

2016

Spatio-temporal modeling of Louisiana land subsidence using high resolution geo-spatial data

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SPATIO-TEMPORAL MODELING OF LOUISIANA LAND SUBSIDENCE USING
HIGH RESOLUTION GEO-SPATIAL DATA

A Dissertation

Submitted to the Graduate Faculty of the
Louisiana State University and
Agricultural and Mechanical College
in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy

in

The Department of Geography and Anthropology

by

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December 2016

Acknowledgements

For this dissertation, I will thank my advisor, Dr. Lei Wang, who had supported my study and life in USA in these years, and I have learned a lot of important knowledge and techniques from him. I will thank Dr. Fahui Wang, Dr. Shelley Meng, Mr. DeWitt Braud and Dr. Chunyan Li, who had given me many important suggestions for my research. I will thank Yaping Xu, a Ph. D student from Louisiana State University, who had given me a lot of support for my research. Finally, I will also thank my family, who had supported my study in USA.

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Abstract

Problems caused by subsidence are very common in many areas of the world, and this kind of problems may be serious and threatening to living people in Louisiana. Adverse subsidence in Louisiana will cause serious problems, such as excessive wetland formation or land loss, if we can't make appropriate treatments, and this topic will also be what we focus on in this research (Kent and Dokka 2012).

For subsidence survey, we can use three kinds of common techniques, leveling, InSAR (Interferometric Synthetic Aperture Radar) and GPS observation (Lu, C. et al. 2012). In this research, high accuracy of subsidence data in Louisiana has been collected by GPS, and Kriged-Kalman Filter (KKF) has been used to process such subsidence data (Mardia et al. 1998). Results by KKF have shown spatio-temporal distributions of subsidence rates from 2011 to 2013, and these results have also been validated by the Bayou Corne Sinkhole knowledge in this research (Cusanza 2013; Jones and Blom 2014; Jones and Blom 2015).

Based on the validated KKF results in this research, we have used some geo-statistics models, such as Geographically Weighted Regression (GWR), the spatial-lag model and the spatial-error model, so as to find which main factors have caused adverse subsidence in the study site in 2013 (Fotheringham et al. 2002; Baller et al. 2001; Wang 2006; Wang et al. 2014). Modeling results have shown that, GWR, the spatial-lag model and the spatial-error model may all be suitable in this research, and Bayou Corne Sinkhole, sediment compaction, groundwater withdrawal and mass

loading of buildings may be the significant and explainable factors causing subsidence in the study site (Abdollahzadeh et al. 2013; Cusanza 2013).

Thus, in this research, we have concluded that KKF, as a unique and valid model based on Kalman Filter, has been used to make an optimal prediction for large area of subsidence in Louisiana (Mardia et al. 1998; Kalman 1960; Zhang 2008; Lu, C. et al. 2012). Besides, main factors for subsidence in the study site can be found by geo-statistics modeling, and these modeling results basically match the former research by the other people (Abdollahzadeh et al. 2013).

Chapter 1 Introduction

1.1 Background

The term “subsidence”, which refers to the downward movement of the Earth’s surface with respect to a reference point (Dokka 2006; Kent and Dokka 2012), can be produced by both the geophysical and anthropogenic factors (Kent and Dokka 2012). Subsidence may cause many adverse effects on our living space such as excessive wetland formation or land loss, if we fail to make appropriate treatments on irregular subsidence (Kent and Dokka 2012).

Many areas all over the world are suffering from serious subsidence problems for relatively different reasons (Hung et al. 2011). For instance, Venice in Italy has been known as a classic city with subsidence phenomenon, because this historical city’s local problems such as stability of buildings, waterways and coastal erosion have been contributing to such phenomenon year by year (Bitelli et al. 2000). The other classic areas emerging dramatic subsidence should include the lower Mississippi Valley and northern Gulf coast from USA, where the contributing factors are multiple such as groundwater withdrawal and pumping oil (Abdollahzadeh et al. 2013; Shinkle and Dokka 2004). And subsidence in this area as “slow disaster”, will threaten critical habitats, large and small cities, farms, and economic infrastructure in several states with eventual inundation by the Gulf of Mexico (Shinkle and Dokka 2004).

The state of Louisiana, which is also located in the lower Mississippi Valley and northern Gulf coast area, is undergoing evident subsidence gradually, especially in its coastal parishes causing a huge area of wetland. To account for this serious problem, the following figure shows the vertical displacement of height for a Louisiana ground point (point name: 1 LSU) in the whole period of 2012, based on the research methods by Shinkle and Dokka in 2004 (Dokka 2006; Shinkle and Dokka 2004):

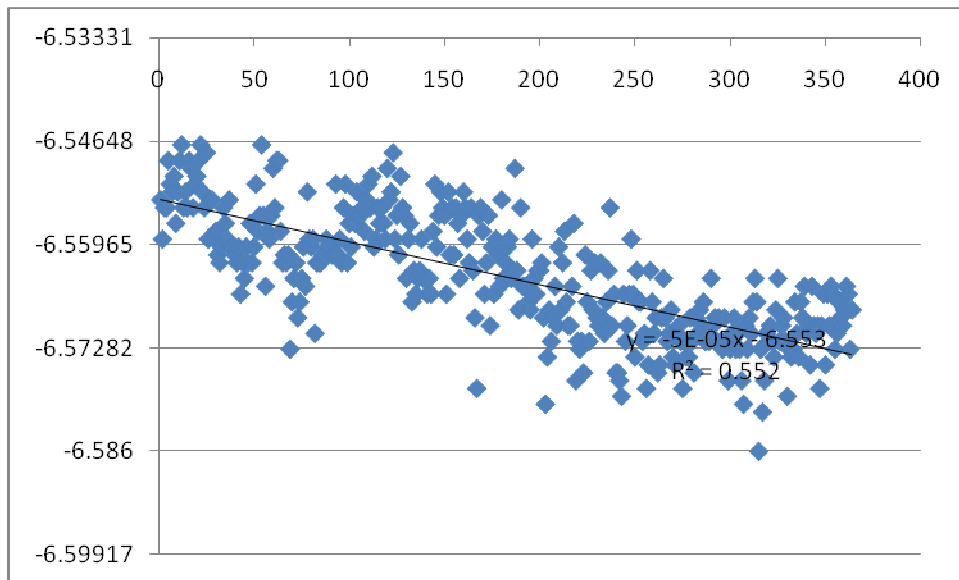


Figure 1 Height changes for one site (1LSU) in Louisiana in 2012, units: day (Horizontal axis), meter (Vertical axis)

From this figure above, using the trendline slope (0.00005), we can calculate the annual subsidence rate which equals 18.3 mm. We should not lose sight of this rate calculated for a serious subsidence problem in such area, because the future cumulative subsidence in a long period, such as 50 to 100 years, will be estimated to a significant result if this subsidence rate is stable over years. Imaginably, at that time, the effects of this subsidence disaster will be felt by the entire country as inundation

gradually destroys America's largest coastal wetland and ravages its energy production heartland (Shinkle and Dokka 2004).

Hence, facing the serious situation for subsidence problem in Louisiana discussed above, relevant researchers should take more and more focus on many important topics of subsidence studies, such as subsidence prediction. Governments should also take powerful actions to control high speed of adverse subsidence if they feel necessary. And this research may be a potential and feasible attempt to monitor, predict and treat subsidence in Louisiana.

1.2 Literature review

The subsidence study can be done with many different academic backgrounds of methods, such as methods on geotechnical engineering, geology, geophysics, geography or Geographic Information System (GIS). As potential geographic researchers, we mainly focus on recent status of subsidence study from geography involved backgrounds, and the literature review results show that relevant papers on subsidence can be classified into two subsets for research topics as follows: how to make high accurate subsidence observation and prediction, and how to collect relevant contributing factors with modeling during dramatic subsidence.

Subsidence observation and prediction:

Generally speaking, until recently, three common kinds of techniques have been widely used in the process of subsidence observation: leveling, GPS observation and InSAR (Interferometric Synthetic Aperture Radar) (Lu, C. et al. 2012).

Early in 1950s, engineers and researchers started to make subsidence survey by means of leveling, usually quantifying the vertical displacement at benchmarks for land subsidence (Shinkle and Dokka 2004). With geodesy methods, the survey accuracy by leveling can be so high at millimeter level, while the temporal resolution is technically limited (Lu, C et al. 2012), and the conventional survey cycles usually exceed ten years. Then since the GPS technique emerged and began to develop widely, GPS survey has become another available method to quantify land subsidence, with millimeter-level point heights and relatively higher temporal resolution, whereas the survey point density will usually be relatively low (Lu, C. et al. 2012). After the new 21st century, the InSAR technique provides an alternative to leveling and GPS observations due to the highly spatial density (Lu, C et al. 2012) (Extracted from: <http://treuropa.com/technique/insar-evolution/>). In the whole InSAR survey imaging process, the phase differences of microwaves from repeat-pass InSAR satellites should be recorded to calculating the displacements of ground downward movements as land subsidence (Extracted from: <http://treuropa.com/technique/insar-evolution/>), nevertheless, this imaging process will also definitely produce multiple categories of unwanted errors, especially atmosphere effect, topographic distortion, and de-correlation noise (Extracted from: <http://treuropa.com/technique/insar-evolution/>). Even if the new advanced InSAR technique, Differential InSAR (DInSAR) which involves differential method with the corresponding DEM (Digital Elevation Model) and emerges in recent years, can reduce or eliminate a lot of topographic distortions, the other errors including atmosphere effect may not be processed yet. Thus, each of

these 3 techniques, Leveling, GPS, and InSAR, has its evident advantages and flaws relatively, and the integration or combination of such techniques has been a common research trend necessarily for developing accurate land subsidence survey.

At the beginning stage of techniques-integration study, the integration of Leveling and GPS observations had been completed by many researchers. Especially, a paper released in 2007 shows that the comparison of historical leveling and recent GPS data can reveal the subsidence rates on Thessaloniki Plain of Greece in the past 50+ years (Psimoulis et al. 2007). Besides, around 2000, a data information system which can connect the leveling network with GPS data had been operated to monitor the ground subsidence in the Southern Po Valley (Bitelli et al. 2000). Also, The NOAA data report by Shinkle and Dokka in 2004 shows that the GPS observation data in the CORS (Continuously Operating Reference Station) had assisted the integrated leveling benchmark data from many epochs, calculating and interpolating the steady state of subsidence rates in the lower Mississippi Valley and Northern Gulf Coast (Shinkle and Dokka 2004; Kent and Dokka 2012), and the figure on interpolated subsidence rates is shown in Figure 2 as follows (Shinkle and Dokka 2004; Kent and Dokka 2012):

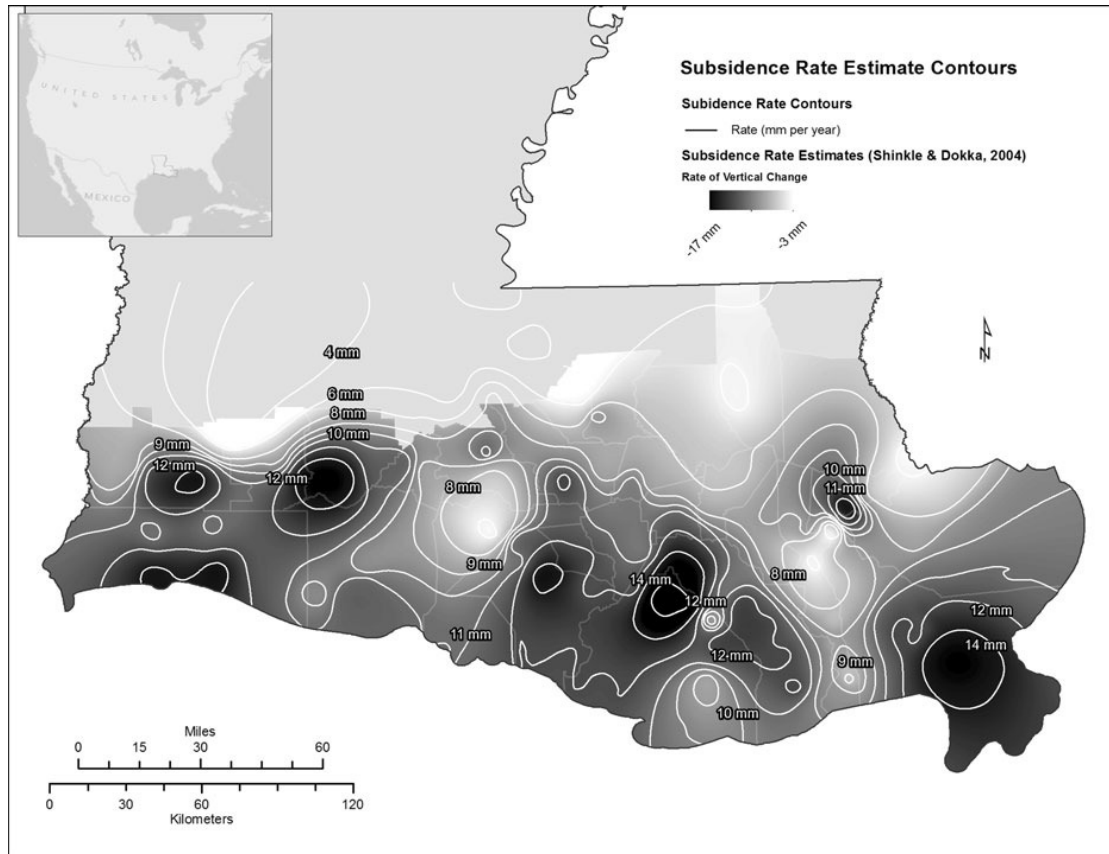


Figure 2 Interpolated rates of leveling subsidence around Louisiana (Shinkle and Dokka 2004; Kent and Dokka 2012)

Hence, this method on leveling and GPS combination can produce higher accuracy of subsidence data and extend the subsidence observation periods from the past to the future (Shinkle and Dokka 2004; Kent and Dokka 2012), never the less, it may be not so feasible to solve the low point density problem well, especially in cases that observation points are distributed less averagely or less randomly in the study area.

Recently, over dozens of papers on subsidence show that the most acknowledged and popular method on subsidence survey, will involve the integration technique between InSAR (DInSAR) and GPS. In this whole integration process, DInSAR should be used instead of ordinary InSAR because DInSAR data has much less

topographic error by using the corresponding DEM (Extracted from: <http://treuropa.com/technique/insar-evolution/>). Moreover, many areas of land subsidence all over the world have been surveyed by this popular integration technique, especially for the case of Appin Township, southwest of Sydney, Australia (Linlin Ge et al. 2003). In this case, GPS data over the same study site had been used to geo-reference the DInSAR results, and what's more, the differential tropospheric delay (atmosphere effect) will be estimated by the GPS data and it will be also interpolated into an image correcting the atmosphere disturbance in the InSAR results (Linlin Ge et al. 2003; Ge 2000) (Extracted from: <http://treuropa.com/technique/insar-evolution/>).

Thus, DInSAR has been regarded as a popular technique to monitor land subsidence, especially combined by GPS, while, this technique may be subject to uncertainties caused by the atmosphere-induced error, satellite orbit error and terrain effect, also, the land coverage which has different surface properties over difference season will cause spatial de-correlation in DInSAR and degraded measurement accuracy (Hung et al. 2011; Hung et al. 2010). Permanent Scatterer Interferometry (PSI), has been proved to reduce the deficiency in DInSAR (Hooper et al. 2004; Hung et al. 2011). PSI can be a relatively recent development from conventional InSAR, relying on studying pixels which remain coherent over a sequence of interferograms, it will provide consistent and stable radar reflections (Burgmann et al. 2000). For the subsidence case over the Choushui River Alluvial Fan in Taiwan, PSI, which reduces errors affecting conventional DInSAR techniques, had been used for a data fusion

work with high precision and low point-density leveling data as a smoothed correction to PSI result (Hung et al. 2011; Lu, C. et al. 2012). This fusion work can make the surveyed result more representative of overall deformation characteristics than PSI field only or leveling only (Hung et al. 2011), and it can also be a good and classic study instance on the integration of PSI (InSAR) and leveling. In this fusion process, a simple “draping” method had been used to merge the PSI result with the leveling one (Hung et al. 2011; Forsberg and Skourup 2005), and the main steps for this “draping” method have been shown as follows (Hung et al. 2011):

Step 1 Interpolate pixel-wise vertical rates of PSI on a 250×250 m grid (Hung et al. 2011);

Step 2 Interpolate the vertical rates at the benchmarks from the grid (Hung et al. 2011);

Step 3 Subtract the PSI-derived rates from the leveling-derived rates at the benchmarks to obtain the differences (Hung et al. 2011);

Step 4 Interpolate the differences on a 250×250 m grid (Hung et al. 2011);

Step 5 Sum the grids of PSI (Step 1) and the grid of difference (Step 4) to form a grid of combined PSI-leveling vertical rates (Hung et al. 2011).

The future studies on data fusion will include an employment of improved method that uses wavelet functions or spectral combination to represent various kinds of subsidence data (Hung et al. 2011; Addison 2002).

In addition, some other kinds of techniques on subsidence survey except leveling, GPS and InSAR, had been used in recent research cases, such as AWC (analog

weather charts) applied to the high precision GPV-MSM (Grid point value of Meso-Scale Model) water vapor data (Zheng et al. 2014). In this case, the spatial distribution of atmospheric delay by water vapor was quantified using AWC, so the atmosphere effect of DInSAR data will be reduced, making GPV-MSM data effective for DInSAR analysis (Zheng et al. 2014; Lu, C. et al. 2012).

Although the integration of such techniques above can make a high accuracy of subsidence survey, recent news show that NASA is developing a new airborne interferometer system named UAVSAR, which will make much higher spatial resolution and accuracy for future subsidence survey than before (Blom et al. 2009).

Furthermore, except the common techniques and their integration, some methods from geo-statistics models can also be used to process subsidence data for high accuracy of prediction, such as Kriged Kalman Filter (Mardia et al. 1998). Kriged Kalman Filter (KKF), which is regarded as a combination or integration of Kalman Filter and Kriging interpolation, can be used to process and predict spatio-temporal data, such as long term point data on subsidence (Kalman 1960; Mardia et al. 1998; Shang et al. 2011; Olea 1999). The long term GPS subsidence data can be especially applied to KKF because of its high temporal resolution and low point density characteristics, and based on GPS points input, a raster data can be produced and large areas of subsidence data near these scatter GPS points can be interpolated and predicted accurately in a long term period (Shang et al. 2011; Lu, C. et al. 2012). Thus, KKF may be a possible and accurate method for surveying and predicting long term subsidence data (Shang et al. 2011).

Modeling of factor data contributing to subsidence:

The factors for subsidence can be classified as geophysical and anthropogenic (Kent and Dokka 2012), and recent study on subsidence in southern coastal Louisiana shows that sediment compaction, low-angle faulting and regional subsidence associated with mass loading appear to be the major factors controlling subsidence in the delta, and the coastal regions outside of the delta undergo slower subsidence, probably related to factors such as fluid withdrawal (ground water, petroleum and natural gas extraction) (Abdollahzadeh et al. 2013). In other words, the natural process of subsidence in many active areas can be mainly contributed to following factors: sediment compaction, faulting, anthropogenic mass loading, groundwater withdrawal, oil pumping and natural gas extraction (Abdollahzadeh et al. 2013; Kent and Dokka 2012). Thus, the methods on how to use appropriate model to establish relationships between subsidence and factors and how to quantify such factors, will be prevailing topics for recent subsidence researchers from a variety of academic backgrounds.

For geophysical factors which contribute to subsidence (Kent and Dokka 2012), faulting that results from a series of dramatic crust movement, has become a good and popular study topic on subsidence, especially for geological and geophysical researchers (Abdollahzadeh et al. 2013; Dolezalova et al. 2009; Brodie et al. 2007). A good instance on fault is the evaluation project of mining subsidence located in Karvina, Czech Republic, using GPS data (Dolezalova et al. 2009). In this project, the subsidence depression from two years of GPS survey data shows the important

influence of the complicated tectonic situation on the behaviour of surface subsidence (Dolezalova et al. 2009). Also, tectonic faults had made the shape of subsidence depression evidently irregular, but on sites without tectonic fault, the subsidence depression had experienced a smooth and regular development, and this research instance can strongly prove the close correlation between the shape of subsidence and the characteristics of fault on the same site (Dolezalova et al. 2009).

As a common and anthropogenic factor related to subsidence (Kent and Dokka 2012), the groundwater withdrawal (Kent and Dokka 2012; Abdollahzadeh et al. 2013) has been favorable to researchers from many backgrounds, mainly because the groundwater can be the most direct factor than other factors which lead to subsidence (Shang et al 2011; Abdollahzadeh et al. 2013). A classic hydrology and GIS (Geographic Information System) case involves a spatial and temporal prediction system for groundwater flow and subsidence in Japanese coastal plain (Zhou et al. 2003). In this case, using hydrology and GIS knowledge, the data required had been converted into GIS data in the database, and the surface water cycle had been simulated to obtain the spatial and temporal groundwater infiltration quantity (Zhou et al. 2003). Then a 3D groundwater flow model based on hydrology, had been established to simulate the groundwater flow and then calculate or predict the corresponding subsidence on different water pumping scenarios (Zhou et al. 2003). Another recent GIS instance involving water withdrawal (Abdollahzadeh et al. 2013) shows the spatial and temporal characteristics of subsidence induced by groundwater over-exploitation in Beijing (Chen et al. 2011; Abdollahzadeh et al.

2013). With data collected by GPS and InSAR, a model on the dynamic variation from hydro-dynamics had been established to analyze the subsidence response to groundwater withdrawal (Chen et al. 2011).

Besides models from hydrology, many geo-statistics models can be much available for quantifying the factors related to subsidence, such as Geographically Weighted Regression (GWR) (Fotheringham et al. 2002). The most recent GWR case on subsidence had been released by a research group from Taiwan, and it also involves the groundwater factor for modeling (Shang et al 2011).

In this GWR case from Taiwan, the study site was selected in Choshuichi Alluvial Fan, the ground subsidence data was collected by GPS observation, and the groundwater levels in 3 underground aquifers were obtained from Water Resources Agency (Shang et al. 2011). And by interpolation, the spatial distribution of subsidence in the study site and the groundwater levels at each GPS station can be estimated for GWR (Shang et al. 2011; Shepard and Donald 1968).

In the GWR modeling process, the groundwater level changes in 3 aquifers were selected as predictors, and subsidence was the dependent variable (Shang et al 2011). GWR is more advantageous than other geo-statistics models for this case because the other models used for subsidence study usually involve a “global” approach, without considering spatial heterogeneity of data, while GWR is proved to show the spatial variation of predictors, with spatially varied coefficients of predictors (Shang et al. 2011; Fotheringham et al. 2002). Thus, by GWR model, all of 4 spatially varied coefficients can be calculated, and using these coefficients, land subsidence in the

study site can be predicted (Shang et al 2011). Then an important comparison between the prediction result from GWR and the one from OLS (Ordinary Least Square) had been made, and it shows that GWR can better approach the real subsidence distribution, with higher accuracy and adjusted R-square (Shang et al 2011; Hayashi and Fumio 2000). While, this GWR case for subsidence can be classic, it still has many drawbacks including the lack of long-term or seasonal GPS data for showing a more detailed correlation between groundwater levels and subsidence (Shang et al. 2011), also, multiple kinds of important factors except groundwater levels, may be collected to access to GWR for more accurate modeling results, and all of these drawbacks will be expected to improved in the future research (Shang et al. 2011; Fotheringham et al. 2002; Abdollahzadeh et al. 2013).

