Land Market Receptiveness to Water-Logging: A Hedonic Pricing Approach Using GIS

Sanchita Chakrovorty* and A.K. Enamul Haque**

Abstract

Most of the cities in developing countries are built on filling wetlands and are also being expanded using continuous land filling and embankments. In coastal areas, cities are doubly threatened as this water is also saline. This paper used these backgrounds to understand how the urban land market is responding to such disasters in a coastal city of Bangladesh. The paper used spatial econometric analysis with GIS data along with a household survey data.

In terms of policy prescription, the study reveals that a parcel of land which is water-logged for a day drops its value by 6%; for 2 days drops it by 8% and for 3 days the value drops by 9% and so on. A public investment to remove water-logging increases the value by 14%, so it is possible to invest to reduce the impact and this can be partially financed by higher taxation of land value gains.

Key words: Geographic Information System (GIS), hedonic pricing, land market, spatial autocorrelation, water-logging, spatial regression.

Introduction

Many urban cities in India, China, and Bangladesh (like Kolkata, Shanghai and Dhaka) experience water-logging problem due to its drainage congestion. Most of these cities are built on wetlands and are being expanded using continuous land filling and embankments. Excessive rainfall and also inefficient management of city drainage and sewerage routes often lead to prolonged water-logging. A study on Shanghai reveals that water-logging induced by torrential rain or typhoon, urban development and changes in land use has potential risk affecting urban inhabitant lifelines and safety (Quan et al., 2010).

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In coastal areas, cities are also threatened by sea level rise and by increased rainfall due to climate change, and this is likely to increase risk to urban inhabitants. A study on Khulna city by the Institute of Water Modeling in Dhaka shows that sea level rise and higher precipitation, which are few of the most critical threats of climate change faced by coastal cities in Bangladesh, together are going to create increased level of water-logging in coastal cities (IWM & Alterra, 2010). This study used a regional climate change model and predicts that as much as 75% of the city areas will be suffering from water-logging due to climate change.

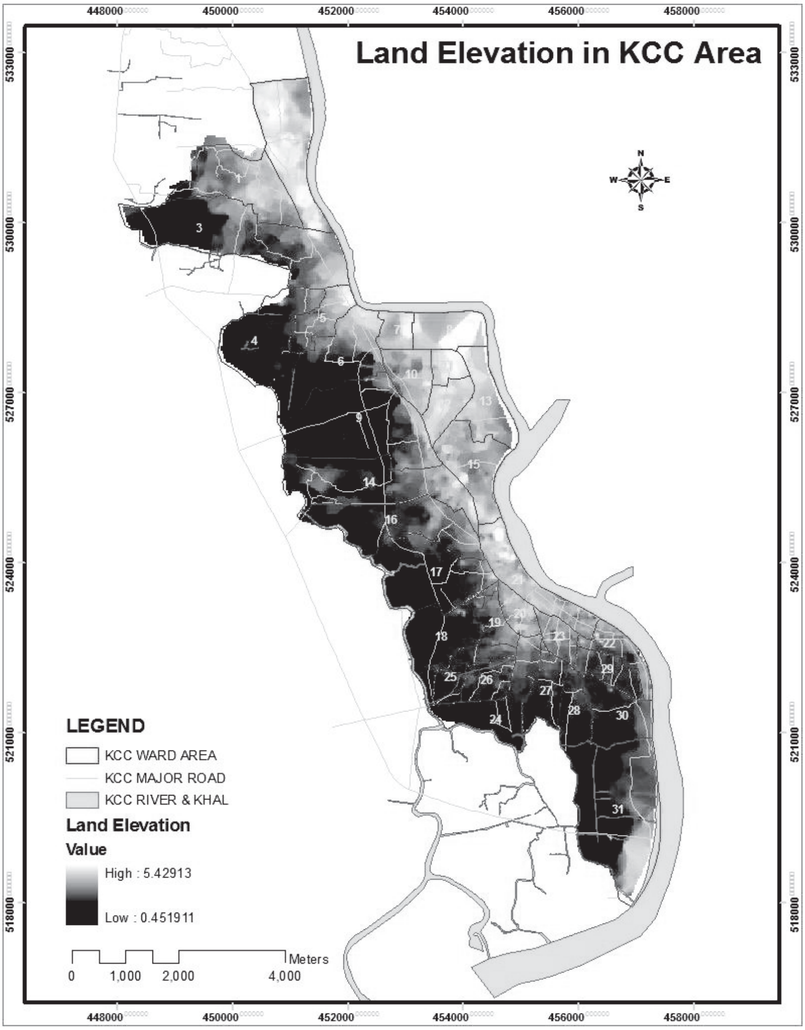
City land use is affected by many factors that include a) urban development plans and nature of existing infrastructure, b) city zoning plan, c) land characteristics (elevation, soil type, etc.), d) urban transportation networks, e) characteristics of the area, and f) the structure of land market. Mukherjee and others found that land use land cover changes are important elements of the global environmental change processes (Mukherjee et al., 2009).

