The Economics of Agricultural Land Use Dynamics in Coconut Plantations of Sri Lanka

by

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Contributed paper for the Australian Agricultural and Resource Economics Society (*AARES*) conference 2011

Melbourne, 8-11 February, 2011

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Abstract

In this study a spatially explicit economic analysis was employed to determine the land use change in a traditional coconut growing district of Sri Lanka. From a theoretical model of land use, an econometric framework was developed to incorporate spatial and individual effects that would affect the land use decision. Markovian transition probabilities derived from the econometric analysis and spatial analysis was used to predict the land use change over the next 30 years. The results revealed that the fragmentation and conversion of coconut lands to urban continue in the areas close to the urban centre and also with less productive lands. Spatial analysis provides further evidence of the positive trend of conversion of coconut lands to urban uses close to the urban areas.

1. Introduction

Conversion of agricultural lands to other land uses has been a concern during recent past in developing as well as developed countries, in particular where the economy is heavily dependent upon the earnings from agricultural products. When the conversion is from agriculture to more intensive land uses, the issue can be more complicated as possible negative externalities of conversion such as amenity and environmental losses may occur. Inability of the market to account for the non-market benefits provided by the agricultural lands and negative externalities associated with farmland conversion to intensive uses have provided a rationale and thrust for the agricultural land conservation programmes around the world. However, such policies have often been criticised on the grounds of them limiting the effective allocation of scarce land.

Numerous studies have examined the effectiveness of public polices of conversion of agricultural lands and other open space uses such as zoning restrictions (Lewis et al (2008), property tax policies/use value programmes (Polyakov and Zhang, 2008), conservation easement programs (Plantinga and Miller 2001), afforestation subsidies (Lewis and Plantinga 2007), and zoning (Carrion_Flores and Irwin 2005, Hite et al. 2003, Lewis 2007). Most of these studies are confined to developed countries mainly due to lack of georeferenced data and ancillary data for meaningful analysis. Almost all these studies look at the broader land use change from agriculture to other uses, with a significant lack of crop specific land use transformation studies using longitudinal spatial data.

Fragmentation and conversion of prime coconut lands to other uses has led to a heated policy debate in Sri Lanka, where coconut farming is supported and protected by government through national level controls and support programmes. In the large coconut plantations (estates), a loss of 30.85 percentage of total acerage has reported during the period between 1982 and 2002. Sri Lankan government allocates a significant amount of funds to provide numerous subsidies for activities such as new plantation, replantation, fertilizer and land improvement to promote coconut farming. Further monetary and human resources allocated for research and extension services are substantial. In addition fragmentation tax was imposed in 2006 to further protect the coconut lands from further fragmentation and conversion to other uses.

This study employs a discrete choice framework to model land use change in a traditional coconut growing area of Sri Lanka. It aims at characterizing the spatial and temporal nature of land use change while identifying the economic, bio physical and geographical factors and processes driving the land use change. The study also looks at the impact of government support schemes, such as plantation subsidies, and research and extension services, on the transformation of land uses from coconut to intensive land uses. The results from econometric analysis and spatial analysis were used to predict the future land use pattern for the study area. The econometric model was estimated with an extensive panel data set developed using satellite images and land use maps for the period of 1981-2009. The state transition probability matrix generated from the econometric results and Markovian Chain analysis was used to predict the future land use change. Based on the Markovian probability analysis a Cellular Automata analysis was performed to predict the spatial distribution of land use change to a future date. Thus this study performs a crop specific land use change analysis which is rarely reported in the literature, especially in the context of a developing economy. It applies econometric and spatial analysis providing insights into the current coconut land use change in Sri Lanka.

The paper is organized as follows. The econometric model and estimation framework are presented in section 2. Section 3 discusses the data generation process while econometric challenges in analysing land use change in the context of discrete choice framework and longitudinal framework are briefly discussed in section 4. Estimation and simulation results are presented in section 5 while section 6 concludes the paper.

2. Conceptual framework and econometric model

The underlying motivation of a landowner with complete foresight operating within a competitive land market to convert a plot of land currently in agricultural use to a developed use[4] is assumed to be the maximisation of the expected returns from his land (Cappozza and Helsely, 1989). As shown by Bockstael (1996) a land owner will convert his plot of land *i* which is assumed to be homogenous and currently in land use *u* to land use *d* in time *t* if,

$$R_{idt/u} - C_{idt/u} \geq R_{jmt/u} - C_{jmt/u} \qquad (1)$$

for all possible land uses (including *u* and *d*) $m = 1, \ldots\ldots\ldots\ldots, M.$, where, $R_{idt|u}$ is the present value of the future stream of returns to parcel *i* in land use *d* at time *t,* given that the parcel was in land use *u* at time *t-1,* $C_{idt|u}$ is the cost of converting parcel *i* from initial land use to land use *d* in period *t.* This model allows comparing the net benefits from converting to possible land uses, conditioned on initial land use. With static expectations on conversion costs and future net returns, the landowner will allocate his land to generate maximum discounted sum of net benefits,

$$R_{idt} - rC_{iudt} \geq R_{iut} \qquad (2)$$

where, *r* is the interest rate. This means that a land should be converted from one use to another when the expected annualized value from the new use is just equal to the old use (opportunity cost of land) plus real annualized conversion cost (expected opportunity cost of conversion capital).

