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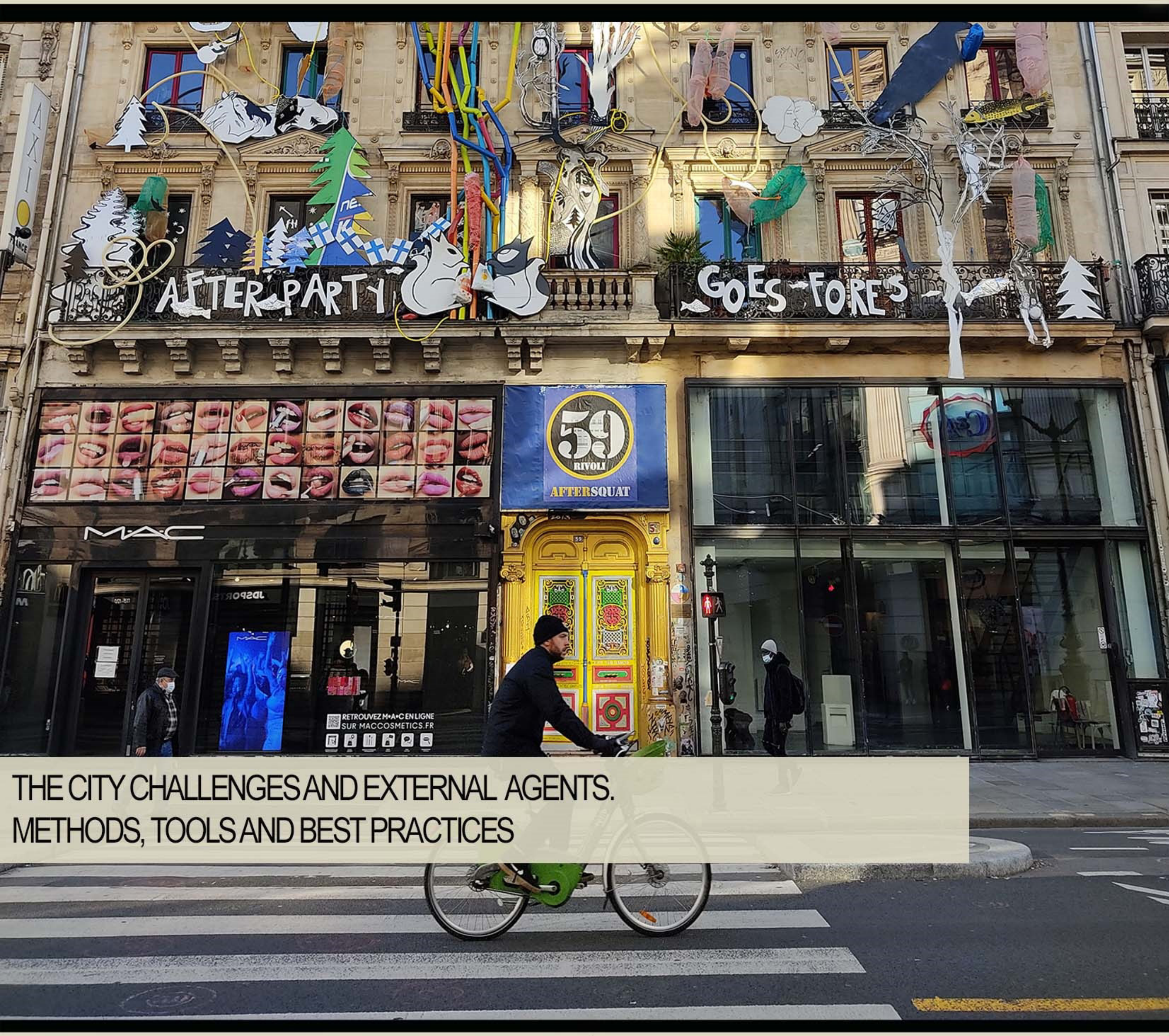

THE CITY CHALLENGES AND EXTERNAL AGENTS. METHODS, TOOLS AND BEST PRACTICES

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Laboratory of Land Use Mobility and Environment
DICEA - Department of Civil, Architectural and Environmental Engineering
University of Naples "Federico II"
Piazzale Tecchio, 80
80125 Naples
web: www.tema.unina.it
e-mail: redazione.tema@unina.it

The cover image is Rue de Rivoli - an emblematic street of Paris connecting Bastille to Concorde – that since May 2020 has been reserved for bicycles and pedestrians, Paris, France, Saturday, Nov. 6, 2021.

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REVIEW NOTES

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Characterization of drivers of agricultural land use change

Akeem Olawale Olaniyi [a]*, Ahmad Makmom Abdullah [b]

[a] Faculty of Environmental Sciences,
Department of Environmental Management,
Kaduna State University, PMB 1010, Kafanchan,
Kaduna State, Nigeria.
e-mail: akeem.olaniyi@kasu.edu.ng
ORCID: https://orcid.org/0000-0002-6500-0824
* Corresponding author

[b] Faculty of Environmental Studies
Department of Environmental Sciences,
Universiti Putra Malaysia, 43400
Serdang, Selangor, Malayisia
e-mail: amakmom@gmail.com
ORCID: https://orcid.org/0000-0001-7533-2411

Abstract
Major factors driving agricultural land use in Malaysia were characterized with Principal Component Analysis (PCA). Discrete variables assumed to drive agricultural land use were converted into spatial data. Vector data subsequently obtained from these conversions were later rasterized before being disaggregated. ASCII data of each of the disaggregated was derived using ArcGIS 10.3.1. A MatLab program was thereafter used to convert the ASCII data into vector column where systematic sampling was performed after Moran I test to select the samples for PCA analysis in SPSS/IBM version 23. The result of the PCA analysis finally aggregated variables driving agricultural land use into: urbanization, availability, ageing and cross sectoral mobility of labour, geophysical, accessibility, and climatic factors. These factors explained about 88 % of the cause of agricultural land use in the study area. The proposed transition of Malaysia to a high income nation will no doubt put additional pressures on the identified drivers (factors) of the agricultural land use, therefore, it is expected that the policy makers put in place measures that will minimize environmental effects of these pressures in order to make the proposed transition sustainable.

Keywords
Agricultural land use; Principal Component Analysis (PCA); Spatial data.

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1. Introduction

Land use and land use change (LULUC) is one of the manners by which mankind influences the natural landscape (Hu et al., 2019; World Bank, 2008; Lechesten et al., 2005) and the processes have been linked to the human socio – economic activities (FAO, 1996; Kleemann et al., 2017; Marchant, 2018; Dinç, & Gül, 2021) with implications on food, water and energy security (IPBES, 2019; Näschen et al., 2019); urban spatial structure (Nuissl et al., 2021) biodiversity loss (Kuemmerle et al., 2016), climatic change (Zucaro & Morosini, 2018) and direct impacts on oceans, terrestrial and freshwater ecosystems (IPBES, 2019; Näschen et al., 2019). Several attempts have been made by researchers to identify the drivers and the dynamics of land use processes with the use of different methodologies and models (Huang et al., 2007; Vasco and Eric, 2010; Qasim et al. 2013), the attempts have not generated specific model that will be suitable for and in all situations (Verburg et al., 2004; Leta et al., 2021). Generally, models of land use change serve as useful tool for assessing the mechanisms (Veldkamp and Fresco, 1999); identifying the drivers (Batty and Longley, 1994; Alexander et al., 2015; Hu et al., 2019); projecting the impacts of land use change (Theobald et al., 1997) and evaluating the effects of alternative policies and management opportunities (Bockstael, 1996; Verburg et al., 2004) due to land use change.

1.1 Models in land use change analysis

Generally land use models are useful for selection of specific drivers (independent variables) for a particular land use class (dependent variable) at a specific scale from several hypothetical driving factors (Kok and Veldkamp, 2000; Verburg et al., 2004). Therefore, the choice of a particular methodology is dependent on what research questions to be answered, the available data and the application of the research outcome (Nelson, 2002; Wester - Herber 2004). Previous researches on land use and land use change analysis have focused on assessment of drivers (Alexander et al., 2015; Wang et al., 2016) and effects of LULUC on climate change (Lambin et al., 2001) soil erosion 11, biodiversity loss (Lambin et al., 2003), food security (Lambin et al., 2003), public health (Shi et al., 2018) and urban spatial structures (Nuissl et al., 2021). However, in this study, attempts were made to describe and validate the methodologies involved in the use of Pricncipal Component Analysis (PCA) for identifying and characerizing important factors driving agricultural land use in the study area with a view to gaining deeper understanding of the process, the drivers, the dynamics and the potential implications for attaining sustainable development in the study area.

1.2 Application of Pricncipal Component Analysis (PCA) in environmental analysis

PCA is a simple and non-parametric test that has been applied over a century (Hotelling, 1933; Pearson, 1901), on socio - economic (Lordan et al., 2012; Nyaga & Doppler, 2009; Fujii, 2008); geophysical datasets (Hassanzadeh et al., 2016; Parker et al. 2013) and environmental datasets (Hassanzadeh et al., 2016) aside the conventional regression analyses, to characterize, model (Jobson, 2002; Jolliffe, 2002; Legendre & Legendre, 1998; Jongman et al., 1995); classify (Cochard-Picon et al., 2012; Jayawardana et al., 2012; Richards et al., 2012) and identify hidden structure/dimension in a dataset (Hassanzadeh et al., 2016; Lordan et al., 2012). PCA is series of linear regressions where a vector line is drawn through an n - dimensional dataset such that the sum – of - squares (n-dimensional) distances from the line to all the points in the dataset are minimal (Jolliffe, 2002) thus significantly reducing the number of dimensions in the dataset before using the datasets for further analysis. The decision of the numbers of components to retain are usually guided by the scree (or broken-stick) test; Kaiser's rule (that eigenvalues should be greater than 1), and the principle that components should explain at least 70 – 80% of the retained variance (Jackson, 1993).

A scree plot helped to determine the maximum number of factors (usually indicated by the point before the eigenvalues plot flattens out) that can be extracted from a dataset. While communalities measured the percentage variability in a data and it is regarded as high when its value is greater than 0.8 (Velicer & Fava, 1998); moderate when 0.7; low when 0.4 and considered not related when less than 0.4 (Costello & Osborne, 2005). Thus, factor loading threshold is 0.4 (Costello & Osborne, 2005) and the criteria used in differentiating between different component (drivers of agricultural land use) is Kaiser's rule which involves retention of any component whose eigenvalue is greater than 1 (Wiktorowicz, 2016). Correction for spatial auto - correlation is an important procedure in land use change analysis because spatially - autocorrelated data contradicts the assumption of independence between data points (Anselin, 2002; Millington et al., 2007) and can undermine the power of the regression coefficients (Kok & Veldkamp, 2001; Chou, 1991).

Like several other statistical techniques, PCA, has limitation of being affected by variable scaling thus automatic data normalization is a required operation before conducting PCA (Abdi & Williams, 2010). Secondly, PCA results could be misleading particularly where the data contain outliers (Sapra, 2010). Essentially, the conduct of PCA becomes necessary where large number of variables exist and for initial reduction in dimensionality of the datasets before further statistical analysis are conducted (Johnstone & Lu, 2009).