Since urban infrastructure are mainly built on private land, it is expected that the land market is taking cognizance of these elements in its consideration and so prices are likely to be influenced by these factors on a plot to plot basis including water-logging characteristics. Therefore, understanding market responses to water-logging will help decision makers to develop a better adaptation plan. This paper used these backgrounds to understand how the land market is responding to such natural disasters in a coastal city of Bangladesh. The paper uses GIS based information with a primary survey of households from Khulna (a coastal city) in order to understand the relationships.

Background on the location of study

Khulna is one of the third largest cities of Bangladesh and is situated in the southwest part of Bangladesh near the largest mangrove forest, Sundarban, and is bounded by two rivers: one in the east and one in the west. Both of these rivers are tidal rivers. The city is administratively divided into 31 wards with a population of 2 million (2001 census) and is growing at a rate of 2% per annum. About 46% of the city's land area is now built up and is used for industrial, commercial and residential purposes, 5% land is under commercial use, 15% land is under industrial use and the remaining part is for residential and other purposes. Topographically, the city is situated at 2.5 meter above the mean sea level with slopes towards west but regionally toward south (Figure 1).

Figure 1. Land elevation of KCC area with rivers and roads



As the population is growing, the City is experiencing a 2% net growth of population per annum (since 2001) which has resulted in a vibrant and an active land market. At the same time due to absence of storm water sewage systems, and due to low maintenance of the city drainage system some parts of the city are already experiencing water-logging during heavy rainfall in the late monsoon (Murtaza, 2001). A previous study by (Haque, 2013) found that 70 percent of the households in the city area were directly or indirectly affected by water-logging. Haque also noted that the amount of damage is increasing exponentially over the years.

Analytical method

Studies on land market often use hedonic pricing models to separate price impact from changes in the characteristics of land. In addition, there is a growing body of literature that uses GIS information to relate land prices to its neighborhood, environmental and other characteristics. Analysis using GIS application to analyze spatial information, such as land record, natural resource features, and public infrastructure location, has become popular in the hedonic literature (Geoghegan et al., 1997). Kong (Kong et al., 2007), Clapp (Clapp et al., 1997), Colakovic (Colakovic & Vucetic, 2012) and many others used GIS based modeling to analyze land prices. Rehdanz showed that the market also responds to the demand for environmental good(Rehdanz, 2002). Mukharjee using GIS data and econometrics estimation found "a positive relationship between land price and its elevation, and a negative relationship between price andadjacency to a stagnant stream" (Mukherjee & Caplan, 2011).

As such, it is possible to use spatial econometrics with GIS information to find out whether in Bangladesh land market responds to environmental characteristics (here water-logging) or not. This study, therefore, uses the GIS-based hedonic price models to analyze impacts of water-logging on land prices.

