0.813	-5.210	-1.427	-5.146	-0.270	-3.363
Soil Type 4	-0.075	-0.479	0.201	1.228	-0.051	-0.257	-1.356	-4.734	0.039	0.343
Soil Type 5	0.128	0.882	0.116	0.587	-0.017	-0.071	-1.228	-1.605	-0.164	-1.072
Soil Type 6	-0.514	-1.940	0.707	2.572	0.965	3.827	-1.055	-2.523	0.527	3.101
Soil Type 7	-0.639	-3.985	0.402	3.091	-0.206	-1.106	-1.692	-4.217	-0.111	-1.179
Soil Type 8	-0.350	-2.983	-0.291	-2.647	-1.086	-5.201	-1.365	-5.393	-0.360	-5.198
Adjusted R^2	0.352		0.730		0.657		0.462		0.785	

Table 5
Simulation Results, 1cm Increase in Summer Rainfall

	Region	% Change Value by Use				Change in Land Share				% Change in Average Land Value	
		Forest	Pasture	Temp Ag	Perm Ag	Forest	Pasture	Temp Ag	Perm Ag	Endogenous Land Use	Ricardian
UNWEIGHTED	North	-3.51	-2.21	-2.71	-5.52	-0.17	0.17	0.03	-0.03	-3.29	1.27
	Northeast	4.86	-0.61	5.54	9.56	0.38	-1.23	0.50	0.35	1.74	2.28
	Center West	-1.52	-1.80	-0.76	-2.06	0.03	-0.13	0.10	-0.00	-1.91	1.50
	Minas Gerais	-1.29	-1.75	-0.53	-1.67	0.04	-0.11	0.09	-0.02	-1.72	1.52
	Southeast	0.35	-1.40	1.08	1.20	0.10	-0.48	0.18	0.19	-0.92	1.70
	South	2.97	-0.92	3.66	5.90	0.20	-0.82	0.56	0.05	0.52	2.03
	Brazil	1.01	-1.32	1.74	2.51	0.14	-0.54	0.30	0.10	-0.50	1.81
WEIGHTED	North	0.88	-4.35	-3.49	2.31	0.80	-0.67	-0.17	0.04	0.17	2.51
	Northeast	1.52	2.46	6.30	5.26	-0.25	-0.34	0.51	0.08	3.12	2.61
	Center West	1.02	-2.70	-1.19	2.98	0.46	-0.54	0.07	0.01	-1.88	2.50
	Minas Gerais	1.04	-2.51	-0.92	3.05	0.40	-0.59	0.06	0.13	-2.36	2.50
	Southeast	1.15	-1.14	0.98	3.60	0.15	-0.63	0.09	0.38	-0.49	2.48
	South	1.36	0.97	4.04	4.56	-0.08	-0.42	0.44	0.05	1.97	2.54
	Brazil	1.22	-0.65	1.77	3.88	0.16	-0.49	0.23	0.10	0.57	2.54

Table 6
Simulation Results, 1cm Increase in Winter Rainfall

	Region	% Change Value by Use				Change in Land Share				% Change in Average Land Value	
		Forest	Pasture	Temp Ag	Perm Ag	Forest	Pasture	Temp Ag	Perm Ag	Endog. Land Use	Ricardian
UNWEIGHTED	North	1.96	-5.74	7.53	3.19	0.59	-1.05	0.45	0.02	0.88	3.72
	Northeast	3.77	6.20	14.13	12.85	-0.83	-0.55	1.16	0.22	6.51	12.34
	Center West	2.66	-0.43	9.90	7.08	0.16	-1.05	0.87	0.02	0.30	7.16
	Minas Gerais	3.97	7.72	14.64	13.82	-0.72	-0.10	0.69	0.14	6.73	13.20
	Southeast	2.68	-0.09	9.96	7.25	0.01	-1.35	0.85	0.48	1.26	7.31
	South	1.52	-9.41	6.06	0.63	0.51	-2.67	2.11	0.05	-3.22	1.46
	Brazil	2.89	0.44	10.89	8.15	-0.18	-1.09	1.13	0.14	2.83	8.14
WEIGHTED	North	2.05	-9.72	0.38	0.02	1.41	-1.51	0.10	0.00	0.64	-0.31
	Northeast	5.02	5.00	9.41	11.27	-0.27	-0.56	0.61	0.22	5.23	9.51
	Center West	3.25	-3.17	4.20	4.72	0.67	-1.24	0.56	0.01	-1.81	3.86
	Minas Gerais	5.36	6.83	10.46	12.49	-0.42	-0.11	0.39	0.14	5.96	10.65
	Southeast	3.30	-2.73	4.40	4.97	0.50	-1.48	0.48	0.50	-0.99	4.08
	South	1.27	-14.28	-2.19	-3.14	1.25	-2.71	-1.38	0.08	-8.93	-3.13
	Brazil	3.58	-2.11	5.04	5.81	0.39	-1.18	0.65	0.14	0.72	4.76