2. Methodology

2.1 Study area

Selangor is one of the 13 states that constitute Malaysia. Selangor is located between latitudes 2.580N and 3.830N and longitudes 101.170E and 102.000E covering about 8000 square kilometers (Fig. 1). The average daily temperature of the state ranges between 210C to 320C while the mean relative humidity is above 80% (Jasim et al., 2013; Suhaila & Deni, 2010). Of the 13 states in Malaysia, Selangor is the most populous (Fig. 2), most urbanized (Fig. 3) and the richest state (Fig. 4) (Alias et al., 2010). Agricultural sector has contributed significantly to the economic development of the state (Alias et al., 2010; Abdullah and Nakaghozi, 2007). Despite the economic transformation of the state, agricultural sector still remained important in the production of food for the growing population (EoN, 2010) and major source of economic stability to Malaysia during the global economic meltdown thus making the sector a major cause of land use change in Malaysia (Abdullah & Hezri, 2008; Abdullah & Nakaghozi, 2007).

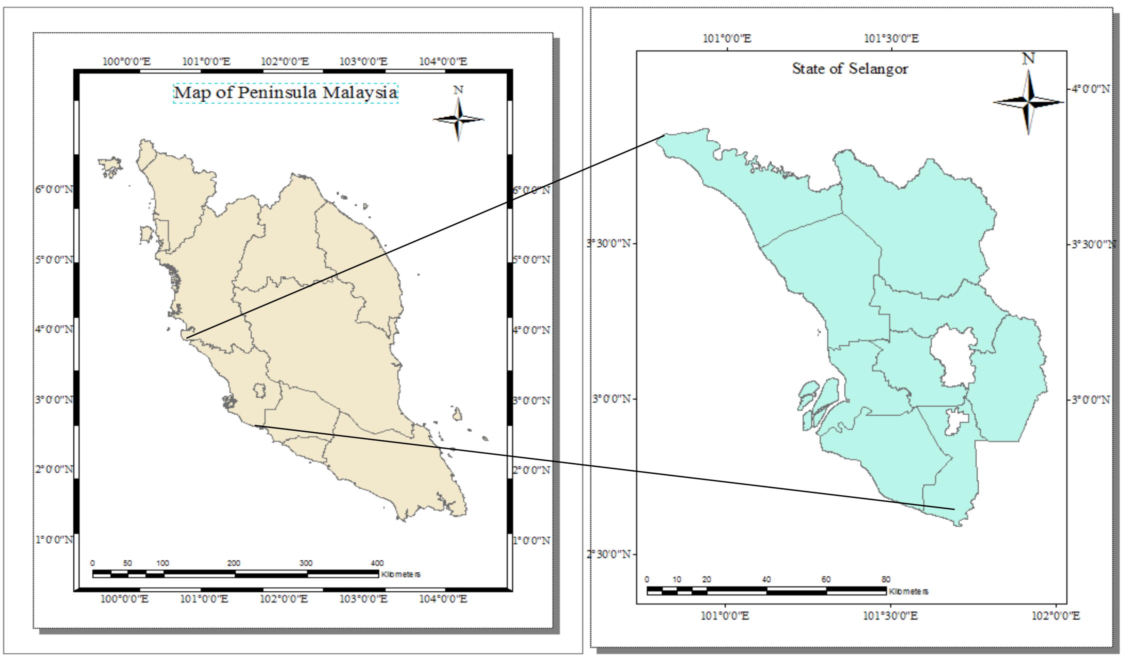


Fig.1 Study area

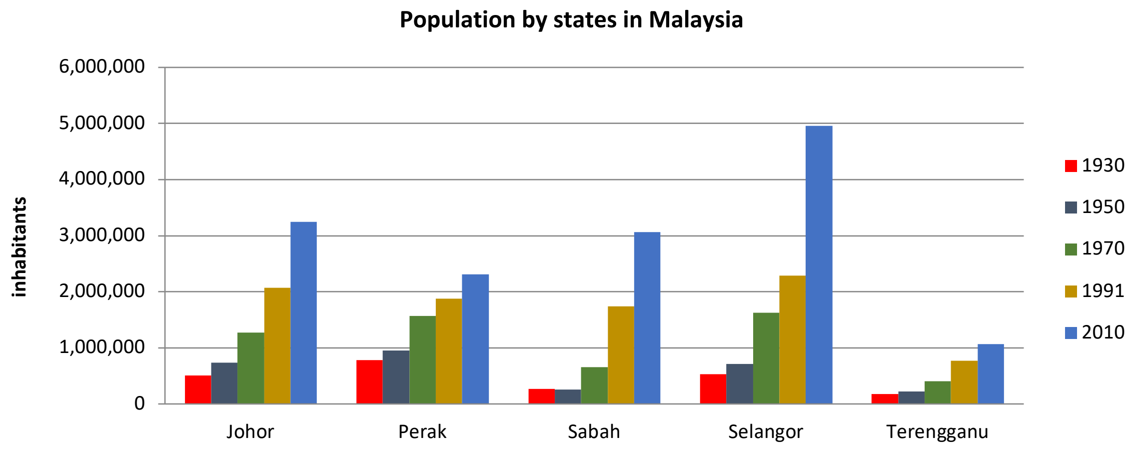


Fig.2 Population data of selected states in Malaysia 1930 – 2010

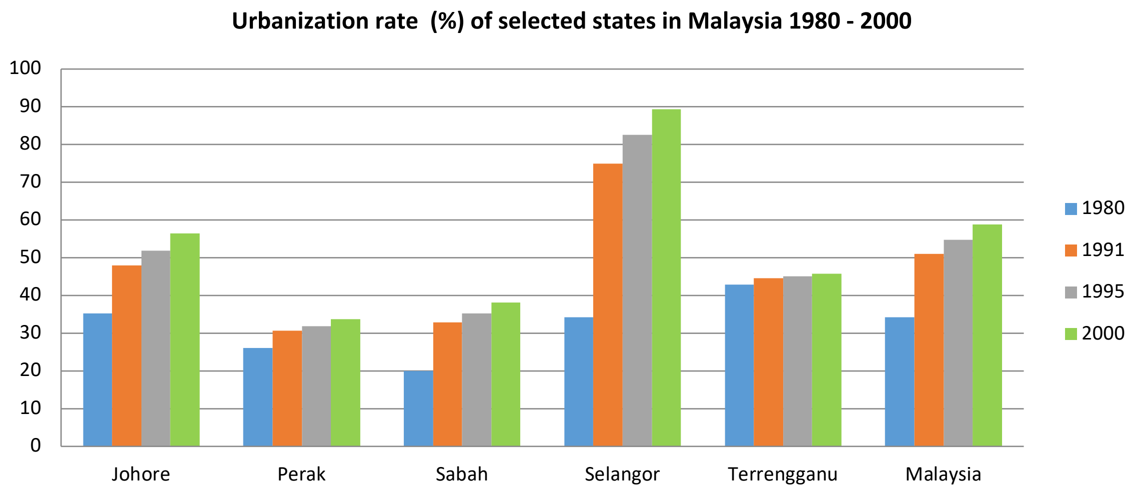


Fig.3 Urbanization rate of selected states in Malaysia 1980 – 2000

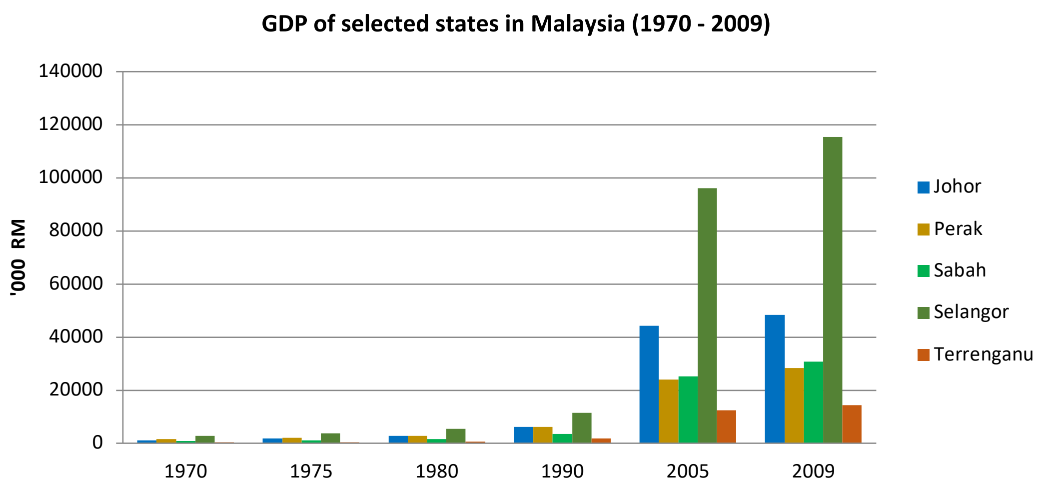


Fig.4 GDP of selected states in Malaysia 1970 – 2009

2.2 Data sources

In conducting this study, it was assumed that the agricultural land use is mainly driven by economic decision (McMorrow and Talip, 2001) therefore locations with low slope, moderate elevation and good soils (Müller et al., 2009; Ioffe et al., 2004) are the most preferred location for agricultural land use (Olaniyi et al., 2013). Climatic factors such as relative humidity, rainfall, temperature and numbers of raining days that are likely to influence agricultural land use were equally selected into the model (Tab.1) (Ge et al., 2008).

Geophysical data derivation

The slope data for the study area were derived from the 1:50,000 contour data using ArcGIS 10.3.1 software and were then converted into a multilayer binary raster data of size 300m (Deng, 2011) to represent the spatial distribution of the landforms (Deng et al., 2006).

Since these data were in form of point, second order inverse distance weightings (IDW) was used to interpolate them to produce a spatial elevation and slope data for the study area (Müller et al., 2008).

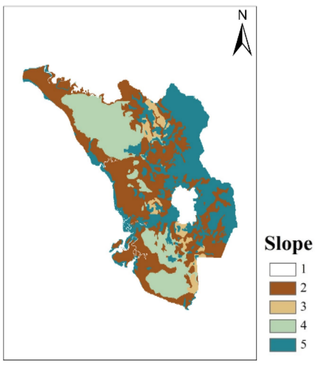
The slope data produced by this method is continuous and was reclassified to several classes (Fig. 5a – 5c) that have been used in related studies (Vasco & Eric, 2010; JUPEM, 2010).

Climatic data

Climatic data such as average annual relative humidity, minimum, maximum, average temperatures and the number of raining days were used to indicate the effects of climate on agricultural land use in the study area (Backlund et al., 2008; Deng et al., 2006).

Kriging spatial interpolation algorithm was used to calculate the value of the variables on each grid before it is imported into the model as parameters (Fig. 5d. – Fig. 5i.) (Deng, 2011). Available evidence from literatures suggest that IDW was the best method for slope interpolation whereas kriging and spline were preferred for climatic dataset because IDW assumes that each measured point has an influence that diminishes with distance (distance decay influence).

However, several studies indicated better performance of kriging over IDW in point estimates (Nusret & Đug, 2009).