Let $j = 0,1\ldots\ldots J$ be the feasible choices of an individual land owner. The returns from land use are treated as stochastic and therefore land use decision can be written in probabilistic terms which comprise a deterministic component V_{idut} of attributes that are observable, and a random component (ε_{idut}) of variables unobservable by the researcher.

$$p\{Y(it) = V_{ijt} + \varepsilon_{ijt} \geq 0\} \qquad (3)$$

[4] Developed use is defined as an irreversible non-agricultural use

In the context of land use change spatial effects refers to spatial dependence, which mainly emphasis on the spatial autocorrelation and spatial heterogeneity. These spatial effects could arise from the omitted variable bias or when unobserved variables are assumed to be absorbed by the error term. According to Anselin (2002) spatial autocorrelation can be defined as the coincidence of value similarity with the locational similarity. Spatial heterogeneity which arises from the structural instability, may be due to non constant error variances (heteroskedasticity). In contrast spatial autocorrelation could arise from the parcel specific data and neighbourhood characteristics which are observable to the land owners at the time of the decision making. Spatial interactions arising due to location of the agents in different zones can be accommodated by the deterministic component which is assumed to be spatially autocorrelated (Vichiensan et al. 2005). Spatial autocorrelation is generally associated with heteroskedasticity, however, incorporating both spatial autocorrelation and heteroskedasticity within the context of discrete dependent variable data analysis is challenging. Hence, only the spatial autocorrelation was taken into account in this study.

Hence, the systematic component of net returns consists of two parts; the first part consists of observed attributes of decision makers influencing the decision to change the land use and can be denoted as $\beta_{du} X_{idut,}$ where β_{du} is a choice specific parameter vector to be estimated, and X_{idut} is a vector of observable parcel specific and location specific variables. The second part captures the spatial dependencies across decision makers and can be denoted as Z_{it}. Hence, the probability of conversion of parcel i from use u to use d in period t^* can be expressed as,

$$p\{Y(it) = \beta_{du} X_{idut} + Z_{it} + \varepsilon_{idut} \geq 0\} \tag{4}$$

Further, the error term ε can be decomposed into two components to allow for both spatial and temporal correlations across observations. One is the individual and choice specific effect $u_{i.}$ (which can be random or fixed) observable by the land owner at the time of the decision making but is not observable by the analyst. The other is the idiosyncratic error component ϵ_{it} which is individual as well as time specific:

$$p\left\{Y\left(it\right)=\beta_{du}X_{idut}+Z_{it}+u_{it}+\varepsilon_{it}\geq 0\right\} \quad (5)$$

The systematic component is a function of initial and final land uses, parcel characteristics which are related to the returns and the cost of conversion, attributes of the local administrative area as well as macro economic factors affecting the land use allocation decision. The observed attributes of plots that are of interest here are land quality measured by soil suitability class and distance to urban centre. Unobserved attributes can be correlated over time and across parcels within local administrative boundaries (Lewis et al. 2008), so that the land use change decision across parcels can be correlated at the DSD (Divisional Secretary Divisions) level. To account for any regional level impacts we include the average population density and the forests density of the respective DSDs.

A plausible way to assess the impact of government support and control programs is to quantify the direct and indirect effects, which are hard to observe and quantify in this particular case. Direct policy interventions directly influence on land owner's decisions and influence the costs and returns of the land use change decision where as indirect effects arise via externalities of a land use decision (Irwin and Bockstael, 2004). Even though there are a number of land use supports and controls in the case of coconut farming in Sri Lanka, it is hard to access the impact of such policy interventions on the individual land owners since there is no mechanism of reporting of such data. A long term support mechanism adopted by government to motivate coconut farmers, subsidies for the coconut sector, and research and extension activities (funds allocated for the specific purpose by government) will be included in the empirical model to see if there is any quantifiable impact of such support programmes over the years.

The unit of the observation of the model is a grid of dimension 500x500 m. Based on the theoretical expectations and practice reported in previous literature, the following econometric model was specified:

$$Y_{ijt} = \alpha + \beta_1 LSC_i + \beta_2 disturb_i + \beta_3 popd_{jt} + \beta 4 forestd_{jt} + \beta 5 avgyld_t$$
$$+\beta_6 subres_t + Z_i + u_{ijt} + \varepsilon_{ijt} \tag{6}$$

where, Y_{ijt} is the land use observed in grid i in time t, in DSD j. The dependent variable is a categorical variable with 5 alternatives consisting of 3 mutually exclusive classes based on the proportion of coconut plantations within a grid. It is expressed in percentage terms so that class 1 = 0 - 49.99% of coconut plantations within a grid, class 2 = 50-74.99%, and class 3 = 75-100% of coconut plantations within a grid. The other two land use alternatives were: urban land (classified when a proportion of urban land in a grid was greater than 50%), and other land use (when the proportion of other land uses within a grid was greater than 50%. α_i is a constant term which captures the individual heterogeneity—the preference of an individual i to choose the j alternative. We assume that the unobserved heterogeneity α is identically and independently distributed. LSC (land suitability class) and disturb (distance to nearest urban centre) are grid specific regressors. Forest density (forestd) and population density (popd) are neighbourhood characteristics. 10 yearly average yield (avgyld) and subsidy and research and extension cost (subres) are macro economic attributes that would have an impact on the land use change Z_i represents the spatial dependence across decision makers. u_{it} is unobserved individual specific random effect (deriving from unobserved heterogeneity) and ϵ_{it} is idiosyncratic error.

