A spatial econometric analysis of residential land prices in Kuwait
Mohamed M. Mostafa

ABSTRACT
Land price mapping has recently drawn considerable attention from academics and practitioners alike. This paper investigates the factors influencing residential land prices in a rather underrepresented part of the world. Owing to land prices’ spatial association and heterogeneity, the study uses both traditional and Bayesian spatial regression techniques to test the impact of population density, the percentage of Kuwaitis among the total population, the total number of schools, traffic accidents, and air pollution as measured by the prevalence of both carbon monoxide (CO, ppm) and ground-level or tropospheric ozone level (O₃, ppb) on residential land prices in Kuwait. The general pattern of the results shows that land prices are driven positively by density, the percentage of Kuwaitis and the existence of educational amenities, while air pollution has a negative impact on prices. The analysis also reveals that land prices in Kuwait tend to cluster in groups/hotspots. It is argued that such an accurate identification of hotspots and the correct understanding of their relation to explanatory variables can help decision-makers to make sound decisions in areas as diverse as planning for amenities and zoning.

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INTRODUCTION
Land prices in Kuwait are among the most expensive in the world. However, since Kuwait neither suffers from high density of land use, as is the case in Tokyo, Japan, nor restricts the building of private individual housing, as is the case in Singapore, it seems that the high residential land prices reflect both market distortions and economic abnormalities (Kaganova, Al-Sultan, & Speakman, 2005). Similar to studies conducted in Saudi Arabia (Abdulaal, 1988) or in the Arab sector in Israel (Kheir & Portnov, 2016, p. 518), land prices in Kuwait ‘reflect location in relation to the central business district and decline exponentially with increasing distance from the center’. In fact, the Persian/Arabian Gulf region represents an interesting study area since several cities in the region, such as Kuwait, Doha, Dubai and Muscat, have been transformed from ‘small ports to metropolitan areas within a very short time’ (Alghais & Pullar, 2018, p. 21). Unlike other parts of the world, Malecki and Ewers (2007) noticed that this

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transformation was not the result of internal migration from rural to urban areas, but rather the result of a huge influx of overseas immigration, especially from East Asian nations.

Residential land use in Kuwait represents a major portion of the various competing urban land uses (Joshua Adegoke, 2014). Since residential land prices in Kuwait reflect a plethora of socioeconomic factors, such as population density, personal relationships, proximity to schools and other amenities, air and toxic pollution, and traffic related noise, the spatial distribution of residential land prices can be a useful urban planning metric (Tsutsumi, Shimada, & Murakami, 2011). Spatial studies dealing with residential land prices in the Arab world are scarce. This research fills this research gap by investigating factors influencing residential land prices in Kuwait. Thus, it contributes significantly to the growing literature on land prices since scientific results ‘can be important if they confirm or disconfirm a theoretical principle’ (Rossiter, 2003, p. 86). More specifically, the paper extends the existing literature dealing with land prices in two ways. First, it applies the analysis to an underrepresented region, namely an Arab country, which makes it possible to generalize results to other Arab nations. Second, it uses Bayesian analysis to check the robustness of the findings. To the best of the author’s knowledge, this paper is the first attempt to use this technique within the context of residential land prices. Thus, the major aim is to answer the following research questions:

- What are the major factors that determine residential land prices in Kuwait?
- Do residential land prices in Kuwait tend to cluster in groups/hotspots?
- Are residential land prices in Kuwait characterized by a ‘market segmentation’ phenomenon?

The paper uses spatial analysis to take into consideration both heterogeneity and dependency in land prices (Paez, Uchida, & Miyamoto, 2001). Heterogeneity implies that ‘functional forms and parameters vary with location and are not homogeneous throughout the data set’ (Hannonen, 2008). Ignoring heterogeneity violates the independency assumptions because of the inherent spatial error autocorrelation (Anselin & Lozano-García, 2009). On the other hand, dependence implies that the variation in land prices is a function of distance.

The paper is organized as follows. The next section reviews the relevant land price literature and develops research hypotheses. The third section presents the research methodology and describes briefly the study area, data sources and major techniques used. The fourth section gives the results. Finally, the last section explores the conclusions, limitations and directions for future land prices research.