Many of the above discussed subsidence cases almost refer to a natural process of subsidence, whereas, in some small areas of sites, subsidence may be produced by loadings from some special human activities, such as mining. And for such cases, especially for mining subsidence, the factors related to subsidence should be much different, such as depth and distance from drift, DEM and slope gradient, groundwater permeability, geology and land use (Kim et al. 2006; Kim et al. 2009; Oh and Lee 2010; Oh et al. 2011).

Hyun-Joo Oh's groups from Korea had made a series of studies on mining subsidence, collecting relevant factor data, and using many classic models from general statistics (Kim et al. 2006; Kim et al. 2009; Oh and Lee 2010; Oh et al. 2011). The study sites for all of cases were located in abandoned coal mines, models such as

frequency ratio, logistic regression, weights of evidence and artificial neural network were tested successively to find the possible relationships between factor data and subsidence, calculating such factors' ratings or weights to map the subsidence hazards by overlaying these ratings or weights, and results for nearly all of tested models show over 90% prediction accuracies at best (Kim et al. 2006; Kim et al. 2009; Oh and Lee 2010; Oh et al. 2011; Freedman 2009). This series of studies on mining subsidence have made big progress, while they also have evident drawbacks. All of tested models involve the “global” approach on subsidence prediction, so spatial heterogeneity of factors had not been considered yet (Shang et al 2011; Kim et al 2006; Kim et al 2009; Oh and Lee 2010; Oh et al 2011). Moreover, the dependent variable, subsidence, had been regarded as a dichotomous one or categorical one (presence-absence), but subsidence is actually a numeric variable, so the modeling process by a dichotomous variable as subsidence may cause a coarse prediction with much less detailed information (Kim et al. 2006; Kim et al. 2009; Oh and Lee 2010; Oh et al. 2011; Freedman 2009).

1.3 Research questions

According to the flaws or drawbacks for recent techniques and methods on subsidence which have been discussed in the literature review chapter, KKF and GWR as two main methods of this research will be selected to process the Louisiana subsidence data. So we can propose two research questions as follows:

1. In the future research process, GPS subsidence data in the coastal area of Louisiana will be collected and processed by KKF, after that, some work will be done to validate these KKF raster results.

Then, can these results by KKF, reflect the real spatio-temporal distribution of subsidence pattern in the study site well, or are these results by KKF valid or not in this research?

2. In the modeling process of factors which contribute to subsidence, multiple kinds of factor data will be collected and GWR model will be selected to process these kinds of data, showing some possible relationships between subsidence and relevant factors.

Then, can results by GWR reflect the spatial heterogeneity of Louisiana subsidence or not (Fotheringham et al. 2002; Shang et al. 2011)? With respect to modeling and prediction accuracies, are results by GWR better than or comparable against the ones by other geo-statistics models, such as the spatial-lag model or the spatial-error model (Wang 2006; Wang et al. 2014; Baller et al. 2001)?

1.4 Research significance

In this research, the KKF method will be used to process long term of GPS subsidence data in Louisiana, in order to overcome the flaw of low point density and predict large area of subsidence accurately, because KKF as the combination of Kalman Filter and Kriging interpolation, not only has features of Kriging interpolation, but also has features of Kalman Filter (Mardia et al. 1998; Lu, C. et al. 2012). So this

method can be unique with respect to subsidence survey and prediction, rather than some other common techniques such as InSAR, especially when large area of subsidence data is too hard to collect (Lu, C. et al. 2012). Besides, KKF may be advantageous to interpolate and predict subsidence accurately because of commonly large interpolation error in the well-known interpolation process such as Kriging (Mardia et al. 1998; Olea 1999; Kalman 1960).

Chapter 2 Research Methods

2.1 Research workflow

Based on the above proposed research questions, the research methods by Mardia et al. in 1998 and Fotheringham et al. in 2002, and the characteristics of data which we are able to collect, methods used in this research can be summarized into a research workflow as follows (Mardia et al. 1998; Fotheringham et al. 2002):

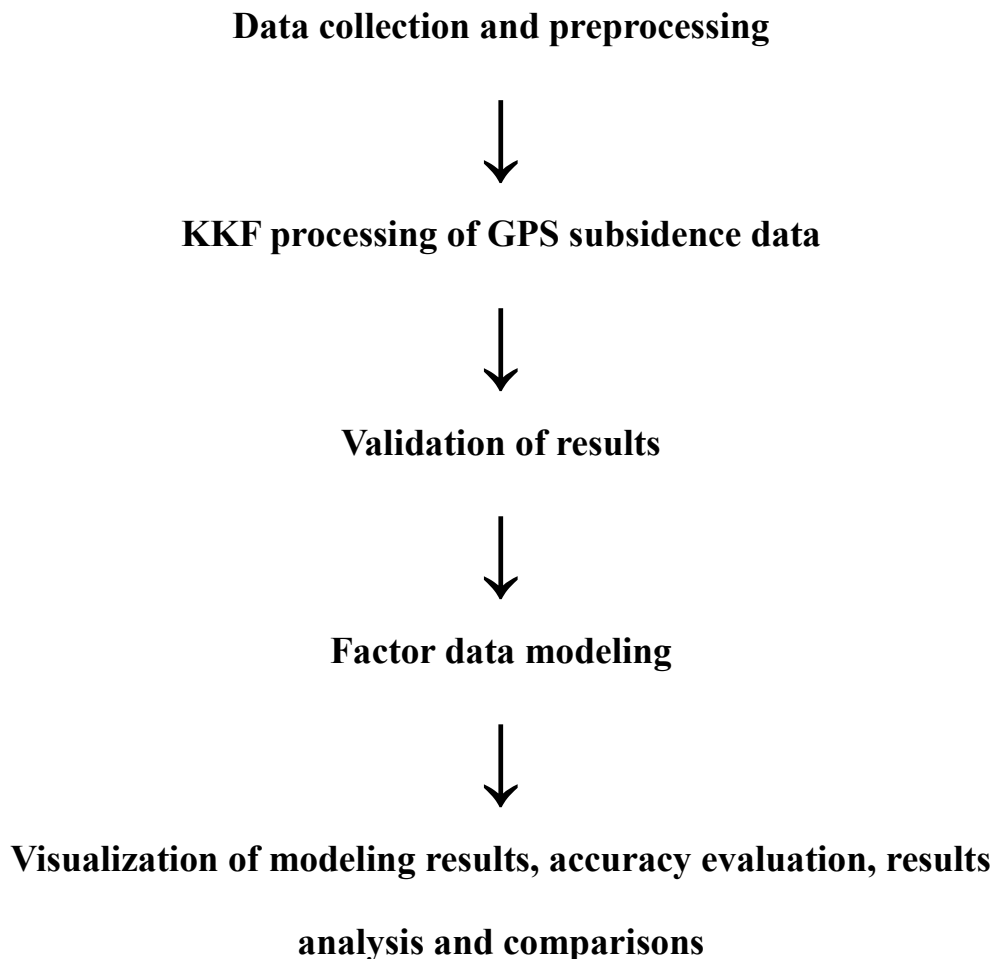


Figure 3 Research workflow

2.2 Data collection

In this research, the whole study site will be confined within the geographic boundaries of the state of Louisiana, USA. And the whole data collection work comprises of two parts as follows: GPS data collection and factor data collection.

2.2.1. GPS data collection

For GPS data collection on subsidence, a ftp server from National Geodetic Survey (NGS) websites is available online to download all sites of GPS data required since 1994 in this research, and the corresponding link can be shown as follows:

<ftp://www.ngs.noaa.gov/cors/rinex/>

From this link and NGS websites, we can find that 18 GPS observation sites as a whole CORS (Continuously Operating Reference Station) system have been installed in Louisiana, and the distribution map of all GPS sites in the study area can be shown as follows:

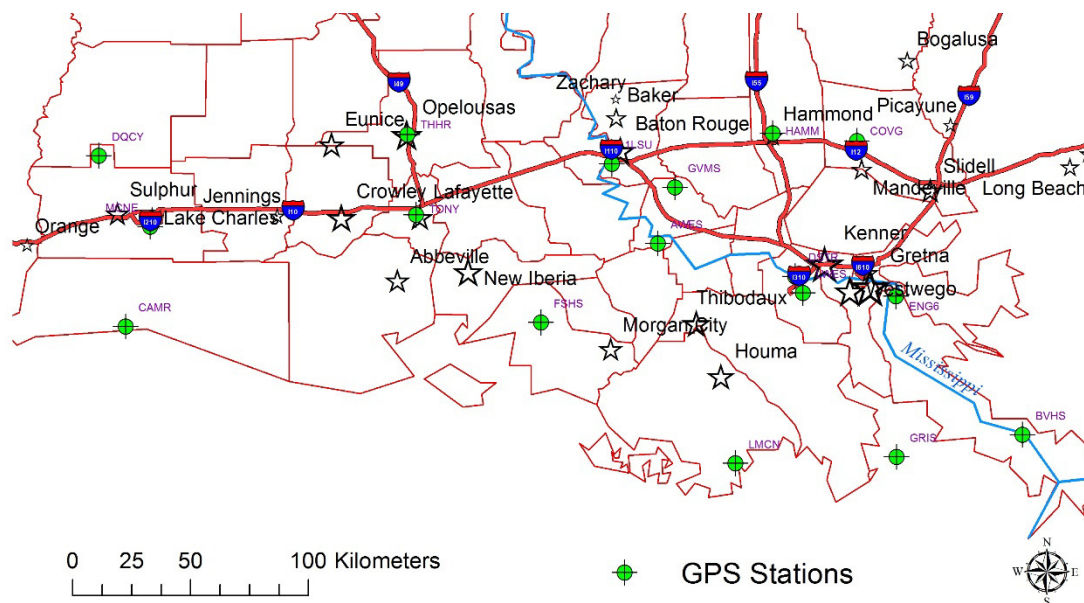


Figure 4 Distribution map for all GPS stations, green points: GPS stations

All of 18 stations of GPS data in last 5 years to now, will be planned to download by this NGS link, and the original format for this set of data is kept compressed Rinex and it is not available for a direct use on subsidence survey, thus, this original set of downloaded data should be preprocessed by geodetic software such as GIPSY by NASA JPL (Jet Propulsion Laboratory) to be converted to the format with longitude, latitude and height of sites. Changes of height will be used for quantifying the subsidence for GPS sites, and by using this GIPSY software by NASA JPL, the height accuracy for all GPS sites can be controlled within 2mm.

2.2.2. Factor data collection

According to the former research on subsidence factors in Louisiana, multiple kinds of data such as groundwater, oil, natural gas, sediment, faulting will be selected to collect (Abdollahzadeh et al. 2013).

For groundwater collection, we can collect and record the data on groundwater levels for all of observation wells in Louisiana online, from the USGS website (Extracted from: <http://groundwaterwatch.usgs.gov/>).

Besides, for factor data collection, the Louisiana Department of Natural Resources have provided a good website to collect required factor data in GIS format, such as oil, gas and sediment (Abdollahzadeh et al. 2013). This website is as follows:

<http://sonris.com>

Also, the distribution map of factor data such as oil and gas in Louisiana parish units can be shown in the following map, and maps for other kinds of factor data such

as sediment can be made as well.

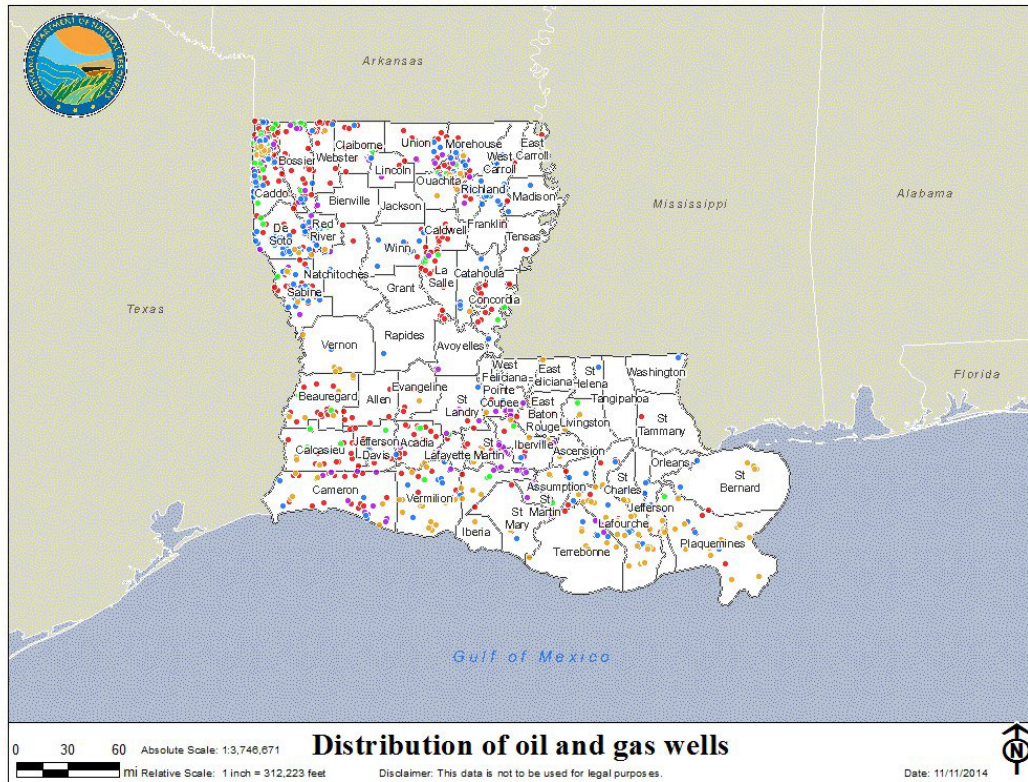


Figure 5 Distribution of oil and gas wells in Louisiana (Extracted from: <http://sonris-www.dnr.state.la.us/gis/agsweb/IE/JSViewer/index.html?TemplateID=18> 1)

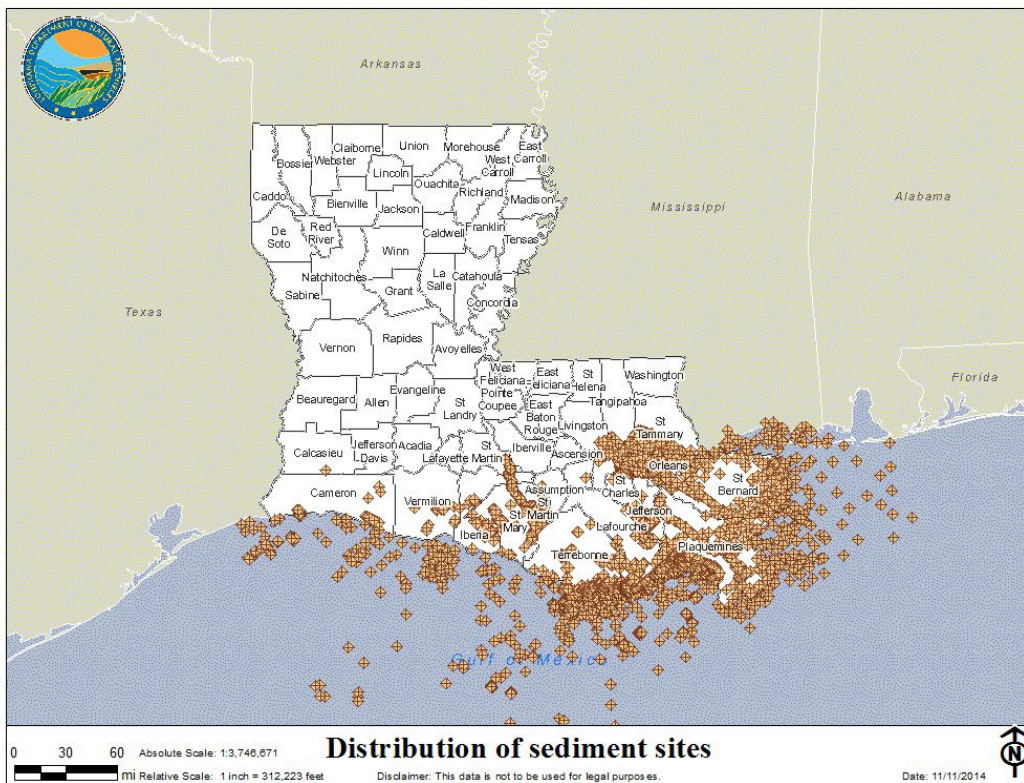


Figure 6 Distribution of sediment measurement sites in Louisiana (Extracted from: <http://sonris-www.dnr.state.la.us/gis/agsweb/IE/JSViewer/index.html?TemplateID=181>)

For factor data collection on anthropogenic mass loading, we can use the image data from the National Land Cover Database (NLCD) website to collect the data of buildings cover in Louisiana (Extracted from: <http://www.mrlc.gov/nlcd2011.php>), and extract useful information on mass loading, such as characteristics of huge city buildings in the study site (Abdollahzadeh et al. 2013; Kent and Dokka 2012).

2.3 Main methods

As is discussed in the research workflow above, the main methods used in this research will include 3 parts as follows:

2.3.1. KKF

Kalman Filter, proposed by Kalman in 1960, can be a feasible method to process dynamic changing data in time series, calculating each state of the optimal estimation for this data (Kalman 1960; Zhang 2008; Mardia et al. 1998). It is a recursive process to make estimations in general state models, by minimizing the converged errors which data contains (Kalman 1960; Mardia et al. 1998; Zhang 2008).

On the other side, Kriging interpolation method from geo-statistics can be used for estimating large area of spatial data from some spatial correlated scatter points nearby, so it can be a possible means to predict data in spatial domain (Mardia et al. 1998; Zhang 2008; Olea 1999).

Then, based on the respective characteristics for such two methods above, a combination work between Kalman filter and Krging interpolation may be possible for data prediction in spatio-temporal domain, and KKF (Kriged Kalman Filter) proves an applicable model to process spatio-temporal data (Mardia et al 1998; Kalman 1960; Zhang 2008; Olea 1999).

The fundamental model of KKF:

First we consider the state space model from Kalman Filter as follows (Mardia et al. 1998; Kalman 1960; Zhang 2008):

$$\mathbf{x}(t) = \mathbf{h}^T \boldsymbol{\alpha}(t) + \boldsymbol{\varepsilon}(t)$$

$$\boldsymbol{\alpha}(t) = \mathbf{P} \boldsymbol{\alpha}(t-1) + \mathbf{K}\boldsymbol{\eta}(t)$$

The upper equation is the observation equation, and the lower one is the system equation, also, $x(t)$ is the observation variable at state t , h is the parameter p -vector,

$\alpha(t)$ is the state p -vector, $\varepsilon(t)$ is the scalar observation error, $P : p \times p$ is the transition matrix, $K : p \times d$ is the innovation coefficient matrix, and $\eta(t)$ is the innovation (or system error or state noise) d -vector (Mardia et al. 1998; Kalman 1960).

Then in spatio-temporal domain, the observation variable $x(t)$ should be extended to $x(s, t)$ for spatio-temporal data (Mardia et al. 1998).

Also, $x(s, t)$ can be decomposed and expressed as follows (Mardia et al. 1998):

$$\mathbf{x}(s, t) = \mathbf{u}(s, t) + \varepsilon(s, t)$$

$$\mathbf{u}(s, t) = \mathbf{h}_1(s) \alpha_1(t) + \mathbf{h}_2(s) \alpha_2(t) + \dots + \mathbf{h}_p(s) \alpha_p(t) = \mathbf{h}(s)^T \alpha(t)$$

Thus, the observation equation of KKF can be shown as follows (Mardia et al. 1998; Kalman 1960):

$$\begin{aligned} \mathbf{x}(s, t) &= \mathbf{h}_1(s) \alpha_1(t) + \mathbf{h}_2(s) \alpha_2(t) + \dots + \mathbf{h}_p(s) \alpha_p(t) + \varepsilon(s, t) \\ &= \mathbf{h}(s)^T \alpha(t) + \varepsilon(s, t) \end{aligned}$$

And the system equation of KKF can also be same as the one of classic Kalman Filter as follows (Mardia et al. 1960; Kalman 1960):

$$\alpha(t) = P \alpha(t-1) + K \eta(t)$$

Moreover, in the observation equation of KKF, the error term $\varepsilon(s, t)$ should be spatial correlated (Mardia et al. 1998), and it is shown as follows (Mardia et al. 1998):

$$\text{cov}(\varepsilon(s, t), \varepsilon(s', t')) = 0 \text{ for } t \neq t' \text{ all } s, s'$$

These two important equations above, the KKF observation equation and the KKF system equation can be regarded as the general format of the KKF model (Mardia et al. 1998). While, for applications to process spatial temporal data, the principle fields should be calculated by the Kriging predictor, and the transition matrix and other parameters should also be specified by EM (Expectation–maximization) algorithm (Mardia et al. 1998; Dempster et al. 1977; Olea 1999).

2.3.2. GWR modeling

Geographically weighted regression (GWR) is proposed to solve problems on spatial heterogeneity in geo-statistics, using a linear multiple regression model with varied coefficients in different geographic areas (Fotheringham et al. 2002; Shang et al. 2011). By calculating varied coefficients as respective weights for predictors, GWR can also be a good tool to show relationships between the dependent variable and predictors, telling us which factor contribute to the dependent variable most in a special geographic area (Fotheringham et al. 2002; Shang et al. 2011).

The fundamental model of GWR:

As a linear multiple regression model, GWR can be shown as follows (Shang et al. 2011; Fotheringham et al. 2002):

$$y(\mathbf{g}) = \beta_0(\mathbf{g}) + \beta_1(\mathbf{g}) x_1 + \beta_2(\mathbf{g}) x_2 + \dots + \beta_n(\mathbf{g}) x_n + \varepsilon$$

The varied coefficients β can be calculated in the following way (Fotheringham et al. 2002; Shang et al. 2011):

$$\beta = (X^T W(g) X)^{-1} (X^T W(g) Y)$$

$W(g)$, is the Gaussian weight function (Fotheringham et al. 2002; Shang et al. 2011) (Extracted from: <http://www.cs.cmu.edu/~schneide/tut5/node12.html>).

GWR modeling on subsidence:

In this research, multiple kinds of collected data with useful attribute information, which contribute to subsidence in Louisiana, such as groundwater, oil, natural gas, sediment, faulting and anthropogenic mass loading, should be totally quantified to numeric data as important inputs to predictors in GWR model, such as groundwater level of each aquifer in a certain site (Fotheringham et al. 2002; Shang et al. 2011; Abdollahzadeh et al. 2013). After GWR modeling, the varied coefficients as GWR results should be identified in census tract unit (Fotheringham et al. 2002; Shang et al. 2011).