3. The Data

The study sample consists of 13,692 grids (500 x500 m) covering seven divisional secretary divisions (DSD) in Kurunegala district which is a traditional coconut growing district in Sri Lanka. The data were derived from a number of sources including United States Geographical Survey (USGS), European digital archive of soil maps (EuDASM), Survey Department of Sri Lanka, Census and Statistics of Sri Lanka, and Coconut Research Institute Sri Lanka (CRI). Land use and other layers of 1990 were obtained from Survey Department of Sri Lanka. Satellite images for 1990, 2001 and 2009 were acquired from the Landsat thematic mapper (TM) images from the USGS website for the month of January. Kurunegala land use sheets south and north maps of 1981 were downloaded from EuDASM and digitized and rectified using the 1990 land use layers. All the images and maps were georeferenced to

GCS_WGS_1984 geographic coordinate system and Universal Transverse_Mercator projection and resampled to 30 m pixel resolution. Using a unique Grid ID, land use shape files, Kurunegala district administrative boundary shape file and land suitability maps were spatially joined. Then seven representative DSDs (Figure1) were clipped using the DSD boundary layer to obtain a sample for the study due to the difficulty of getting cloud free quality images for the whole district. The land maps were also converted to raster files and raster images for the 4 years were initially classified into 6 land suitability classes: forest, water, urban, coconut, other agriculture, and rocks using ERDAS Imagine software.

Using the images, the proportion of coconut, urban and developed land uses percentages were calculated for each grid and reclassified maps of five classes were developed for each year (Figure 2). Three broad land suitability classes for coconut; highly suitable, moderately suitable and marginally suitable were assigned to each grid from the spatially joined maps. The percentage of land covered by forest within a DSD division was also calculated and density of forest (per ha of total area) was calculated for each year. The centroids were calculated for each grid and then the Euclidean distance to urban centre from each grid was computed. The data on population were obtained from the publications of Census and Statistics of Sri Lanka while average yield of coconut, subsidy, research and extension costs were obtained from the Coconut Research Institute Sri Lanka (CRI). The resulting data set consisted of land use and other information for 4 years with approximately 10 years interval (Table 1).

4. Econometric Challenges and Methodology

The study analyses the land use change between five distinct nominal categories of land uses over a period of 30 years. When observed data are nested within clusters or repeatedly measured over time, the observations are likely to be correlated. There are likely to be unobserved factors that affect land owner’s decision at the time of decision making, which are unobservable to the researchers. Hence, the collected data in this study may be best used in a multinomial response panel data model which accounts for unobserved effects correlated over time and space. Discrete choice framework has been successfully employed in analysing land use change (Carrion-Flores and Irwin 2004, Polyakov and Zhang 2008, Lewis 2009), however applications of polytomous responses incorporating spatial effects, in particular within panel data framework have been rare. In addition, the few available estimation methods are computationally intensive.

There are two possible types of effects that the unobserved characteristics which vary across individuals may exhibit: fixed effects which assume the effects to be constant across time, and random effects (RE) that assume that the effects are part of a composite error term, but vary by individuals. Fixed effects approach allows the unobserved heterogeneity to be correlated with the included variables; however, it is theoretically as well as computationally cumbersome to estimate fixed effects for non linear models with short panels (Greene 2001). [5]

Similar to other discrete panel models, estimating multinomial logit models within panel data setup has been quite challenging since RE are not tractable and inference requires evaluation of multi dimensional integrals (Malchow-Møller and Svarer 2003). For non linear models, analytical solutions with RE can only be obtained for Poisson model with Gamma distributed random effects and negative binomial models with Gamma distributed effects (Cameron and Trivedi 2009). When there is a single common random effect shared by all the observations in a particular group, (Greene (2001) shows the exact integration and closed form of the likelihood function can only be maximised by Poisson and by negative binomial models with log gamma heterogeneity and stochastic frontier models. In applying this approach in estimating multinomial logit model with RE, the multinomial problem is generally transformed to a Poisson model with random intercepts (Malchow _Møller and Svarer 2003, Chen and Kuo, 2001).

Another popular approach to estimating non linear multinomial discrete response models with RE is the quadrature solution which applies adaptive Gauss-Hermite quadrature in the maximisation of likelihood function. This approach has been widely applied in the context of probit RE (Guilky and Murphy (1993), Bock (1972)) multinomial logit models (Grilli and Rampichini 2007) and Poisson model (Greene

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[5] Due to the problems of incidental parameters and proliferation of parameters due to inclusion of dummy variables in estimating, it is practically difficult to implement the non linear fixed effects models with large no of observations, large number of alternatives and small T.

2000). Methods of adaptive quadrature use fewer points per dimension and are computationally feasible for models with small number of RE (Hedeker 2003), however, extension of quadrature beyond two dimensions appears to be impractical (Greene 2001). The class of multivariate generalised linear models also uses Gauss-Hermite quadrature in combination with various algorithms in the maximisation of likelihood function. This has been applied to multinomial logit models with RE (e.g. Hedeker (2003), and Hartzel et al. (2001)). However the quadrature method has been limited in application due to it being computationally burdensome.

Simulated maximum likelihood approach which uses simulated (Monte Carlo simulation using a random number generator) integral in the maximization process has also been used to incorporate RE in non linear, in particular multinomial response models. Mixed logit models or random parameter logit models which extends random effects model to more flexible random parameters formulation have been extensively used in recent years (Hole (2007), Hanna and Uhlendorff (2006), Train (2000), Revelt and Train (1998) McFadden and Train (1996)). Nonetheless, the mixed logit models are more appropriate for clustered data (Cameron and Trivedi, 2005) that typically come from choice experiment studies, than for georeferenced panel data.