LITERATURE REVIEW AND DEVELOPMENT OF THE HYPOTHESES

There has been a plethora of empirical research investigating residential land prices over the last two decades. For example, Shimizu and Nishimura (2007) used ordinary least squares (OLS) hedonic price models to estimate Tokyo’s residential and commercial land prices over a 25-year period. They found major differences in price structure based on location, reflecting diverging attitudes between suppliers’ pricing schemes and end-user preferences. Using piecewise parabolic regression, Colwell and Munneke (2003) investigated residential land prices with respect to the inner city. They estimated the residential land price gradient over a 900-square mile portion in Chicago, Illinois, based on more than 1000 observations of land sales over the period 1995–97. Results indicate that land price elasticity is significantly different from 1. In a similar vein, Clapp, Rodriguez, and Kelley Pace (2001) examined residential land prices in Fairfax, Virginia. They used a hedonic simultaneous price model and reported a dramatic change in land-value surface over time. Using Taipei land price data, Lin and Evans (2000) estimated the relationship between land price and plot size when plots were small. They reported an increase in
land per unit as the lot size increases. Hannonen (2008) investigated the structure of urban land prices in Finland and found that predictive model power can be significantly improved when robust models are used instead of the traditional OLS.

In a study investigating the relationship between Afro-American clusters, land use and land value, Luo and Wei (2004) analyzed residential land prices in Milwaukee, Wisconsin. They used geospatial methods such as kriging and grid sampling to analyze the underlying spatial structure of land prices in a Midwestern US city. Results showed that race plays an important role in accounting for the uneven distribution of land prices. Similarly, Tsutsumi et al. (2011) used a computer-aided system to predict urban land prices in Tokyo’s metropolitan areas. Using governmental land price surveys in 2006, they used several demographic and environmental variables, such as population density, level of urbanization and time to the closest metro station, to develop accurate maps for land prices in Tokyo. In a similar vein, Azar, Ferreira, Abed, and Kazzaz (1999) used geographical information systems (GIS) to investigate urban land prices after the end of the civil war in Beirut, Lebanon. Xu and Li (2014) integrated GIS, empirical models and data visualization techniques to examine the spatial distribution of land prices in China. Using several real estate indices, Sirmans and Slade (2012) examined co-integration and causality between urban land prices and property prices. Based on land price transactions representing 20 US metropolitan areas between 1991 and 2009, they found that residential land prices exhibit the most volatility compared with commercial and industrial land use. Similarly, Li (2009) analyzed land price change in Beijing and identified plots with a dramatic increase in a dynamic market. Sampathkumar and Santhi (2010) examined land price trends in central Chennai city, India. Using artificial neural network techniques, they predicted an annual increase of 17% in land prices in Chennai.

Although the use of OLS hedonic price models seems to be the first choice in the land price literature, some authors used game-theoretic designs to investigate factors influencing residential land prices. For example, Qin, Zhang, Huang, and Pu (2005) applied a ‘game among cities’ theoretic model to investigate the dynamics of land prices in China. They argued that land prices are determined as the outcome of a competitive ‘game’ among different local governments. In a similar vein, Wu (2007) used a game-theoretic approach to investigate rational behaviour among local governments in determining land prices within their own jurisdictions. Wu argued that local governments sometimes resort to lower land prices to attract investors when the benefits of such a decision outweigh the costs incurred. Wu, Zhang, Skitmore, Song, and Hui (2014) used a game-theoretic model to investigate land transfer prices. They found that ‘although the individual strategy of each local government is locally rational, the intensity of competition is such that the combined effect of all the local governments involved is non-rational’.

In the existing literature, variables such as density, personal relationships, proximity to schools and other amenities, air and toxic pollution, and traffic-related noise and car accidents have been constantly linked to residential land prices (Enríquez Sierra, Barreto Nieto, Correa Caro, & Campo Robledo, 2013; Glaesener & Caruso, 2015; Hu, Yang, Li, Zhang, & Xu, 2016; Kheir & Portnov, 2016; Kim, Park, & Kweon, 2007; Larsen & Blair, 2014; Lee, 2015; Wen & Goodman, 2013). For example, in a study investigating factors influencing residential land prices in Tokyo and Kitakyushu, population density, the presence of obnoxious facilities and average elevation were found to be significantly related to urban land prices (Gao & Asami, 2007). In a spatial analysis of land prices in Belgium, Goffette-Nagot, Reginster, and Thomas (2011, p. 1261) argued that ‘high density reinforce competition for land, and is synonymous of high land prices’. They also found that a linguistic border is a strong spatial land price barrier, while environmental variables are not significantly related to land prices. Based on a US county-level land price analysis, Hardie, Parks, Gottlieb, and Wear (2000) combined Ricardian and von Thunen land price models to investigate factors influencing land prices the US South. They found that population density, level of urbanization and household income are significantly
related to land prices across 1459 counties. Manning (1988) examined factors influencing land prices in 94 US metropolitan areas. Results indicated that population density is positively linked to land price. Joshua Adegbeke (2014) found that the general drivers of urban land prices are population density, the level of development as well as several motivational drivers. In a study analyzing land prices in Colombia, Enríquez Sierra et al. (2013) found a significant relationship between land price and density and proximity to schools and other amenities. Similar results linking land price and population density were reported in studies conducted in China (Du, Thill, & Peiser, 2016; Zhang, Lin, Wu, & Skitmore, 2017), Japan (Kanasugi & Ushijima, Forthcoming), and Austin, Texas (Yu, Zhang, & Pang, 2017). The discussion presented above suggests the following hypothesis:

**Hypothesis 1:** Population density is positively related to residential land price.

The literature based on social interaction theory argues that human behaviour is motivated not only by economic but also by social goals (Woolcock, 1998). The social interaction paradigm has been introduced to land price economics by authors such as Robison and Siles (1999). Empirical evidence for the social interaction paradigm within the context of land prices was provided by Siles, Robison, Johnson, Lynne, and Baveridge (2000). Based on 600 usable questionnaires, they investigated land valuation in Michigan, Illinois and Nebraska and found significant differences in land prices offered to strangers, relatives, neighbours and influential people. The authors concluded that ‘relationships alter the terms of trade’ (p. 132). This result confirms the fact that economic transactions, such as land valuation, are affected by personal relationships. In a study in Oregon, Perry and Robison (2001) also found that land transactions between relatives and neighbours are more frequent compared with those between strangers. They investigated land transactions in Oregon from 1992 to 1997 in order to quantify the impact of personal relationships and found that ‘transactions between relatives and neighbours involved special considerations with greater frequency than did those between strangers’ (p. 385). In as similar vein, Robison and Siles (1999) found that negative social interaction impedes land transactions. This result is very important since it suggests that in a country such as Kuwait, where nationals tend to cluster, there will be no social interaction between Kuwaitis and strangers. A positive relation between social interaction and land prices has also been reported by Cortright (2009) and Pivo and Fisher (2011). The discussion presented above suggests the following hypothesis:

**Hypothesis 2:** The percentage of Kuwaitis is positively related to residential land price.

There is compelling evidence linking urban amenities such as schools and sports facilities to residential land prices (Clapp, Nanda, & Ross, 2008; Espey & Owusu-Edusei, 2001; Kim & Zabel, 2007; Uyar & Brown, 2007). The theoretical framework linking accessibility to land prices is known in the literature as land rent theory (Alonso, 1964). This theory argues that a higher land rent reflects better accessibility to social services and environmental amenities (Murakami, 2018). Several authors have reported strong support to this theory. For example, Daniere (1994) analyzed residential land prices in Cairo (Egypt) and Manila (Philippines) and found that low-income households tend to cluster in areas well connected to public transportation and with a regular source to potable water. Studies conducted by Cummings, Di Pasquale and Kahn (2002) in the city of Philadelphia and Eisenberg and Keil (2000) in the United States found a positive and significant relationship between higher educational level and increased residential land prices. Similarly, Lavee (2015) and Jordan, Birkin, and Evans (2012) demonstrated that low educational levels and high unemployment are associated with lower residential land prices. Controlling for neighbourhood quality and other time-invariant factors, Reback (2005) found a
positive effect of quality schools on land prices. When analyzing the relationship between school districting and land prices in Seoul, Korea, Lee (2015, p. 1) found that ‘land prices increase by about 13% points more on average and by about 26% points across boundaries in the better school districts’. Applying an entropy-based method, Franklin and Waddell (2003) also found easy access to schools and universities increases land and housing prices in the vicinity. The discussion presented above suggests the following hypothesis:

**Hypothesis 3:** The total number of schools is positively related to residential land price.

Factors such as air and water pollution, traffic noise, and accidents have also been extensively investigated in the literature (Espey & Lopez, 2000; Leggett & Bockstael, 2000). In fact, there is a general consensus among researchers that traffic externalities can influence residential land prices. For example, in a study in Seoul, Kim, Park, and Kweon (2007) analyzed the relationship between traffic accidents, noise and residential land prices. Using hedonic price models, they found that an increase of 1% in traffic accidents and/or noise is associated with a decline of 1.3% in urban land prices. The authors also estimated the traffic noise cost US $347,000/km. Using hedonic price models, Nijland, Van Kempen, Van Wee, and Jabben (2003) found a negative impact for traffic noise and accidents on land prices in the Netherlands. The discussion presented above suggests the following hypothesis:

**Hypothesis 4:** The total number of traffic accidents is negatively related to residential land price.

Studies on the proximity to air and toxic pollution facilities have generally found a negative influence on land prices (Kiel, 1995; Kohlhase, 1991; Michaels & Smith, 1990). For example, Brainard, Jones, Bateman, Lovett, and Fallon (2002) found a negative association between CO and NO₂ emissions and several land indices in Birmingham, UK. Burnell (1985) argued that although residential land prices might increase due to the existence of concentrated industrial land nearby, industrial pollution negatively affects such residential land prices. In a study focusing on land prices in the UK, Pragnell (2003) showed empirically that air pollution caused by incinerators had a negative effect on land prices up to 1.6 km from the incinerator. In a similar study conducted in England, Rivas Casado, Serafini, Glen, and Angus (2017) found that pollution decreases land prices by up to 10% in areas such as Marchwood, Newhaven and Allington. Literature reporting negative relationship between pollution and land prices include studies by Espey and Lopez (2000), Leggett and Bockstael (2000), and Zhao, Simons, Fan, and Fen (2016). The discussion presented above suggests the following hypotheses:

**Hypothesis 5a:** Air pollution, as measured by CO ppm, is negatively related to residential land price.

**Hypothesis 5b:** Air pollution, as measured by O₃ ppb, is negatively related to residential land price.

The research hypotheses are shown in Figure 1.