The calculating process of GWR can be made by ArcGIS software, and the results on varied coefficients can be visualized as raster files (Fotheringham et al. 2002; Shang et al. 2011).

For analysis work of results, GWR results can be made a comparison with OLS ones, with respect to prediction accuracy on subsidence, expecting to show the advantage of GWR (Fotheringham et al. 2002; Shang et al. 2011; Hayashi and Fumio 2000). Thus, after GWR modeling process in this research, we could know the possible distribution of main factors on fast subsidence rates for each census tract in the study site in Louisiana, which can be used for making special and correct treatments on subsidence in certain areas (Shang et al. 2011).

2.3.3 The spatial-lag model and the spatial-error model

In this research, we will use the GWR model to show the spatial heterogeneity of factor data which contributes to subsidence in Louisiana (Fotheringham et al. 2002; Shang et al. 2011). While, if the GWR results can't reflect the spatial heterogeneity so well and clearly, we will have to consider other geo-statistics models, such as the spatial-lag model or the spatial-error model, so as to make a better modeling process (Baller et al. 2001; Wang 2006; Wang et al. 2014).

The fundamental model of OLS:

In the modeling process of geographical data, when there is no clear spatial autocorrelation or spatial dependency for this set of data, we can simply use the OLS (Ordinary Least Square) model to show the relationships between the dependent variable and the independent variables (Wang 2006; Wang et al. 2014; Hayashi and Fumio 2000; Knecht et al. 2010). And the fundamental model is as follows:

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$$

y is the dependent variable vector, and X is the independent variables vector, β is the regression coefficients vector, and ε is the errors vector (Hayashi and Fumio 2000; Wang 2006; Wang et al. 2014).

While, when there is spatial dependency for this set of geographical data, the residuals will not be independent each other and the OLS model will not be suitable (Hayashi and Fumio 2000; Wang 2006; Wang et al. 2014; Knecht et al. 2010). So the spatial-lag model should be introduced, considering spatial dependency (Baller et al. 2001; Wang 2006; Wang et al. 2014; Knecht et al. 2010). The dependent variable mean

in neighboring areas named “spatial lag” will be added as an extra independent variable, based on the OLS model (Baller et al. 2001; Wang 2006; Wang et al. 2014; Knecht et al. 2010). So the fundamental model of spatial-lag is as follows:

$$\mathbf{y} = \rho \mathbf{W}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$$

ρ is the spatial lag regression coefficient, \mathbf{W} is the weights matrix (Baller et al. 2001; Wang 2006; Wang et al. 2014; Knecht et al. 2010). While, the spatial-lag model is not an autoregressive one in time-series analysis, so another model named spatial-error model should be introduced for time-series modeling (Baller et al. 2001; Wang 2006; Wang et al. 2014; Knecht et al. 2010). The error term will be regarded as autoregressive, based on the OLS model (Baller et al. 2001; Wang 2006; Wang et al. 2014; Knecht et al. 2010). So the fundamental model of spatial-error is as follows:

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{u}$$

$$\mathbf{u} = \lambda \mathbf{W}\mathbf{u} + \boldsymbol{\varepsilon}$$

λ is the spatial autoregressive coefficients vector, $\boldsymbol{\varepsilon}$ is independent (Baller et al. 2001; Wang 2006; Wang et al. 2014; Knecht et al. 2010).

Thus, like the GWR model, the spatial-lag model and the spatial-error model can be also used to make the factor data modeling process. In the modeling process, like GWR, the factor data will be the independent variables and the subsidence one will be the dependent variable (Fotheringham et al. 2002; Shang et al. 2011).

Chapter 3 Spatio-temporal Pattern Visualizations of Subsidence

3.1 The general equations for KKF and main processing steps

As the research workflow shows, the KKF processing for GPS subsidence data can be operated after data collection. And the chapter for research methods also shows the fundamental model of KKF as follows:

$$\begin{aligned}x(s, t) &= \mathbf{h}_1(s) \alpha_1(t) + \mathbf{h}_2(s) \alpha_2(t) + \dots + \mathbf{h}_p(s) \alpha_p(t) + \varepsilon(s, t) \\ &= \mathbf{h}(s)^T \mathbf{a}(t) + \varepsilon(s, t)\end{aligned}$$

$$\mathbf{a}(t) = \mathbf{P} \mathbf{a}(t-1) + \mathbf{K} \eta(t)$$

The upper equation above is the observation equation for KKF and the lower one is the state equation (Kalman 1960; Mardia et al. 1998), $x(s, t)$ is the observation variable for spatio-temporal data, h is the parameter p -vector, $a(t)$ is the state p -vector, $\varepsilon(t)$ is the scalar observation error, $P : p \times p$ is the transition matrix, $K : p \times d$ is the innovation coefficient matrix, and $\eta(t)$ is the innovation (or system error or state noise) d -vector (Mardia et al. 1998; Kalman 1960).

While, in the application for KKF processing, we should specify all of essential and intermediate parameters, such as our GPS subsidence data processing (Mardia et al. 1998). The past research work by Mardia et al. shows the specification method for the KKF model parameters, so from this method we can summarize that which essential variables or parameters should be summarized, and these essential

parameters are the covariance matrix, the bending energy matrix B , the principal fields, the parameter matrix h , the transition matrix P (Mardia et al. 1998; Kalman 1960).

Besides, based on these specified parameters, we can also summarize the main steps for KKF processing as follows (Mardia et al. 1998; Kalman 1960):

Step 1: Based on the characteristics for our collected data, make a variogram and fit a model to this variogram (Mardia et al. 1998; Olea and Ricardo 1991).

Step 2: Use the model from the last step to generate the covariance matrix for this set of data (Mardia et al. 1998; Olea and Ricardo 1991).

Step 3: Use the covariance matrix from the last step to calculate the bending energy matrix B (Mardia et al. 1998).

Step 4: Use the B matrix from the last step to generate the principal fields (Mardia et al. 1998).

Step 5: Use the principal fields from the last step to calculate the parameter matrix h from Kalman Filter (Mardia et al. 1998).

Step 6: Use Kalman Filter and EM algorithm to generate the transition matrix P , and also generate the spatio-temporal field $\alpha(s, t)$ (Mardia et al. 1998; Dempster et al. 1977; Shumway and Stoffer 1982; Olea 1999).

Step 7: Use the spatio-temporal field $\alpha(s, t)$ from the last step to make a interpolation in time series (Mardia et al. 1998; Dempster et al. 1977; Shumway and Stoffer 1982; Olea 1999).

Step 8: Use the interpolation result from the last step to make a raster, showing the distribution of subsidence rates in the study site (Mardia et al. 1998).

Before we can process the collected data by GPS observation, this set of original data should be preprocessed by the geodetic software such as NASA's GIPSY, and the final format of data by preprocessing will be longitude, latitude and height for the GPS station, then we can use the change of heights to calculate the subsidence rate. In this research, all of the preprocessing work by GIPSY (the version: 6.2) has been finished by Zhengsong Chen from Hubei Earthquake Administration in China.

In this research, we plan to process the GPS subsidence data by KKF, so as to show the distribution of subsidence rates in the study site, thus, in the following, we will discuss how to generate the variogram model for our subsidence research, and also show the final processing results by KKF (Mardia et al. 1998; Olea and Ricardo 1991).

3.2 Variogram

The semi-variogram (or variogram) modeling is essential for KKF processing, because KKF is a special type of Kriging interpolation method (Mardia et al. 1998; Olea and Ricardo 1991; Olea 1999). And the calculation formula for the semi-variogram (or variogram) is as follows:

$$\gamma(h) = \frac{1}{2N} \sum ((Z(x) - Z(x+h))^2)$$

The variable h is the distance of each pair of points in the study site, N is the total number of point pairs (Olea and Ricardo 1991).

In this research, we will collect GPS data from 18 coastal stations in Louisiana, and use this set of data to calculate the average subsidence rate each year from 2011 to 2013. The distribution map of coastal stations in the study site is as follows:

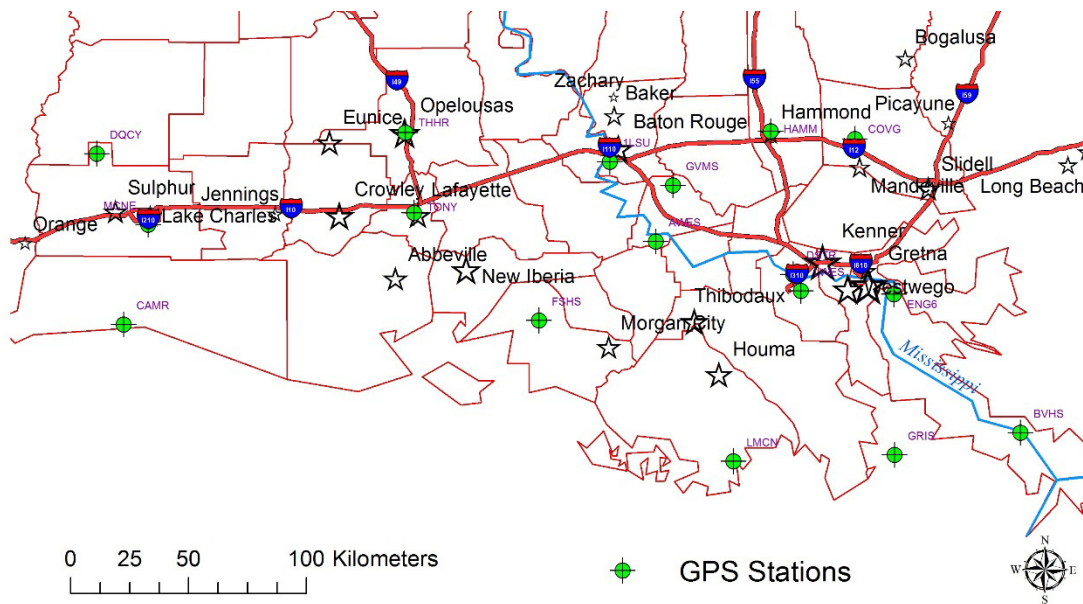


Figure 7 Distribution of 18 GPS stations in the study site, green points: GPS stations

Next, after the whole set of original data has been preprocessed by GIPSY by Zhengsong Chen, we can start to calculate the average subsidence rate each year for each GPS station in the study site. The preprocessing results by GIPSY by Zhengsong Chen show the each day's height value in one year for each GPS station, so we can use all of height values for one GPS station in one year to generate a straight line by Ordinary Least Square (OLS), and the slope for this straight line will be used to calculate the each year's subsidence rate for the GPS station (Shinkle and Dokka 2004;

Hayashi and Fumio 2000). Thus, we can summarize the calculation formula for the subsidence rate as follows:

$$\text{Each year's subsidence rate} = \text{the slope} * \text{one year}$$

(Shinkle and Dokka 2004; Hayashi and Fumio 2000)

Based on this calculation formula and the research methods by Shinkle and Dokka in 2004, Hayashi and Fumio in 2000, we can calculate each year's subsidence rate from 2011 to 2013 for all of GPS stations as follows (Shinkle and Dokka 2004; Hayashi and Fumio 2000):

Table 1 Each year's subsidence rate (2011-2013) for all of GPS stations in the study site, marked by Rate 2011, Rate 2012 and Rate 2013 (Unit: m/year)

Site	Longitude	Latitude	Slope 2011	Slope 2012	Slope 2013	Rate 2011	Rate 2012	Rate 2013
ILSU	-91.1803	30.40742	0.000002	-0.000005	-0.000003	0.00073	-0.0183	-0.01095
AWES	-90.983	30.10027	0.000005	-0.000002	-0.000003	0.001825	-0.00732	-0.01095
BVHS	-89.4064	29.33681	-0.000007	-0.000004	-0.000002	-0.002555	-0.001464	-0.00073
CAMR	-93.3251	29.7985	0.000009	0.000008	-0.000004	0.03285	0.002928	-0.00146
COVG	-90.0955	30.47591	0.000002	0.000007	0.000003	0.00073	0.002562	0.001095
DQCY	-93.4453	30.45118	0.00012	0.00002	-0.00002	0.0438	0.00732	-0.0073
DSTR	-90.3822	29.96456	0.000001	-0.00001	-0.000005	0.000365	-0.00366	-0.001825
ENG5	-89.9417	29.87896	-0.000001	-0.000009	0.000009	-0.000365	-0.003294	0.003285
ENG6	-89.9421	29.87918	0.000003	-0.000008	-0.00001	0.001095	-0.002928	-0.00365
FSHS	-91.5022	29.80531	-0.000004	0.000001	-0.00001	-0.00146	0.000366	-0.00365
GRIS	-89.9573	29.26553	-0.000002	-0.000002	0.000002	-0.0073	-0.00732	0.0073
GVMS	-90.9036	30.31439	0.000003	-0.000006	-0.000002	0.001095	-0.002196	-0.00073
HAMM	-90.4676	30.51308	0.00017	0.000005	0.000002	0.06205	0.00183	0.00073
LMCN	-90.6613	29.25498	-0.000002	-0.000002	0.000004	-0.0073	-0.00732	0.0146
LWES	-90.3494	29.90037	-0.000002	0.000002	0.000001	-0.0073	0.000732	0.00365
MCNE	-93.2177	30.18057	0.000003	0.000007	-0.000002	0.001095	0.002562	-0.0073
THHR	-92.0806	30.52935	0.00011	0.000009	0.000002	0.04015	0.003294	0.000073
TONY	-92.0451	30.22138	0.000006	0.000002	0.000009	0.00219	0.00732	0.003285

Based on calculation results for subsidence rates, and the research methods by Mardia et al. in 1998 and Olea and Ricardo in 1991, we can generate a

semi-variogram as follows, using the semi-variogram formula above (Mardia et al. 1998; Olea and Ricardo 1991):

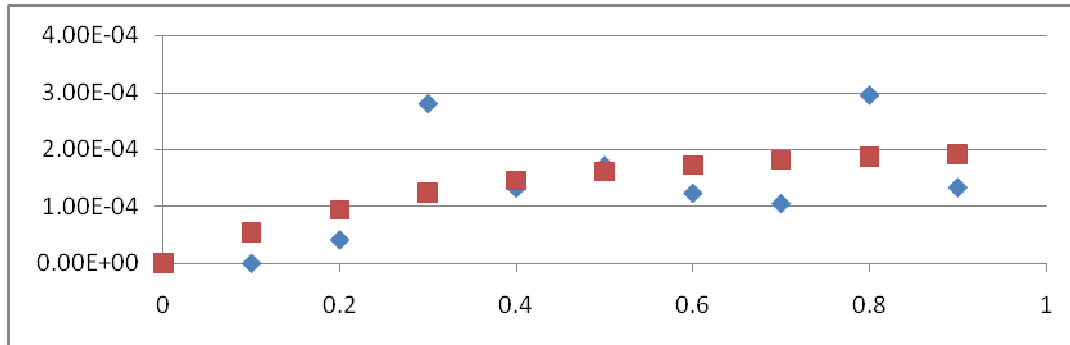


Figure 8 Semi-variogram for calculated subsidence rates in the study site, blue points: averaged γ values, red points: the fitted exponential model, the horizontal axis unit: degree

For this semi-variogram, we have fixed the bin size and number of bins in the horizontal axis h , so as to calculate the average γ value in each bin (blue points in the above figure) (Olea and Ricardo 1991; Mardia et al. 1998). Then based on the points for these γ values, we can use a model to fit these points (red points in the above figure) (Olea and Ricardo 1991; Mardia et al. 1998).

In this research, the bin size is fixed to 0.1, and the number of bins is fixed to 10. Then we choose the exponential model to fit, and the equation of fitted model is as follows (Olea and Ricardo 1991; Mardia et al. 1998):

$$\gamma = 1.7316E-08 + 0.0002 (1 - e^{-3.0798h})$$

3.3 Final processing results

As chapter 3.1 shows, the above KKF process, including calculating and specifying all kinds of variables and parameters for collected spatio-temporal GPS

data can be coded into an executable program based on ArcGIS software. In this research, based on the above generated variogram and the research method by Mardia et al. in 1998, the coded program for KKF has been done to process subsidence rate data from GPS observation, with the help of ArcGIS software, and the final results are as follows (Mardia et al. 1998):

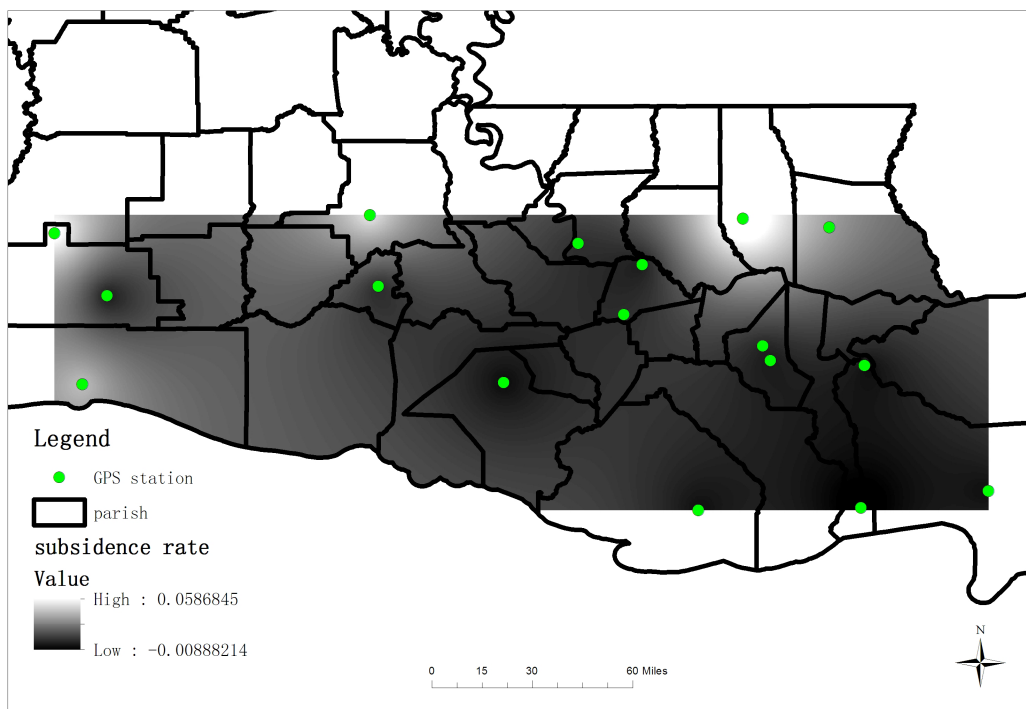


Figure 9 Distribution of subsidence rates in 2011, green points: GPS stations (The map data for parishes is extracted from: <http://atlas.lsu.edu>)

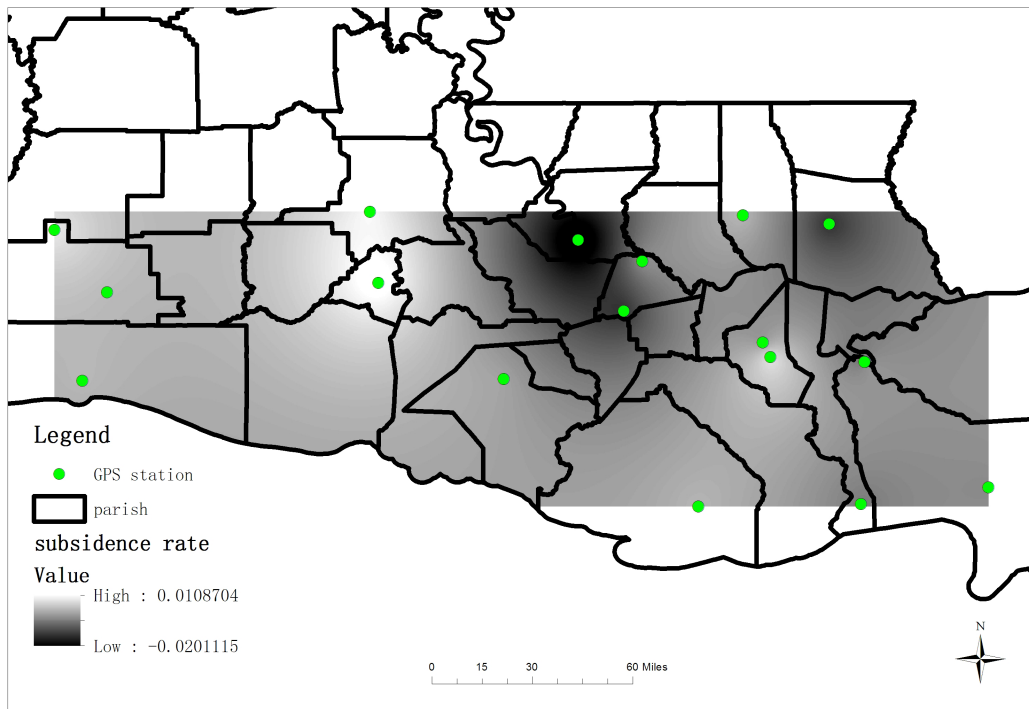


Figure 10 Distribution of subsidence rates in 2012, green points: GPS stations (The map data for parishes is extracted from: <http://atlas.lsu.edu>)

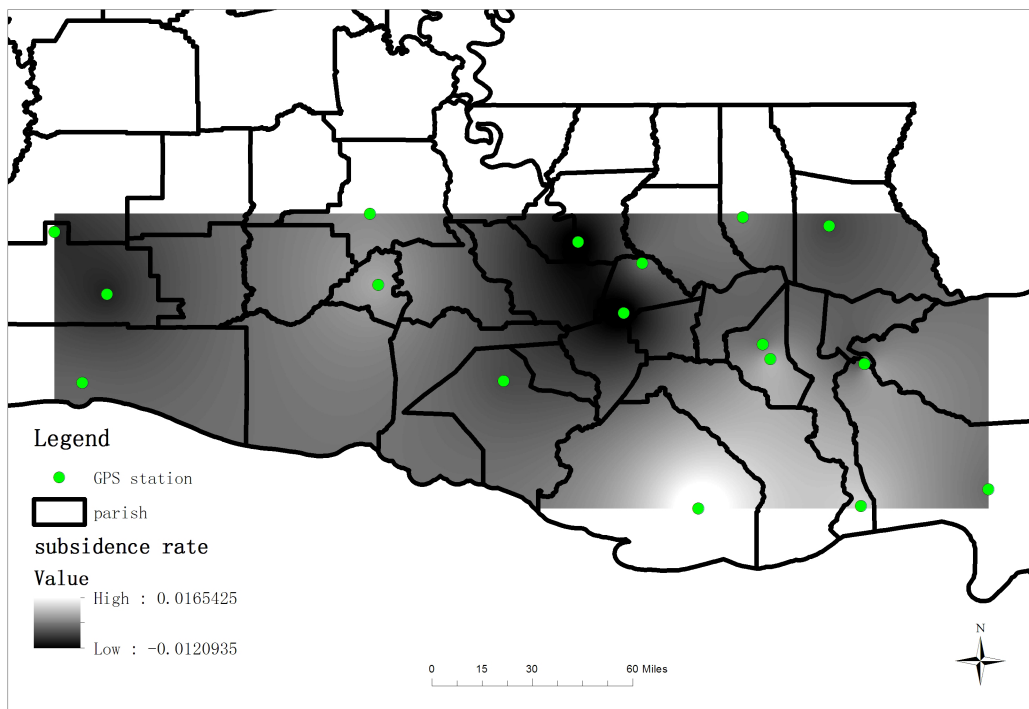


Figure 11 Distribution of subsidence rates in 2013, green points: GPS stations (The map data for parishes is extracted from: <http://atlas.lsu.edu>)

For each of 3 figures above (Figure 10, 11, 12), the dark color represents the area with the high subsidence rates, and the light one represents the area with low subsidence rates. From these 3 figures above on final processing results by KKF, we can find the spatio-temporal pattern of subsidence rates distributions in 2012 is similar to the one in 2013, and we can also find that there is a stable “subsidence dark valley” with relative high subsidence rates around New Orleans area. Besides, we can also estimate that, the subsidence rate within this “subsidence dark valley” from January 1st 2012 to December 31st 2013 equals to about 10 mm per year.