Spatial autocorrelation is generally associated with heteroskedasticity and the problem is serious in models with discrete dependent variables (McMillen 1992). Both these effects are likely to result in uncertainty in model estimation and thereby generate both spatial and temporal autocorrelation in spatial models. Literature is short on models incorporating spatial dependence within discrete choice framework compared to the linear models. Moreover, such modelling and analytical tools in the context of panel data framework are even more rare, especially when it comes to large samples. Correcting spatial error autocorrelation using spatial coding or sampling to eliminate nearest neighbours is a widely adopted technique (Carrion_Flores and Irwin 2004). The few available models for discrete choice analysis based on microeconomic theory, includes dynamic spatial probit model (Wang et al., 2011), Spatial multinomial model (Mohommadian and Kanaroglou (2003), and spatial mixed logit models (Vichiensan et al. 2005) (Mohommadian et al. 2005) and spatial expansion model (McMillen1992).

In analysing the spatial land use change data with multinomial responses within panel structure a variety of models within RE framework have been employed. These include models which account for both the panel structure (Polyakov and Zhang (2008) as well as spatial effects Wang et al. (2011) Wang and Kockelman 2006)) and modelling is mostly based on the mixed logit framework. In modelling the coconut land use decision, the unobserved characteristics which vary across individuals can be captured by the RE in the multinomial specification. Further, by including the spatial dependence term in the deterministic component of the choice function, the missing variables which would have caused the spatial heterogeneity can also be captured by the RE (Vichiensan et al. 2005). In the case of RE, probit model is easier to implement computationally than the logit model (Madala 1987). Hence a multinomial probit random effects model is likely to account for the unobserved spatial and temporal correlations and provide consistent estimates. However, an intricate analysis of spatial dependence is beyond the scope of this basic multinomial random effects framework. In this study we hypothesize that the long term government support schemes (subsidies, research) are likely to reduce coconut land being converted to urban or other agricultural uses. Also, higher the suitability of land for coconut farming, less likely it is to be converted to other uses, as such land parcels are less likely to get permission for conversion from the government. As the proximity to urban and marketing centres decreases, the possibility of a coconut land converting to urban uses is expected to be higher (Ricardo and Von Thunen's theory).

Methodology

When dealing with a qualitative dependent variable which falls into several mutually exclusive categories that is unordered, multinomial distribution in assumed and RE can be introduced to capture unobserved heterogeneity. Hence, multinomial probit model with random effects can be used to estimate the coefficients. Following Greene (2001) a non linear model with single common random effect shared by all observations in group *i* can be specified as,

$$\left\{Y_{it} \left| x_{it}\alpha_i \right.\right\} = g\left(y_{it}, \beta' x_{it}, \alpha_i, \theta\right) \tag{7}$$

where the individual specific effect α_i has the specified distribution $h(\alpha_i \setminus \theta)$. Then the unconditional density of the i^{th} observation can be given as,

$$f\left(y_{i1}, y_{i2} \ldots . y_{it(i)}, \alpha_i \;\middle|\; x_{i1}, \ldots \ldots x_{iT}, \beta, \theta\right) h(\alpha_i) = \int \left[\prod_{t=1}^{T} g\left(y_{it} \;\middle|\; x_{it}, \alpha_i, \beta, \theta\right)\right] h(\alpha_i \backslash \theta) \tag{8}$$

In order to form the likelihood function for the observed data, α_i need to be integrated out of this, and the log likelihood function can be written as:

$$\log L = \sum_{i=1}^{N} \log \left[\alpha_i \prod_{i=1}^{\tau(i)} g\left(y_{it} \middle| x_{it}, \alpha_i, \beta, \theta\right)\right] h\left(\alpha_i \backslash \theta\right) d\alpha_i \tag{9}$$

As there is no analytical solution for the above univariate integral, numerical integration is generally used, and normally distributed RE are assumed (Cameron and Trivedi 2009). RE models treat individual specific effects (α_i) as unobserved random variables with the specified distribution, often assumed to be normal distribution. Then α is eliminated by integrating over the distribution (Green 2001).

We applied a method analogous to the mixed logit model in which the multinomial data were transformed into a set of binary data by expanding the observations and allowing for pair wise comparison of alternatives. The expanded data set consisted of 5 duplicate records of each observation, while the grids were identified by a unique identification number, so that, a new binary variable was developed for each record. Random effects were specified to capture unobserved characteristics that vary across individuals. When panels are short and estimation methods are limited, random effects assumption seems to be more appealing (Pesaran et al. 1996)[6]. With random effects, non linear probit specification is more computationally feasible compared to logit specification (Greene (2001), Maddala (1987)). Using this transformed data, and taking category 3 (coconut percentage >75%) as the base category, a binary probit panel model with random effects and spatial effects was estimated. Markov transition probabilities[7] were calculated using the econometric results. Using the probability

[6] Small T inconsistency in fixed effects models motivates the use of random effects models in panel settings (Maddala 1987).

[7] The state transition probability (π_j) is the probability that the process is in state *j* at time *n*, $\pi_j(n) = \Pr\{X_n = j\}$ and the state probability vector (Π(n), consist of all of the state probabilities for a given time n, $\prod(n) = [\pi_0(n)\pi_1(n)\pi_2(n)........]$ where, the sum over elements in (Π(n)) equals to one. (www.utdallas.edu)

matrix, transition probabilities for the land use classes for the next 30 years period were predicted.

Spatial analysis

Classified land use raster maps created using ArcGis and ERDAS imagine were converted to IDRISI raster files in order to carry out the spatial simulations. In this study two techniques were employed in modelling land use change; Markov Chain Analysis and Cellular Automata Analysis. A Markovian process models future state of a system based on the immediately preceding state. It is based on a probability matrix[8] for the land use change for two given periods which is used as the basis to project for a later period. However, it does not provide information on spatial distribution of occurrence within each land use category (Petit et al., 2001). Cellular Automata Analysis (CAA) applies set of rules that relates the new state to its previous state and its neighborhood thus, incorporating the spatial interactions. CAA can be used effectively with Markovian Chain Analysis to model the spatial developments of a location (Parker et al., 2003). Taking 1981 and 2009 as the initial and final land use images, Markov Chain Analysis[9] was performed to obtain transition probabilities for the 5 categories considered. Using the output from the Markov Chain analysis, the Cellular Automata analysis was performed to predict the land use change spatially.