The Spatial Econometric Model

The following price equation is used to estimate the hedonic price model. The fundamental hedonic equation along with attributes is:

$$\mathrm{P} = \mathrm{f}(\mathrm{E}, \mathrm{L}, \mathrm{A}, \mathrm{N}) \tag{1}$$

Where, E is a set of environmental variables and in this study it is the duration of water-logging, L is a set of location variables related to the plot that includes plot type (L1) and land elevation (L2), A is a set of variables that define access characteristics to the plot and it includes the type of road (A1) and proximity to the road (A2), and N is a set of neighborhood characteristics that includes population (N1), income of the plot resident (N2) and type of structure in the plot (N3).

The general estimation equation for hedonic model is specified as,

$$P_i = \alpha + \sum_{j=1}^{n}\left(\beta_j x_{ij}\right) + \varepsilon \tag{2}$$

where P is price of land, x_{ij}*'s* are the characteristics *j* of plot *i*, subscript *i* refers to plot. x_j*'s* are divided in several attributes of a plot *(j)* like neighborhood characteristics (e.g., population, education facility), environmental characteristics (e.g., water-logging), accessibility characteristics (e.g., road structure type, proximity to nearest road, city, shopping mall) and socio-economic characteristics (e.g., income).

In general, consumers compete at several markets to determine the price they are willing to pay and the coefficient of environmental characteristics, in this case water-logging, shows the contribution of water-logging in formation of the price of land.

Consumers might pay higher property prices if the land or house is located in a preferred area. Also they might accept lower price for living in such areas(Rehdanz 2002).The total amount of utility a consumer receives from the purchase of products is subject to the total amount of characteristics purchased. In this way, this study wanted to estimate the natural disaster effects (i.e., water-logging) in determining land values.

Theoretically, when a consumer maximizes their satisfaction U = U (z, Ω), where z, set of consumables, and Ω set of characteristics (in this case land), then consumers' maximization of utility is subject to $I = z + V(\Omega)$, where I is income, prices of z are assumed to be 1 as *numariare,* V(Ω) is the cost of purchasing the characteristics, and Ω = {xj's} is the set of characteristics of land. Thus, the marginal value of a characteristics x_j is given by:

$$\frac{\partial V}{\partial x_j} = \frac{\partial U / \partial x_j}{\partial U / \partial z} \qquad (3)$$

This equation (3) can be used to value the cost of water-logging in an urban area.

As the main objective of this study is to estimate the implicit price effects of natural disasters on land, water-logging is taken as a variable which is related to tidal surges as well as rainfall and drainage congestion. Understanding the loss of land price due to water-logging is, therefore, considered an effect of natural disasters which is relevant for Khulna city. Other variables in the model are taken from different studies which used similar models (Malpezzi, 2003; Ismail, 2005; Butsic et al., 2009). The property with a short distance from a road is expected to have a positive and higher impact on it (Can & Megbolugbe, 1997).

Many economists have stressed that economic theory does not suggest an appropriate functional form for hedonic price equations (Rosen, 1974; Freeman, 1979; Halverson & Pollakowski, 1981; Cassel & Mendelsohn, 1985; Amin, 2009). Consequently it is reliable to try several functional forms and utilize a multiple regression equations (Cassel & Mendelsohn, 1985). This study has used Mukherjee et. al. (Mukherjee &, Caplan, 2011) specification and estimation technique which used spatial lag model to remove spatial-autocorrelation from the model. Land prices models often suffer from spatial lag effect because price of a plot land is not independent of the price of the plot in the neighborhood. Models used in previous studies included both linear and non-linear specifications.