3.4 Validation of KKF results

By KKF, the distributions of subsidence rates in 2011, 2012 and 2013, have been generated, while, are these KKF results valid in this research? Thus, some work should be done, so as to validate these KKF results.

Firstly, we validate the model by using the cross-validation approach (Geisser and Seymour 1993). Each time, a spatio-temporal field was calculated by leaving one GPS station out, and compare the KKF modeled data with the GPS station data (Geisser and Seymour 1993). It is expected that if the surface motion rate data have strong spatial and temporal continuity, some GPS stations would be well replicated by the KKF model. The Root Mean Square Error (RMSE) was used to evaluate how the predicted surface motion rates were compared to the observed surface motion rates (Geisser and Seymour 1993). Figure 3 shows the RMSEs of the GPS stations, based on research methods by Geisser and Seymour in 1993 and Mardia et al. in 1998

(Geisser and Seymour 1993; Mardia et al. 1998). The GPS stations located inland have greater RMSE values (up to 40 mm/year), suggesting that those stations could not be replaced by model prediction. The reason might be in that the inland area is more directly related to human activities and therefore the land surface motion process could be very complex and hard to be predicted from the surrounding GPS stations. Therefore, more GPS stations need to be allocated towards the inland to capture the spatial continuity. The alternative to building more GPS stations is to use some regression models to enhance the spatio-temporal prediction model.

The stations “LWES”, “BVHS”, and “LMCN” have quite low RMSE (~5 mm/year). These stations are located where major wetlands and swamps of Louisiana are preserved. The spatio-temporal model predicted the land surface motion rate well even if there were some missing data.

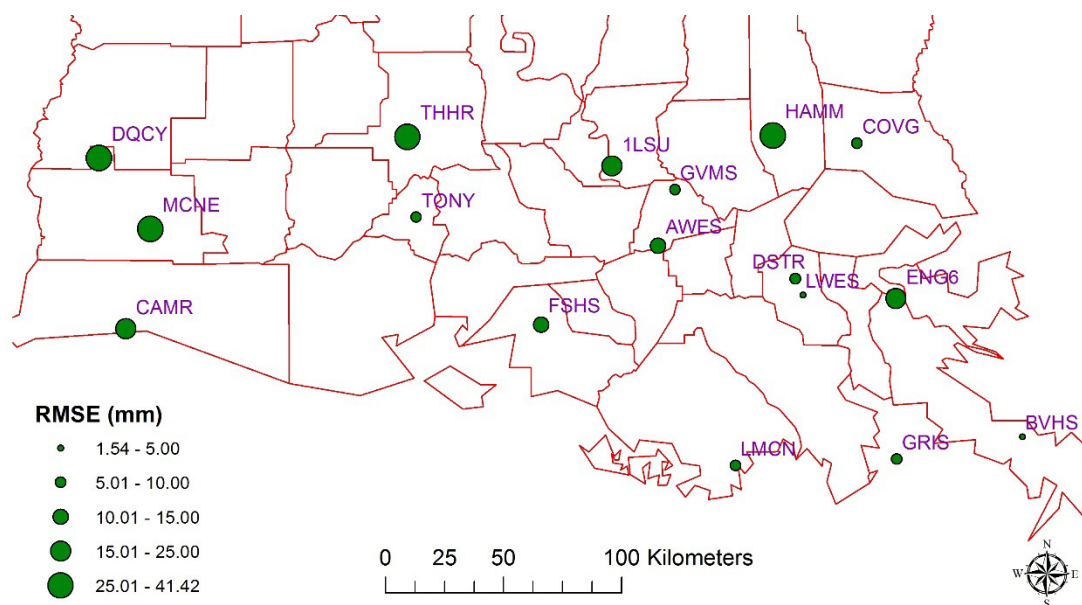


Figure 12 RMSE of the GPS stations from cross-validation

Sinkhole should be a threatening phenomenon, especially for people living in bayou areas all over the world. Indeed, such well-known phenomenon had emerged near Bayou Corne in Louisiana in August, 2012, and we term it “Bayou Corne Sinkhole” (Cusanza 2013; Jones and Blom 2014). The collapse of one cavern in the salt dome under the bayou had resulted in this sinkhole, and the sinkhole size had been increasing from 1 hectare (Cusanza 2013; Jones and Blom 2014). The government had given emergent warnings to people who were living near Bayou Corne, and many people were forced to evacuate (Cusanza 2013; Jones and Blom 2014).

For this sinkhole in Bayou Corne, the former study by experts shows that the sidewall collapse rather than faulting had formed this threatening sinkhole, which involves the disturbed rock zone filling the cavern void (Jones and Blom 2014; Louisiana Department of Natural Resources 2013b). Besides, by radar interferometry, experts had also detected the pre-event and post-formation surface deformation near Bayou Corne, showing the significant vertical and horizontal ground movement (Jones and Blom 2014; Jones and Blom 2015).

On the other hand, this vertical downward surface movement detected by radar interferometry, can be observed in the form of subsidence, so we can use subsidence to signify sinkholes (Jones and Blom 2014; Jones and Blom 2015; Dokka 2006; Kent and Dokka 2012). Besides, the precursory surface movement detected by radar interferometry in Bayou Corne, means that the surrounding subsidence may be accelerated even prior to the sinkhole event (Jones and Blom 2014; Jones and Blom

2015). In fact, such accelerating subsidence near Bayou Corne had been surveyed by many organizations such as Fenstermaker and Itasca when the sinkhole emerged in 2012, and these organizations are still monitoring the sinkhole (Jones and Blom 2014; Jones and Blom 2015; Fenstermaker 2014; Itasca 2013).

In this research, so as to validate the generated KKF results, the Bayou Corne Sinkhole location should be added to the distribution maps of subsidence rates from 2011 to 2013 as follows, based on the research methods by Mardia et al. in 1998, Kent and Dokka in 2012, Jones and Blom in 2014 and in 2015 (Mardia et al. 1998; Cusanza 2013; Jones and Blom 2014; Jones and Blom 2015):

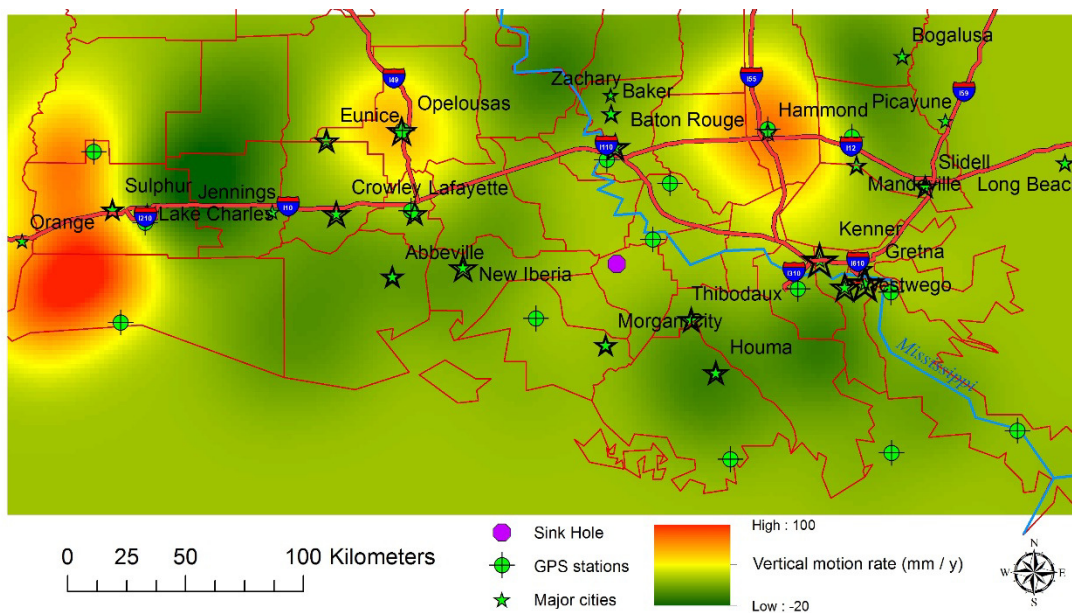


Figure 13 Distribution of subsidence rates (Unit: mm/year) in the study site in 2011 by KKF, green points: GPS stations, purple point: the Bayou Corne Sinkhole location

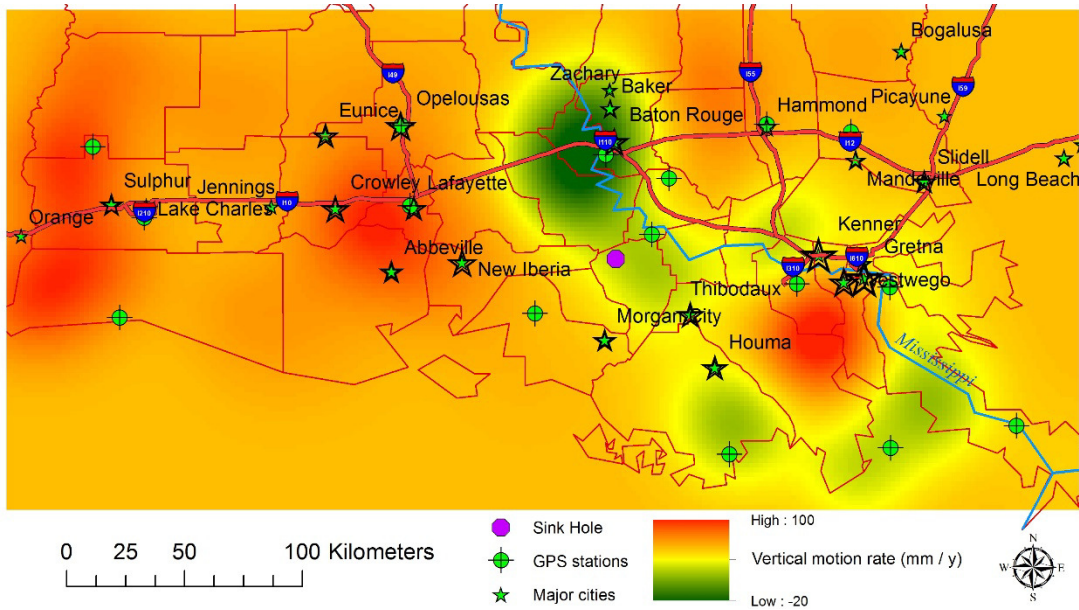


Figure 14 Distribution of subsidence rates (Unit: mm/year) in the study site in 2012 by KKF, green points: GPS stations, purple point: the Bayou Corne Sinkhole location

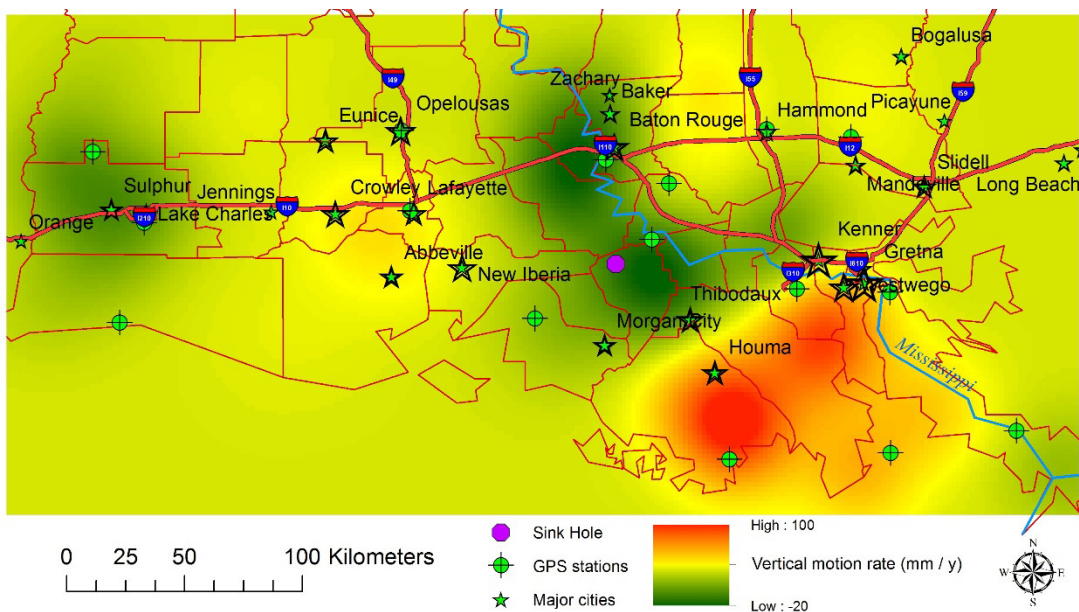


Figure 15 Distribution of subsidence rates (Unit: mm/year) in the study site in 2013 by KKF, green points: GPS stations, purple point: the Bayou Corne Sinkhole location

Figure 13 shows the spatial distribution of subsidence rate in the period of 2011, about one year prior to the Bayou Corne Sinkhole event. This distribution in 2011 appears to be uniform, with no significantly high subsidence area. There was no

obvious subsidence in this area during the year 2011. The vertical motion rate (Kent and Dokka 2012) around Bayou Corne were positive, ranging from 0 to 0.005m per year (5 mm/year). It was consistent with the previous reports that the surface in this area had even made a slight upward movement in 2011 (Jones and Blom 2014). Thus, from Figure 4, we have not detected any significant precursory subsidence or vertical ground displacement around Bayou Corne Sinkhole in the period of 2011 (Dokka 2006; Kent and Dokka 2012). In contrast to Figure 13, Figure 14 shows a much different and abnormal distribution of land vertical motion rates close to the sinkhole event (August 2012), with a significant accelerating subsidence to the north of Bayou Corne. The surface motion subsidence rate was about -15mm/year near Baton Rouge and north of Bayou Corne. Likewise, Figure 15 shows the spatial pattern of the surface motion in 2013 after the sinkhole event. The negative motion (subsidence) was found around Baton Rouge and the Bayou Corne Sinkhole (Dokka 2006; Cusanza 2013). And it is interesting to see that the center of the negative motion area coincides with the sinkhole (Cusanza 2013). However, the relatively large RMSEs of the GPS stations around the sinkhole (Figure 12) suggest that to better monitor the abrupt changes such as sinkhole events, more GPS stations are required.

Thus, from all of figures (Figure 13, 14, 15), we can confirm that the land area around Bayou Corne had experienced an abrupt change caused by the sinkhole event in August 2012. The upward motion rate (5 mm/year) in 2011 was changed to -14 mm/year downward motion in 2013 because of the sinkhole. Many research organizations also reported the negative land vertical motion caused by Bayou Corne

Sinkhole. For example, Itasca measured the land subsidence rate near Bayou Corne at about -0.4 inch/year (about -10 mm/year) (Itasca 2013). Our result is consistent with the previously reported land vertical motion around the Bayou Corne (Louisiana Department of Natural Resources 2013b; Fenstermaker 2014; Jones and Blom 2014, 2015).

Besides, so as to validate KKF results in this research, for the same set of data, we can also use results by Empirical Bayesian Kriging to compare and show the differences (Extracted from: <http://www.esri.com/news/arcuser/1012/empirical-byesian-kriging.html>) (Olea 1999). Based on the research method by Kent and Dokka in 2012, the results by Empirical Bayesian Kriging are as follows, with contours and the Bayou Corne Sinkhole location (The interpolation method is extracted from: <http://www.esri.com/news/arcuser/1012/empirical-byesian-kriging.html>) (Cusanza 2013; Kent and Dokka 2012):

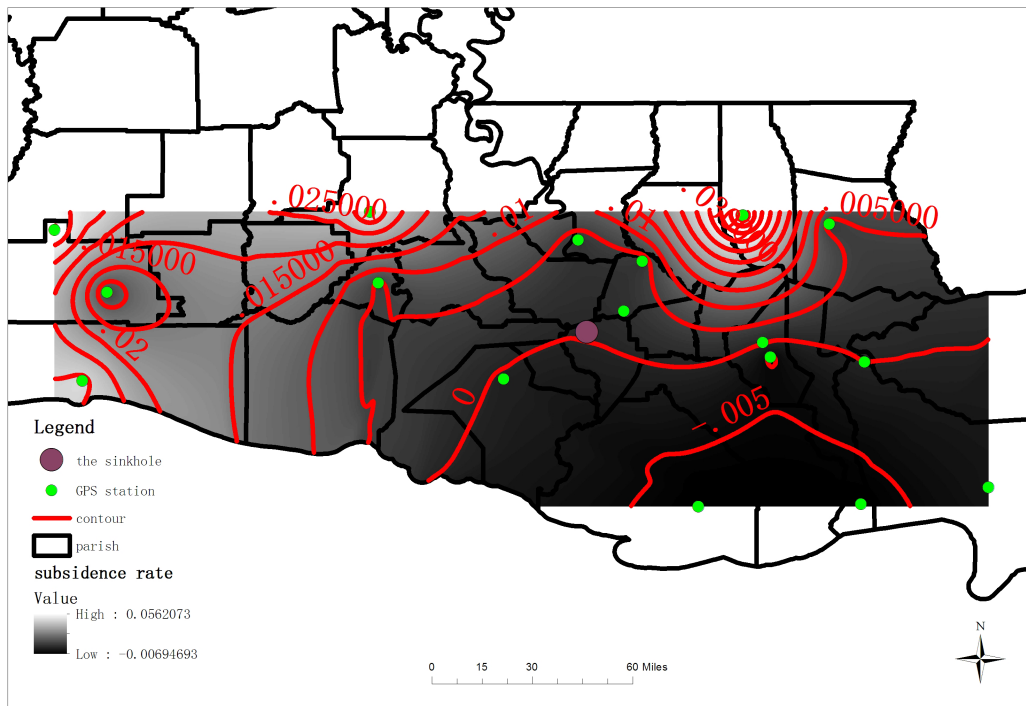


Figure 16 Distribution of subsidence rates with contours (Unit: m/year) in 2011 by Empirical Bayesian Kriging, green points: GPS stations, purple point: the Bayou Corne Sinkhole location (The map data for parishes is extracted from: <http://atlas.lsu.edu>)

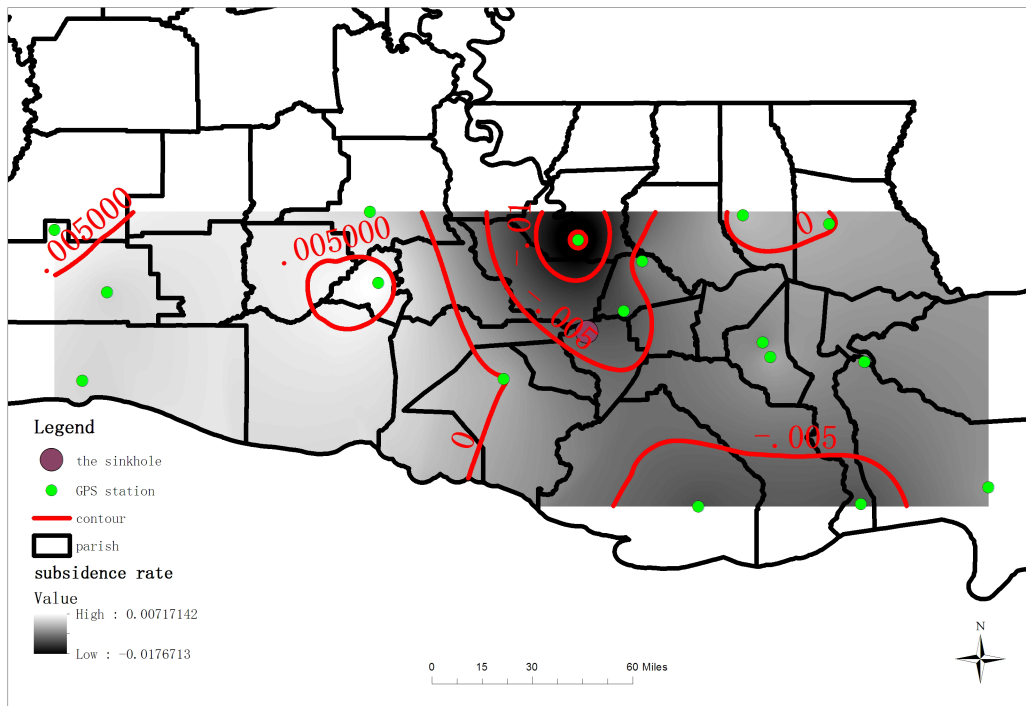


Figure 17 Distribution of subsidence rates with contours (Unit: m/year) in 2012 by Empirical Bayesian Kriging, green points: GPS stations, purple point: the Bayou Corne Sinkhole location (The map data for parishes is extracted from: <http://atlas.lsu.edu>)

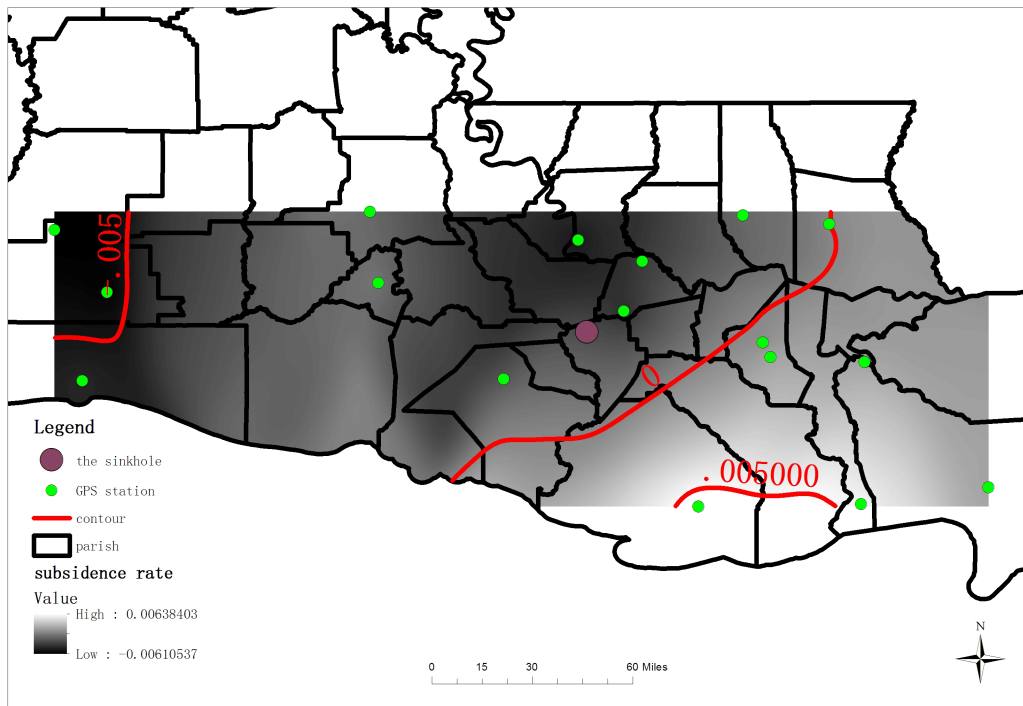


Figure 18 Distribution of subsidence rates with contours (Unit: m/year) in 2013 by Empirical Bayesian Kriging, green points: GPS stations, purple point: the Bayou Corne Sinkhole location (The map data for parishes is extracted from: <http://atlas.lsu.edu>)

Comparisons between Figure 13 and Figure 16 show that, in 2011, the result by Empirical Bayesian Kriging is a little similar to the one by KKF. From contours we can find that the distribution of subsidence rates in Figure 13 and the one in Figure 16 are similar, while, we can also find some clear differences. We can find that in Figure 13 the subsidence rates near Bayou Corne are positive, ranging from 0 to 0.005m/year, but in Figure 16 that these values are about zero.