**METHODOLOGY**

**Study area**

With a total area of 17,818 km², Kuwait is one of the smallest Arab nations. From north to south, the country is only 200 km; it is around 170 kilometres from east to west. The last census conducted in 2012 estimated the total population at around 4 million inhabitants, of which around two-thirds are non-Kuwaitis (AlSanad, 2015). The whole country is a flatland and the highest elevation is about 300 metres above sea level (Figure 2). Although less than 10% of its total area is inhabited, Kuwait is divided into six provinces called ‘Muhafazat’ (Figure 3). The country
is highly urbanized and there are no distinguishable differences across the different provinces in terms of physical and transport infrastructure (Burney, Alenezi, Al-Musallam, & Al-Khayat, 2016).

Kuwait occupies the north-western part of the Arabian/Persian Gulf and it is among the richest nations in the world in terms of per capita income. The country has around 10% of the world’s proven oil reserves, and oil represents more than 90% of government revenues. The country has recently witnessed a rapid economic transformation, a key aspect of which has been the high demand for land for residential and commercial purposes. This high demand has recently caused both market distortions in price and economic abnormalities, which makes land prices in Kuwait among the highest in the world. As shown in Figure 4, the residential land price in Kuwait can fetch around KWD1500/m², while commercial land price can reach up to KWD3000/m² (the current exchange rate is KWD1 = US$3.30).

![Figure 1. Research model and hypotheses.](image)
Figure 2. Elevation map of Kuwait (masl).

Figure 3. Administrative map of Kuwait.

Figure 5 shows the location of the sample data used in this study. Note that only Kuwaiti nationals and companies are allowed private ownership of land in Kuwait. With the exception of the Free Trade Zone, foreign investors are not allowed to own or lease real estate or land in Kuwait. Thus, compared with a freely balanced market, the structure of real estate market in Kuwait is characterized by the (1) the dominance of multi-apartment buildings transactions; (2) underrepresentation of commercial properties; (3) the absence of some categories such as hotels in the Kuwaiti private market; and (4) underrepresentation of industrial and warehouse properties as a percentage of total market turnover (Renaud, 1997). Such distortions arise
from the fact that only some commercial and few farm properties are privately owned. In fact, Kaganova et al. (2005, p. 295) argued that land prices in Kuwait contribute about 72% to individual house prices, with:

only a few cities in the world, mainly in Asia, have a comparable or a higher proportion, and all these cities are characterized by either very high density of land use (Tokyo, Hong Kong), or by special governmental policies restricting development of individual houses (Singapore, Moscow).
Data sources
Urban residential land prices data in Kuwait for 2015 were obtained from the National Bank of Kuwait (NBK) (2016) Annual Report. Following Hu et al. (2016), the present paper uses the logged price to correct for skewness in residential land prices. This transformation is common in the hedonic pricing literature as it also left-truncates land price data at zero. Data related to population density and population distribution, schools, air quality and traffic accidents in Kuwait are all taken from Kuwait’s Central Statistical Bureau’s (CSB) (2016) Annual Report. Note that data availability in Kuwait limits the statistical approach to the first administrative division of provinces into districts, which limits the type of amenities that can be analyzed. Summary statistics of all variables used in the study are listed in Appendix A.

Econometric analysis
Spatial autoregressive regression (SAR) and spatial error model (SEM)
In contrast to OLS, both SAR and SEM can deal with spatial autocorrelation and heterogeneity. This can be achieved by incorporating spatial lags into the model. A spatial lag is simply a weighted average of each datum point with its neighbours. The weight matrix, which plays an important role in accurate estimations, is based on the spatial lag concept (Plümper & Neumayer, 2010). Following Klemm and Van Parys (2012), the reciprocal geographical distance between

Figure 5. Study area and location of residential land sample data.
two neighbours \(i\) and \(j\) was used to build the spatial weight matrix. Formally, an SAR model is expressed in a matrix notation:

\[
y = \lambda \mathbf{W}y + X \mathbf{\beta} + \mathbf{\epsilon}
\]

(1)

while an SEM regression maybe written as:

\[
y = X \mathbf{\beta} + \mathbf{u}
\]