Data and variables

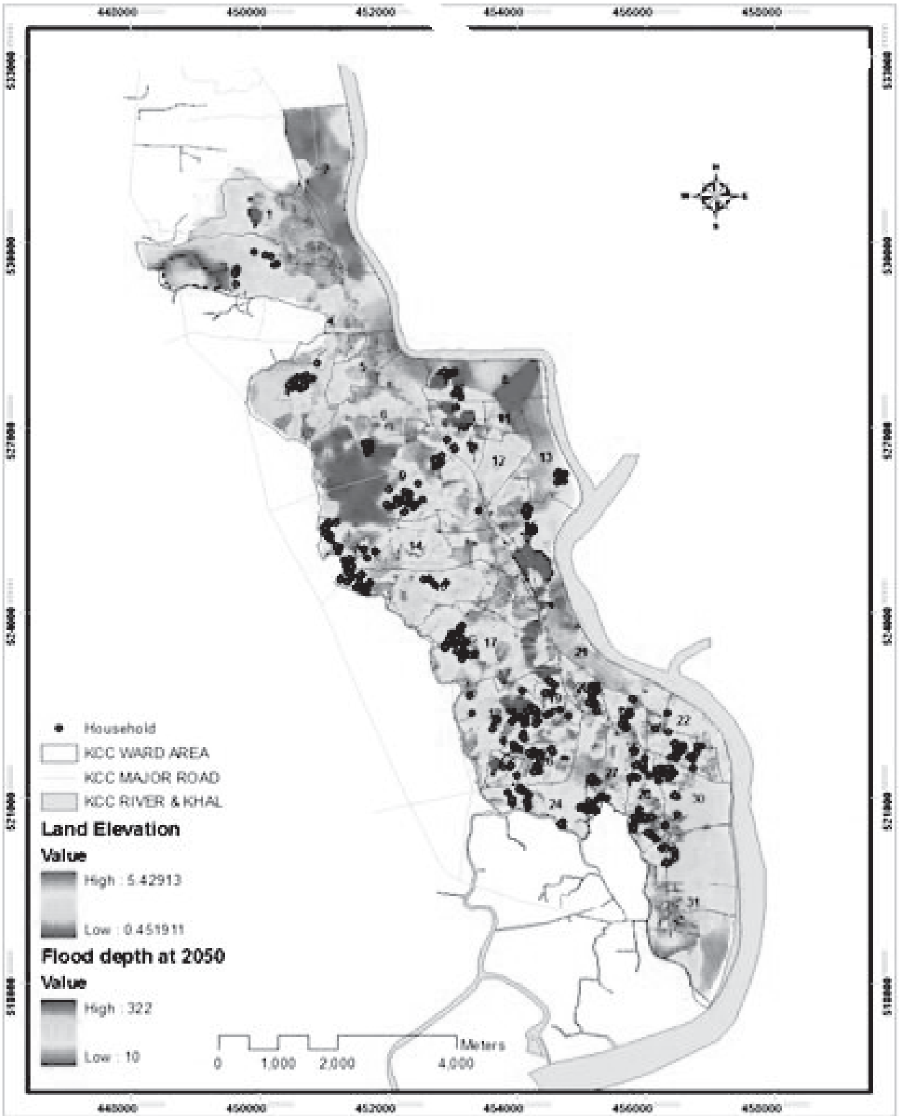
Three types of data are used in this study. Price and plot specific ELAN data were collected using a primary household survey. A total of 400 household were surveyed in Khulna city using a systematic stratified random sampling method based on the basis of house category [concrete (168), semi-concrete (148), and kacha/jhupri (84)] in the city. These data were supplemented and also triangulated using FGDs and in-depth key informant interviews with different stakeholders. Stakeholders include government offices, local representatives, NGO and others involved in disaster management activities. A total of 18 NGOs/community leaders/local representatives and 7 officers of the government and city corporations were interviewed. Figure 2shows the sample plot points on the map which will likely to be inundated at future projected flood of 2050 with land elevation.

Land price data were collected in two different ways – household survey and local land registration offices. Data collection scheme is shown in Table 1.

Table 1. Data collection method and data sources

Data collection method	Data Sources
Primary data collection	Household survey In-depth interview Focus Group Discussion
Secondary data collection	BBS (2010) (Haque 2013) Land Registration Office
Interpolation through GIS	IWM SHELTECH

Figure 2. Locating sample households in GIS map of Khulna



Secondary Data sources

Data on population density was taken from a recent ADB study on Khulna city (ADB 2011). Actual **Land price** data were collected from Land Registration Office in Khulna for each ward for the year 2011 by land classification type (low land, habitable and commercial plots).