Comparisons between Figure 14 and Figure 17 show that, in 2012, the result by KKF and the one by Empirical Bayesian Kriging are also similar, while we can also find clear and big differences. One of these differences is that in Figure 14, we can find a subsidence area near Bayou Corne at about -0.01m/year, but in Figure 17 we can't find such subsidence area near Bayou Corne.

Comparisons between Figure 15 and Figure 18 show that, in 2013, the result by KKF and the one by Empirical Bayesian Kriging are very different. The distribution of subsidence rates in Figure 15 shows there is a clear subsidence area near Bayou Corne at about -0.01m/year , while from contours in Figure 18, this distribution is so different that the subsidence rates near Bayou Corne are clearly less, ranging from 0 to -0.005m/year .

From the above comparisons, we can summarize that by Empirical Bayesian Kriging rather than KKF, the processed results in this research are very different because of significant interpolation error, and they can't also be validated by the Bayou Corne Sinkhole knowledge (Olea 1999; Cusanza 2013; Jones and Blom 2014; Jones and Blom 2015). Thus, because of smaller interpolation error, KKF is advantageous to other models for processing subsidence data, and KKF results have been validated well in this research (Olea 1999; Mardia et al. 1998; Kalman 1960).

3.5 Summary and discussion

In this chapter, we have discussed the KKF model to process the GPS subsidence data. Based on the research work by Mardia et al. in 1998, the steps on how to calculate the essential parameters in the KKF model have been summarized (Mardia et al. 1998). Then based on our subsidence data collected, we have calculated each year's subsidence rate for each of coastal observation stations, and as an application example, we have repeated the calculation process for essential parameters, and generated the final results by KKF processing (Mardia et al. 1998). From these final

results, we can summarize that in coastal Louisiana areas, from 2012 to 2013, the “subsidence dark valley”, which shows areas with clear high subsidence rates at about 10 mm each year, was keeping almost near the same area (New Orleans area) in the coast of Louisiana. What’s more, so as to validate these KKF results, the disaster knowledge of Bayou Corne Sinkhole in 2012, have been used in this research. Subsidence near Bayou Corne had been accelerated during the sinkhole year (2012), and this accelerating subsidence area had also been expanding since 2012. What’s more, the subsidence rate near Bayou Corne had been stabilized at nearly 10mm per year during and after the sinkhole accident (2012-2013), and this stabilized subsidence rate is basically consistent with the measured subsidence rate at about 0.4 inch/year near the Bayou Corne Sinkhole from the Itasca-Subsidence Report, validating our study by KKF (Itasca 2013; Jones and Blom 2014; Jones and Blom 2015). Thus, we can conclude that the results by KKF are basically valid in this research.

We can also summarize that, the first step of KKF processing, the variogram modeling can be so important to the final processing results (Mardia et al. 1998; Kalman 1960; Olea and Ricardo 1991; Olea 1999). Thus, in the variogram modeling process, we should fix a proper value for the bin size, and also a proper one for the number of bins, by observing the distances between the model line and the points for average variogram in each bin (Olea and Ricardo 1991). If these distances are mostly near, the variogram modeling process can be good (Olea and Ricardo 1991).

Chapter 4 Modeling of Factor Data Contributing to Subsidence

4.1 The introduction of GWR and its application steps

As the chapter for research methods shows, the fundamental equations for GWR (Geographically Weighted Regression) (Fotheringham et al. 2002; Shang et al. 2011) are as follows:

$$y(g) = \beta_0(g) + \beta_1(g) x_1 + \beta_2(g) x_2 + \dots + \beta_n(g) x_n + \varepsilon$$

$$\beta = (X^T W(g) X)^{-1} (X^T W(g) Y)$$

y is dependent variable, x_1, x_2, \dots, x_n are predictor variables, g is known coordinates for observation points (Fotheringham et al. 2002; Shang et al. 2011), β are the varied coefficients as the GWR results (Fotheringham et al. 2002; Shang et al. 2011), and $W(g)$, is the Gaussian weight function (Fotheringham et al. 2002; Shang et al. 2011) (Extracted from: <http://www.cs.cmu.edu/~schneide/tut5/node12.html>)

Thus, in this research, the GWR modeling process for subsidence rates data can be summarized as the following steps:

Step 1: Factors data collection and quantification (Fotheringham et al. 2002)

Step 2: Data input as variables and operating GWR model in ArcGIS
(Fotheringham et al. 2002)

Step 3: Results visualization and accuracy evaluation (Fotheringham et al. 2002)

In the following, we will discuss these steps in details for this research, and show the results by GWR and evaluate the modeling accuracy.

4.2 Factor data collection and quantification

As the former research by Abdollahzadeh et al. in 2013 and the above data collection chapter for GWR modeling show, the types of factors data for subsidence rates in this research, should be groundwater withdrawal data, oil and gas pumping data, sediment data, faulting and mass loading data (Shang et al. 2011; Abdollahzadeh et al. 2013). Besides, as the last chapter shows, the disaster named “Bayou Corne Sinkhole”, which emerged in 2012, had caused accelerating subsidence in the study site after 2012, so we should collect and quantify the factor data for this well-known sinkhole in Louisiana (Cusanza 2013; Jones and Blom 2014; Jones and Blom 2015). In this research, we focus on the subsidence situations for the coastal census tracts in Louisiana, so all of coastal census tracts near GPS stations in the study site are the selected geographic units from which we will collect factor data for GWR. And for factor modeling in this research, the study site with all of selected census tracts can be mapped as follows:

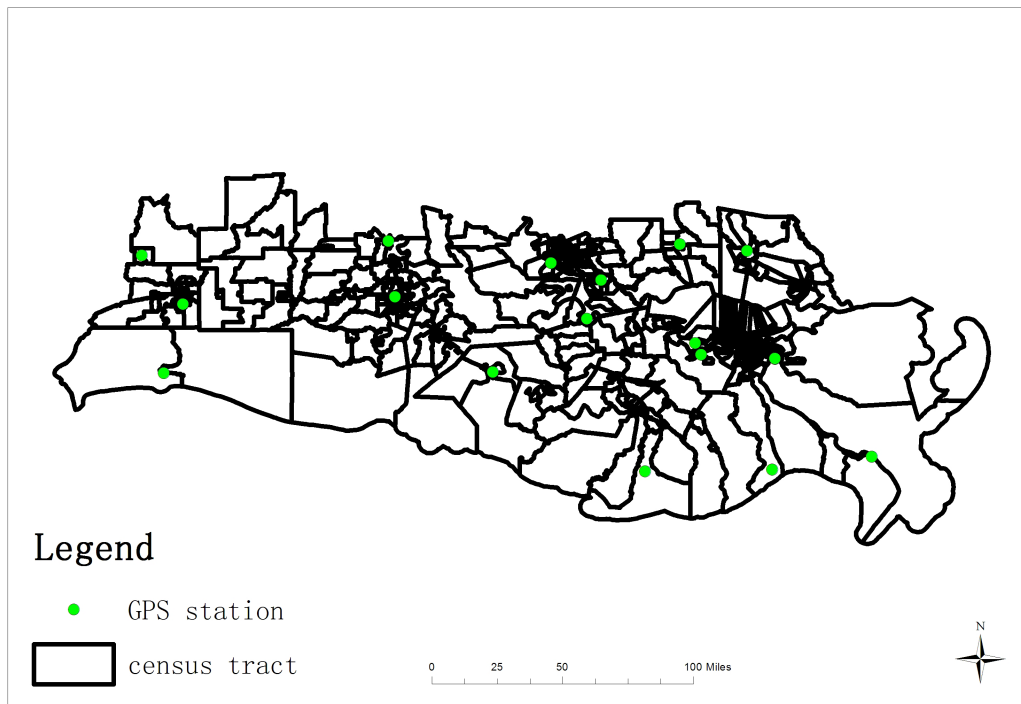


Figure 19 Study site with 736 census tracts, green points: GPS stations (The map data for census tracts is extracted from: <http://atlas.lsu.edu>)

Thus, in the following, for these 736 coastal census tracts in the study site in Louisiana, we will discuss how to collect and quantify these types of factor data in details.

Groundwater withdrawal:

The former research by Shang et al. in 2011 shows that, many areas of subsidence relates to the groundwater level variations very much, based on the GWR modeling results (Shang et al. 2011; Abdollahzadeh et al. 2013). Thus, for data collection of groundwater level changes, we should use the USGS website online to download data from all of available water wells in the study site above (Extracted from: <http://groundwaterwatch.usgs.gov/>) (Shang et al. 2011). In this research, we decide to record changes of the groundwater levels for all of available wells in the

period of 2013 (Shang et al. 2011), then based on these points of changes for groundwater levels in the study site, we will make an interpolation process by Inverse Distance Weighting (IDW) method (Shang et al. 2011; Shepard and Donald 1968). This interpolation raster result shows the predicted distribution for average changes of groundwater level in the study site. Then, for quantifying the groundwater data, we should record the average pixel value in each selected census tract as the average change of groundwater level in the period of 2013 for each census tract, and these recorded values are the quantified groundwater data as a factor for subsidence.

So based on the research method by Shepard and Donald in 1968, the average change of groundwater level for each census tract in the study site can be mapped as follows (Shepard and Donald 1968):

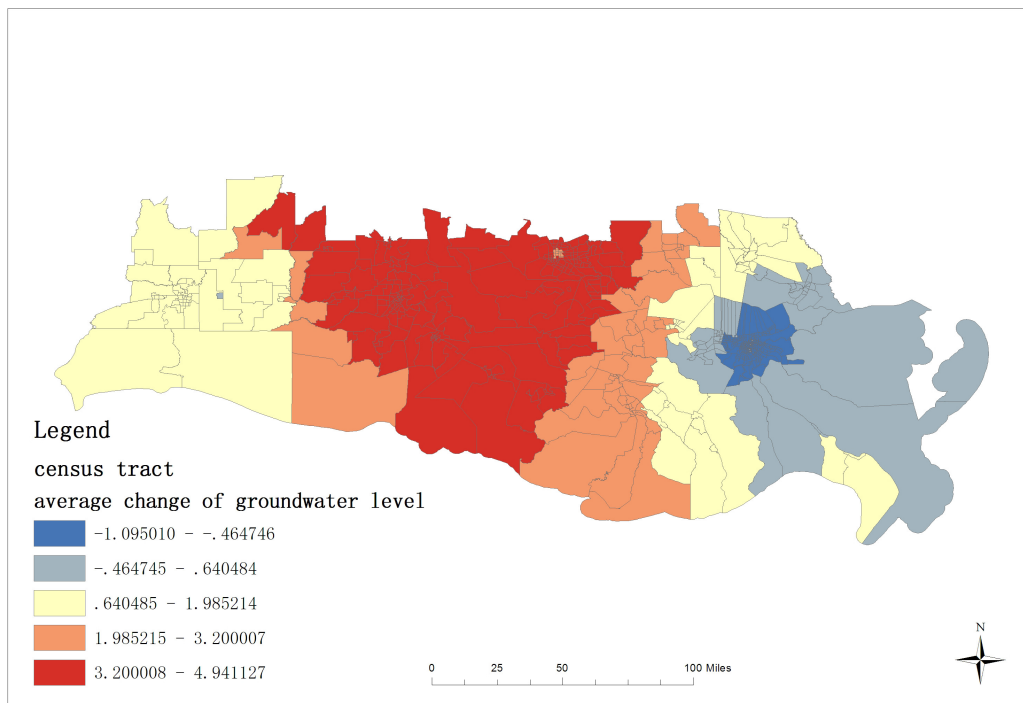


Figure 20 Average change of groundwater level for census tract (unit: feet) (The map data for census tracts is extracted from: <http://atlas.lsu.edu>)

Oil and gas pumping:

For oil and gas data collection, we can use the SONRIS website as the above data collection chapter shows, and download the data on wells for oil and gas pumping in the study site (Abdollahzadeh et al. 2013) (Extracted from: <http://sonris.com> & <http://sonris-www.dnr.state.la.us/gis/agsweb/IE/JSViewer/index.html?TemplateID=181>).

Based on this data from the SONRIS website, we can calculate and map the density of pumping wells for each census tract in the study site as follows:

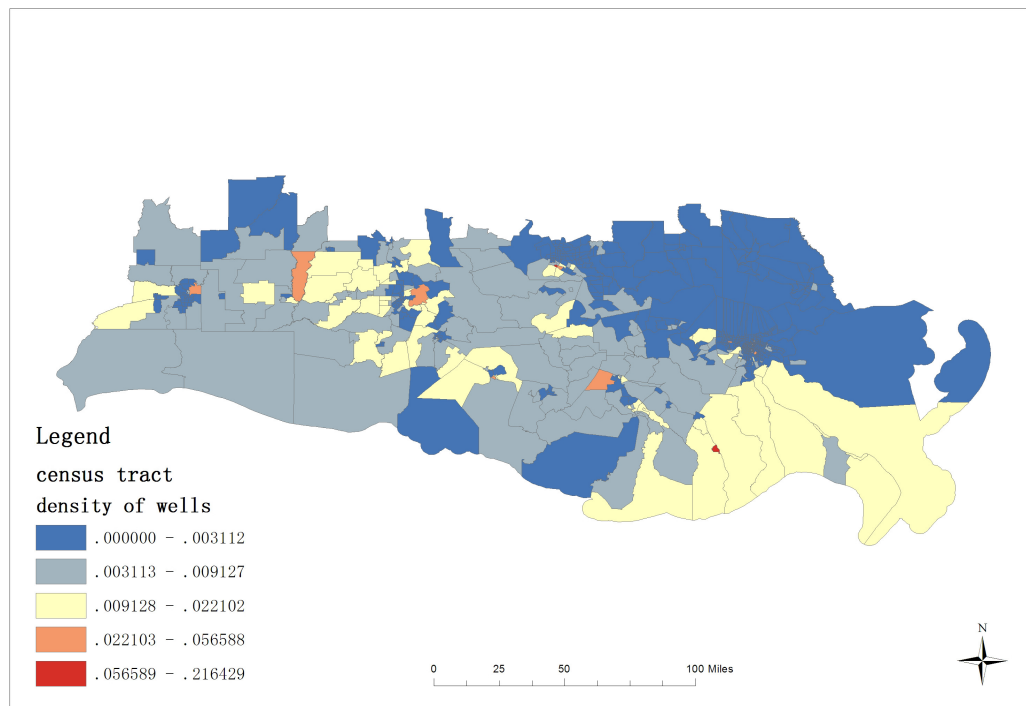


Figure 21 Density of oil and gas pumping wells for census tract (The map data is extracted from: <http://sonris.com> & <http://sonris-www.dnr.state.la.us/gis/agsweb/IE/JSViewer/index.html?TemplateID=181> & <http://atlas.lsu.edu>)

Sediment:

For sediment data collection, the SONRIS website also provides sediment sampling data to download (Abdollahzadeh et al. 2013) (Extracted from: <http://sonris-www.dnr.state.la.us/gis/agsweb/IE/JSViewer/index.html?TemplateID=181>). After downloading this data, we can check the thickness of clay, sand and clay-sand mixture at each sampling site from the data attributes, and interpolate all sampling sites of data by Empirical Bayesian Kriging (Olea 1999) (Extracted from: <http://sonris.com> & <http://sonris-www.dnr.state.la.us/gis/agsweb/IE/JSViewer/index.html?TemplateID=181> & <http://www.esri.com/news/arcuser/1012/empirical-byesian-kriging.html>):

Then after the interpolation raster result is generated, for quantifying sediment data, in this research, we decide to record average pixel value as the average thickness of clay-sand mixture for each census tract, and map this quantification result in the study site as follows (the interpolation method is extracted from: <http://www.esri.com/news/arcuser/1012/empirical-byesian-kriging.html>):

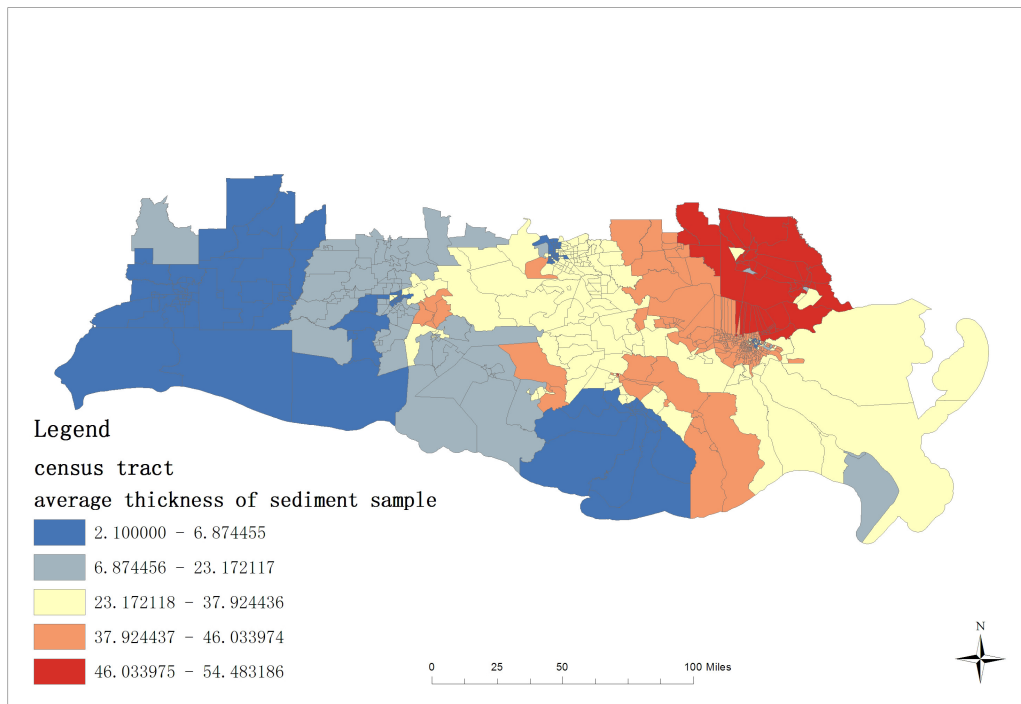


Figure 22 Average thickness of clay-sand mixture sample for census tract (unit: feet)
(The map data for sediment is extracted from: <http://sonris.com> &
<http://sonris-www.dnr.state.la.us/gis/agsweb/IE/JSViewer/index.html?TemplateID=181>;
the map data for census tracts is extracted from: <http://atlas.lsu.edu>)

Faulting:

As the above chapter for faulting data collection shows, we can download faulting data also from the USGS website, and by checking the map of faulting data and data attributes, we can find the rates, years and moving directions of faulting in Louisiana (Extracted from: <http://earthquake.usgs.gov/hazards/qfaults/>) (Abdollahzadeh et al. 2013). And from these data attributes, we can easily find that for all of coastal census tract in the study site, the faulting features are nearly the same, such as rate, moving direction and years. Thus, we will not consider the faulting data with no clear spatial heterogeneity as a factor, because the coefficients for the faulting data for different GPS station may be the same value, if we use GWR (Fotheringham et al. 2002; Shang et al. 2011).