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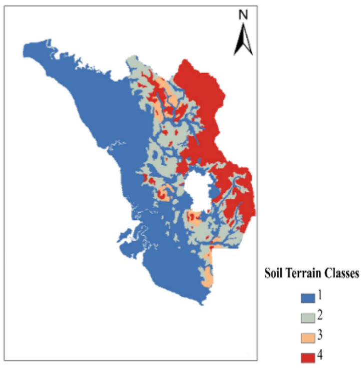

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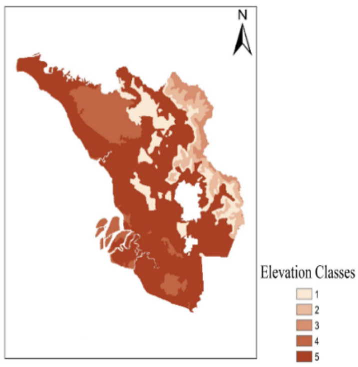

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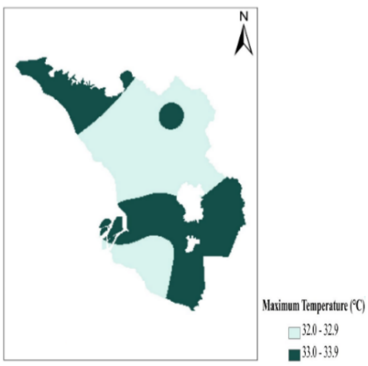

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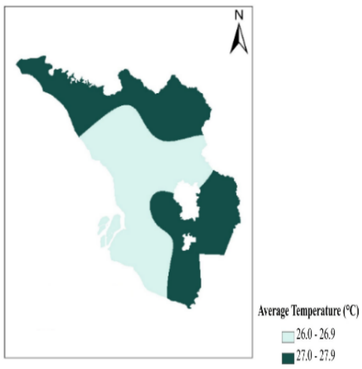

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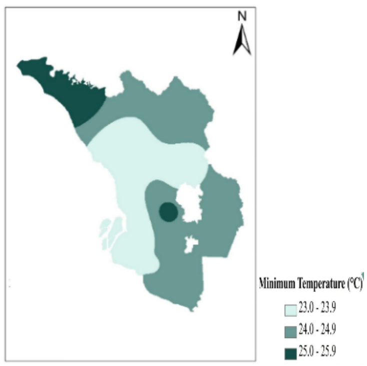

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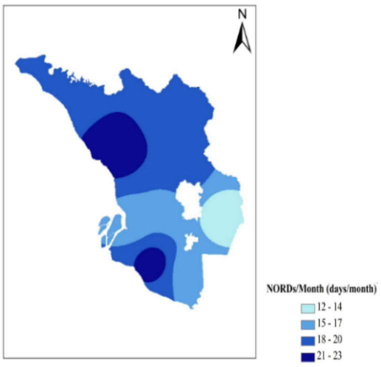

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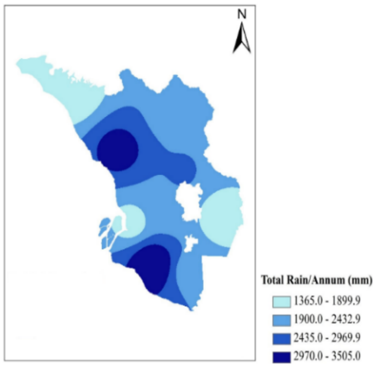

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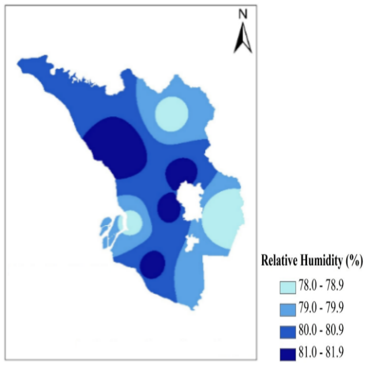

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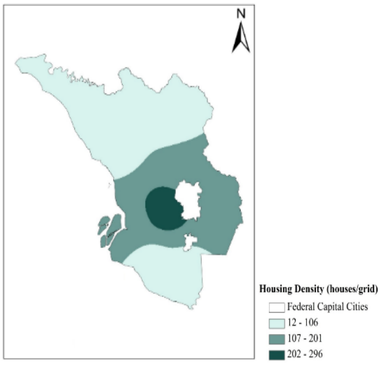

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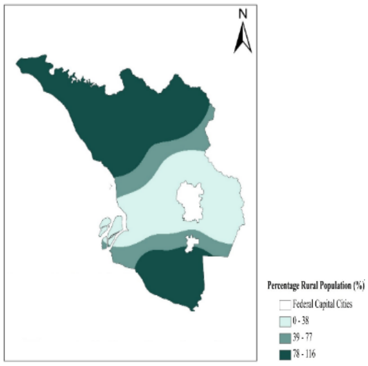

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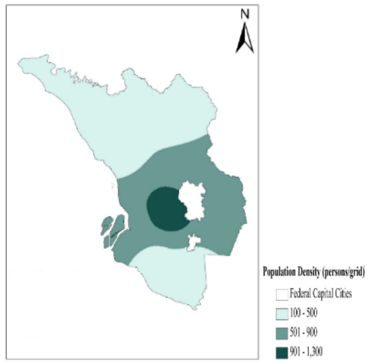

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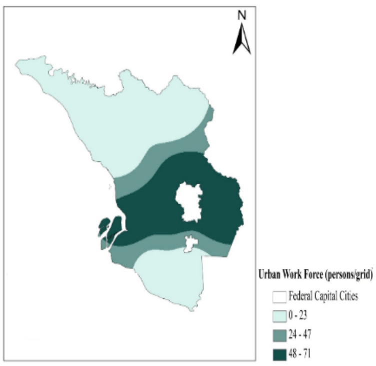

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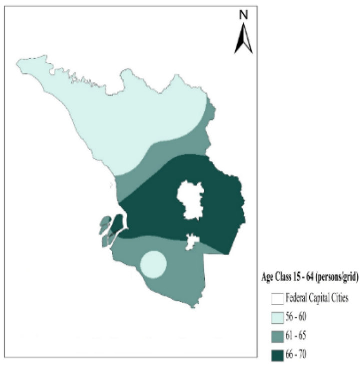

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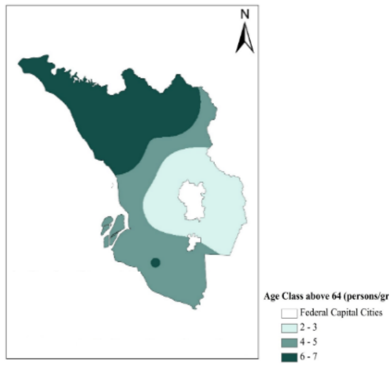

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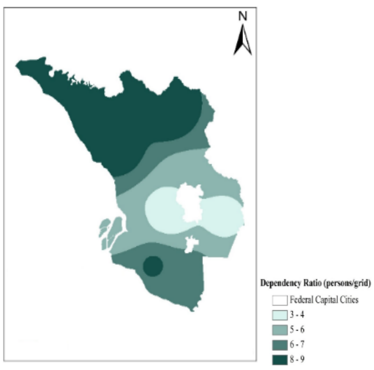

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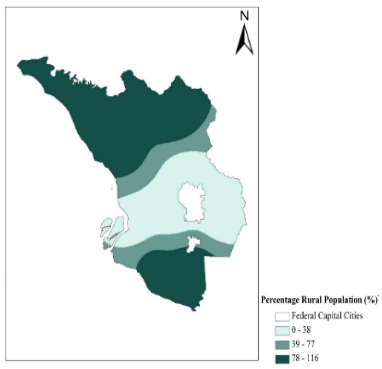

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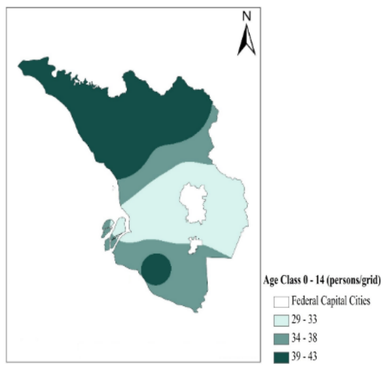

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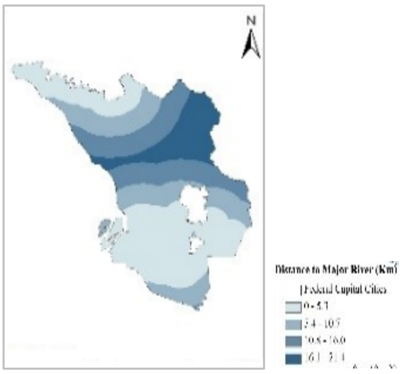

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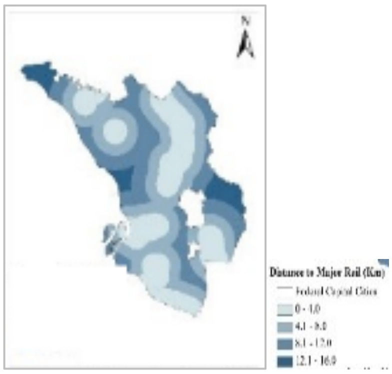

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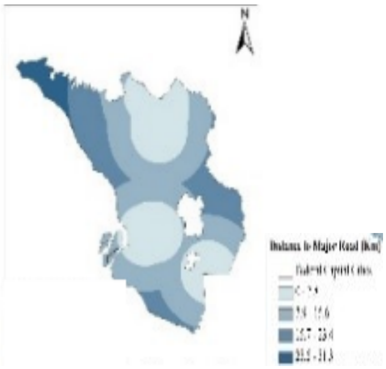

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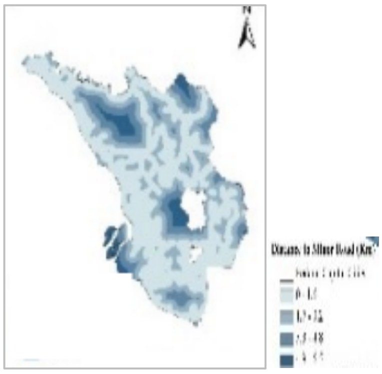

(v)

Fig.5 (a) Slope classes (b) Terrain classes (c) Elevation classes (d) Maximum Temperature (e) Average Temperature (f) Minimum Temperature (g) No of raining days (h) Total Rain (i) Relative Humidity (j) Housing density (k) % Rural Population (l) Population density (m) Urban work force (n) Age class 15-64 (o) Age class >65 (p) Dependency ratio (q) % Rural population (r)Age class 0-14 (s) Distance to major river (t) Distance to rail (u) Distance to major road (v) Distance to minor road

Socioeconomic factors

Socioeconomic variables applied in this study were age category, housing density, urban work force, rural work force, agricultural GDP and non-agricultural GDP.

The socioeconomic variables were disaggregated into district levels. Spline interpolation algorithm (Muller & Zeller, 2002) was employed to convert socio – economic data into a 300m grid cells (Zhuang et al., 2002; Gao & Deng, 2002; Deng et al., 2008).

Spline interpolation was used for spatializing the socio - economic dataset because of the need to retain the observed measurements at points where they were measured (Deng, 2011).

Effects of accessibilities on agricultural land use in this study area were determined by estimating the densities of each mean of transportation (road, rail and river) within each grid cell (Simone et al., 2010; Dai et al., 2005). This was done by estimating the road, rail, and river lengths per square grid cell to obtain road, rail and river densities respectively (Simone et al., 2010; Deng et al., 2008).

All these were digitized from 1:50,000 topographic maps with the ArcMap module of ArcGIS 10.3.1

The impact of urbanization as a proxy for availability of labour and market for agricultural produce was estimated using housing, population densities per grid cell, road densities and percentage urban population. The agricultural productivity in this study area was estimated using spatial distribution of agricultural and non - agricultural GDP.

These variables were estimated from the amount of available labour per unit cell in the rural and or in urban location with assumption of zero mobility of labour and locational productivity of labour. The values were then interpolated using IDW method (Fig.5j – Fig.5v) (Olaniyi et al., 2012). All data were resampled to grid size

(300m) to make them have common spatial extent and resolutions (Huang et al., 2007) thus resulting in 206,736 pixels per disaggregated variable.