GIS data

Land elevation, roads, rivers, land use and plot type related data were collected from Institute of Water Modeling (IWM) and Sheltech (a developer company). **Land elevation** data were taken from digital elevation model (DEM) provided by IWM that was projected in Everest-Bangladesh Transverse Mercator (BTM) coordinate system. This variable was considered in meter unit from mean sea level. Point shape-files were generated using latitude and longitude data of 400 households and were projected using Everest-Bangladesh Transverse Mercator (BTM) coordinate system. **Proximity to nearest road** was calculated from GIS data using the shortest distance method.

Variables

Location characteristics or neighborhood were included to control for local amenities that contribute to the price of a property. Proximity to roads will likely have a positive effect on the value of land. **Road type** (paved and semi-paved) variable is also generated as the nearest road from land parcel and defined as a dummy variable i.e., paved road indicates 1 and 0 other wise. Average **land price** of the study area is BDT 357,888 per decimal and about 89 percent of study area is residential. Plots with high **elevation** and plots located beside a paved road is likely to suffers less damage than a low elevated plot and are likely to fetch higher price in the market. At the same time plot type is an important determinant of land price. Commercial plots are likely to be of higher value compared to non-commercial plots. Therefore, a binary variable **Residential** (=1) has been used in the model. Average **number of days of water-logging** in a plot over the past three years was used as a variable in the model. In terms of characteristics of the locality, we have used population as a proxy variable. **Population** density was not found to be useful because wards with bigger landmass might have low density due to the fact that some areas might be uninhabitable. In terms of characteristics of the buyer, income has been used. Table 2 shows the descriptive statistics[1] for a number of variables (dependent and explanatory) used in the model.

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1 Results were estimated using STATA/SE-11

Table 2. Dependent and explanatory variables:Definitions and descriptive statistics

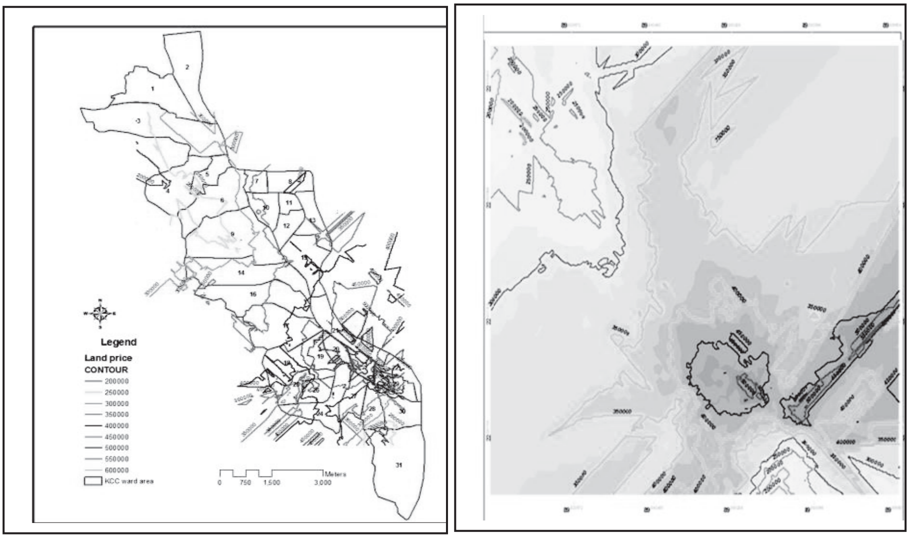
Term	Description	Mean	Std. Dev	Min.	Max.
Land price	Per decimal land value (BDT)	3,58,082	1,16,597.6	1,35,004	7,27,272
Water-logging	Days of water-logging	24.34	31.24	1	180
Plot type	Situated in residential area=1,0 otherwise.	0.89	0.31	0	1
Land elevation	land elevation in meters from mean sea level	2.54	0.72	1.23	4.704
Road type	Situated beside nearest paved road=1, 0 otherwise.	0.60	0.48	0	1
Proximity	Proximity to nearest road in meter	20.62	28.83	0.01	226.21
Population	Population of year 2010 in every ward	33,542.13	9,444.39	18,110	54,420
Income	Income of the resident	13,090	8641.7	2,000	38,000
Structure type	Structure type on plot. Concrete house=1, 0 otherwise	0.41	0.49	0	1