(2)

\[
\mathbf{u} = \rho \mathbf{W}u + \mathbf{\epsilon}
\]

(3)

where \(y\) is a dependent variable vector; \(\lambda\) is a spatial lag parameter to be estimated; \(\mathbf{W}y\) is a vector of spatial lags of the dependent variable \(y\); \(X\) is a vector representing the independent variables in the model; \(\mathbf{\beta}\) is a vector of parameters to be estimated; \(\mathbf{\epsilon}\) and \(\mathbf{u}\) are error term vectors; \(\rho\) is a spatial lag regression parameter to be estimated; and \(\mathbf{W}u\) is vector representing spatial lags of the disturbance term \(u\). Within a spatial context, Moran’s \(I\) can be used to detect spatial dependency (Anselin, 1995). Moran’s \(I\) statistic can be computed using:

\[
I = \frac{n}{S_0} \sum_i \sum_j \omega_{ij}(x_i - \bar{x})(x_j - \bar{x}) \sum_i (x_i - \bar{x})^2
\]

(4)

where \(\bar{x}\) is the mean of the \(x\) variable; \(\omega_{ij}\) represent the weight matrix elements; and \(S_0\) represents the sum of the elements of the weight matrix \((S_0 = \sum_i \sum_j \omega_{ij})\).

**Bayesian spatial regression**

Similar to traditional spatial models, Bayesian spatial regression models can account for the spatial correlation in the data, which refers to the fact that land prices tend to be spatially clustered (Huang, Abdekl-Aty, & Darwiche, 2010). This spatial dependence is known in the literature as the ‘ripple effect’ (Pijnenburg, 2017). To model residential land prices in Kuwait, a Bayesian conditional autoregressive (CAR) model was used (Besag, York, & Mollié, 1991). The general CAR model is a generalized linear mixed model given by:

\[
Y_k | \mu_k \sim f(y_k | \mu_k, \nu^2) \text{ for } k = 1, \ldots, K
\]

\[
g(\mu_k) = x_k^T \mathbf{\beta} + O_k + \psi_k,
\]

\[
\mathbf{\beta} \sim N(\mu_\beta, \Sigma_\beta).
\]

(5)

The Gaussian CAR model maybe written as:

\[
Y_k \sim N(\mu_k, \nu^2) \text{ and } \mu_k = x_k^T \mathbf{\beta} + O_k + \psi_k
\]

(6)

where the vector of regression parameters is denoted by \(\mathbf{\beta} = (\beta_1, \ldots, \beta_p)\). Note that it is possible to include non-linear covariate effects into the model by incorporating polynomial basis functions of the covariates or natural cubic spline in \(X\). The term \(\nu^2\) is a scale parameter for the Gaussian likelihood. Usually, this scale parameter is assigned a conjugate inverse-gamma prior distribution. A number of different spatial random effects models for \(\psi\) can be implemented as suggested by Besag et al. (1991), Leroux, Lei, and Breslow (2000) and Lee and Mitchell (2012).

To conduct the CAR model within a Bayesian framework, a Markov chain Monte Carlo (MCMC) method is used to estimate the posterior distribution. The length of the MCMC chain is set to 50,000, with 10,000 burn-in cycles. Samples are saved every 10 cycles. All analyses were performed using R statistical software package version 3.3 (R Core Team, 2017).
RESULTS

Spatial autocorrelation and hotspot detection
To check the presence of spatial autocorrelation, a Moran’s $I$ test for residuals and for study variables was conducted. Global Moran’s $I$ for regression residuals was significant at the 0.05 level ($0.06, p = 0.0246$). Moran’s $I$ test for the logged land price was also significant ($0.36, p < 0.001$) (Figure 6). Since Moran’s $I$ correlation ranges from $-1$ to $1$, the positive value obtained here indicates that high land prices are surrounded by other high land prices, which implies a spatial clustering of land prices in Kuwait. The paper also tested for complete spatial randomness using both the $G$-function (nearest neighbour distance) and $K$-function (reduced second-moment measure). Figures 7 and 8 indicate clustering: a greater proportion of land prices have nearest neighbours at each distance than expected under complete randomness. Figure 8 also confirms the existence of spatial dependence because the $K$-function depicted is much higher than the simulated complete randomness situation. These findings cast doubt on the OLS results and call for the use of spatial models.

Since Moran’s $I$ test showed a non-random spatial distribution of residential land price in Kuwait, it was investigated whether prices cluster in groups, indicating a spatial aggregation. Spatial clusters are generally referred to in the literature as ‘hotspots’. Land price hotspots mapping is a descriptive technique that has recently drawn considerable attention from academics and practitioners alike (Wang et al., 2013). This is because the accurate identification of hotspots and the correct understanding of their relation to explanatory variables can help the decision-maker in analytical works such as planning for amenities and zoning. Qian, He, Chiew, and He (2012) argued that hotspot mapping methods can be classified into three main categories: choropleth mapping, point mapping and kernel density estimation (KDE). Since KDE is the most widely used mapping technique (Van Patten, McKeldin-Coner, & Cox, 2009), it was used to detect hotspots in land prices.