2.3 Data preparation for statistical analysis

Conversion of ASCII data into vector columns

The raster format of each variable used in this study was converted into ASCII format. The matrix – based ASCII data were converted to vector column using a code written in matlab program. The total number of columns in this file equalled to the sum of all variables hypothesized to influence agricultural land use (Luijten et al., 2006).

Spatial autocorrelation test

Spatial autocorrelation is a metric used to describe and compare the structure of a spatial dataset (Niu et al., 2018; Hu et al., 2021). Correcting problem due to spatial autocorrelation is an important operation in spatial analysis (Hu et al., 2019; Griffith, 2003; Anselin, 2001) because spatial autocorrelation contradicts the assumption of independence between data points (Millington et al. 2007; Anselin, 2002; Munroe et al. 2002; Lennon, 2000); leads to underestimation of uncertainty thus undermining the power of regression coefficients (Griffith, 2003; Wikle, 2003; Ver Hoef et al. 2001; Kok & Veldkamp, 2001; Chou, 1991; Anselin & Griffith, 1988). Therefore, spatial autocorrelation was conducted in this study with the use of Moran's I test (Millington et al. 2007; De Pinto and Nelson, 2002; Cliff & Ord, 1973) to indicate locations (and this (above twenty eight pixels where samples were selected by systematic sampling techniques (Prishchepov et al., 2013; Millington et al. 2007).

Spatial sampling

After Moran I test (which assist to detect location where samples are to be picked; such as to eliminate spatial autocorrelation), a systematic sampling technique implemented in matLab software was used to select 68,962 pixels from the available 206,736 pixels from both the dependent and independent variables (Prishchepov et al. 2013; Prishchepov et al. 2011). The samples selected represented 30% of the available total number of pixels (Prishchepov et al. 2013; Millington et al. 2007; Verburg et al. 2002). This sampling technique and size was equally applied by Prishchepov et al. 2011 who picked 132,015 (0.25%) samples from 52million pixels in their studies (Prishchepov et al. 2013; Millington et al. 2007; Verburg et al., 2004; Cheng & Masser, 2003; De Pinto & Nelson, 2002; Muller & Zeller, 2002; Carmel et al. 2001; Overmars, 2000).

Disaggregation of hypothesized drivers of agricultural land use

The factors hypothesized to drive agricultural land use applied in this study were spatially explicitly disaggregated into 88 (Tab.1). Xie et al., (2005); Easterly et al., (2003); Brumm et al., (2003); Burnside and Dollar, (2000) have also utilized large variables in similar studies. Of these 88 hypothesized drivers of agricultural land use, Hierarchical Partitioning (HP) statistics was used to rank variables according to their predictive power on the dependent agricultural land use (Millington et al., 2007; Aspinal, 2002).

2.4 Data analysis

Correlation coefficients

In land use change analysis, independence between predictor variables is an important criterion for the application of statistical method. Independence (frequency tables and measures of association) of variables hypothesized to drive agricultural land use was assessed using descriptive statistics (Gobin et al., 2002). This procedure is important to remove redundant datasets (Goetzke et al., 2008; Millington et al., 2007; Menard, 2002) thus, highly correlated variables were rather retained.

Factor analysis

Factor analysis, was performed with the use of principal component analysis (PCA) in order to identify specific dimension in the independent variable (IVs) (Cu Van Pham et al., 2009; Demirci et al., 2006; Agilent Technologies, 2005) using varimax rotation so as to differentiate IVs by factors and to obtain maximum variance (Cu Van Pham et al., 2009). The criterion used in retaining variable was component having eigenvalues greater than 1 - Kaiser's rule.

	IVs	Level of measurement	Unit of measurement	References
	Age above 64			
1		"	2 - 3	Olaniyi et al. 2012
2		"	4 - 5	Olaniyi et al. 2012
3		"	6 - 7	Olaniyi et al. 2012
	Age 15 to 64			
4		"	56 – 60	Olaniyi et al. 2012
5		"	61 – 65	Olaniyi et al. 2012
6		"	66 – 70	Olaniyi et al. 2012
	Age 0 to 14			
7		"	29 – 33	Olaniyi et al. 2012
8		"	34 – 38	Olaniyi et al. 2012
9		"	39 – 43	Olaniyi et al. 2012
	Housing Density			
10		"	12 – 107	Olaniyi et al. 2012
11		"	107 – 202	Olaniyi et al. 2012
12		"	202 – 296	Olaniyi et al. 2012
	Rural Work Force			
13		"	0 – 23	Verburg & Chen, 2000
14		"	24 – 47	Verburg & Chen, 2000
15		"	48 – 71	Verburg & Chen, 2000
	Urban Work Force			
16		"	0 – 21	Deng, 2011
17		"	22 – 43	Deng, 2011
18		"	44 – 65	Deng, 2011
	Population Density			
19		"	100 – 500	Deng, 2011
20		"	501 – 900	Kok & Veldkamp 2001
21		"	901 – 1,300	Kok & Veldkamp 2001
	Percent Urban Population			
22		"	0 – 31	Deng, 2011
23		"	32 – 63	Kok & Veldkamp 2001
24		"	64 – 95	Kok & Veldkamp 2001

	Percent Rural Population			
25		"	0 – 38	Verburg & Chen, 2000
26		"	39 – 77	Verburg & Chen, 2000
27		"	78 – 116	Verburg & Chen, 2000
	Distance to Major Rail			
28		"	0 – 4.0	Deng, 2011
29		"	4.1 – 8.0	Deng, 2011
30		"	8.1 – 12.0	Deng, 2011
31		"	12.1 – 16.0	Deng, 2011
	Distance to Major Road			
32		"	0 – 7.8	Deng, 2011
33		"	7.9 – 15.6	Deng, 2011
34		"	15.7 – 23.4	Deng, 2011
35		"	23.5 – 31.3	Deng, 2011
	Distance to Major River			
36		"	0 – 5.3	Deng, 2011
37		"	5.4 – 10.7	Deng, 2011
38		"	10.8 – 16.0	Deng, 2011
39			16.1 – 21.4	Deng, 2011
	Distance to Minor Road			
40		"	0 – 1.6	Deng, 2011
41		"	1.7 – 3.2	Deng, 2011
42		"	3.3 – 4.8	Deng, 2011
			4.9 – 6.5	Deng, 2011
	Total rain (mm)			
43		"	1,900	Kok & Veldkamp 2001
44		"	2,435	Kok & Veldkamp 2001
45		"	2,972	Kok & Veldkamp 2001
46		"	3,510	Kok & Veldkamp 2001
	Terrclass			
47		"	1	Deng, 2011
48		"	2	Deng, 2011
49		"	3	Deng, 2011
50		"	4	Deng, 2011
51		"	5	Deng, 2011
	Soil Group			
52		"	1	Deng, 2011
53		"	2	Deng, 2011
54		"	3	Deng, 2011
55		"	4	Deng, 2011
56		"	5	Deng, 2011
	Soil Suitability Classes			
57		"	1	Verburg & Chen, 2000
58		"	2	Verburg & Chen, 2000
59		"	3	Verburg & Chen, 2000
60		"	4	Verburg & Chen, 2000
	Slope Class			
61		"	1	Mottet et al. 2006
62		"	2	Mottet et al. 2006
63		"	3	Mottet et al. 2006
64		"	4	Mottet et al. 2006

65	"	5	Mottet et al. 2006
66	"	6	Mottet et al. 2006
Relative Humidity (%)			
67	"	79	Verburg & Chen, 2000
68	"	80	Verburg & Chen, 2000
69	"	81	Verburg & Chen, 2000
70	"	82	Verburg & Chen, 2000
Average Temperature ^{0}C			
71	"	27	Verburg & Chen, 2000
72	"	28	Verburg & Chen, 2000
Elevation Class			
73	"	1	Vasco and Eric, 2010
74	"	2	Vasco and Eric, 2010;
75	"	3	Vasco and Eric, 2010
76	"	4	Vasco and Eric, 2010
77	"	5	Vasco and Eric, 2010
78	"	6	Vasco and Eric, 2010
	"	7	Vasco and Eric, 2010
Maximum Temperature ^{0}C			
79	"	32	Serra et al. 2008
80	"	33	Serra et al. 2008
Minimum Temperature ^{0}C			
81	"	23	Serra et al. 2008
82	"	24	Serra et al. 2008
83	"	25	Verburg & Chen, 2000
NORDs(days/mth)			
84	"	13	Kok & Veldkamp 2001
85	"	15	Kok & Veldkamp 2001
86	"	18	Kok & Veldkamp 2001
87	"	20	Kok & Veldkamp 2001
88	"	23	Kok & Veldkamp 2001
Spatial Effects	Every 30th	Every 30th	Muller and Zeller, 2002

NORDs: Number of Raining Days; Max Temp: Maximum Temperature; Min Temp : Minimum Temperature

Tab.1 Hypothesized drivers of agricultural land use in Selangor

3. Findings

The result on Tab.1 showed the hypothesized drivers of agricultural land use in the study area. From the table, about 27 potential factors driving agricultural land use were selected into the study. These 27 hypothesized variables were later disaggregated into 89 (Tab.1).

From the 89 variables, hierarchical partitioning test selected and identified 26 most significant variables influencing agricultural land use in the study area. The descriptive statistics of the 27 significant variables were presented on Tab.2.

The PCA extracted 7 principal components which explained 88.1 % of the agricultural land use in the study area (Tab.3 and 4). PC 1, explained 33.3 % of the variance, with loadings between 0.679 and 0.892. This component indicated influence of urbanization on agricultural land use (Tab.3 and 4).

PC 2 showed impacts of availability of farm labour with highest loading being 0.825 and least being 0.531. This factor explains 21.2% of the total variation (Tab.3 and 4). PC 3 is highly correlated with three variables representing ageing of the farm labour with highest loading being 0.844 and least being 0.709.

This factor explained 12.2% of the driving forces behind agricultural land use (Tab.3 and 4). The component 4 indicated the transfer/release of labour from the agricultural sector to the industrial sector. This factor explained 7.3% of the reason behind agricultural land use with loading varying from 0.766 to 0.867 (Tab.3 and 4).

PC 5 is a factor that can be used to represent the effects of geophysical factors in agricultural land use. This factor was captured by elevation, terrain and slope class.

This factor explained 5.8% of the total variation of the original data (Tab.3 and 4)with loading between 0.705 to 0.851. PC 6 indicated importance of accessibility on agricultural land use.

This factor explains 4.4% of the total variance and it was captured by distance to minor road, distance to major road and distance to major river (Tab.3 and 4). PC 7 can be used to describe the effects of climate variables on agricultural land use in the study area. This factor explained 4.0% variation in agricultural land use (Tab.3 and 4) with variables such as maximum temperature, total rainfall and relative humidity being most important variables.