Note: Results were estimated using STATA/SE-11

Kriging analysis

To develop a correspondence between samples (400), with location coordinates (latitude and longitude), land elevation and land price distribution, land price contour map is created using GIS-based Kriging method and is shown in Figure 3. It shows that using GIS based information the price contour map can be produced but in this analysis non-geographic information like proximity to road, plot characteristics, etc. , were not included to measure the impact. Therefore, spatial regression analysis has been used later.

Figure 3. Land price contour across KCC area using Ordinary Krigging method



Note: Results were estimated using ArcGIS 9.3 software

Spatial Regression Model

To begin, OLS estimation technique was used to estimate the coefficients of Equation (4). Except for type of road (L1), plot type (A1) and type of structure in the plot (N3), other explanatory variables were also logged to find a better model (Equation 5).

$$P = \alpha + \beta_1 E + \beta_2 L1 + \beta_3 L2 + \beta_4 A1 + \beta_5 A2 + \beta_6 N1 + \beta_7 N2 + \beta_8 N3 + \varepsilon \quad (4)$$

$$P = \alpha + \beta_1(\log E) + \beta_2 L1 + \beta_3(\log L2) + \beta_4 A1 + \beta_5(\log A2) + \beta_6 (\log N1) + \beta_7(\log N2) + \beta_8(N3) + \varepsilon \quad (5)$$

Where, P is price per decimal of land, L1 is plot type =1 for Residential & 0 otherwise, L2 is land elevation measured in meters, A1 is nearest road type =1 for paved road & 0 otherwise, A2 is proximity to road is measured in meters, Ln is natural log, E is duration of water-logging measured in days, N1 is ward population, N2 is income of the household, N3 is type of housing structure =1 for pacca house & 0 otherwise.

Despite transforming the variables into log scale, it was observed that water-logging is highly correlated with land elevation, house type and income of the resident in the plot. Therefore, these variables were dropped from the final model (Equation 6)

$P = \alpha + \beta_1$ Ln (days of water-logging) $+\beta_2$ (plot type) + β_4 (nearest access road type) + β_5 Ln (proximity to the nearest road) + β_6 Ln (population of the ward) + ε (6)

The results from STATA, ArcGIS and Spacestat are shown in Table 3.

Table 3. Ordinary Least Square estimation result [Dependent variable: Land price (BDT)