The KDE can be regarded as a non-parametric technique that can be employed to estimate a random variable’s probability density. Thus, it assesses the existence of specific land prices at a...
spatial unit given ‘similar’ land prices at neighbouring spatial units. This is done by placing a symmetrical surface around a spatial point’s centre and evaluating the distances between the centre and the locations of land prices within the surface (Yu, Liu, Chen, & Wang, 2014). Following Fotheringham, Brundson, and Charlton (2000), the following KDE function was employed:

$$f_n(x) = \frac{1}{nh} \sum_{i=1}^{n} K \cdot (d_i/h)$$  \hspace{1cm} (7)$$

where $f_n(x)$ is the spatial unit $x$ density estimate; $n$ is the number of land prices near location $x$ within a radius of the predefined bandwidth $b$; $K$ is a measure for the distance-decay effect; and $d_i$

Figure 7. G-function test for complete spatial randomness.

Figure 8. Simulated K-function test for complete spatial randomness (1000 runs).
is the distance between the spatial unit $x$ and the spatial unit where the $i$th land price is located. Several KDE functions have been proposed in the literature, including the Gaussian, the triangular and the quartic functions (Loo, Yao, & Wu, 2011; Xie & Yan, 2008). However, it has been shown that the choice of a particular density function does not significantly alter the results (Yu et al., 2014).

Figure 9 shows land price hotspots in Kuwait. As shown, KDE produces a continuous interpolated surface that is not constrained by geopolitical boundaries. It is clear that hotspots for both residential and commercial land prices are located in the eastern coastal areas of Kuwait on or near the Arabian/Persian Gulf. Since KDE can change considerably based on the bandwidth selected (Brunsdon & Comber, 2015), the optimal bandwidth method proposed by Bowman and Azzalini (1997) was used to obtain the KDE. This result is similar to those reported by Meulen and Mitze (2014, p. 325) who found that prices in Berlin’s residential property market tend to

![Figure 9. Optimal kernel densities for residential (top) and commercial (bottom) land prices in Kuwait.](image)
pinpoint particular hotspots with ‘a significant clustering of similar rental price values around individual observations’.

**OLS, SAR, SEM and CAR models**

Following Buck (2016), OLS regression was conducted initially in order to serve as both a baseline for comparisons with spatial and Bayesian spatial models and as a test for theoretical groupings. Using both Pearson correlation and variance inflation factor (VIF) methods indicated the absence of multicollinearity among explanatory variables. Figure 10 shows the correlations among study variables. It can be seen that the highest correlation was around ±0.6. Table 1 shows the OLS results linking land prices to several explanatory variables. It can be seen that density, percentage of Kuwaitis and total number of schools are positively and significantly related to land price, which confirms hypotheses 1–3. Traffic accidents were not significantly related to land price. One measure of air quality (CO, ppm) was negatively and significantly related to land price, which confirms hypothesis 5a. Finally, O3 (ppb) was not significantly related to land price.

Table 1 also presents the results of the SAR and the SEM spatial regression models. The results are generally in line with the OLS results; however, the AIC for the SAR model is the lowest, indicating a better fit for the data. In fact, it is well documented that ‘OLS coefficients are biased when some spatial autocorrelation of the explained variable is present in the data’ (Goffette-Nagot et al., 2011, p. 1263).

![Figure 10. Pearson product-moment correlations among the study variables.](image)
From Table 1 it is also clear that almost all coefficients for the study variables are smaller in spatial regression models compared with the traditional OLS model. This implies that ignoring land prices’ spillovers in adjacent districts can falsely inflate the exogenous variables impact. In fact, it is well documented that OLS coefficients are biased in the existence of spatial autocorrelation (Goffette-Nagot et al., 2011).

To check the robustness of the findings, a Bayesian CAR spatial regression was also conducted. The general framework of Bayesian spatial regression MCMC-based simulation method involves three steps: (1) constructing the prior probability distributions; (2) determining the likelihood function; and (3) sampling for a prespecified posterior probability distribution (Ntzoufras, 2009). Based on Stegmueller’s (2013) seminal work, a low precision value of 0.0001 was set, indicating a low degree of belief in the prior distribution. Following Vatter, Stadelmann-Steffen, and Danaci (2014), a uniform prior bounded between 0 and 100 was used as a diffuse prior. Bayesian spatial results are shown in Table 2, which indicates a general consensus with the SAR and SEM

### Table 1. Ordinary least squares (OLS), spatial autoregressive regression (SAR) and spatial error model (SEM) results.