S/No	IVs	Min	Max	Mean	Std Dev
1	age above 64	2	5	4	1
2	age 0 to 14	29	40	37	3
3	average Temp	27	28	27.89	0.84
4	dep ratio	5	8	7	1
5	ds2majral	0	75,240	21,473.9	15,802.7
6	ds2majrd	0	89,120.2	35,056.2	20,048.2
7	ds2minrd	0	73899.9	12,813.2	15,719.2
8	ds2majrv	0	63,488	11,562	13,654
9	elevation	1	9	6.97	3.05
10	age 15 to 64	56	68	59	4
11	housing density	12	296	67	77
12	maxtemp	32.3	35.6	33.6	0.71
13	mintemp	23	25	22.3	0.69
14	NORDs	13	23	18.8	4.8
15	percent rural	7.1	100	58.9	3
16	percent urban	0	92.9	40.8	34.7
17	pop density	100	1,400	300	40
18	rel.humidity	79	82	81.98	0.89
19	rural GDP	49	194	109	37
20	Ruralwkfc	4	59	33	20
21	Slope	1	4	2.3	1.42
22	soil class	1	5	3.43	1.33
23	soil suitability	1	4	2.29	1.31
24	Terrain	1	5	3.45	1.32
25	total rain	1,360	3,510	2,489	6.74
26	urban GDP	0	8,935	1,282.4	2,606.2
27	Urbanwkfc	0	64	26	23

Average temp: average temperature; dep ratio: dependency ratio; ds2majral: distance to major rail; ds2majrd: distance to major road; ds2minrd: distance to minor road; ds2majrv: distance to major river; NORDs: number of raining days; pop density: population density; rel humidity: relative humidity; ruralwkfc: rural work force; rural GDP: rural gross domestic product; urban GDP: urban gross domestic product; urban wkfc: urban work force.min: minimum; max : maximum; std dev: standard deviation

Tab. 2 Summary of the hypothesized drivers of agricultural land use

Total Variance Explained									
	Initial Eigenvalues			**Extraction Sums of Squared Loadings**			**Rotation Sums of Squared Loadings**		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	8.665	33.327	33.327	8.665	33.327	33.327	7.154	27.516	27.516
2	5.499	21.151	54.478	5.499	21.151	54.478	3.967	15.258	42.775
3	3.178	12.222	66.700	3.178	12.222	66.700	2.787	10.718	53.493
4	1.892	7.279	73.978	1.892	7.279	73.978	2.369	9.110	62.603
5	1.497	5.759	79.738	1.497	5.759	79.738	2.318	8.914	71.517
6	1.144	4.400	84.137	1.144	4.400	84.137	2.243	8.626	80.143
7	1.031	3.965	88.102	1.031	3.965	88.102	2.069	7.959	88.102
8	0.802	3.083	91.186						
9	0.637	2.448	93.634						
10	0.544	2.092	95.726						
11	0.366	1.408	97.134						
12	0.294	1.130	98.264						
13	0.233	0.896	99.160						
14	0.120	0.462	99.621						
15	0.037	0.141	99.762						
16	0.027	0.105	99.868						
17	0.015	0.058	99.925						
18	0.013	0.049	99.974						
19	0.005	0.019	99.993						
20	0.002	0.006	99.999						
21	0.000	0.001	100.000						

Extraction Method: Principal Component Analysis

Tab.3 Variance explained by the identified components

Rotated Component Matrix[a]							
IVs	**Component**						
	1	2	3	4	5	6	7
ds2majrd_1	0.278	-0.372	-0.202	-0.005	0.210	**0.807**	0.041
ds2minrd_1	-0.001	0.222	0.268	-0.009	0.165	**0.772**	0.132
ds2majrv_1	-0.001	0.222	0.668	-0.009	0.165	**0.762**	0.132
elev _3	0.388	0.083	0.531	0.118	**0.851**	0.214	0.567
terrclas_1	0.275	-0.034	0.453	0.343	**0.773**	0.125	0.785
slopeclass_2	0.562	0.461	0.212	0.407	**0.717**	0.224	0.249
suit_1	0.119	0.164	0.992	0.231	**-0.705**	0.015	0.845
ubnwkfc21_42	**0.892**	-0.100	0.947	-0.014	-0.08	0.132	0.169
ubnwkfc42_64	**-0.881**	-0.040	-0.073	0.466	0.838	0.131	0.089
ubnwkfc0_21	**0.846**	0.235	-0.133	-0.064	-0.073	0.016	0.107
pctubn31_62	**0.805**	0.540	0.582	-0.017	-0.129	0.227	0.194
popden100_500	**0.799**	0.177	0.316	-0.067	-0.107	0.077	0.179
hden12_107	**0.679**	0.177	0.316	-0.067	-0.107	0.077	0.179
rurwkfc0_33	-0.176	**0.825**	-0.073	0.464	0.837	-0.041	0.090
age15to64_56_60	0.288	**0.773**	0.308	**-0.867**	-0.963	0.177	0.185
age15to6460_64	-0.119	**0.723**	-0.092	**0.859**	0.217	-0.015	0.129
age15to6464_68	-0.122	**0.694**	-0.007	**-0.766**	0.914	-0.035	-0.006
ag0to14_37_40	0.199	**0.677**	0.316	-0.067	-0.107	0.177	0.179
agabv64_3_4	0.160	**0.635**	**0.844**	-0.051	-0.008	0.112	0.096

IVs	Rotated Component Matrix[a] Component						
	1	2	3	4	5	6	7
agabv64_4_5	0.287	**0.603**	**-0.803**	-0.041	-0.112	0.118	0.135
pctrur69_100	0.195	**0.588**	**-0.709**	-0.065	-0.022	-0.216	0.057
pctrur0_38	-0.180	**0.531**	-0.073	0.466	0.838	-0.040	0.089
maxtemp_32	0.318	-0.463	-0.142	-0.008	-0.050	0.077	**-0.837**
maxtemp_33	0.105	0.581	-0.079	-0.033	0.671	0.315	**0.834**
totalrain_2435	-0.045	-0.002	0.034	0.886	0.106	-0.161	**-0.732**
relhum_80	0.334	0.185	0.002	-0.045	-0.029	0.182	**0.649**

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization

a. Rotation converged in 8 iterations.

Tab.4 Components extracted by principal component analysis and varimax rotation method

4. Discussion

4.1 Impact of urbanization

Industrialization and urbanization are very important determinant of the rate of agricultural land conversion into non - agricultural uses. Futhermore, high population densities might result to increase in agricultural land use for horticultural products and animal protein which may lead to the conversion of arable farmland into orchards and fish ponds (Olaniyi et al., 2012; Mottet et al., 2006) or lead to rural dwellers abandoning their farmlands for more profitable and non – agricultural activities (Mazzeo & Russo, 2016; Rigg, 2006; Rigg & Nattapoolwat, 2001).

4.2 Availability of agricultural labour

This study indicated that availability of labour for agricultural production is the most important factor in agricultural land use in the study area accounting for 40 – 60% of the cost of production (Arshad et al., 2007). Despite the high labour requirement in agricultural production, available agricultural labour in Malaysia has been decreasing from 1980 till date as a result of economic transformation (Arshad et al., 2007; Vincent and Rozali, 2005). Since 1990, the average and marginal return per labour in the agricultural sector is below what is obtained in the other sectors, outflow of labour from agricultural to non-agricultural sectors will continued to be experienced in Malaysian agricultural economy (Arshad et al., 2007) thus leading to observed aging of agricultural labour (Olaniyi et al., 2011; Arshad et al., 2007; MDoA, 2003).

4.3 Ageing of farm labour

Malaysian agricultural production like every other country's agricultural production is suffering due to ageing of the farm labour (Hayrol Azril et al., 2009; Ezhar et al., 2007). While agricultural transformation has been acknowledged to assist the country to achieve the expected economic growth and development to a high income country National Transformation 2050 (2021 - 2050), ageing of the farmers would be impediments to achieving this ambition. The ageing problem will exacerbate the rural-urban income differential. Government's reactions to the farmers ageing condition defer. For instance, in France and Korea, the government were buying out ageing farmers and granting them secure lifelong pensions and thereafter attract youth agropreneurs after farm consolidation. In Malaysia ageing of farmers has led to the reliance on migrant labor as a source of labour.

4.4 Cross sectoral mobility of labour

Several factors are responsible for inter sectoral mobility of labour. Geenaway et al. 2000 argued that globalization, trade, technological changes and differences in inter sectoral returns on labour investments are the major factors causing labour mobility. Significant agricultural transformation as a result of technological advancement witnessed in Malaysia has led to the release of farm labour to the industrial sector due to higher rate of return on labour in the secondary and the tertiary sectors has equally favoured the release (Bakar, 2021; World Bank, 2019). However, as land is also becoming scarce because of the government's policy of restraining the expansion of farmland to forest areas. There is an indication that the future of agriculture in the country will be dependent on intensive farming (Sidique & Shaharudin, 2019).

4.5 Geophysical factors

This study has found the location of the agricultural land use to be closely related to the geo-physical condition of the area. Elevation and slope are two important geophysical factors influencing suitability of a location for agricultural usage. For example, Huang et al., 2007 reported a decrease of 0.50C – 0.60C in temperature and an increase of 92mm in rainfall for every 100m increase in elevation. Also, at a higher elevation, agricultural land use is less probable because, the difficulty of the terrain will make the agricultural activities on such land not to be feasible (Qasim et al., 2013). Likewise, agriculture on steeper slopes and poorer soils will be more difficult and less profitable (Bender et al., 2005; Mottet et al., 2006).

Drivers of agricultural land use include availability of suitable agricultural land (FAO, 1976). Variables used to capture this factor in this study include soil suit_1; terrain class 1, elevation class_3 and slope class_2. Agricultural land uses were found to be prominent on flat or relatively gentle slope. These areas are locations where agricultural practices could be done with ease and (Qasim et al., 2013; Koulouri and Giourga 2007). Suitable agricultural land is the land that is characterized by elevation between the range of 750m – 1000m; slope between 0 - 150 and terrain class 1 (Qasim et al., 2013).

4.6 Accessibility

Distance to transportation infrastructures has been identified as a major driver of agricultural land use. (Deng, 2011; Vasco and Eric, 2010) since accessibility serves as the means of transportation of agricultural produce to the local markets and inputs to the farm. Available literatures have indicated that land use is related by the transportation systems through the movement of passengers and freights. The influence mechanism of accessibility on land use and landscape pattern is complex and is a function of socio – economic, demographic and cultural factors, land availability, land demand and spatial policy (Yongwei et al., 2020) and has been linked to the land fragmentation (Yongwei et al., 2020; Kaphegyi et al., 2012) and landscape pattern.

4.7 Climatic factors

Effects of climatic factors is crop specific and dependent on the stage of growth of the crop and could be synergistic with other non - climatic factors to produce greater impacts (Siwar et al., 2011; Anete & Amusa, 2010). In Malaysia, where temperature of most planted areas is already at the optimum range, slight fluctuation in temperature is not likely to the affect yield but rainfall variability would limit agricultural productivity (MMD, 2009). While, oil palm and coconut prefer warm and humid conditions (Kumar et al., 2009). However, excessive humid condition would impact their development because of the reduction in the transpiration ability, reduce pollination, embryo and fruit development (Kumar et al., 2009); provide suitable condition for the spread of bud rot diseases in oil palm (Arshad et al., 2012). High temperature would diminish rainfall, reduce soil moisture due to increase in evaporation, impair the growth of crops in non – irrigated areas and increase the risk of pests, diseases and weeds on crops (Siwar et al., 2011; Al - Amin & Siwar, 2008).