5. Results and Discussion

The transition between land use categories obtained from the cross tabulation performed in the GIS analysis between the images are shown in table 1. It shows that the majority of large coconut patches remain stable within the first transition period, while in the second period there was a significant transition to second category, where coconut covers 50-75% of a grid. The extent of coconut lands shows a considerable decrease with number of grids covering higher coconut percentages decreasing, while grids with more than 50% of urban land use increasing throughout the period. During the last period from 2001- 2009, however, the decrease of large coconut patches has been relatively reduced. This may be partly due to the strict enforcement of land fragmentation tax implemented since 2006. It is also worth noting that significant

[8] Marko transition probability matrix P contains one step transition probabilities P_{ij} so that probability of transitioning from state i to state j in m steps (m-step transition probabilities)

$$P_{ij}^{(m)} = \Pr\{X_{n+m} = j | X_n = i\}$$

[9] The procedure involved is not discussed in this paper.

transition from category ‘other agricultural uses’ to coconut land uses has taken place over time, nevertheless it can hardly compensate to the loss of prime coconut lands to urban development.

Estimation results shown in table 2 are in accordance with the expectations and indicate that the land owners behave rationally. Category 3 was used as the base category so that we can explain the land use change in coconut covering more than 75% of a grid to other categories. The conversion specific constants of the alternative categories agree with the GIS analysis that the transition from category 3 (> 75%) to 2 (> 50%) shows a statistically significant positive relationship while to other categories show a decreasing trend. As the distance to urban centre increases conversion to grids with lower coconut percentages has decreased while the conversion to grids with more urban percentage has increased. This implies that more intensive coconut farming is practised further away from the urban centre, and land owners opt to keep growing coconut, or to convert to urban uses with higher rental value rather than converting to other uses. In other words Von Thunen’s theory of observing varying land uses as a function of distance to the urban centres holds.

In highly suitable land areas as well as moderately suitable areas for coconut, conversion from the grids with highest coconut percentage to lower percentages or to other uses is low, while conversion to urban uses is high. This is in accordance with the Ricardian theory that more productive lands are used for coconut or converted to urban uses with higher rent rather than to others less profitable uses. As expected, in highly populated DSDs conversion of grids with large coconut percentage to urban and other uses has increased and the estimates of the coefficient are statistically significant. In DSDs with higher forest density too, conversion to grids with urban and lower percentage of coconut has increased.

Coefficients on subsidy, research and extension cost shows positive relationship with lower categories of coconut and urban uses. This implies that even with increasing government support in terms of subsidies and research and extension services, the area under coconut has decreased. The highest conversion seems to be to the grids with <50% of coconut. This implies that the government support mechanisms have not had an effect on the conversion of coconut lands. Even though the coconut farming as well as the coconut based industries has been heavily subsidized in terms of input supply, research and knowledge transfer, conversion of prime coconut lands have continued over the last 30 years. Similarly increase in average yield over the years has not been sufficient to prevent the conversion of coconut lands. The incentives provided by the productivity growth to continue coconut farming is most likely to have offset by the parallel increase in the cost of production. Spatial dependence term which is significant over all 4 categories shows a positive relationship with conversion to urban and other agricultural uses implying that in areas where large coconut lands are closer or surrounded by urban uses the conversion to urban uses has increased and same with the other uses category. In areas with lower coconut percentages the conversion of large plantations has decreased. Overall the empirical results imply that the magnitude of increase in the net revenue from coconut due to productivity growth, government support or other form of incentives has not been able to match with the expected returns from converting coconut lands to urban uses in peri urban areas.

Markov Chain analysis performed for the next 30 years, based on the state transition matrix (Figure 3) built from econometric estimates shows an increase in the second category (coconut 50-75%) in the first few years while a decrease in the other two coconut categories and other agricultural uses category. Category representing urban land uses >50 % shows a slow but continuous increase for the next 30 years. The results of the Markov probability analysis (Figure 4) performed using IDRISI software shows a sharp increase for the urban category for the first few years and then a constant upwards trend paralleled with a decreasing trend for the other categories. This prediction is purely based on the previous state and does not account for the economic and bio physical factors affecting the land use change. Spatial prediction performed using CA_Markov for the next 30 years (Figure 5) clearly shows an increase in urban areas around the current main urban and market centres, and main roads network. It also shows a significant decrease in grids with >75% coconut while substantial number of grids with <75% coconut. Despite the fact, that the predictions do not account for the possible socio-economic or bio physical factors that could influence the land use decision, it implies that the conversion of coconut lands in peri urban areas will be continued in the next 30 years.

6. Conclusion

In this paper, we apply a model of agricultural land use decision derived from a theoretical model of land use decision making to study the land use change in a traditional coconut growing district of Sri Lanka. This study uses a more intensive classification of land uses and a grid based analysis of land use change and the results are largely consistent with the expectations. The spatial predictions are also in accordance with the expected results and further approve the decrease in the large coconut plantations into other uses, mainly for urban uses. It was also noted that the class of other lands which includes agricultural and forest lands have converted significantly to coconut and urban uses, showing a decrease in the area for the past 30 years as well as for the predicted period. As a result, even though with the continued conversion and fragmentation of coconut lands in prime areas, the area under coconut has not decreased considerably. However, this conversion from other agricultural lands or forest lands to coconut can hardly compensate to the loss of lands in prime coconut growing areas. In the last period (2001-2009) the conversion of large coconut lands to other classes has been quite low, and this can be partly attributed to the land fragmentation tax implemented in year 2006. Even though assessing the direct impact of the fragmentation tax empirically is hard given the short period of its implementation, the transition maps provide crude evidence that supports the fragmentation tax in limiting the conversion of large coconut lands.