Mass loading:

In this research, the loading from buildings in the study site may produce subsidence (Abdollahzadeh et al. 2013). Thus, for loading data collection, we can use the image data after classification and extraction of buildings in the study site, from the National Land Cover Database (NLCD) website, to convert into the GIS map of buildings cover for all of census tracts as follows (Extracted from: <http://atlas.lsu.edu/> & <http://www.mrlc.gov/nlcd2011.php>):

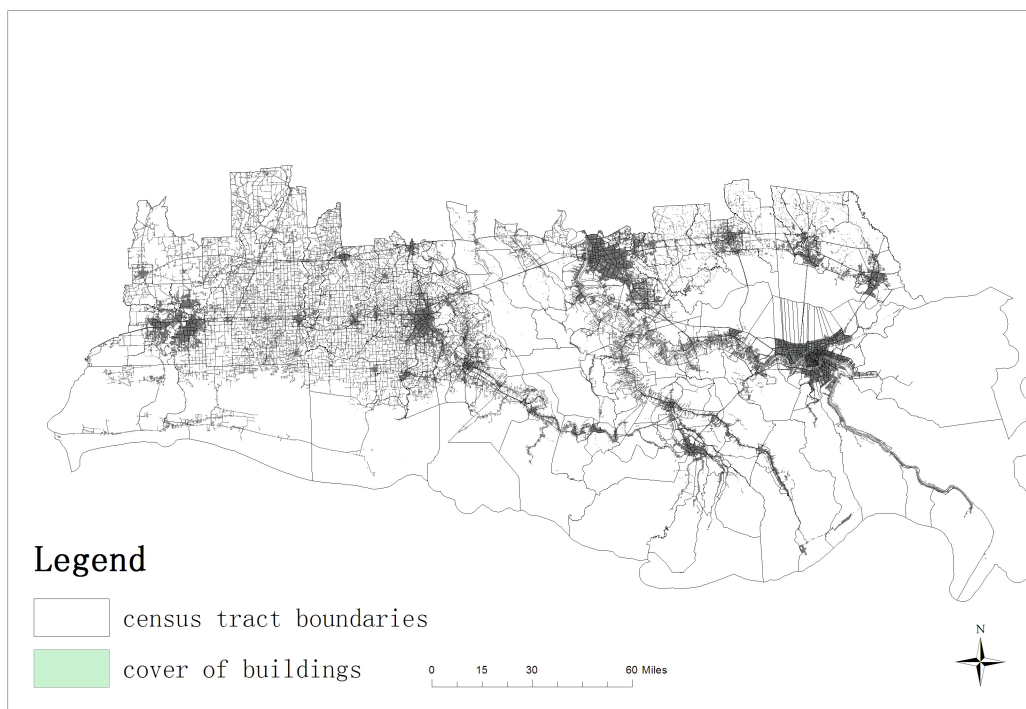


Figure 23 Cover of buildings for each census tract in the study site (The map data is extracted from: <http://atlas.lsu.edu/> & <http://www.mrlc.gov/nlcd2011.php>)

Then by ArcGIS, we can check the data attribute and record the total area of buildings cover for each census tract. Then based on the recorded area value, we can calculate the percentage of building loading area for each census tract to quantify the mass loading data as a factor. So the mass loading data in the study site can be quantified and mapped as follows:

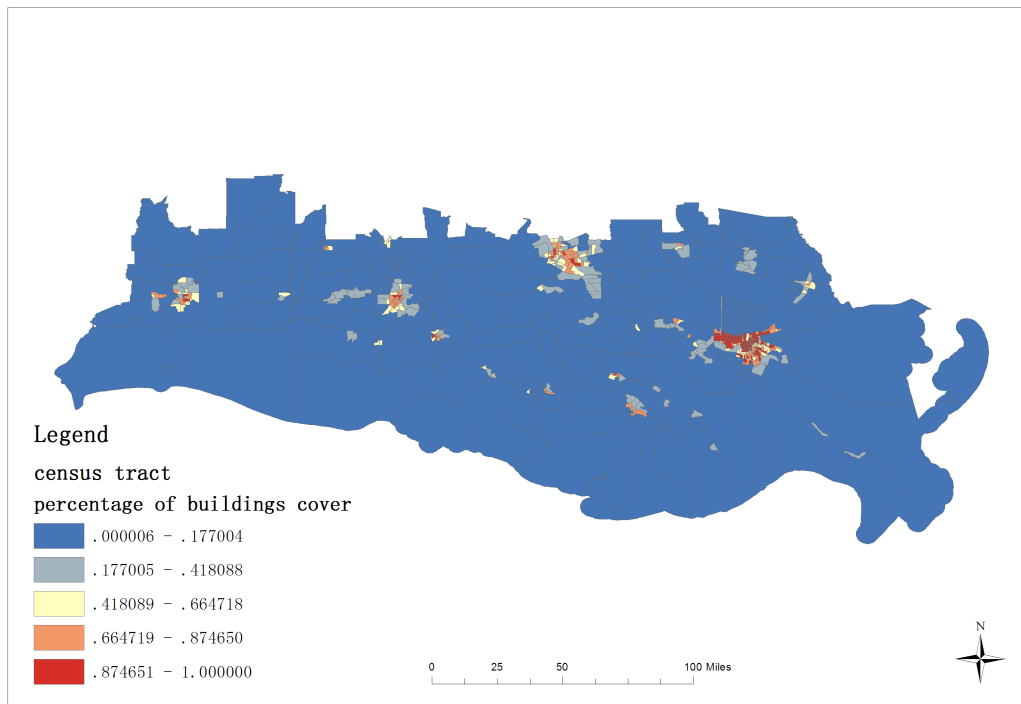


Figure 24 Percentage of buildings loading for each census tract (The map data is extracted from: <http://atlas.lsu.edu/> & <http://www.mrlc.gov/nlcd2011.php>)

Factors for the Sinkhole:

The literature review in this research shows that some special human activities, such as mining accidents, can cause adverse subsidence in our living world (Kim et al. 2006; Kim et al. 2009; Oh and Lee 2010; Oh et al. 2011). Besides, the former research by Korean experts shows that depth and distance from drift, DEM and slope gradient, groundwater permeability, geology and land use are the main factors for mining subsidence (Kim et al. 2006; Kim et al. 2009; Oh and Lee 2010; Oh et al. 2011; Coal Industry Promotion Board 1997; Coal Industry Promotion Board 1999).

Likewise, as mining accidents which cause subsidence, sinkholes near bayou areas should also be caused by the collapse of underground caverns, and the last chapter shows that Bayou Corne Sinkhole by a cavern collapse, had been causing

accelerating subsidence in the study site after the sinkhole year (2012) (Kim et al. 2006; Kim et al. 2009; Oh and Lee 2010; Oh et al. 2011; Cusanza 2013; Jones and Blom 2014; Jones and Blom 2015). The factors for sinkhole subsidence should be much similar to the ones for mining subsidence, and the former research also shows many factors such as distance to the sinkhole and sinkhole depth can contribute to accelerating subsidence (Kim et al. 2006; Kim et al. 2009; Oh and Lee 2010; Oh et al. 2011; Cusanza 2013; Jones and Blom 2014; Jones and Blom 2015; Coal Industry Promotion Board 1997; Coal Industry Promotion Board 1999). Thus, besides the common factors, we should also collect and quantify factor data for sinkhole subsidence in the period of 2013, and in this research, we can calculate and record the inverse distance from the Bayou Corne Sinkhole location to the geographic center of each census tract in the study site, using ArcGIS (Kim et al. 2006; Kim et al. 2009; Oh and Lee 2010; Oh et al. 2011; Cusanza 2013; Coal Industry Promotion Board 1997; Coal Industry Promotion Board 1999).

For factor data quantification, based on the research methods by Kim et al. in 2006, Kim et al. in 2009, Oh and Lee in 2010, Oh et al. in 2011, Coal Industry Promotion in 1997 and 1999, we can map the inverse distances from the Bayou Corne Sinkhole location to the geographic center of each census tract as follows (Kim et al. 2006; Kim et al. 2009; Oh and Lee 2010; Oh et al. 2011; Cusanza 2013; Coal Industry Promotion Board 1997; Coal Industry Promotion Board 1999):

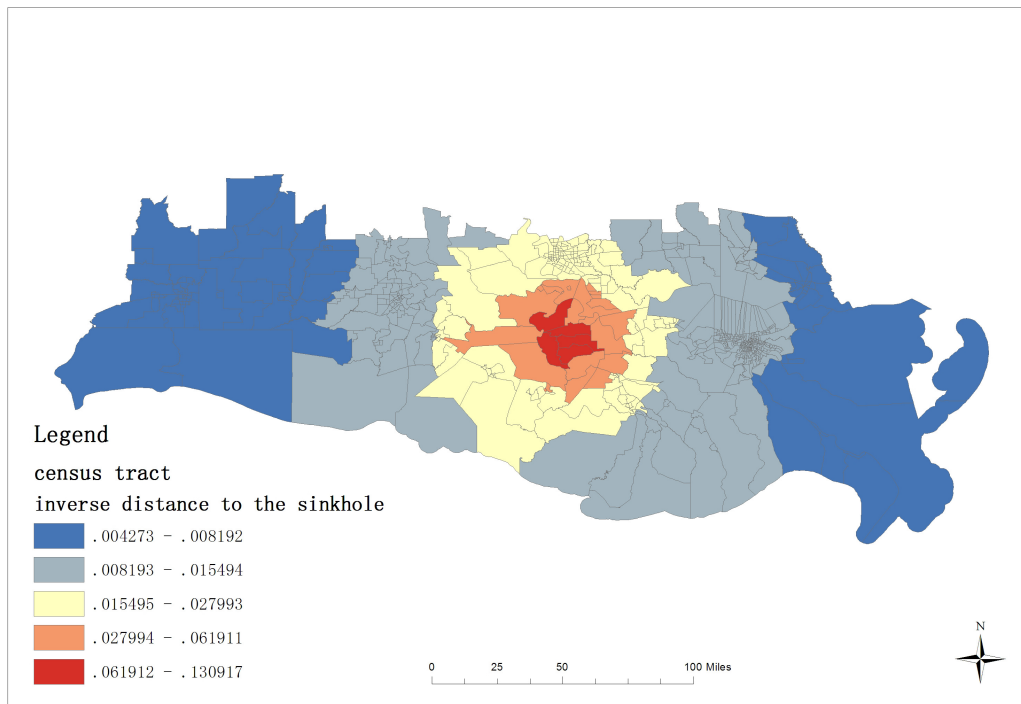


Figure 25 Inverse distances from the Bayou Corne Sinkhole location to the geographic center of each census tract in the study site (unit: 1/km) (The map data for census tracts is extracted from: <http://atlas.lsu.edu>)

4.3 GWR results

After the above factor data quantification process, we can start GWR modeling. Firstly, we should fix which types of quantified factor data above should be input as the predictor variables in the GWR model, on the other hand, by KKF, the subsidence rates data in 2013 should be input as the dependent variable in the GWR model (Fotheringham et al. 2002).

In this research, we decide to pick up 5 types of quantified factor data (groundwater, oil/gas, sediment, loading and inverse distance from the sinkhole location) as the predictor variables (Abdollahzadeh et al. 2013; Fotheringham et al. 2002). And for the average subsidence rate for each census tract in 2013, based on the

research method by Mardia et al. 1998, we can use the processed result from last chapter, and record the average pixel value in each census tract as the dependent variable as follows (Mardia et al. 1998; Fotheringham et al. 2002):

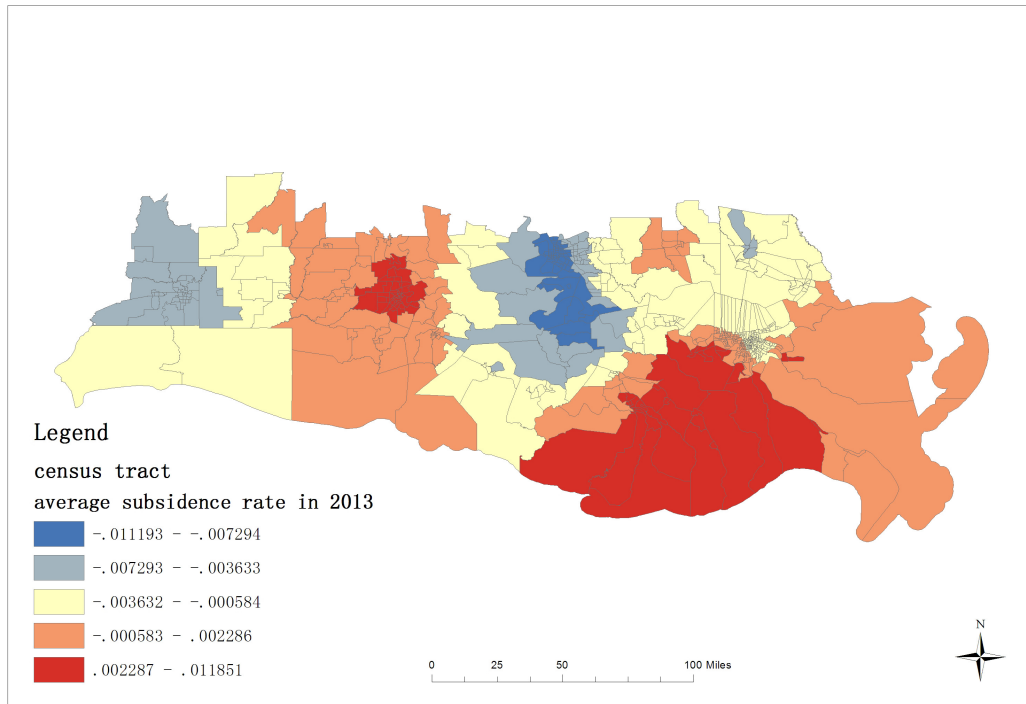


Figure 26 Average subsidence rate for each census tract in 2013 (unit: m per year)
(The map data for census tracts is extracted from: <http://atlas.lsu.edu>)

Next, GWR can be done in ArcGIS. In this research, based on the research method by Xu and Wang in 2015, Fotheringham et al. in 2002, the GWR results, the varied coefficients of factor data with the significance level (95%) and the local R square value for each census tract in the study site, will be calculated and mapped as follows (Fotheringham et al. 2002):

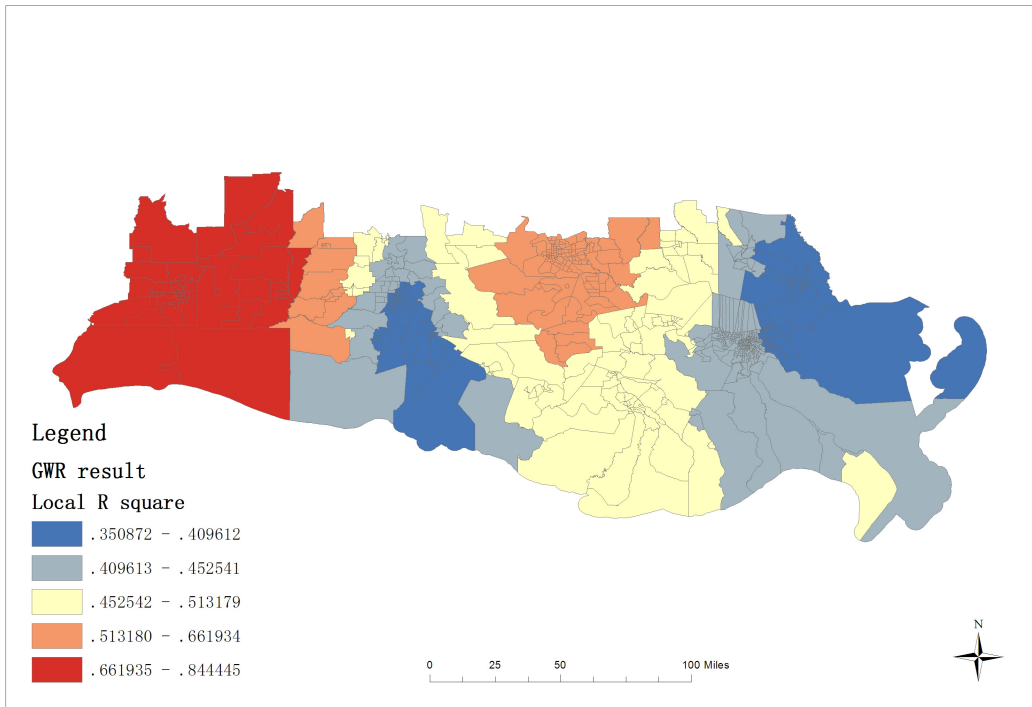


Figure 27 Local R square values for census tracts (The map data for census tracts is extracted from: <http://atlas.lsu.edu>)

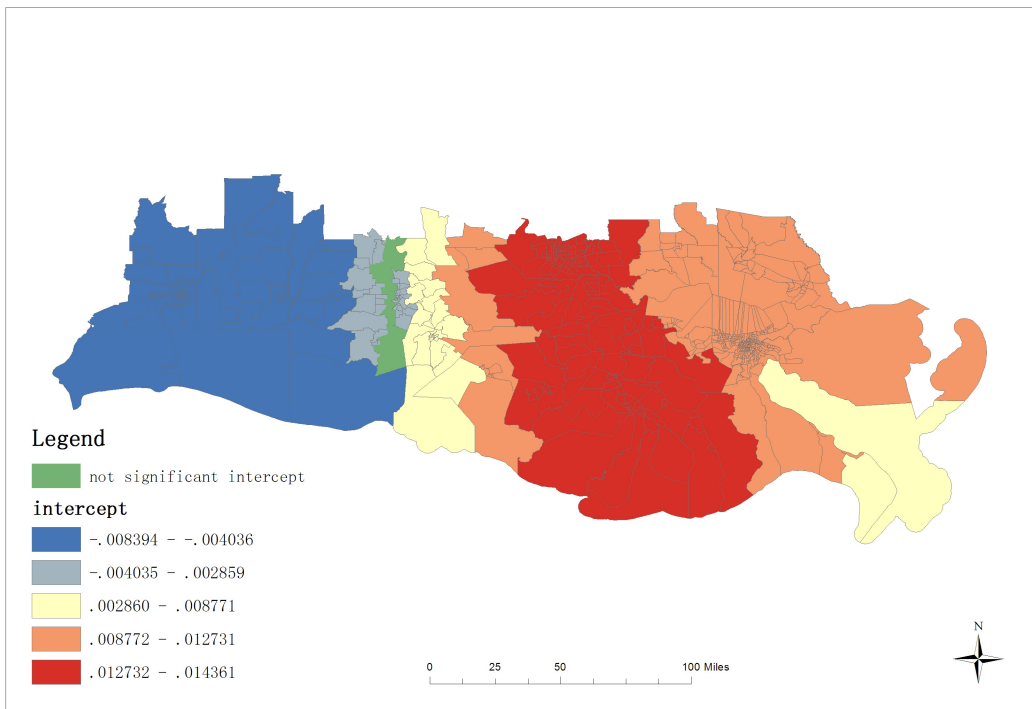


Figure 28 Intercept for census tracts (The map data for census tracts is extracted from: <http://atlas.lsu.edu>)

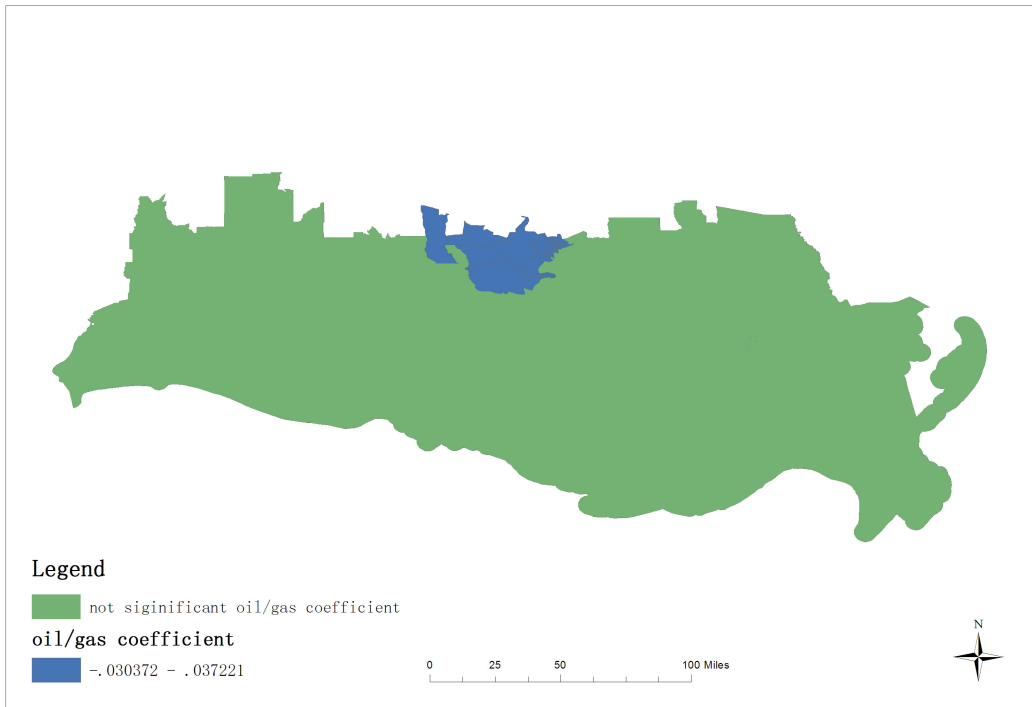


Figure 29 Oil/gas coefficients for census tracts (The map data for census tracts is extracted from: <http://atlas.lsu.edu>)

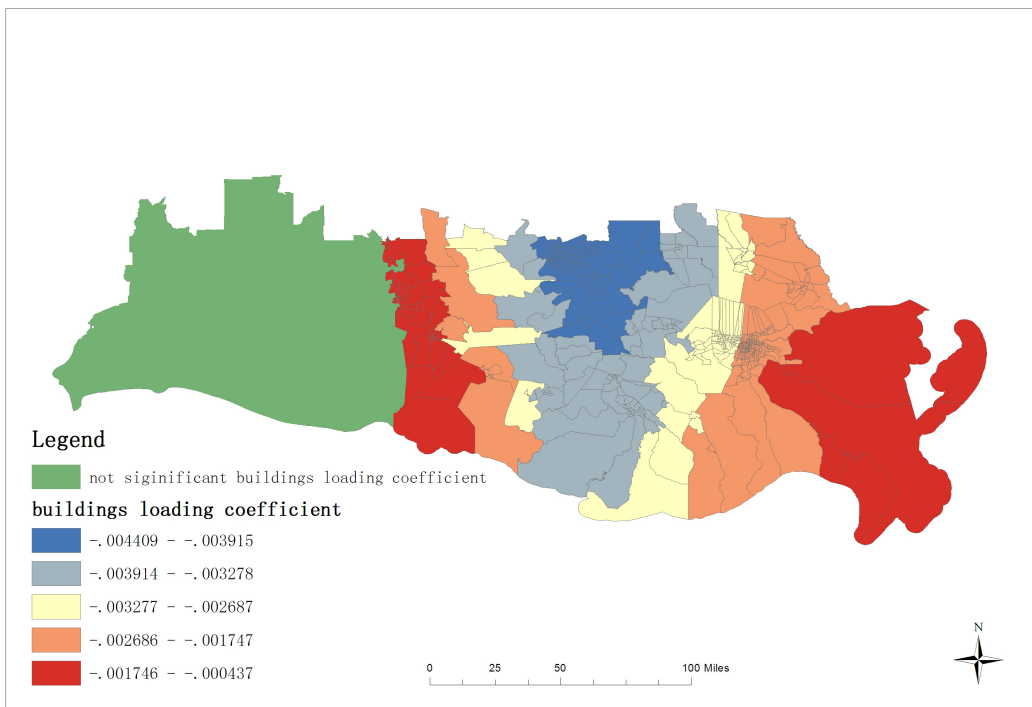


Figure 30 Buildings loading coefficients for census tracts (The map data for census tracts is extracted from: <http://atlas.lsu.edu>)