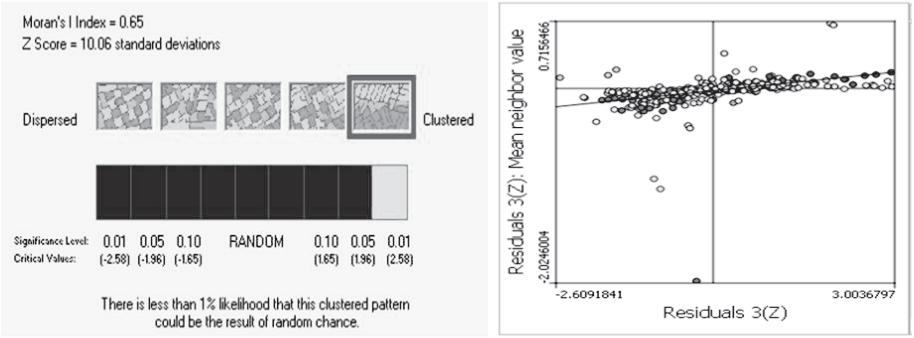
Explanatory variables	OLS-1 [linear]		OLS-2 [lin-log]		OLS-3 [lin-log]	
	Coef	SE	Coef	SE	Coef	SE
Intercept	252673***	39890	566831**	211611	1192936***	196174.5
Duration of water-logging (E)	-149.40	187.3	-10243.5*	4907	-24326.6***	4654
Plot type (L1)	-3717.75	18218	-2048.7	16524	2897	17279
Land elevation (L2)	54894.4***	7986	130854.9***	20674	-	-
Road type (A1)	27455*	11408	20007.2*	11469	30724.9**	11860
Proximity to road (A2)	-362.8*	204.9	-8321.1*	3453.7	-6325.7*	3626
Population (N1)	-1.66***	0.57	-49394.6***	18106.9	-75469.6***	18540
Income of residents (N2)	1.78***	0.64	24137	8787.7	-	-
Type of structure (N3)	-10518.9	11111	-11267.3	11023	-	-
Summery Statistics						
R^2	0.27		0.29		0.20	
Adjusted R^2	0.25		0.27		0.19	
N			400		400	
AIC			10342.7		10357.78	
Log Likelihood			-5162		-5172.89	
Joint F statistics			20.27		20.51	
Jarque-Bera Test			0.006		0.005	
Breusch-Pagan Test			0.0001		0.003	
Koenker-Bassett Test			0.0003		0.002	
White			0.002		0.002	
Durbin-Watson			0.32		0.33	
Spatial Dependence test (OLS-3)						
Moran's *I* (error)	-		-		5.701***	
Lagrange Multiplier (lag)	-		-		20.14***	
Robust LM (lag)	-		-		5.78***	
Lagrange Multiplier (SARMA)	-		-		49.18***	

*** Shows significance at 1% level, ** Shows significance at 5% level, * Shows significance at 10% level.

Note:1) Duration of water-logging (E), proximity to road (A2), population (N1) are natural log transformed variable in OLS-2 and OLS-3 model.2) OLS-1 result was estimated using STATA-11/SE, OLS-2 and OLS-3 results were estimated using ArcGIS 9.3, Spacestat 3.6. SE – Standard Error.

Since land price data often suffers from spatial auto-correlation, it has been tested using Moran I-test[2] and significance level of Lagrange Multiplier (lag). Figure 4 shows the result using a scale from dispersed to clustered. It also confirms that the null-hypothesis of no spatial autocorrelation is rejected at 1% level of significance as the pattern of residual observed from the GIS data is clubbed as 'clustered'.

Figure 4. Moran's I test for spatial autocorrelation



Note: First figure was estimated using ArcGIS 9.3 and the second one was estimated using Spacestat 3.6.

To remove spatial autocorrelation from the model, Mukherjee and Caplan's correction method (Mukherjee & Caplan, 2011) was followed in this estimation using spatial lag model.[3] The result with introducing a spatial weight matrix[4] is shown in Table 4.

2 $I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j} z_i z_j}{S_0 \sum_{i=1}^{n} z_i^2}$; Where z_i is the deviation of an attribute for the future i from its mean $(z_i - X)$, $w_{i,j}$ is the spatial weight between feature *i* and *j*, n is equal to the total number of features, and S_0 is the aggregate of all the spatial weights.

3 $P_i = \alpha + \rho W P_i + \ln[\sum_{j=1}^{n}(\beta_j x_{ij})] + \varepsilon; \varepsilon \approx N(0, \sigma^2 I)$. Here W is the additional regressor.

4 Weight matrix W_i represents a measure of spatial proximity between two parcels of land *i* and *j* ((Kaltsas, Bosch, & McGuirk, 2000). This study followed *Wij =1,* if centroid of j is within 100 meter distance of *i* with *k* nearest centroids of 1 and 0 otherwise.