Of particular interest in the land use change analysis is the relationship of change to the distance to urban centre and land suitability classes. The prime lands are maintained as coconut or converted to urban lands with high rental value, and does not seem to be converting to other agricultural uses. The study area is a traditional coconut growing area with highly suitable productive lands for coconut and a rational land owner would not want to convert coconut lands to any other agricultural use which explains the behaviour of a profit maximising land owners. From the econometric analysis, government supports in the form of subsidies or research and extension services do not seem to be preventing coconut land use conversion. This is a crude analysis of the impact of such services since it does not account the qualitative component of the support and only measures the amount of funding. However, the decreasing amount of land under coconut, in particular large plantations, provide some evidence that such support schemes have not been very effective in preventing fragmentation or conversion. This study substantiate the fact that net revenue generated by coconut through productivity growth or government supported incentive schemes has not been sufficient to protect the coconut lands in peri urban areas. However, the impact of such policies can be reasonably estimated from an analysis corresponding to the individual decision making level. Hence, the next step would be to analyse the land use change using a polygon based analysis which are approximated to the rough plantation estate boundaries. Even though in this analysis we have only considered few local administrative areas of the coconut triangle of Sri Lanka, this preliminary econometric and spatial analysis exercise provides insights into the current situation prevailing in the coconut triangle and provides the basis for more intricate analysis of the situation.

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Table1: Transition between land use categories as a percentage

	Coconut <50%	Coconut 50- 75%	Coconut 75%	Urban > 50%	Other > 50 %
Year 1981-2001					
Coconut 50%	.432	.372	.112	.0342	.0496
Coconut 50-75%	.125	.456	.381	0.011	.0269
Coconut >75%	.0493	.137	.785	.017	.012
Urban % > 50%	.214	.071	.071	.643	0.00
Other% > 50%	.364	.119	.082	.034	.404
Year 1990-2001					
Coconut < 50%	.774	.106	.0134	.092	.016
Coconut 50- 75%	.465	.456	.060	.012	.061
Coconut 75%	.146	.418	.427	. 076	.045
Urban > 50%	.146	.019	.023	. 760	.045
Other > 50%	.403	.110	.050	.036	.400
Year 2001-2009					
Coconut < 50%	.793	.091	.027	.081	.007
Coconut 50- 75%	.262	.623	.105	.017	.009
Coconut >75	.053	.405	.533	.062	.003
Urban > 50%	.203	0.00	.012	.783	.029
Other > 50%	.395	.240	.043	.017	.300

Table 2: Descriptive statistics

Variable	Description	Average	Min	Max
disuc1.....5	Distance to urban centre	13927.64 m	98.57m	34114.1m
resex1.....5	Subsidy Research cost	Rs. Mn[10] 51.729	Rs. Mn 71.7	Rs Mn 17.1
popd1.....5	Population density Per sq.km	49841.56	15757.53	94701.05
avgyld1….5	Average yield (nuts/ha)	5885.81	4700	6736.14
ford1.......5	Forest density ha per sq.km	167.76	59.89	410.03
Soil1c1...c5	Land suitability class=highly suitable	.1328659	0	1
Soil2c1...c5	Land suitability class=moderately suitable	.0320187	0	1

[10] One Australian dollar = Sri Lankan Rs.112.233
One US dollar= Sri Lankan Rs. 111

Table 3: Model estimation results

	coefficients	Standard errors	z
Constant	-0.6523624	.011669	-55.91
Category1	-10.03899	1.061998	-9.45
Category2	3.955422	1.058596	3.74
Category 4	-11.77347	1.979737	-5.95
Category 5	-4.491795	1.561683	-2.88
Distance to urban centre			
Category1	-1.39e-06	1.95e-06	-0.71
Category2	-.0000151	2.00e-06	-7.55
Category4	0.0000294	3.50e-06	8.41
Category 5	0.0000461	2.90e-06	15.91
population density			
Category1	1.99e-06	6.00e-07	3.33
Category2	-2.99e-06	6.03e-07	-4.96
Category4	0.0000118	1.24e-06	9.57
Category 5	3.82e-06	1.08e-06	3.53
Subsidy, research and extension			
Category1	0.0054853	.000326	16.83
Category2	0.0011896	.0003181	3.74
Category4	0.001906	.0006312	3.02
Category 5	-.0046884	.0005089	-9.21
Highly suitable soil			
Category 1	-.0304375	.040278	-0.76
Category 2	-.0510338	.0416376	-1.23
Category 4	.1443753	.0711951	2.03
Category 5	-.2714253	.0552438	-4.91
Moderately suitable soil			
Category 1	-.0941196	.0307526	-3.06
Category 2	0.1378713	.0313844	4.39
Category 4			

Category 5	-.1027928	.0564449	-1.82
Forest density	-.607333	.043543	-13.95
Category 1			
Category 2	.0110554	.0006702	16.49
Category 4	.0017358	. 0006499	2.67
Category 5	.0021815	.0013938	1.57
	-.0091719	.00104	-8.82
10 yearly Average Yield			
Category 1	.0015705	.0000885	17.75
Category 2	.0002015	.000087	2.31
Category 4	.000709	.0001685	4.21
Category 5	-.001673	.000156	-10.72
Spatial dependence			
Category 1	-.0543147	.0181981	-2.98
Category 2	-.1258454	.0185247	-6.79
Category 4	.1041271	.032429	3.21
Category 5	.3689424	.0247765	14.89
lnsig 2u	-3.76183	.023046	
sigma_u	.1524506	.0017567	
rho.	.0227133	.0005116	