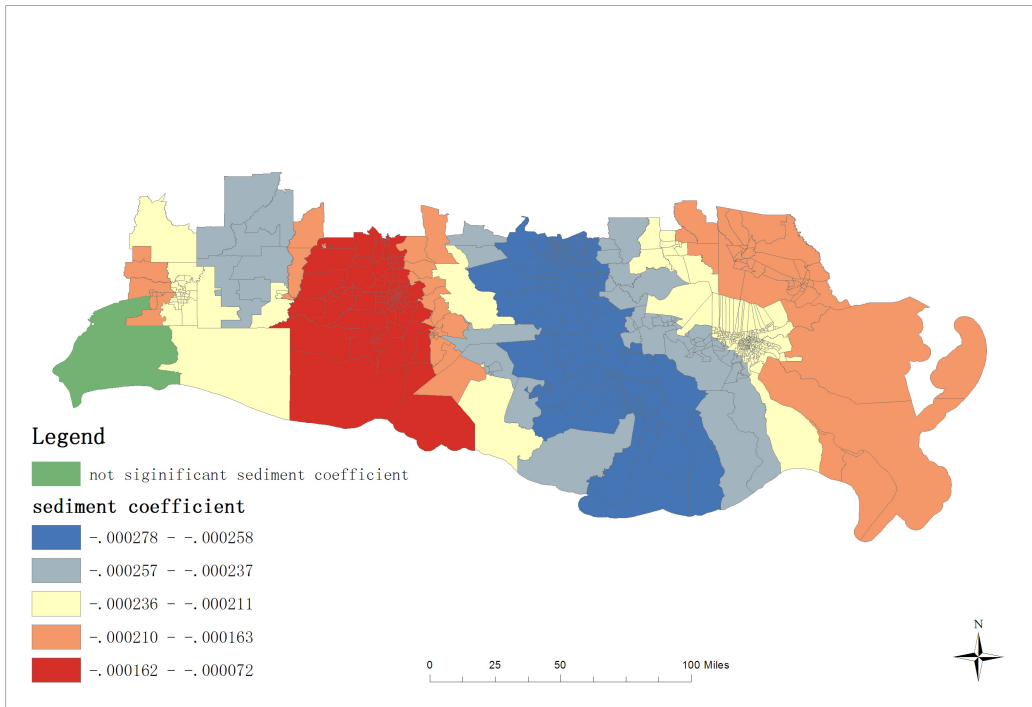


Figure 31 Sediment coefficients for census tract (The map data for census tracts is extracted from: <http://atlas.lsu.edu>)

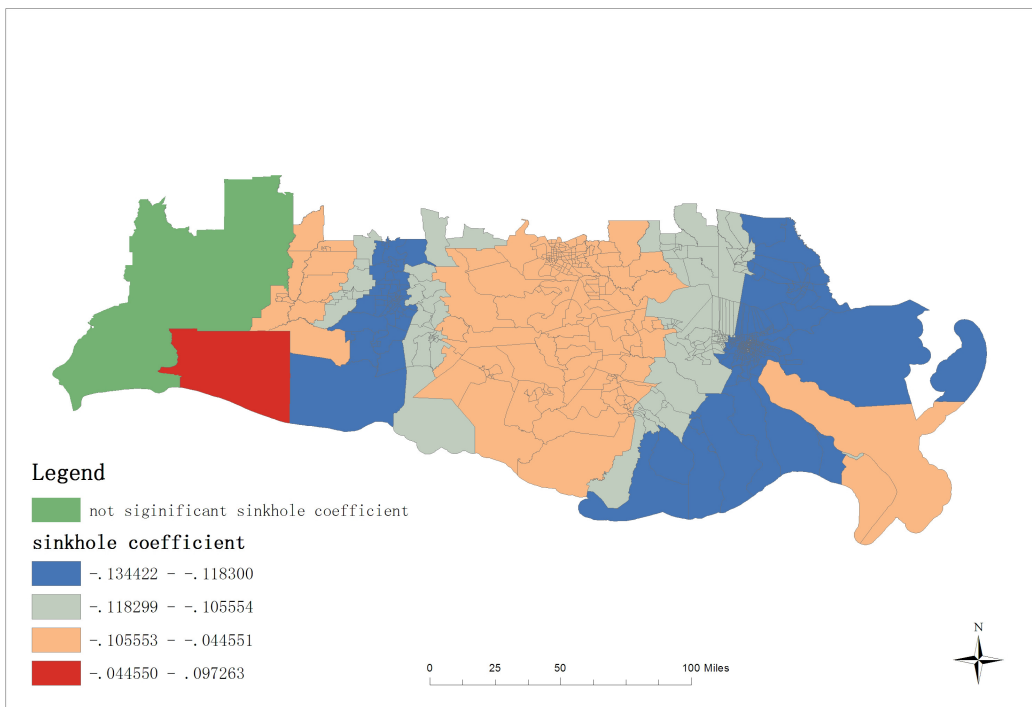


Figure 32 Sinkhole coefficients (inverse distances to sinkhole location) for census tracts (The map data for census tracts is extracted from: <http://atlas.lsu.edu>)

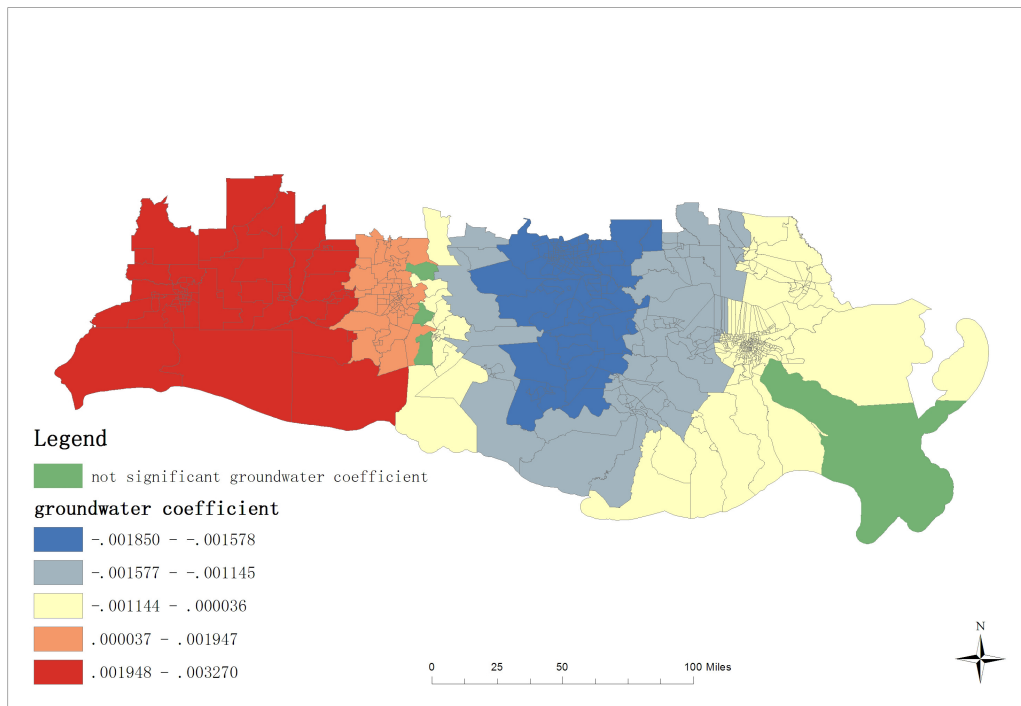


Figure 33 Groundwater coefficients for census tracts (The map data for census tracts is extracted from: <http://atlas.lsu.edu>)

4.4 Accuracy evaluation for GWR results

Besides the GWR modeling results are generated, we should also evaluate the modeling accuracy. In this research, from the GWR output report we find that the total R square value is about 0.6650 (60.50%), and the adjusted R square value is about 0.6583 (65.83%). Based on the GWR results, and the research methods by Shang et al. in 2011 and Xu and Wang in 2015, the spatially varied coefficients for all kinds of factor data are also calculated as follows (Shang et al. 2011; Xu and Wang 2015):

Table 2 Modeling results by GWR

	25% quartile	50% quartile	75% quartile
Intercept	0.010387	0.011762	0.012591
Oil/gas	-0.010249	0.011426	0.012289
Buildings loading	-0.003346	-0.002593	-0.002250
Sediment	-0.000247	-0.000232	-0.000220
Sinkhole	-0.123039	-0.118171	-0.100977
Groundwater	-0.001400	-0.000982	-0.000830
Total R square	0.6650		
Adjusted R square	0.6583		

What's more, likewise, we will use Ordinary Least Square (OLS) for modeling these above 5 types of factor data in this research (Hayashi and Fumio 2000). By the OLS method from Hayashi and Fumio's research in 2000, the coefficients for all types of factor data can be generated as follows (Hayashi and Fumio 2000):

Table 3 Modeling results by OLS

	Value	P-value
Intercept	0.001497	0.003253
Oil/gas	0.032674	0.006506
Buildings loading	-0.001732	0.000009
Sediment	-0.000006	0.597827
Sinkhole	-0.127309	0.000000
Groundwater	-0.000226	0.020218
R square	0.168077	-
Adjusted R square	0.162379	-

By contrasting the GWR results to the OLS ones, we can clearly find that the total R square value by GWR (about 0.6650) is much larger than and the total R square by OLS (about 0.1681), and the adjusted R square value by GWR (about 0.6583) is also much larger than the adjusted R square value by OLS (about 0.1624). This means that nearly much more amount of subsidence rates data can be explained by the above 5 types of factor data, by using GWR rather than OLS (Shang et al. 2011; Xu and Wang 2015). Besides, the results by GWR (Figure 27) also show that, the local R square values for census tracts are spatially varied much. The local R square value in the study site can range from 0.350872 (about 35.09%) to 0.844445 (about 84.44%), showing clear spatial heterogeneity for all census tracts (Fotheringham et al. 2002; Shang et al. 2011; Xu and Wang 2015).

For each factor contributing to subsidence, such as groundwater, oil/gas, sediment, building loading and inverse distance from the sinkhole location, Table 2 shows that all of coefficients for census tracts are spatially varied much, with clear spatial heterogeneity for the contributing factor weights, and maps for GWR results also show clear spatial clusters for each kind of coefficients, meaning that there may be spatial dependency for the subsidence data in this research (Shang et al. 2011; Xu and Wang 2015; Knecht et al. 2010).

Next, we will discuss and explain the significance levels for all kinds of coefficients in these maps for GWR results as follows:

From Figure 29, we can find that the oil/gas coefficients for nearly all of census tracts in the study site are not significant. While, this result does not match the former research by Abdollahzadeh et al. in 2013 because in the process of oil/gas data collection, we can't collect the important production data and the density data of wells have to be collected and used in this research (Extracted from: <http://sonris.com>). So if we can collect much production data, the modeling results may show more coefficients with clearly significant levels.

From Figure 30, we can find that for most of census tracts in the study site, the buildings loading coefficients are clearly significant. The green colored area in the figure shows that for census tracts in this area, the factor for buildings loading is not significant, and low percentage of buildings cover in this area may cause this result. Besides, the negative values for the coefficients in Figure 30 also show that, for all of census tracts in the study site, the subsidence rate and the buildings loading factor are

negatively correlated. This negative correlation can be explainable because more percentage of buildings loading area may mean more loading volume for the census tract, which contributes to subsidence in the coastal area of Louisiana (Abdollahzadeh et al. 2013).

Figure 31 shows that for nearly all of census tracts in the study site, the sediment coefficient is significant, and this result basically match the former research by Abdollahzadeh et al. in 2013 (Abdollahzadeh et al. 2013). Besides, the negative value for the sediment coefficient shows that, the subsidence rate and the sediment factor are negatively correlated. This negative correlation can be explainable because in the process of sediment formation, more thickness for the sediment sample will mean more significant compaction process which can cause clear subsidence (Sclater and Christie 1980).

Figure 32 shows that the sinkhole coefficient is very significant for nearly all of census tracts in the study site, except for some census tract which are too far from the Bayou Corne sinkhole (Cusanza 2013). For nearly all of census tracts with the significant levels, the negative correlation between the subsidence rate and the sinkhole factor can be explainable because in most situations, the nearer the area is from the sinkhole location (the larger inverse distance), the faster the subsidence rate in this area is, and this correlation can also be consistent with the real expanding situation for the Bayou Corne Sinkhole in the monitoring process from August 2012 (Cusanza 2013; Jones and Blom 2014; Jones and Blom 2015).

Finally, from Figure 33, we can also find that the groundwater coefficients for nearly all of census tracts are clearly significant. The groundwater coefficients for the green colored area in the figure are not significant, because the small changes for groundwater levels in this area may cause less subsidence (Shang et al. 2011). Besides, unlike coefficients for the other factors, the groundwater coefficients show that the correlation between subsidence rate and the groundwater factor are clearly positive for many census tracts while this correlation is also clearly negative for the other census tracts in the study site. Either the positive correlation or the negative correlation can be explainable in this research because different layers of groundwater aquifers in the study site may cause different correlations (Shang et al. 2011). The former research by Shang et al. 2011 shows that, in the process of groundwater withdrawal, the correlation can be positive because the decreasing groundwater level will cause an increasing internal pressure for the unconfined aquifer which can make the aquifer compress and the ground move downward in the study site, and the correlation can also be negative because the confined aquifer may uplift because of decreasing loading of the unconfined aquifer (Shang et al. 2011; Dokka 2006; Kent and Dokka 2012).

Thus, in this research, the modeling results by GWR are clearly better than the ones by OLS, showing the spatially varied R square values and factor coefficients with the significance levels for all of census tracts in the study site (Shang et al. 2011; Xu and Wang 2015). This means that the GWR model is suitable in this research, and the results by GWR can reflect the spatial heterogeneity for factor data which

contributes to subsidence in the study site (Fotheringham et al. 2002; Shang et al. 2011).

4.5 Results by the spatial-lag model and the spatial-error model

In this research, the GWR results show that there is clear spatial heterogeneity for subsidence data in the coastal area of Louisiana, while the spatial dependency may not be considered much for this model (Fotheringham et al. 2002; Shang et al. 2011; Knegt et al. 2010). Thus, to consider spatial dependency for subsidence data in this research, some geo-statistics model such as the spatial-lag model and the spatial-error model will be considered to make factor modeling results (Baller et al. 2001; Wang 2006; Wang et al. 2014; Knegt et al. 2010).

For the spatial-lag modeling, like by GWR, we can also input the above quantified factor data as independent variables, and the above subsidence rates data as the dependent variable, likewise, for the spatial-error modeling, we will make the same inputting process for variables (Baller et al. 2001; Wang 2006; Wang et al. 2014).

The spatial-lag model and the spatial-error model can be used by GeoDa software (Anselin et al. 2006; Baller et al. 2001; Wang 2006; Wang et al. 2014). And based on the research methods by Baller et al. in 2001, Wang in 2006 and Wang et al. in 2014, the modeling results are as follows (Baller et al. 2001; Wang 2006; Wang et al. 2014):

Table 4 Modeling results by the spatial-lag model and the spatial-error model

	Spatial-lag		Spatial-error	
	Value	P-value	Value	P-value
Intercept	0.000111	0.10093	0.003880	0.65776
Oil/gas	0.000453	0.76952	0.000683	0.65352
Buildings	-0.000115	0.02064	-0.000235	0.00566
Sediment	0.000003	0.04730	-0.000155	0.00000
Sinkhole	-0.014953	0.00000	-0.020276	0.00001
Groundwater	0.000032	0.01113	-0.000149	0.30124
W	0.995309	0.00000	-	-
λ	-	-	0.998261	0.00000
R square	0.986052	-	0.986781	-

From the above table, we can easily find that the R square value by the spatial-lag model (about 0.986052) and the one by the spatial-error model (about 0.986781) are nearly the same. The P-value for the coefficient W in the spatial-lag model is less than 0.00001 (much smaller than 0.05), showing that the coefficient W is very significant in this research, and the P-value for the coefficient λ in the spatial-lag model is also less than 0.00001 (much smaller than 0.05), also showing that the coefficient λ is significant in this research (Baller et al. 2001; Wang 2006; Wang et al. 2014). Thus, either the spatial-lag model or the spatial error model can be so valid and advantageous in this research, showing clear spatial dependency for the subsidence rates data as the dependent variable (Knecht et al. 2010).

On the other hand, the R square value by the spatial-lag model (about 0.986052) and the one by the spatial-error model (about 0.986781) in the above table show that, most percentage of subsidence rates data as the dependent variable, can be explained by 5 types of factor data (groundwater, oil/gas, sediment, building loading and the inverse distance from the sinkhole location) in this research (Abdollahzadeh et al. 2013; Shang et al. 2011). Besides, from the P-values in the above table, we can easily find that for the spatial-lag model, all coefficients for factor data except the oil/gas and sediment coefficients, are clearly significant (clearly small than 0.05), while, for the spatial-error model, unlike the result by the spatial-lag model, the groundwater coefficient is not significant but the sediment coefficient is more clearly significant.

Thus, from the above table, we can conclude that either the result by the spatial-lag model or the one by the spatial-error model may basically match the former research by Abdollahzadeh et al. in this research which shows that the groundwater, oil/gas, sediment and mass loading are the main factors for subsidence in the coastal area of Louisiana (Abdollahzadeh et al. 2013). And next, we will discuss and explain the significance levels for all of important independent variable coefficients as follows (Wang et al. 2014):

Firstly, either in the spatial-lag model or in the spatial-error model, the P-value for the inverse distance coefficient (about or less than 0.00001, much smaller than 0.05), shows that this coefficient is very significant in this research (Wang et al. 2014). This also means that the Bayou Corne Sinkhole should be the most important contributing factor for the accelerating subsidence in the study site in Louisiana, and

the minus value for the coefficient also means that the variable for subsidence rates in 2013 and the one for the inverse distance from the sinkhole location are negatively correlated (Wang et al. 2014). In this research, we mark minus value as the downward ground movement or subsidence, so this negative correlation shows that the nearer the area is from the sinkhole location (the larger inverse distance), the faster the subsidence rate in this area is, and this correlation can also be consistent with the real expanding situation for the Bayou Corne Sinkhole in the monitoring process from August 2012 (Cusanza 2013; Jones and Blom 2014; Jones and Blom 2015).

Secondly, either in the spatial-lag model or in the spatial-error model, the P-value for the buildings loading coefficient (clearly smaller than 0.05), shows that this coefficient is significant in this research (Wang et al. 2014). Like the sinkhole factor, the mass building loading should be also the important contributing factor for the accelerating subsidence in the study site in Louisiana, and the minus value for the coefficient also means that the variable for subsidence rates in 2013 and the one for the mass building loading level are negatively correlated (Wang et al. 2014). So in this research, the more area of loading percentage the buildings have in the census tract, the faster the subsidence rate in this area is.

Thirdly, in the spatial-error model, the P-value for the sediment coefficient (less than 0.00001), shows that this coefficient is significant, and the sediment compaction process should be an important contributing factor for the accelerating subsidence in the study site in Louisiana (Wang et al. 2014). Besides, the negative value for the coefficient means that the variable for subsidence rates in 2013 and the one for the

sediment sample thickness are negatively correlated (Wang et al. 2014) (Extracted from: <http://sonris.com>). This negative correlation can be explainable because in the process of sediment formation, more thickness for the sediment sample will mean more significant compaction process which can cause clear subsidence (Sclater and Christie 1980).

Fourthly, in the spatial-lag model, the P-value for the groundwater coefficient (about 0.01113, smaller than 0.05), shows that this coefficient is also significant, and the change of groundwater level should also be an important contributing factor for the accelerating subsidence in the study site in Louisiana (Wang et al. 2014; Shang et al. 2011). Besides, the positive value for the coefficient also means that the variable for subsidence rates in 2013 and the one for the change of groundwater level are positively correlated (Wang et al. 2014; Shang et al. 2011). This positive correlation can also be explainable because in the process of groundwater withdrawal, the decreasing groundwater level will cause an increasing internal pressure for the underground aquifer which can make the aquifer compress and the ground move downward in the study site (Shang et al. 2011; Dokka 2006; Kent and Dokka 2012).

Finally, either in the spatial-lag model or the spatial-error model, the P-value for the oil/gas pumping coefficient (much larger than 0.05) shows that this coefficient is not significant, and the positive value for this coefficient also shows that the variable for subsidence rates in 2013 and the density of oil/gas wells are positively correlated (Wang et al. 2014). The former research by Abdollahzadeh et al. shows that oil/gas pumping is the main factor for subsidence in the coastal area of Louisiana, while, the

coefficient for the oil/gas factor is not significant in this research because the data collection for the oil/gas factor may not be so valid, and the production data for oil/gas wells may be more suitable and valid than the point density data, but we lack of production data in this research (Abdollahzadeh et al. 2013) (Extracted from: <http://sonris.com>).

4.6 Summary and discussion

In this chapter, based on the processed results by KKF from last chapter, we have used GWR to model the factor data which contribute to subsidence in the study site in Louisiana. The modeling results show that the GWR model can be suitable for factor modeling in this research, with the spatially varied local R square values and coefficients for each type of factor data (Xu and Wang 2015; Shang et al. 2011). We also use OLS to model the same factor data, comparing the modeling results with the ones by GWR. The results of comparisons show that the total R square value by GWR is much larger than the one by OLS, and the adjusted R square value by GWR is also much larger than the one by OLS, so we can conclude that there is clear spatial heterogeneity for subsidence data in 2013, in this research (Xu and Wang 2015; Shang et al. 2011; Fotheringham et al. 2002).

Besides, so as to consider spatial dependency rather than spatial heterogeneity, we have used other geo-statistics models, such as the spatial-lag model and the spatial-error model in this research (Kneigt et al. 2010). The modeling results show that either the spatial-lag model or the spatial-error model can be valid and

advantageous in this research, with the high significance level (Wang et al. 2014; Shang et al. 2011; Knecht et al. 2010). While, although the modeling results shows that either the spatial-lag model or the spatial-error model can be suitable to model factor data in this research, there are also some flaws in the factor modeling process. One big flaw can be that for quantifying the oil and gas data, we can only collect the wells data with the wells distribution, and we can't collect the data on the production for each well which contributes to subsidence directly, thus, the density of wells rather than the production for oil/gas wells is considered as an independent variable in the factor modeling process, the modeling results show that the oil/gas coefficient is not significant and these results doesn't match the former research very much (Abdollahzadeh et al. 2013; Wang et al. 2014) (Extracted from: <http://sonris.com>).

Chapter 5 Research Conclusions and Final Summary

5.1 Research conclusions

As Chapter 4 and Chapter 5 show, this research consists of two main parts: in the first main part we have processed GPS data by KKF, and in the second main part we have modeled factor data by geo-statistics models. Thus, conclusions in this research can also be divided into two main parts as follows:

5.1.1 Conclusions from KKF results

In this research, by KKF, GPS data from Louisiana stations has been collected and processed, and distributions of subsidence rates in the coastal area from 2011 to 2013 has also been generated. For KKF results, we have summarized three main conclusions as follows:

The first conclusion is that Ordinary Least Square (OLS) can be a valid model to calculate each year's subsidence rates for all of GPS stations in this research (Hayashi and Fumio 2000; Dokka and Shinkle 2004). In this research, the preprocessed result by NASA's GIPSY shows each day's longitude, latitude and height for all of GPS stations in the study site, so we must calculate each year's subsidence rate validly, from the observed 365 or 366 days' height values for each GPS station. By OLS, a straight line has been generated and this line can show the changing trend of height values in one year for each station, thus, the slope for this straight line can be used to calculate each year's subsidence rate (Hayashi and Fumio 2000; Dokka and Shinkle

2004). The final KKF results in Chapter 3 which show the distribution of subsidence rates each year, have been validated by Bayou Corne Sinkhole knowledge, and this also means that the calculation of each year's subsidence rate by OLS is valid (Cusanza 2013; Jones and Blom 2014; Jones and Blom 2015). Besides, in the former research, experts had used OLS to calculate the rate of water level changes in one period, and this similar calculation can also validate our calculation of each year's subsidence rate (Dokka and Shinkle 2004).