5. Conclusion

The drivers of agricultural land use in Selangor, Malaysia have been identified and characterized with the use of PCA. Use of PCA as a statistical tool in this study is based on its ability to reduce and categorize the variables into their components. Significant variables retained in the study were chosen by inspecting the components with eigenvalues higher than the unity. The appropriateness of PCA for these datasets were determined with Kaiser – Meyer – Olkin (KMO) and Bartlett's tests. Kaiser-Meyer-Olkin (KMO) measure was used to test whether the partial correlations among variables are minimal. While Bartlett's test was used to ascertain whether the correlation matrix was an identity matrix or not. Eventually, major drivers of agricultural land use that were identified in this study include availability of agricultural labour, urbanization, accessibility, climatic factors, geophysical factors and availability of suitable agricultural land. These six variables driving agricultural land use in the study area can be broadly categorized into geophysical, climatic and socio - economic factors. For the geophysical factors, variables such as slope, soil series, elevation and land suitability, climatic variables include number of raining days, relative humidity, maximum and average temperatures while for the socio – economic factors, variables such as availability of farm labour, accessibility and urbanization are very important. The story of Malaysian transition from low to middle - income country is one of the world's most successful one. However, the government target of achieving high income status by the year 2030 may not be possible without inclusive growth in the agricultural sector. This proposed economic growth would bring about increased pressures on the agricultural resources in the study area (FAO, 2020 & 2002). Expected demographic increase consequent upon the economic growth would further increase pressures on the agricultural resource inputs (land, labour, capital and management) therefore the need for the policy makers to put in place measures that would minimize environmental effects of these impacts in order to make the proposed transition sustainable.

References

Abdullah, A.S. & Hezri, A.A. (2008). From forest landscape to agricultural landscape in the developing tropical countries of Malaysia: Pattern, Process and their Significance on Policy. *Environmental Management*, 42, 907 – 917. https://doi.org/10.1007/s00267-008-9178-3

Abdullah, S.A. & Nakagoshi, N. (2007). Forest fragmentation and its correlation to human land use change in the state of Selangor, Peninsular Malaysia. *Forest Ecology and Management*, 241, 39 - 48. https://doi.org/10.1016/j.foreco.2006.12.016

Abdullah, F.A. & Abu Samah, B. (2013). Canadian Center of Science and Education 120 Factors Impinging Farmers' Use of Agriculture Technology. *Asian Social Science,* (9), 3. http://dx.doi.org/10.5539/ass.v9n3p120

Alias, N.Z., Abdul Rashid, M.A. & Kok - Chye, J.F. (2010). State of Selangor. *Economic Research*, Vol. ER/001/2011. Malaysian Rating Corporation Berhad (364803-V). KDN No: PP 14787/11/ 2011(026546).

Agilent Technologies (2004). Principal components analysis.

Al – Amin, A.Q. & Siwar, C. (2008). The economic dimensions of climate change: impacts and adaptation practices in Malaysia", Proceedings of the 9th international business research conference, Novotel Hotel, Melbourne, Australia, 24 – 26th November, 2008.

Alexander, P. et al. (2015). Drivers for global agricultural land use change: Te nexus of diet, population, yield and bioenergy. *Global Environmental Change,* 35, 138 – 147 (2015). https://doi.org/10.1016/j.gloenvcha.2015.08.011

Anete, A.A. & Amusa, T.A. (2010). Challenges of agricultural adaptation to climate change in Nigeria: a synthesis from the literature. *Journal of Field Action,* 4.

Anselin, L. (2001). Spatial Effects in Econometric Practice in Environmental and Resource Economics. In: *American Journal of Agricultural Economics*, Vol. 83 (3), pp. 705 – 710.

Anselin, L. (2002). Under the hood: issues in the specification and interpretation of spatial regression models, *Agricultural Economics*, 27: 247 – 267. https://doi.org/10.1111/j.1574-0862.2002.tb00120.x

Anselin, L. & Griffith, D.A. (1988). Do spatial effects really matter in regression analysis ? *Pap. Regional Sci. Assoc.* 65, 11 – 34. https://doi.org/10.1111/j.1435-5597.1988.tb01155.x

Arshad, F.M., Abdullah, R.M.N., Kaur, B. & Abdullah, M.A. (2007). *50 years of Malaysian agriculture: transformational issues, challenges and direction*. Penerbit UPM, Serdang.

Arshad, M.A., Armanto, E.M. & Zain, M.A. (2012). Evaluation of climate suitability of oil palm (Elaeis guineensis Jacq.) cultivation. *Journal of Environmental Science and Engineering*, 272 – 276.

Aspinall, R.J. (2002). Use of logistic regression for validation of maps of the spatial distribution of vegetation species derived from high spatial resolution hyperspectral remotely sensed data. *Ecological Modelling*, 157, 301 - 312. https://doi.org/10.1016/S0304-3800(02)00201-6

Backlund, P., Janetos, A.C. & Schimel, D. (2008). *The effects of climate change on agriculture, land resources, water resources, and biodiversity*. Climate Change Science Program Synthesis and Assessment Product 4.3, Washington, DC.

Bakar, B.B. (2021). The Malaysian agricultural industry in the new millennium: issues and challenges. Retrieved from: htpp//core.ac.uk/download/pdf/162013301.pdf. accessed on 2021/03/16.

Batty, M. & Longley, R. (1994). Urban modeling in computer-graphic and geographic information system environments. *Environment and Planning B*, 19, 663 – 688. https://doi.org/10.1068/b190663

Bender, O., Boehmer, H.J., Jens, D. & Schumacher, K.P. (2005). Using GIS to analyze long term cultural landscape change in Southern Germany. *Landscape Urban Planning*, 70(2), 111 – 125. https://doi.org/10.1016/j.landurbplan.2003.10.008

Bockstael, N.E. (1996). Modeling economics and ecology:The importance of a spatial perspective. *Am. J. Agric. Econ.,* 78, 1168 – 1180. https://doi.org/10.2307/1243487

Burnside, C. & Dollar, D. (2000). Aid, policies and growth. *American Economic Review*, 90, 847 – 868.

Carmel, Y., Kadmon, R. & Nirel, R. (2001). Spatiotemporal predictive models of Mediterranean vegetation dynamics. *Ecological Applications*, 11: 268 – 280. https://doi.org/10.1890/1051-0761

Cheng, J., Masser, I. (2003). Urban growth pattern modelling, a case study of Wuhan, P.R.China. *Landscape and Urban Planning*, 62(4), 199 - 217. https://doi.org/10.1016/S0169-2046(02)00150-0

Chou, Y.H. (1991). Map resolution and spatial autocorrelation *Geogr. Anal.*, 23, 228 – 246. https://doi.org/10.1111/j.1538-4632.1991.tb00236.x

Cliff, A. & Ord, J.K. (1973). *Spatial autocorrelation.* London: Pion Press.

Cochard-Picon, C., Pilon, R., Tarroux, E., Pages, L., Robertson, J. & Dawson, L. (2012). Effect of species, root branching order and season on the root traits of 13 grass species. *Plant and Soil,* 353, 47 – 57. https://doi.org/10.1007/s11104-011-1007-4

Costello A.B. & Osborne J.W. (2005). *Best practices in exploratory factor analysis: four recommendations for getting the most from your analysis,* practical assessment, research & evaluation, 10,(7). Retrieved from: http://pareonline.net/getvn.asp?v=10&n=7 (accessed: 2021/01/30).

Cu, P.V., Charrette, P. & Dieu, D.T. (2009). Application of the principal component analysis to explore the relation between land use and solid waste generation in the Duy Tien district, Ha Nam Province, Vietnam. *Journal of Science, Earth Sciences,* 25, 65 – 75.

Dai, E., Wu, S., Shi, W., Cheung, C. & Shaker, A. (2005). Modeling change-pattern-value dynamics on land use: An integrated GIS and artificial neural networks approach. *Environmental Management, 36*(2), 1 – 17.https://doi.org/10.1007/s00267-004-0165-z

De Pinto, A. & Nelson, G.C. (2002). Correcting for spatial effects in limited dependent variable regression: Assessing the value of "Ad-Hoc" techniques. Paper prepared for the American Agricultural Economics Association annual meeting, Long Beach, California. https://doi.org/ 10.22004/ag.econ.19782

Dendoncker, N., Rounsevell, M. & Bogaert, P. (2007). Spatial analysis and modelling of land use distributions in Belgium. *Computers, Environment and Urban Systems, 31*(2), 188 – 205. https://doi.org/10.1016/j.compenvurbsys.2006.06.004

Deng, X.Z., Huang, J.K., Rozelle, S. & Uchida, E. (2006). Cultivated land conversion and potential agricultural productivity in China. *Land Use Policy,* 23(4), 372 – 384. https://doi.org/10.1016/j.landusepol.2005.07.003

Deng, X.Z., Su, H.B. & Zhan, J.Y. (2008). Integration of multiple data sources to simulate the dynamics of land systems. *Sensors*, 8(2), 620 – 634. https://doi.org/10.3390/s8020620

Deng, X. (2011). *Modeling the dynamics and consequences of land system change.* Higher Education Press, China. 250.

Dinç, G. & Gül, A. (2021). Estimation of the future land cover using Corine Land Cover data. *Tema. Journal of Land Use, Mobility and Environment,* 14 (2), 177 - 188. http://dx.doi.org/10.6092/1970-9870/7671

Easterly, W., Levine, R. & Roodman, D. (2003). *New data, new doubts: a comment on Burnside and Dollar's aid, policies and growth's*. National Bureau of Economic Research, Cambridge, Mass. NBER Working Paper 9846,

EoN, (2010). Agriculture in Malaysia. Encyclopedia of Nations. Retrieved from: http://www.nationsencyclopedia.com/economies/Asia-andthe-Pacific/Malaysia-AGRICULTURE.html. (accessed on 16/03/2021)

Ezhar, T., Rahim, M. S., Zainal Abidin, M., Mohamed Rezal, H. & Zamre, Y. (2007). *Micro agro - based entrepreneurs' readiness in facing agricultural challenges.* IPSAS Monograph Series Bil. 1/2007, University Putra Malaysia Publisher, Serdang, Malaysia.7.

Grifith, D.A. (2003). Spatial autocorrelation and spatial filtering: gaining understanding through theory and scientific visualization New York, Springer-Verlag.

Guo, G., Wen, Q. & Zhu, J. (2015). The impact of ageing agricultural labor population on farmland output: from the perspective of farmer preferences. *Mathematical Problems in Engineering,* https://www.hindawi.com/journals/mpe/2015/730618/

Food and Agriculture Organization FAO (1976). *A framework for land evaluation* (Soils Bulletin No. 32). Rome: Food and Agriculture Organization of the United Nations.

FAO, 1996. Report of the World Food Summit (Rome: FAO).

FAO, (2002). *The role of agriculture in the development of least-developed countries and their integration into the world economy*. Retrieved from: http://www.fao.org/3/y3997e/y3997e.pdf. (accessed on 2021/01/03)

FAO, (2020). *Agriculture at a crossroad: International assessment of agricultural knowledge, science and technology for development.* Retrieved from: http://www.fao.org/fileadmin/templates/est/Investment/Agriculture_at_a_Crossroads_Global_Report_IAASTD.pdf. (accessed on 06/10/2021)

Franklin, S.B., Gibson, D.J., Robertson, P.A., Pohlmann, J.T. & Fralish, J.S. (1995). Parallel analysis: a method for determining significant principal components. *Journal of Vegetation Science,* 1, 99 – 106. https://doi.org/10.2307/3236261

Fujii, T. (2008). How well can we target aid with rapidly collected data? Empirical results for poverty mapping from Cambodia. *World Development, 36*(10), 1830–1842. https://doi.org/10.1016/j.worlddev.2007.10.013

Gao, Z.Q. & Deng, X.Z. (2002). Analysis on spatial features of LUCC based on dataset of land use and land cover change in China. *Chinese Geographical Science*, 12(2), 107 – 113. https://doi.org/10.1007/s11769-002-0017-9

Ge Q.S., Dai, J.H., He, F.N., Pan, Y. & Wang, M.M. (2008). Land use changes and their relations with carbon cycles over the past 300 years in China. *Science in China Series D – Earth – Sciences*, 51(6), 871 – 884.