Table 4. Spatial lag model result: After correcting spatial autocorrelation[Dependent variable: land price]

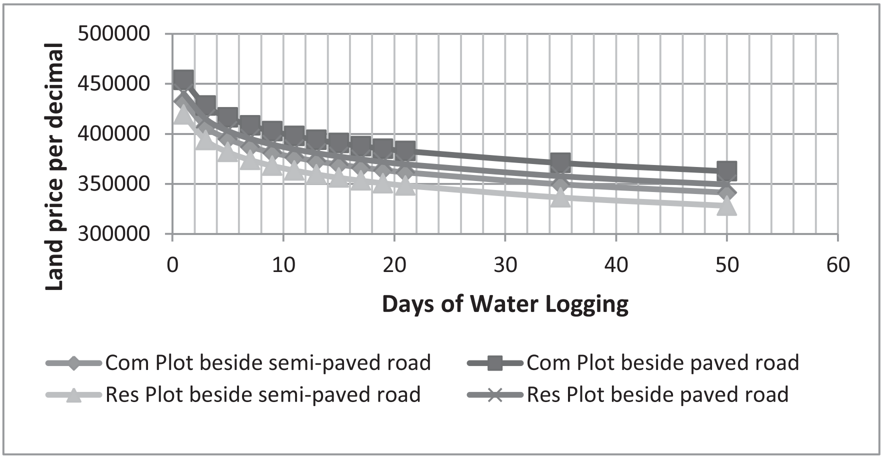
Explanatory variables	Coefficient	Standard error
Intercept	9,96,554.6***	1,79,016
Log of water-logging duration [LNWLD] (E)	-23,267.56***	4,158.64
Plot type [RESIPLOT] (L1)	-13,200.57	15,653.2
Road type [PROAD] (A1)	21,270.02**	10,650.2
Log of proximity to road [LNDISTANCE] (A2)	-4,683.56*	3,244.26
Log of population [LNPOP] (N1)	-62,871.27***	16,803.83
Rho (Wlandprice)	0.259***	0.029
R-squared	0.35	
AIC	10,284.3	
Log Likelihood	-5,135.15	
Breusch-Pagan Test	0.00005***	
Spatial B-P Test	0.006	
Likelihood Ratio Test	75.48***	
N	400	

NOTE: *** Shows significance level at 1%, **Shows significance level at 5%, *Shows significance level at 10%. Results were estimated using open GeoDa.

The coefficient of the Ln (duration of water-logging) is negative implying that land price is negatively related to the number of days of water-logging at the plot. On average, it means a 6% drop in land price (per decimal) due to 1 day of water-logging[5]. In our sample, maximum duration of water-logging is about 25 days for which the land price will drop by 14%. Figure 5 shows the relationship between land price (per decimal) and days of water-logging along with plot and nearest road type. Commercial plot beside paved road indicates higher price than semi-paved road and with the increase of water-logging (in days), land price decreases sharply upto 21 days. The same trend shows for residential plot beside semi-paved road and paved road, with the water-logging duration changing.

5 $[(B_1/1 \text{ day})/\text{Average land price}]*100$

Figure 5. Relationship between water-logging and land price by Plot and Road Type



At the same time, commercial plots fetch 4% higher price, on average, and paved road increases land price by 6%.Results for Ln (proximity to nearest road) also exhibit a negative spatially dependent pattern with the land value. Using the coefficient it can be shown that for each 10 meter distance land price drops by 0.13%.

Conclusion

This research was designed to find out the pecuniary gains from protecting a piece of land from water-logging. This has been major issue in every urban area in developing countries. Combining the hedonic price models with GIS based models the study shows that benefits of land price do accrue to the plot owners. However, marginal impact of protecting land from water logging is far less compared to other development intervention by the government, like making paved roads and allowing land use change. Study also found that land price decreases for every day of water-logging in urban locations.

In terms of policy prescription, the study reveals a very interesting result. If a parcel of land is not water-logged and a similar second parcel of land is water-logged for a day, the drop in price is nearly 6% but if it is water logged for a 2nd consecutive day the drop is about 8% and for a 3rd day of water logging it is about 9% and so on. This means, incentives to invest to protect land from water logging diminishes for parcels of land which go under water for longer period. On the other hand, a public investment to reduce water-logging significantly increases value of land, nearly 14% in case of Khulna city. This could lead to higher land tax collection for the city governments, a direct benefit from drainage improvement in cities.

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