Table 7
Simulation Results, 1 °C Increase in Summer Temperature

	Region	% Change Value by Use				Change in Land Share				% Change in Average Land Value	
		Forest	Pasture	Temp Ag	Perm Ag	Forest	Pasture	Temp Ag	Perm Ag	Endog. Land Use	Ricardian
UNWEIGHTED	North	-15.11	41.22	4.84	-18.13	-7.44	7.46	0.21	-0.23	-3.67	12.74
	Northeast	-15.12	41.83	4.96	-18.16	-5.85	8.77	-1.59	-1.34	23.72	12.79
	Center West	-15.43	32.98	6.42	-19.04	-5.39	6.47	-0.98	-0.09	24.39	9.31
	Minas Gerais	-16.63	6.46	12.64	-22.36	-2.91	1.90	1.57	-0.56	6.47	-2.58
	Southeast	-15.94	18.31	9.50	-20.63	-3.16	5.45	0.64	-2.93	13.14	2.98
	South	-17.50	-8.19	17.29	-24.62	-1.54	-3.05	5.02	-0.43	3.11	-9.93
	Brazil	-16.02	21.47	9.55	-20.63	-4.29	4.20	0.94	-0.84	10.77	3.84
WEIGHTED	North	-10.40	35.47	17.13	10.74	-6.60	5.70	0.76	0.13	-2.41	21.02
	Northeast	-10.37	35.69	17.13	11.20	-5.46	5.80	-0.14	-0.21	22.29	21.07
	Center West	-12.98	29.80	17.04	4.33	-4.82	4.95	-0.12	-0.01	22.77	17.39
	Minas Gerais	-21.96	10.72	16.70	-16.31	-4.04	3.23	1.49	-0.68	9.91	4.82
	Southeast	-17.62	19.40	16.75	-6.94	-3.89	4.49	1.10	-1.70	14.39	10.65
	South	-27.59	-0.52	16.51	-27.78	-3.81	-0.23	4.51	-0.47	5.61	-2.96
	Brazil	-17.13	21.22	16.88	-4.64	-4.75	3.77	1.41	-0.44	11.90	11.60

Table 8
Simulation Results, 1°C Increase in Winter Temperature

	Region	% Change Value by Use				Change in Land Share				% Change in Average Land Value	
		Forest	Pasture	Temp Ag	Perm Ag	Forest	Pasture	Temp Ag	Perm Ag	Endog. Land Use	Ricardian
UNWEIGHTED	North	-4.03	-28.86	-9.65	-24.58	4.02	-3.97	0.19	-0.24	-6.85	-16.72
	Northeast	-3.13	-23.73	-9.70	-18.25	3.11	-4.12	1.23	-0.22	-15.60	-11.91
	Center West	-2.28	-18.86	-9.76	-12.22	2.63	-2.97	0.37	-0.02	-14.13	-7.36
	Minas Gerais	-0.40	-7.03	-9.89	2.67	1.11	-0.88	-0.56	0.33	-6.43	3.49
	Southeast	-0.48	-7.67	-9.82	1.75	0.81	-1.07	-0.56	0.83	-6.17	2.88
	South	4.68	32.91	-10.38	55.40	-1.20	5.84	-5.13	0.50	19.01	38.58
	Brazil	-0.88	-8.29	-9.88	1.60	1.73	-1.10	-0.78	0.14	-4.77	1.99
WEIGHTED	North	1.15	-25.24	-13.43	-18.13	4.38	-3.83	-0.37	-0.18	-1.53	-19.94
	Northeast	3.78	-21.92	-13.54	-12.08	4.15	-4.11	-0.05	0.01	-13.47	-16.24
	Center West	6.25	-18.80	-13.64	-6.33	3.73	-3.56	-0.16	-0.01	-13.70	-12.75
	Minas Gerais	11.91	-11.49	-13.88	7.68	3.14	-2.86	-0.84	0.56	-9.55	-4.55
	Southeast	11.57	-11.79	-13.78	6.82	2.78	-3.07	-1.11	1.40	-7.21	-4.94
	South	28.40	10.73	-14.69	55.73	2.80	1.52	-4.96	0.64	4.86	20.71
	Brazil	10.73	-12.80	-13.85	6.34	3.50	-2.51	-1.35	0.35	-6.86	-5.95

Table 9
Simulation Results, 1cm Increase in Annual Rainfall and 1°C Increase in Annual Temperature

	Region	% Change Value by Use				Change in Land Share				% Change in Average Land Value	
		Forest	Pasture	Temp Ag	Perm Ag	Forest	Pasture	Temp Ag	Perm Ag	Endog. Land Use	Ricardian
UNWEIGHTED	North	-19.85	-7.63	-0.90	-39.85	-2.51	1.86	1.08	-0.42	-17.22	-1.48
	Northeast	-10.54	12.72	14.09	-17.41	-3.36	2.78	1.56	-0.99	6.64	13.49
	Center West	-16.46	4.66	4.75	-25.57	-2.81	2.51	0.40	-0.10	1.77	9.74
	Minas Gerais	-14.80	3.28	15.64	-11.39	-2.59	1.03	1.72	-0.16	2.33	15.09
	Southeast	-13.82	6.54	9.71	-12.63	-2.24	2.68	1.14	-1.58	3.77	15.16
	South	-9.73	6.50	15.54	24.25	-1.81	-0.43	2.14	0.09	10.75	27.65
	Brazil	-13.52	4.71	11.28	-12.00	-2.57	1.44	1.61	-0.49	1.99	13.80
WEIGHTED	North	-6.73	-12.67	-1.78	-7.45	0.44	-0.83	0.40	-0.01	-7.48	-1.08
	Northeast	-1.05	13.11	17.60	13.04	-2.23	0.88	1.20	0.14	9.91	13.40
	Center West	-3.69	-1.08	4.06	4.54	-0.50	0.00	0.49	0.01	-1.11	8.72
	Minas Gerais	-7.27	1.58	10.05	2.97	-1.41	0.27	1.09	0.05	0.43	12.88
	Southeast	-4.16	0.81	6.10	7.03	-0.83	-0.35	0.59	0.59	1.18	11.83
	South	-5.07	-5.76	1.15	10.68	-0.28	-1.08	1.19	0.17	-2.65	15.23
	Brazil	-4.68	0.46	7.66	5.62	-0.99	-0.14	1.02	0.11	0.88	10.60