Gobin A., Camping, P. & Feyen, J. (2002). Logistic modelling to derive agricultural land use determinants: A case study from Southeastern Nigeria. *Agriculture, Ecosystems and Environment*, (89), 213 – 228. https://doi.org/10.1016/S0167-8809(01)00163-3

Goetzke, F. (2008). Network effects in public transit use: evidence from a spatially autoregressive mode choice model. *Urban Studies*, (45), 407 – 417. https://doi.org/10.1177/0042098007085970

Greenaway, D., Upward, R. & Wright, P. (2000). Sectoral transformation and labour market flows. *Oxford Review of Economic Policy, 16*,(3), 57 - 75. https://doi.org/10.1093/oxrep/16.3.57

Hassanzadeh, Z., Ghavami, R. & Zareh, M.K. (2016). Radial basis function neural networks based on the projection pursuit and principal component analysis approaches: QSAR analysis of fullerene[C60]-based HIV-1 PR inhibitors*. Medicinal Chemistry Research, (25*), 19–29. https://doi.org/ 10.1007/s00044-015-1466-x

Hayrol Azril, M. S., Md Salleh, H. & Bahaman, A.S. (2009). Level of Agro-based Website Surfing among www.ccsenet.org/ass Asian Social Science Vol. 9, No. 3; 2013 124 Malaysian Agricultural Entreprenuers: A Case Study of Malaysia. *Journal of Agriculture and Social Science,* (5), 55 - 60.

Hotelling, H. (1933). Analysis of a complex of statistical variables into principal components. *Journal of Educational Psychology,* (24), 417–441. https://doi.org/10.1037/h0071325

Hu, Y., Batunacun, X., Zhen, L. & Zhuang, D. (2019). Assessment of Land-Use and Land Cover Change in Guangxi, China. *Scientific Reports,* 9: 2189 | https://doi.org/10.1038/s41598-019-38487-w

Huang, Q.H., Cai, Y.L. & Peng, J. (2007). Modeling the spatial pattern of farmland using GIS and multiple logistic regression: a case study of Maotiao River Basin, Guizhou Province, China. *Environmental Model Assessment*, (12), 55 – 61. https://doi.org/10.1007/s10666-006-9052-8

Ioffe, G., Nefedova, T. & Zaslavsky, I. (2004). From spatial continuity to fragmentation: the case of Russian farming. *Annals of the Association of American Geographers*, (94), 913 – 943. https://doi.org/10.1111/j.1467-8306.2004.00441.x

Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services [IPBES] (2018). *Summary for policymakers of the assessment report on land degradation and restoration of the Intergovernmental Science Policy Platform on Biodiversity and Ecosystem Services*. Scholes, R., Montanarella, L., Brainich, A., Barger, N., ten Brink, B., Cantele, M., Erasmus, B. , Fisher, J., Gardner, T., Holland, T.G., Kohler, F., Kotiaho, J.S., Von Maltitz, G. , Nangendo, G., Pandit, R., Parrotta, J., Potts, M.D., Prince, S., Sankaran, M. & Willemen L. (eds.). IPBES secretariat, Bonn, Germany. 44 pgs. IPBES. https://doi.org/10.5281/zenodo.3237392.

IPBES (2019). *Summary for Policymakers of the Global Assessment Report on Biodiversity and Ecosystem Services of the Intergovernmental Science Policy Platform on Biodiversity and Ecosystem Services.* Díaz, S., Settele, J., Brondízio, E.S., Ngo, H.T. Guèze, M., Agard, J., Arneth, A., Balvanera, P. Brauman, K.A., Butchart, S.H.M., Chan, K.M.A., Garibaldi, L.A., Ichii, K., Liu, J., Subramanian, S.M., Midgley, G.F., Miloslavich, P., Molnár, Z., Obura, D., Pfaff, A., Polasky, S., Purvis, A., Razzaque, J., Reyers, B., Roy-Chowdhury, R., Shin, Y.J., Visseren-Hamakers, I.J., Willis, K.J. & Zayas, C.N. (eds.). Bonn: IPBES. https://doi.org/10.5281/zenodo.3553579.

Jackson, D.A. (1993). Stopping rules in principal components analysis: A comparison of heuristical and statistical approaches. *Ecology,* 74(8), 2204 – 2214. https://doi.org/10.2307/1939574

Jasim, M.R., Mat Jafri, M.Z. & Lim, H.S. (2013). Combining multiple regression and principal component analysis for accurate predictions for column ozone in Peninsular Malaysia. *Atmospheric Environment.* (71), 36 – 43. https://doi.org/10.1016/j.atmosenv.2013.01.019

Jayawardana, D.T., Ishiga, H. & Pitawala, H.M.T.G.A. (2012). Geochemistry of surface sediments in tsunami-affected Sri Lankan lagoons regarding environmental implications. *International Journal of Environmental Science and Technology,* 9, 41 – 55. https://doi.org/10.1007/s13762-011-0016-4

Jobson, J.D. (2002). Applied multivariate data analysis. New York, NY: Springer Verlag

Jolliffe, I.T. (2002). Principal component analysis (2nd eds.). Springer series in statistics. New York, NY: Springer.

Jongman, R.H.G., Ter Braak, C.J. & Van Tongren, O.F. (1995). *Data analysis in community and landscape ecology* (p. 299). Cambridge: Cambridge University Press

Kaphegyi, T.A.M., Dees, M., Zlatanova, D., Ueffing, C., Dutsov, A. & Kaphegyi, U. (2012). Rapid assessment of linear transport infrastructure in relation to the impact on landscape continuity for large ranging mammals. *Biodiversity and Conservation,* 22,(1), 153 – 168. https://doi.org/10.1007/s10531-012-0409-9

Kleemann, J., Baysal, G., Bulley, H.N.N., & Fürst, C. (2017). Assessing driving forces of land use and land cover change by a mixed-method approach in North - Eastern Ghana, West Africa. *J. Environ. Manag.* 196, 411 – 442. https://doi.org/10.1016/j.jenvman.2017.01.053

Kok, K. & Veldkamp, T.A. (2001). Evaluating impact of spatial scales on land use pattern analysis in Central America. *Agriculture, Ecosystems and Environment,* 85(1- 3), 205 – 221. https://doi.org/10.1016/S0167-8809(01)00185-2

Koulouri, M. & Giourga, C. (2007). Land abandonment and slope gradient as key factors of soil erosion in Mediterranean terraced lands. *Catena,* 69, 274 – 281. https://doi.org/10.1016/j.catena.2006.07.001

Kuemmerle, T., Levers, C., Erb, K., Estel, S., Jepsen, M.R., Müller, D., Plutzar, C., Stürck, J., Verkerk, P.J., Verburg, P.H. & Reenberg, A. (2016). Hotspots of land use change in Europe. *Environmental Research Letters*, *11*. https://doi.org/10.1088/1748-9326/11/6/064020

Lambin, E.F., Geist, H.J. & Lepers, E. (2003). Dynamics of Land-Use and Land-Cover Change in Tropical Regions. *Annual Review of Environment and Resources*, 28, 205 – 241.

Legendre, P. & Legendre, L. (1998). *Numerical ecology*. Amsterdam: Elsevier. pgs. 853.

Lennon, J.J. (2000). Red-shifts and red herrings in geographical ecology.*Ecography*, 23:101 – 113. https://doi.org/10.1111/j.1600-0587.2000.tb00265.x

Lesschen, J.P., Verburg, P.H., & Staal, S.J. (2005). *Statistical methods for analyzing the spatial dimension of changes in land-use and farming systems, LUCC Report Series No. 7.* The International Livestock Research Institute, Nairobi Kenya and LUCC Focus 3, Office, Wageningen University, The Netherlands.

Leta, M.K., Demissie, T.A., & Tränckner, J. (2021). Modeling and Prediction of Land Use Land Cover Change Dynamics Based on Land Change Modeler (LCM) in Nashe Watershed, Upper Blue Nile Basin ethiopia. *Sustainability,* 13, 3740. https://doi.org/10.3390/su13073740

Lordan, G., Soto, E. J., Brown, R. P. C., & Correa-Valez, I. (2012). Socioeconomic status and health outcomes in a developing country. *Health Economics,* 21, 178 – 186. https://doi.org/10.1002/hec.1703

Luijten, J., Miles, L., & Cherrington, E. (2006). *Land use change modeling for three scenarios for the MAR region ICRAN – MAR project.* UNEP WCMC, 2006 Technical Report. 3.

Malaysian Department of Statistic (MDoS) (2010). *Yearbook of Statistics, Malaysia.* Malaysian Department of Statistics (MDoS), 2010. Yearbook of Statistics, Malaysia, 2010. Malaysian Department of Statistics, Kuala Lumpur, Malaysia.

Malaysian Meteorological Department (MMD), (2009). *Climate change scenarios for Malaysia 2001 - 2099 scientific report by numerical weather prediction.* Technical Development Division. Malaysian Meteorological Department Ministry of science, Technology and Innovation.

Marchant, R., Richer, S., Boles, O., Capitani, C., Courtney-Mustaphi, C.J., Lane, P., Prendergast, M.E., Stump, D., De Cort, G., Kaplan, J.O. et al. (2018). Drivers and trajectories of land cover change in East Africa: Human and environmental interactions from 6000 years ago to present. *Earth-Sci. Rev.* 178, 322 – 378. https://doi.org/10.1016/j.earscirev.2017.12.010

Mazzeo, G. & Russo, L. (2016). Aspects of Land Take in the Metropolitan Area of Naples. *Tema Journal of Land Use, Mobility and Environment,* 9 (1), 89 - 107. doi: http://10.6092/1970-9870/3727.

Demirci, A., McAdams, M.A., Alagha, O. & Karakuyu, M. (2006). The relationship between land use change and water quality in Kucukcekmece Lake watershed. 4th GIS Days in Turkey, Istanbul, 27-34.

McMorrow, J., & Talip, M.A. (2001). Decline of forest area in Sabah, Malaysia: Relationship to state policies, land code and land capabilities. *Global Environmental Change,* 11, 217 – 230. https://doi.org/10.1016/S0959-3780(00)00059-5

Menard, S. (2002). *Applied logistic regression analysis: quantitative applications in the social sciences.* Sage Publication, Thousand Oak, CA, USA.

Millington, J.D.A., Perry, G.L.W. & Romero – Calcerrada, R. (2007). Regression techniques for examining land use/land cover change: A case study of a Mediterranean landscape. *Ecosystems,* 10: 562 – 578. https://doi.org/10.1007/s10021-007-9020-4

Mottet, A., Ladet, S., Coque, N. & Gibon, A. (2006). Agricultural land use change and its drivers in mountain landscapes: A case study in the Pyrenees. *Agriculture, Ecosystems and Environment*, 114, 296 – 310. https://doi.org/10.1016/j.agee.2005.11.017

Muller, D. & Zeller, M. (2002). Land use dynamics in the central highlands of Vietnam: a spatial model combining village survey data with satellite imagery interpretation. *Agricultural Economics,* 27, 333 – 354. https://doi.org/10.1111/j.1574-0862.2002.tb00124.x

Müller, D. & Munroe, D.K. (2008). Changing rural landscapes in Albania: cropland abandonment and forest clearing in the post socialist transition. *Annals of the Association of American Geographers,* 98, 855 – 876. https://doi.org/10.1080/00045600802262323

Müller, D., Kuemmerle, T., Rusu, M. & Griffiths, P. (2009). Lost in transition: determinants of post-socialist cropland abandonment in Romania. *Journal of Land Use Science,* 4, 109 – 129. https://doi.org/10.1080/17474230802645881

Munroe, D.K., Southworth, J., & Tucker, C.M. (2002). The dynamics of land-cover change in western Honduras: exploring spatial and temporal complexity. *Agricultural Economics,* 27, 355 - 369. https://doi.org/10.1111/j.1574-0862.2002.tb00125.x

Näschen, K., Diekkrüger, B., Evers, 1 , M., Höllermann, B., Steinbach, S. & Thonfeld, F. (2019). The impact of land use/land cover change (LULCC) on water resources in a Tropical Catchment in Tanzania under different climate change scenarios. *Sustainability,* 11, 7083; http://doi:10.3390/su11247083

Nelson, G.C. (2002). Introduction to the special issue on spatial analysis for agricultural economists. *Agricultural Economics*, 27, 197 – 200. https://doi.org/10.1111/j.1574-0862.2002.tb00116.x

Niu, L., Luo, W., Jiang, M. & Lu, N. (2018*). Land - use degree and spatial autocorrelation analysis based on big data in Kunming City.* In 97–100, https://doi.org/10.1109/ICITBS.2018.00033 (IEEE, 2018).