| Variable          | OLS        | SAR        | SEM        |
|-------------------|------------|------------|------------|
| Intercept         | -1.3953    | -2.6797    | 0.3486     |
|                   | (3.4030)   | (2.9715)   | (3.0266)   |
| Density           | 0.0004***  | 0.0003***  | 0.0003***  |
|                   | (0.0001)   | (0.0000)   | (0.0000)   |
| Kuwaitis (%)      | 0.0427***  | 0.0378***  | 0.0364***  |
|                   | (0.0154)   | (0.0131)   | (0.0137)   |
| Schools           | 0.0243***  | 0.0200***  | 0.0214***  |
|                   | (0.0063)   | (0.0056)   | (0.0061)   |
| Traffic accidents | 0.0106     | 0.0107     | 0.0093     |
|                   | (0.0055)   | (0.0046)   | (0.0049)   |
| CO (ppm)          | -2.7030*** | -2.5647*** | -2.5389    |
|                   | (0.5530)   | (0.0473)   | (0.0515)   |
| O₃ (ppb)          | 0.1502     | 0.0134     | 0.0112     |
|                   | (0.0706)   | (0.0600)   | (0.0642)   |

Likelihood Ratio test | 5.3795 | 1.3831
Asymptotic standard error | 0.1228 | 0.1582
Wald statistic | 8.7320*** | 6.7943***
Akaike information criterion (AIC) | 11.687 | 8.3079 | 12.304

Note: Significance levels: $p < 0.05$*; $p < 0.01$**; $p < 0.001$*** (standard errors).

From Table 1 it is also clear that almost all coefficients for the study variables are smaller in spatial regression models compared with the traditional OLS model. This implies that ignoring land prices’ spillovers in adjacent districts can falsely inflate the exogenous variables impact. In fact, it is well documented that OLS coefficients are biased in the existence of spatial autocorrelation (Goffette-Nagot et al., 2011).

To check the robustness of the findings, a Bayesian CAR spatial regression was also conducted. The general framework of Bayesian spatial regression MCMC-based simulation method involves three steps: (1) constructing the prior probability distributions; (2) determining the likelihood function; and (3) sampling for a prespecified posterior probability distribution (Ntzoufras, 2009). Based on Stegmueller’s (2013) seminal work, a low precision value of 0.0001 was set, indicating a low degree of belief in the prior distribution. Following Vatter, Stadelmann-Steffen, and Danaci (2014), a uniform prior bounded between 0 and 100 was used as a diffuse prior. Bayesian spatial results are shown in Table 2, which indicates a general consensus with the SAR and SEM

### Table 2. Bayesian conditional autoregressive (CAR) spatial regression results.

| Estimate | 2.5%  | 50%  | 97.5% |
|----------|-------|------|-------|
| Intercept| -1.4380 | -2.2610 | 4.3607  | 11.2804  |
| Density  | 0.0004 | 0.0003 | 0.0005 | 0.0008 |
| Kuwaitis (%) | 0.0390 | -0.0100 | 0.0211 | 0.0521 |
| Schools  | 0.0239 | 0.0010 | 0.0217 | 0.0311 |
| Traffic accidents | 0.0105 | -0.0111 | 0.0010 | 0.0112 |
| CO (ppm) | -2.5610 | -2.8500 | -1.6322 | -0.3516 |
| O₃ (ppb) | -0.1159 | -0.1510 | 0.0100 | 0.1527 |
| $\sigma^2$ | 0.3428 | 0.2013 | 0.5211 | 1.7723 |
| $\tau^2$  | 0.0411 | 0.0113 | 0.0318 | 0.0545 |
| $\phi^2$  | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
models. Figure 11 shows both the trace and kernel density plots of the posterior marginal distributions for major parameters resulting from fitting the Bayesian spatial regression model. It is evident from the trace graph that the mean of the Markov chain is stable and constant over the graph, indicating that the MCMC has reached its stationary distribution. Figure 12 shows the interpolated posterior median of spatial random effects. In this graph, blue–green areas are regions where the log-odds (thus, the probability) of land prices in Kuwait are lower than expected given the study explanatory variables used, while the red–yellow areas are regions where the log-odds of land prices are higher than expected.