Log likelihood = -29895.671

Figure 1: Study area: Kurunegala district of Sri Lanka

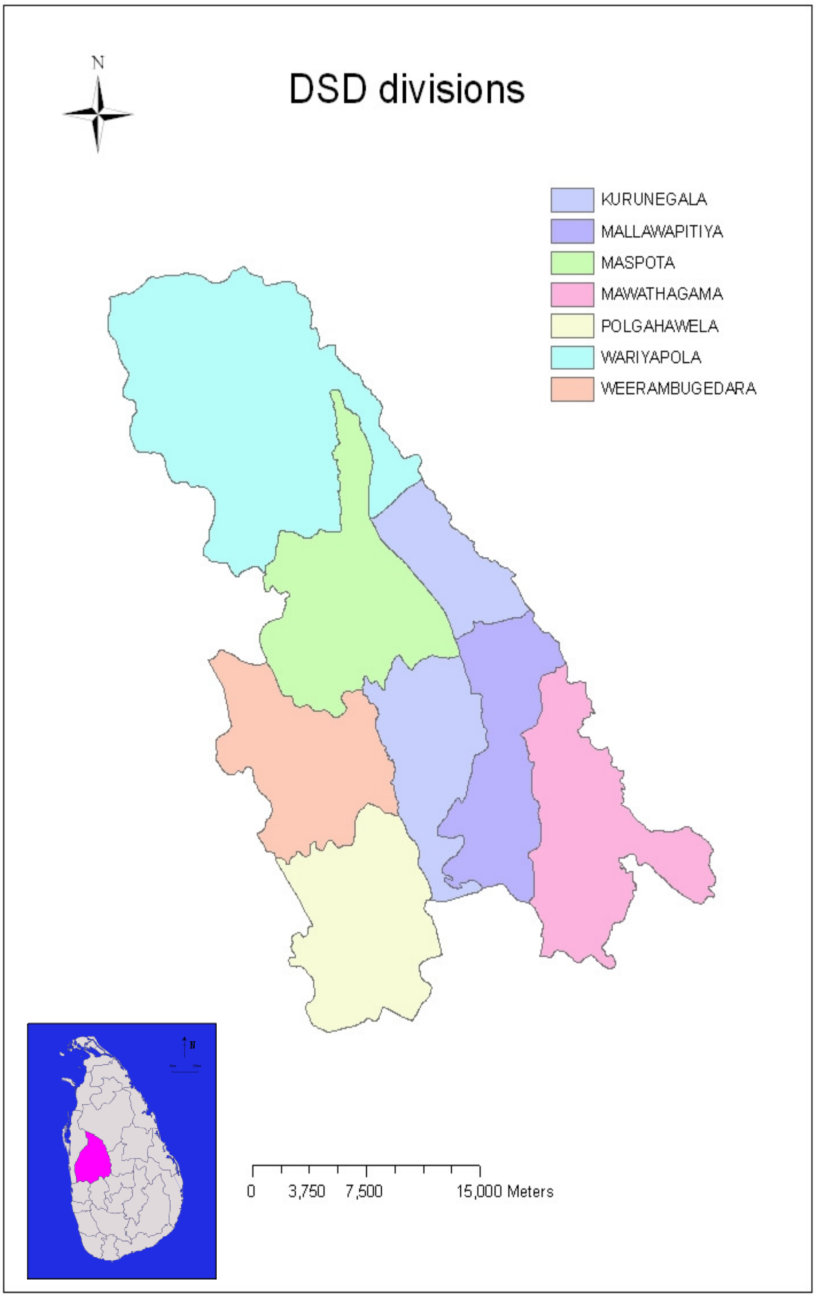

Figure 2: Land use in 2009

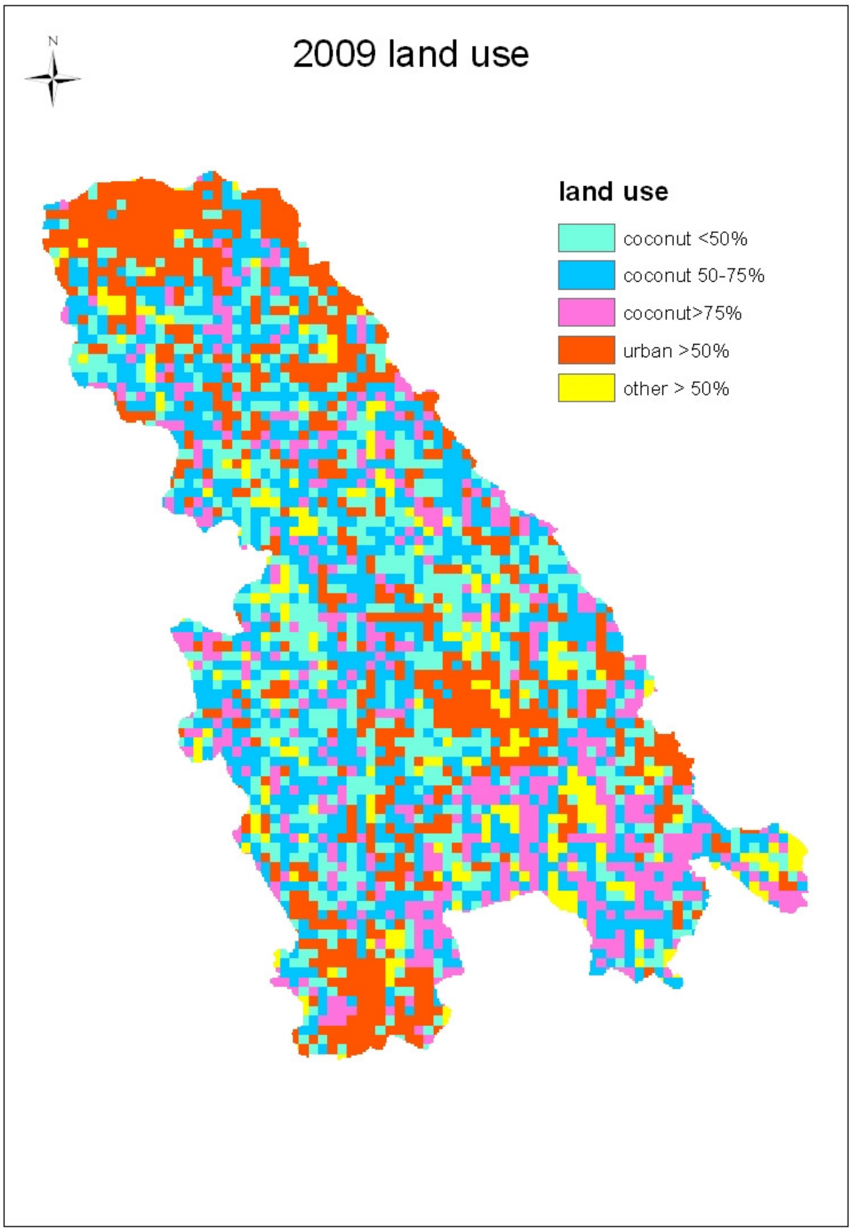

Figure 3: Markov Chain Analysis based on state transition