Nuissl H. & Siedentop S. (2021) Urbanisation and Land Use Change. In: Weith T., Barkmann T., Gaasch N., Rogga S., Strauß C., Zscheischler J. (eds) *Sustainable Land Management in a European Context. Human-Environment Interactions*, Vol 8. Springer, Cham. https://doi.org/10.1007/978-3-030-50841-8_5

Nusret, D. & Dug, S. (2009). *Applying the inverse distance weighting and kriging methods of the spatial interpolation on the mapping the annual precipitation in Bosnia and Herzegovina.* International Environmental Modelling and Software Society (iEMSs) 2012. International Congress on Environmental Modelling and Software Managing Resources of a Limited Planet, Sixth Biennial Meeting, Leipzig, Germany R. Seppelt, A.A. Voinov, S. Lange, D. Bankamp (Eds.) http://www.iemss.org/society/index.php/iemss-2012-proceedings.

Nyaga, E.K. & Doppler, W. (2009). Combining principal component analysis and logistic regression models to assess household level food security among smallholder cash crop producers in Kenya. *Quarterly Journal of International Agriculture,* 48, 5 – 23.

Olaniyi A.O., Abdullah, A.M., Ramli, M.F. & Alias, M.S. (2013). Agricultural land use in Malaysia: an historical overview and implication for food security. *Bulgarian Journal of Agricultural Science.*, 19(1).

Olaniyi, A.O., Abdullah, A.M., Ramli, M.F. & Alias, M.S. (2012). Assessment of drivers of coastal land use change in Malaysia. *Ocean and Coastal Management*, 67: 113 – 123. https://doi.org/10.1016/j.ocecoaman.2012.05.029

Olaniyi, A.O., Abdullah, A.M., Ramli, M.F. & Alias, M.S. (2011). Effects of socio – economic factors on agricultural land use in Malaysia. *Elixir Agriculture* 37, 3790 – 3797.

Omar, S.C., Shaharudin, A. & Tumin, S.A. (2019). *The status of the paddy and rice industry in Malaysia, Kuala Lumpur.* Khazanah Research Institute. Agricultural transformation and inclusive growth: The Malaysian experience. Retrieved from:

http://documents1.worldbank.org/curated/en/617611574179512389/pdf. (accessed on 2021/03/12)

Overmars, K. (2000). Quantification of spatial autocorrelation and an application of spatial autoregressive model in land use change analysis. Internal Report. Wageningen University and Research Centre, Wageningen.

Parker, M. L., Reeves, J.N., Matzeu, G.A., Buisson, D.J.K. & Fabian, A.C. (2018). Using principal component analysis to understand the variability of PDS 456. *Monthly Notices of the Royal Astronomical Society*, 474, (1), 108 – 114. https://doi.org/10.1093/mnras/stx2803

Prishchepov, A.V., Radeloff, V.C., Müller, D., Dubinin, M. & Baumann, M. (2011). *Determinants of agricultural land abandonment in Post-Soviet European Russia "Will the „ Brics decade" continue? – prospects for trade and growth"* 23 - 24 June 2011 Halle (Saale), Germany.

Prishchepov, A.V., Radeloff, V.C., Müller, D., Dubinin, M. & Baumann, M. (2013). Determinants of Agricultural Land Abandonment in Post-Soviet European Russia. *Land Use Policy, 30*(1):873 – 884. https://doi.org/10.1016/j.landusepol.2012.06.011

Qasim, M., Hubacek, K., Termansen, M. & Fleskens, L. (2013). Modelling land use change across elevation gradients in district Swat, Pakistan. *Reg Environ Change*, https//www.doi 10.1007/s10113-012-0395-1.

Richards, C. L., Rosas, U., Banta, J., Bhambhra, N. & Purugganan, M. D. (2012). Genome-wide patterns of arabidopsis gene expression in nature. *Genetics,* 8, 482 – 495. https://doi.org/10.1371/journal.pgen.1002662

Rigg, J. & Nattapoolwat, S. (2001). Embracing the global in Thailand: Activism and pragmatism in an era of de-agrarianisation. *World Development*, 29(6), 945–960. https://doi.org/10.1016/S0305-750X(01)00021-3

Rigg, J. (2006). Land, farming, livelihoods and poverty: Rethinking the links in the rural South. *World Development*, 34(1), 180 – 202. https://doi.org/10.1016/j.worlddev.2005.07.015

Sidique, S.F. & Shaharudin, A. (2019). *Malaysia's Agricultural Transformation: National Food Security*. Draft, Institute of Agricultural and Food Policy Studies, Universiti Putra Malaysia.

Simone Z.D., Armando, M. & Barbara S. (2010). Simulation of urban development in the City of Rome. Framework, methodology, and problem solving. *The Journal of Transport and Land Use*, 3(2), 85 – 105.

Siwar, C., Alam, M.M., Murad, M.W. & Al – Amin, A.Q. (2011). Impacts of climate change on agriculture and food security issues in Malaysia: An Empirical Study on Farm Level Assessment. *World Applied Sciences Journal, 14*(3), 431 – 442. https://ssrn.com/abstract=2941495

Suhaila, J. & Deni, S.M. (2010). Trends in Peninsular Malaysia rainfall data during the southwest monsoon and northeast monsoon seasons: 1975 – 2004. *Sains Malaysiana*, 39(4), 533 – 542.

Theobald, D.M., Miller, J.M., & Hobbs, N.T. (1997). Estimating the cumulative effects of development on wildlife habitat. *Landscape and Urban Planning,* 39, 25 – 36. https://doi.org/10.1016/S0169-2046(97)00041-8

Vasco, D. & Eric, K. (2010). *Explaining land-use change in Portugal 1990-2000.* 13th AGILE international conference on geographic information science 2010 pp 1 – 11 Guimarães, Portugal.

Veldkamp, A. & Fresco, L.O. (1999). CLUE: a conceptual model to study the conversion of land use and its effects. *Ecological Modelling*, 85, 253 – 270. https://doi.org/10.1016/0304-3800(94)00151-0

Velicer W.F. & Fava J.L. (1998). Effects of variable and subject sampling on factor pattern recovery, *Psychological Methods,* vol. 3, 231-251. https://doi.org/10.1037/1082-989X.3.2.231

Verburg, P.H., Schot, P.P., Dijst, M.J. & Veldkamp, A. (2004). Land use change modelling: Current practice and research priorities, *GeoJournal,* 61, 309 – 324.

Verburg, P.H., Soepboer, W., Veldkamp, A., Limpiada, R., Espaldon, V. & Mastura, S.S.A. (2002). Modeling the spatial dynamics of regional land use: the CLUE-S model. *Environmental Management*, 30(3):391 - 405. https://doi.org/10.1007/s00267-002-2630-x

Ver Hoef, J.M., Cressie, N. & Fisher, R.N. (2001). *Uncertainty and spatial linear models for ecological data.* Pages 214 – 237. In C. T. Hunsaker, M. F. Goodchild, M. A. Friedl, and T. J. Case, editors. Spatial uncertainty in ecology. Springer-Verlag, New York, New York, USA.

Vincent, J.R. & Rozali, M.A. (2005). *Managing natural wealth environment and development in Malaysia.* (Eds.) Resources for the future press, Washington D.C. USA.

Wang, Q., Ren, Q. & Liu, J. (2016). Identifcation and apportionment of the drivers of land use change on a regional scale: Unbiased recursive partitioning-based stochastic model application. *Agriculture, Ecosystems & Environment*, 217, 99 – 110. https://doi.org/10.1016/j.agee.2015.11.004

Wester-Herber, M. (2004). Underlying concerns in land-use conflicts--the role of place-identity in risk perception. *Environmental Science and Policy*, 7(2), 109 - 116. https://doi.org/10.1016/j.envsci.2003.12.001

Wikle, C.K. (2003). Hierarchical Bayesian models for predicting the spread of ecological processes. *Ecology*, 84: 1382 – 1394. https://doi.org/10.1890/0012-9658(2003)084[1382:HBMFPT]2.0.CO;2

Wiktorowicz, J. (2016). Exploratory factor analysis in the measurement of the competencies of older people. *Econometrics,* 4(54). https://doi.org/10.15611/ekt.2016.4.03

World Bank (2008). *World development indicators online.* The World Bank, Development Data Group, Washington, DC. Retrieved from: http://go.worldbank.org/U0FSM7AQ40. 2021.001.030.

World Bank (2019). *The status of the paddy and rice industry in Malaysia.* Kuala Lumpur: Khazanah Research Institute. Agricultural Transformation and Inclusive Growth The Malaysian Experience. Retrieved from:

http://documents1.worldbank.org/curated/en/617611574179512389/pdf. (accessed on 2021/03/16)

Xie, Y., Mei, Y., Guangjin, T. & Xuerong, X. (2005). Socio – economic driving forces of arable land conversion: A case study of Wuxian City China. *Global Environmental Change* 15, 238 – 252. https://doi.org/10.1016/j.gloenvcha.2005.03.002

Yongwei Liu, Y., Cao, X. & Li, T. (2020). Influence of accessibility on land use and landscape pattern based on mapping knowledge domains: review and implications. *Journal of Advanced Transportation,* 5(2). https://doi.org/10.1155/2020/7985719

Zhuang, D.F., Liu, M.L. & Deng, X.Z. (2002). Spatialization model of population based on dataset of land use and land cover change in China. *Chinese Geographical Sciences*, 12(2), 114 – 119. https://doi.org/10.1007/s11769-002-0018-8

Zucaro, F. & Morosini, R. (2018). Sustainable land use and climate adaptation: a review of European local plans. *Tema. Journal of Land Use, Mobility and Environment,* 11(1), 7 - 26. http://dx.doi.org/10.6092/1970-9870/5343

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Author’s profile

Akeem Olawale Olaniyi

He is a lecturer at the Department of Environmental Management of Kaduna State University. He bagged his PhD in Environmental Analysis and Modelling at the Universiti Putra Malaysia in 2013. He has published several papers, attended conferences/workshops and has collaborated with other professionals in some global studies, reviews and publications.

Ahmad Makmom Abdullah

He is a Professor of Ecophysiology and Air Pollution Modelling at the Department of Environmental Sciences, Faculty of Environmental Management, Universiti Putra Malaysia, Malaysia. He has to his credit publications of articles in frontline journals in his field. He has attended several conferences, partner with professionals in conducting studies (international and national) in ecophysiology and air pollution and has supervised several Bachelor, Masters and PhD students.