CONCLUSIONS, LIMITATIONS AND FUTURE RESEARCH

The objective of this study was to examine the influence of population density, percentage of Kuwaitis among total population, total number of schools, traffic accidents and air pollution as measured by the prevalence of both CO and ground-level or tropospheric O3 levels on residential land prices in Kuwait. Both traditional and Bayesian spatial models were employed to account for spatial autocorrelation and heterogeneity in land prices. A major result is that land prices in Kuwait are influenced by population density, which corroborates previous research.
investigating residential land price in other parts of the world (Goffette-Nagot et al., 2011; Hardie et al., 2000). The present paper also found that land prices in Kuwait are influenced by the percentage of Kuwaitis in the population, which lends strong support to social capital theory arguing that human behaviour is motivated not only by economic but also by social goals (Woolcock, 1998). Educational amenities also have a positive and significant influence on land prices. This result is in line with previous research reporting a positive relationship between higher educational level and increased residential land prices (Clapp et al., 2008; Espey & Owusu-Edusei, 2001; Uyar & Brown, 2007). Surprisingly, a significant relationship between lethal traffic accidents and land prices was not found. This is probably because all provinces in Kuwait experience high numbers of traffic accidents. In fact, traffic accidents are classified as one of the top five leading causes of death, resulting in around 8% of all deaths in Kuwait (Ziyab & Akhtar, 2012). Air pollution was negatively and significantly related to land prices in Kuwait. This result supports previous research investigating factors influencing residential land prices (Brainard et al., 2002).

To the best of the author’s knowledge, there have been no studies investigating factors influencing land prices in Kuwait. Thus, the findings might be important as they indicate the urban structure in the country, which is regarded as a useful metric in urban planning. Understanding how residential land prices are clustered in Kuwait can help the decision-maker to establish transportation networks and zoning. The results can help policy-makers to estimate the implicit value of ‘non-market attributes’ composing land prices in Kuwait. The way land prices are clustered in Kuwait might be an indication of the existence of what is called in the literature ‘market segmentation’ – a phenomenon that arises ‘when consumers’ demand for a particular structural or location-specific characteristic is highly inelastic and that the preference for this characteristic is shared by many other consumers’ (Glaesener & Caruso, 2015). Such market segmentation can lead to the emergence of sub-markets in residential land prices in which ‘persistent and significant disparities in attribute prices are present across urban space’ (Orford, 2000, p. 1645). Although in a free market residential land prices are usually determined by supply and demand,
in Kuwait such prices occur within top-to-bottom administrative planning. Thus, such allocation might result in market distortions and economic abnormalities in land prices. Since less than 10% of its total area is inhabited, local variability in land prices in Kuwait displays a remarkable spatial heterogeneity that differs significantly from developed countries. It should also be noted that in Kuwait, as in many other Arab countries, a sizeable proportion of land transactions are performed informally, which limits the analysis to only formal markets.

Like other studies, this study is not without its limitations. First, this paper has focused only on one type of land, namely residential land. Future research may replicate this study on other types of land, such as commercial or agricultural land, to test the robustness of the findings. Although the focus was on several socioeconomic factors influencing land prices in Kuwait, future studies can investigate the impact of other hedonic factors such as proximity to parks, views of green spaces, the seaside, lakes and waterfalls on land prices. Owing to data availability, it was not investigated how the degree of education, income per capita and the presence of marginal or segregated neighbourhoods may affect land prices. Future research employing spatial econometric models may study the influence of such factors on land prices. Since residential land prices might be determined by a complex interaction between socioeconomic and hedonic variables, future research may also investigate the impact of such interaction on land prices. This study examined the influence of air quality only on land prices; however, water quality may also influence land prices (Leggett & Bockstael, 2000). Thus, future research can study the effect of water quality on residential land prices in Kuwait. For example, it may develop theoretical econometric choice models incorporating both ‘green amenities’ and the distance to ‘economic opportunities’. Since planning constraints can easily change land prices, which might, in turn, affect hotspots, future research might investigate how the change in planning constraints might impact on land price hotspots. Note, too, that land prices in Kuwait were investigated using a cross-sectional rather than a longitudinal design, which implies that much more emphasis was placed on observing land price behaviour than in observing changes in such dynamic behaviour. Thus, future research may employ a longitudinal approach to observe changes in land prices in Kuwait over time. Finally, this research investigated factors influencing residential land prices in a single Arab nation. It would be interesting to extend this kind of research to other Arab countries in order to see if the results hold.

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### APPENDIX A

**Table A1.** Definition and descriptive statistics of study variables.

| Variable          | Definition                                           | Mean  | SD    |
|-------------------|------------------------------------------------------|-------|-------|
| log Price         | Natural logarithm of land price                      | 6.95  | 0.42  |
| Density           | Population density (population/area)                | 2917.66 | 2718.47 |
| Kuwaiti (%)       | Kuwaitis as a percentage of the total population     | 39.05 | 10.43 |
| Schools           | Total number of primary and secondary schools        | 101.60 | 17.31 |
| Traffic accidents | Traffic accidents resulting in death                 | 78.43 | 46.80 |
| CO (ppm)          | Carbon monoxide in the air (parts per million)       | 0.8528 | 0.1800 |
| O₃ (ppb)          | Ground-level or tropospheric ozone level (parts per billion) | 27.20  | 2.19  |