probability matrix (Econometric analysis)

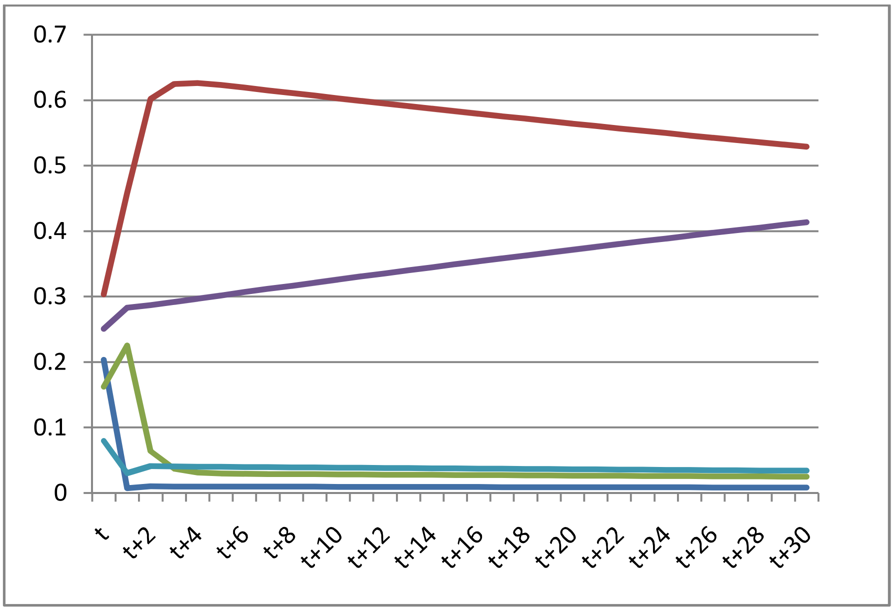

Figure 4: Markov Chain Analysis based on Markov transition probability matrix

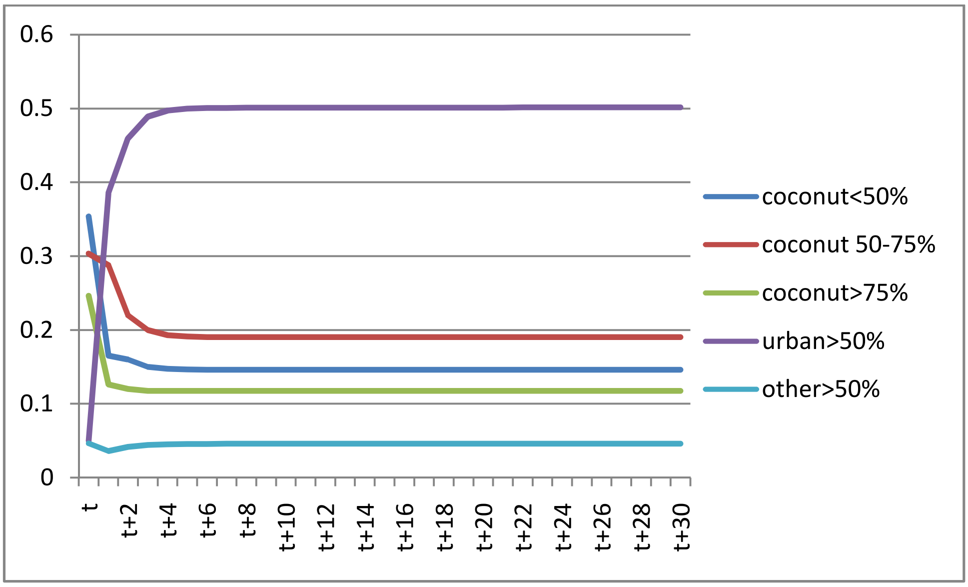

Figure 5: Predicted land use for next 30 years