The second conclusion is that Kriged Kalman Filter (KKF) is suitable to process GPS data and predict the subsidence rates pattern each year in the study site, in this research. KKF can overcome the flaw of low density for GPS stations and predict large areas of subsidence rates around all of GPS stations in the study site (Mardia et al. 1998; Lu, C. et al. 2012). The KKF results show a significant accelerating subsidence area near Bayou Corne, and these results have been validated by Bayou Corne Sinkhole knowledge (Cusanza 2013; Jones and Blom 2014; Jones and Blom 2015). Besides, KKF as an extended type of Kriging interpolation, has been used to interpolate and generate a raster of subsidence rates distribution in this study, thus, as the KKF results from Figure 13, 14 and 15 show, the distance of less than 10 miles between the dark colored accelerating subsidence area and the exact Bayou Corne location (the purple point), should be allowed because of the interpolation error by KKF (Mardia et al. 1998; Cusanza 2013; Olea and Ricardo 1991; Olea 1999).

The third conclusion is that KKF results in this research can be useful for detecting and monitoring ground movement related disasters near bayou areas, such

as sinkholes (Jones and Blom 2014; Jones and Blom 2015). KKF results in Chapter 3 show the subsidence rates patterns, and changes for these patterns will also signify vertical downward ground movement related to disasters (Jones and Blom 2014; Jones and Blom 2015; Dokka 2006). Besides, the KKF results have been validated by Bayou Corne Sinkhole knowledge, and this also means that we can use KKF results to not only visualize the distribution pattern of subsidence rates each year, but also signify the development situation for the sinkhole (Jones and Blom 2014; Jones and Blom 2015; Cusanza 2013).

5.1.2 Conclusions from factor modeling results

In this research, some geo-statistics models, such as GWR, have been used to model factor data contributing to subsidence in the study site of Louisiana. And for factor modeling results, we have also summarized three main conclusions as follows:

The first conclusion is that GWR is suitable for modeling factor data in this research, because the modeling results show that there is clear spatial heterogeneity for subsidence data in the study site (Fotheringham et al. 2002; Shang et al. 2011). The local R square values for all of census tracts are spatially varied, and the coefficients for each type of factor data are also spatially varied (Xu and Wang 2015; Shang et al. 2011). Besides, the results by GWR are much different from the ones by OLS, and this also means that there is clear spatial heterogeneity for subsidence data and GWR is advantageous (Fotheringham et al. 2002; Shang et al. 2011).

The second conclusion is that either the spatial-lag model or the spatial-error model is suitable for modeling factor data in this research. We have used the

spatial-lag model and the spatial-error model for factor modeling rather than GWR, and modeling results show that, a large R square value can be generated, and this means that most subsidence rates data can be explained by the spatial-lag model (Shang et al. 2011).

The third conclusion is that Bayou Corne Sinkhole disaster, sediment compaction, loading of buildings, and groundwater withdrawal are four significant and explainable factors which contribute to subsidence in the study site in 2013 (Abdollahzadeh et al. 2013; Cusanza 2013). As Chapter 4 shows, 5 types of factor data, groundwater, oil/gas, sediment, buildings loading and inverse distance from the sinkhole location have been used for modeling, results either by the spatial-lag model or by the spatial-error model show that the P-value for the inverse distance coefficient (about or less than 0.00001, much smaller than 0.05) is very significant, and the negative correlation between the subsidence rate and the inverse distance from the sinkhole can be explained that, the near the area is from the sinkhole location, the faster the subsidence rate in this area is (Cusanza 2013; Jones and Blom 2014; Jones and Blom 2015; Wang et al. 2014). Either in the spatial-lag model or in the spatial-error model, the P-value for the buildings loading coefficient is clearly smaller than 0.05, this means that buildings loading coefficient is significant in this research, and the negative correlation between the subsidence rate and the buildings loading can be explained that, the more loading percentage the buildings in the area have, the faster the subsidence rate in this area is (Wang et al. 2014). In the spatial-error model, the P-value for the sediment coefficient is less than 0.00001, this means that sediment compaction factor can also be

significant in the study site in 2013, and the negative correlation between the subsidence rate and the sediment sample thickness can be explained that, more sediment sample thickness will mean more significant sediment compaction process which can cause clear subsidence (Wang et al. 2014; Sclater and Christie 1980) (Extracted from: <http://sonris.com>). In the spatial-lag model, the P-value for the groundwater coefficient (about 0.01113) is smaller than 0.05, this also means that the groundwater coefficient is significant, and the positive correlation between the subsidence rate and the change of groundwater level can be explained that, in the groundwater withdrawal process, the decreasing groundwater level will cause an increasing internal pressure for the underground aquifer which can make the aquifer compress and the ground move downward in the study site (Wang et al. 2014; Shang et al. 2011; Dokka 2006; Kent and Dokka 2012). Besides, either in the spatial-lag model or in the spatial-error model, the P-value for the oil/gas coefficient (much larger than 0.05) shows that the oil/gas pumping factor is not significant in this research because we lack of production data for oil/gas wells (Wang et al. 2014) (Extracted from: <http://sonris.com>).

5.2 Final summary and future work

In this research, we focus on a popular topic in Louisiana: subsidence (Dokka 2006). For this research topic, the adverse situation which subsidence produces, especially in coastal Louisiana, has been presented in the background chapter. Figures for heights of GPS observations assist the claim that the subsidence problem is

common in Louisiana (Hung et al. 2011), and based on the estimation from these figures, we can predict that Louisiana state will experience land loss in the form of wetland in the near future (Shinkle and Dokka 2004). Thus, from now on, we should focus on the subsidence study and take action to prevent serious subsidence for our coastal land.

After the subsidence problem is presented, the literature review work has been done to show the recent research progress on subsidence by researchers. One big part of literature review involves subsidence observation and prediction. About this part, three kinds of common observation techniques, leveling, GPS and InSAR have been discussed with respect to their different advantages and flaws (Lu, C. et al. 2012). Besides, we focus on the techniques combinations to improve the observation levels on subsidence, and the KKF model has also been introduced as a new method to process subsidence data (Mardia et al. 1998). The other big part of literature review involves modeling of factors contributing to subsidence. In this part, the contributing factors on subsidence have been presented by the former research, groundwater withdrawal, oil and gas pumping, sediment compaction, faulting and mass loading (Abdollahzadeh et al. 2013). After that, we have discussed the former modeling methods on subsidence factors, and concluded that most of modeling process lack of local view or spatial heterogeneity, and we need some new methods such as GWR to solve this problem (Fotheringham et al. 2002; Shang et al. 2011).

Then based on our literature review work, we have proposed research questions in this research, and also research workflow. The main research workflow involves

two important research techniques, KKF processing and factor modeling such as GWR. Thus, in the following chapters, we have discussed these two techniques and their application on subsidence data in details, showing how to use these techniques to process Louisiana subsidence data based on the workflow.

Chapter 3 shows that KKF can be a good method to predict subsidence rates in coastal Louisiana, interpolating GPS data in time series (Mardia et al. 1998; Kalman 1960). By this method, points of spatio-temporal data can be processed into a raster format for prediction in the study site, and the well-known Bayou Corne Sinkhole knowledge can be used to validate the prediction result by KKF (Mardia et al. 1998; Kalman 1960; Cusanza 2013; Jones and Blom 2014; Jones and Blom 2015).

Chapter 4 shows the modeling process of factor data contributing to Louisiana subsidence such as GWR. Before factor modeling, the process of quantification for the factor data should be important, and the processed result by KKF from last chapter should be also the input data as the dependent variable (Fotheringham et al. 2002). Finally, the modeling results show that GWR can be suitable for factor modeling in this research, with clear spatial heterogeneity for subsidence data in 2013, and either the spatial-lag model or the spatial-error model can be also suitable for modeling factor data, with clearly significant coefficients (Xu and Wang 2015; Wang et al. 2014; Shang et al. 2011; Kneigt et al. 2010; Fotheringham et al. 2002).

Thus, in this research, we have introduced a new and unique model based on Kalman Filter, KKF, to make optimal and valid prediction for large area of subsidence, because Kalman Filter has a unique feature for the optimal prediction (Mardia et al.

1998; Kalman 1960; Zhang 2008; Lu, C. et al. 2012). Besides, many kinds of factor data, rather than only one kind in the former research, have been used for geo-statistics modeling, so as to find the main factors for subsidence, and these modeling results basically match the former research by the other people (Abdollahzadeh et al. 2013; Shang et al. 2011).

Although our work in this research has produced some new progress on subsidence research in coastal Louisiana, there are also some big flaws or disadvantages which are improvable in the future work.

The first improvable point is that in the KKF processing, most point distances for the GPS observation points are not so near, and if we consider the subsidence prediction in the whole state area instead of the coastal one, good results by KKF may not be generated because the variogram model doesn't fit the data so well with low spatial autocorrelation (Kneigt et al. 2010; Mardia et al. 1998; Olea and Ricardo 1991). Thus, for future study, if we would like to predict subsidence rates in the whole Louisiana area by KKF, we should collect more points of GPS data and the point distances should also be much nearer (Kneigt et al. 2010; Mardia et al. 1998; Olea and Ricardo 1991).

The second improvable point is that in the oil and gas data collection for factor modeling, we can only collect the well data on the distribution online, while, if we can collect the production data for each well, the modeling results may reflect an explainable coefficient for the oil and gas pumping factor with a significant level (Extracted from: <http://sonris.com>) (Abdollahzadeh et al. 2013; Wang et al. 2014).

The last improvable point is that we don't consider faulting data in the factor modeling process, because we can't easily find spatial heterogeneity for faulting data in the study site, thus, we should focus on how to quantify the faulting data well with some other knowledge in the future study, and this improvement can produce more types of factor data in the factor modeling process and better modeling level or accuracy (Shang et al. 2011; Fotheringham et al. 2002; Abdollahzadeh et al. 2013).

References

- A. S. Fotheringham, C. Brunson, M. Charlton. Geographically Weighted Regression: The analysis of spatially varying relationships. Wiley, 2002.
- Abdollahzadeh, M.; Dixon, T. H.; Malservisi, R. Geodetic subsidence rate in coastal Louisiana. American Geophysical Union, Fall Meeting 2013. December 2013.
- Anselin, L., A. K. Bera, R. Florax, and M. J. Yoon. GeoDa: An Introduction to Spatial Data Analysis. *Geographical Analysis* 38 (1): 5-22.
- Baller, R. D., L. U. C. Anselin, S. F. Messner, G. Deane, and D. F. Hawkins. 2001. Structural Covariates of U. S. County Homicide Rates: Incorporating Spatial Effects. *Criminology* 39 (3): 561-588.
- Blom, R. G., Chapman, B. D., Dokka, R. K., Fielding, E. J., Hensley, S., Ivins, E. R., Lohman, R. B. Hazards of gulf coast subsidence: crustal loading, geodesy, InSAR and UAVSAR observations. American Geophysical Union, Fall Meeting 2009. December 2009.
- Brodie, Kate, Fettes, Douglas, Harte, Ben, Schmid, Rolf (29 January 2007). Structural terms including fault rock terms. International Union of Geological Sciences.
- Burgmann, R., Rosen, P.A., Fielding, E. J. (2000), "Synthetic aperture radar interferometry to measure earth's surface topography and its deformation", *Annual Review of Earth and Planetary Sciences* 28, pp. 169-209.
- Carolina Pagli, Freysteinn Sigmundsson, Thora A madottira, Pall Einarsson, Erik Sturkell. Deflation of the Askja volcanic system: Constraints on the deformation source from combined inversion of satellite radar interferograms and GPS measurements. *Journal of Volcanology and Geothermal Research*, 2006. 152, 97-108.

- Changfeng Yuan, Xuchun Wang, Ning Wang, Qianqian Zhao. Study on the effect of tunnel excavation on surface subsidence based on GIS data management. *Procedia Environmental Sciences*, 2012. 12, 1387 – 1392.
- CHEN Beibei, GONG Huili, LI Xiaojuan, LEI Kunchao, ZHANG Youquan, LI Jiwei, GU Zhaoqin, DANG Yanan. Spatial-temporal characteristics of land subsidence corresponding to dynamic groundwater funnel in Beijing municipality, China. *Chin. Geogra. Sci.*, 2011. 21(6), 753–764.
- Chih-Heng Lu, Chuen-Fa Ni, Chung-Pai Chang, Jiun-Yee Yen, Wei-Chia Hung: Integrations of multiple observations and inversion of subsidence parameters in Choushui River Fluvial Plain of central Taiwan. AGU Fall Meeting, San Francisco, 3-7 December 2012.
- Coal Industry Promotion Board, CIPB (1997). A study on the mechanism of subsidence over abandoned mine area and the construction method of subsidence prevention. Coal Industry Promotion Board, Seoul, 97-06, pp 1-67.
- Coal Industry Promotion Board, CIPB (1999). Fundamental investigation report of the stability test for Gosari. Coal Industry Promotion Board, Seoul, 99-06, pp 7-22.
- Cusanza, Kris. “Bayou Corne evacuation could last for years” NBC 33. Retrieved 24 July 2013.
- Daniel R. Roman, Yan Ming Wang, William Henning, and John Hamilton. Assessment of the New National Geoid Height Model, GEOID03. 2004 ACSM/TAPS Conference and Technology Exhibition. Nashville, Tennessee, April 16-21, 2004.
- David A. Freedman (2009). *Statistical Models: Theory and Practice*. Cambridge University Press.
- Dempster, A.P.;Laird, N.M.;Rubin, D.B.. Maximum Likelihood from Incomplete Data via the EM Algorithm. *Journal of the Royal Statistical Society*.1977. Series B 39 (1): 1–38.

- Dokka, R. K. Modern-day tectonic subsidence in coastal Louisiana. *Geol*, 2006. 34(4), 281–284.
- Fahui Wang, Quan Tang and Lei Wang. Post Katrina population loss and uneven recovery in New Orleans, 2000-2010. *Geographical Review*. Volume 104, Issue 3, 310-327, July 2014.
- Fahui Wang. *Quantitative methods and Application in GIS [M]*. CRC Press. 2006.
- Fengshuang Zhang, Wanju Bo. Primary discussion about the application of GPS results to research of ground subsidence. *Science of Surveying and Mapping*, 2012. 4, 37-39.
- Forsberg, R., Skourup, H. Arctic Ocean gravity, geoid and sea-ice freeboard heights from ICESat and GRACE. *Geophysical Research Letters*, 2005, 32(21), L21502.
- Gabriele Bitelli, Flavio Bonsignore, Marco Unguendoli. Levelling and GPS networks to monitor ground subsidence in the Southern Po Valley. *Journal of Geodynamics*, 2000. 30, 355-369.
- Geisser, Seymour (1993). *Predictive Inference*. New York, NY: Chapman and Hall. ISBN 0-412-03471-9.
- Guoquan Wang, M. ASCE, Jiangbo Yu, Timothy, J. Kearns, Jesse Ortega. Assessing the accuracy of long-term subsidence derived from borehole extensometer data using GPS observations: Case study in Houston, Texas. *J. Surv. Eng.* 2014. 140(3), 05014001.
- Guoyun Zhou, Tetsuro Esaki, Jiro Mori. GIS-based spatial and temporal prediction system development for regional land subsidence hazard mitigation. *Environmental Geology*, 2003. Volume 44, Issue 6, 665-678.
- Hana DOLEŽALOVÁ, Vlastimil KAJZAR, Kamil SOUČEK, Lubomír STAŠ. Evaluation of mining subsidence using GPS data. *Acta Geodyn. Geomater.*, 2009. Vol. 6, No. 3 (155), 359–367.

- Hasanuddin Z. Abidin, H. Andreas, Rochman Djaja, Dudy Darmawan, M. Gamal. Land subsidence characteristics of Jakarta between 1997 and 2005, as estimated using GPS surveys. *GPS Solut*, 2008, 12, 23–32.
- Hayashi, Fumio (2000). *Econometrics*. Princeton University Press.
- Hyun-Joo Oh, Saro Lee. Assessment of ground subsidence using GIS and the weights-of-evidence model. *Engineering Geology*, 2010. 115, 36–48.
- Hyun-Joo Oh, Saro Lee. Integration of ground subsidence hazard maps of abandoned coal mines in Samcheok, Korea. *International Journal of Coal Geology*, 2011. 86, 58–72.
- Hyun-Joo Oh, Seung-Chan Ahn, Jong-Kuk Choi, Saro Lee. Sensitivity analysis for the GIS-based mapping of the ground subsidence hazard near abandoned underground coal mines. *Environ Earth Sci*, 2011. 64, 347–358.
- J. X. Zhang. *Scale, Uncertainty and Fusion of Spatial Information [M]* Wuhan: Wuhan University Press, 2008.
- Jones, C. and Blom, R., “Pre-event and post-formation ground movement associated with the Bayou Corne Sinkhole” (2015).
- Jones, C. and Blom, R., Bayou Corne, Louisiana, sinkhole: Precursory deformation measured by radar interferometry. *Geology*, February 2014, v. 42, no. 2, p. 111-114.
- Kalman, R. E. A new approach to linear filtering and prediction problems. *Journal of Basic Engineering*, 1960. 82 (1), 35–45.
- Kanti V. Mardia, Colin Goodall, Edwin J. Redfern, Francisco J. Alonso. The Kriged Kalman filter. *Test*, 1998. Vol. 7, No.2, 217-285.
- Kenan Li. Temporal changes of coastal community resilience in the gulf of Mexico

region. A LSU thesis, 2011.

Kent, J., Dokka, R. Potential impacts of long-term subsidence on the wetlands and evacuation routes in coastal Louisiana. *GeoJournal*, 2012. 4, 641-655.

Ki-Dong Kim, Saro Lee, Hyun-Joo Oh, Jong-Kuk Choi, Joong-Sun Won. Assessment of ground subsidence hazard near an abandoned underground coal mine using GIS. *Environ Geol*, 2006. 50, 1183–1191.

Ki-Dong Kim, Saro Lee, Hyun-Joo Oh. Prediction of ground subsidence in Samcheok City, Korea using artificial neural networks and GIS. *Environ Geol*, 2009. 58, 61–70.

Knegt, De, Coughenour, M. B., Skidmore, A. K., Heitkonig, I. M. A., Knox, N. M., Slotow, R., Prins, H. H. T. (2010). Spatial autocorrelation and the scaling of species-environment relationships. *Ecology* 91: 2455-2465.

L Ge. Development and testing of augmentations of continuously-operating GPS networks to improve their spatial and temporal resolution, PhD Thesis, School of Surveying and Spatial Information Systems, The University of New South Wales, Sydney NSW 2052, AUSTRALIA, UNISURV S-63, xvi+230pp.

Linlin Ge, Eric Cheng, Xiaojing Li, and Chris Rizos. Quantitative subsidence monitoring the integrated InSAR, GPS and GIS approach. The 6th International Symposium on Satellite Navigation Technology Including Mobile Positioning & Location Services Melbourne, Australia, 22–25 July 2003.

Louisiana Department of Natural Resources, 2013b, Blue Ribbon Commission initial technical briefing:
http://dnr.louisiana.gov/assets/OC/BC_All_Updates/Plans_Reports/BlueRibb.04.05.13.pdf (May 2013).

Louisiana Department of Natural Resources, Fenstermaker Area Survey:
http://dnr.louisiana.gov/assets/OC/BC_All_Updates/Plans_Reports/Fenstermaker.Jan.2014.areasurvey.pdf (January 2014).

- Louisiana Department of Natural Resources, Itasca-Subsidence Report:
http://dnr.louisiana.gov/assets/OC/BC_All_Updates/Itasca.results.1152013.pdf
(October 2013).
- McLachlan, G. J. (2004). *Discriminant Analysis and Statistical Pattern Recognition*.
Wiley Interscience.
- Michael Poland, Roland Burgmann, Daniel Dzurisin, Michael Lisowski, Timothy
Masterlark, Susan Owen, Jonathan Fink. Constraints on the mechanism of
long-term, steady subsidence at Medicine Lake volcano, northern California,
from GPS, leveling, and InSAR. *Journal of Volcanology and Geothermal
Research*, 2006. 150, 55– 78.
- Minxue Zheng, Kaoru Fukuyama, Kazadi Sanga-Ngoie. Application of InSAR and
GIS techniques to ground subsidence assessment in the Nobi Plain, central Japan.
Sensors, 2014. 14, 492-509.
- Olea, R.A. (1999). *Geostatistics for engineers and earth scientists*. Kluwer Academic
Publisher.
- Olea, Ricardo (1991) A. *Geostatistical Glossary and Multilingual Dictionary*. Oxford
University Press. pp. 47, 67, 81.
- P. Psimoulis, M. Ghilardi, E. Fouache, S. Stiros. Subsidence and evolution of the
Thessaloniki plain, Greece, based on historical leveling and GPS data.
Engineering Geology, 2007. 90, 55–70.
- Paul S. Addison. *The Illustrated Wavelet Transform Handbook*, Institute of Physics,
2002.
- Robbins, Herbert (1956). “An Empirical Bayes Approach to Statistics”. *Proceedings
of the Third Berkeley Symposium and Mathematical Statistics and Probability*,
Volume 1. *Contributions to Theory of Statistics*: 157-163.
- Rong-Kang Shang, Yi-Shiang Shiu, Kuo-Chen Ma. Using geographically weighted

regression to explore the spatially varying relationship between land subsidence and groundwater level variations: A case study in the Choshuichi alluvial fan, Taiwan. International Conference on Spatial Data Mining and Geographical Knowledge Services, ICSDM 2011, Fuzhou, China, June 29 - July 1, 2011.

Sclater, J. G. and Christie, P. A. F. 1980. Continental stretching: an explanation of the post-mid-Cretaceous subsidence of the Central North Sea Basin. *Journal of Geophysical Research*, 85, 3711-3739.

Sergey Samsonov, Kristy Tiampo, John Rundle, and Zhenhong Li. Application of DInSAR-GPS Optimization for derivation of fine-scale surface motion maps of southern California. *Transactions on Geoscience and Remote Sensing, IEEE*, 2007. Vol.45, No.2, February 2007.

Shepard and Donald (1968). "A two-dimensional interpolation function for irregularly-spaced data". *Proceedings of the 1968 ACM National Conference*. pp. 517-524.

Shinkle, K., & Dokka, R. Rates of vertical displacement at benchmarks in the lower Mississippi Valley and the northern Gulf Coast. *NOAA Technical Report 50*, 2004.

Shumway, R.H. and D.J. Stoffer (1982). An approach to time series smoothing and forecasting using the EM algorithm, *Journal time series analysis*, 3, 253-264.

Tazlo Strozzi, Urs Wegmiiller, Luigi Tosl, Gabriele Bitelli, Volker Spreckels. Land Subsidence Monitoring with differential SAR interferometry. *Photogrammetric Engineering & Remote Sensing*, 2011. Vol. 67, No. 11, November 2001, 1261-1270.

The ArcGIS resource website. Extracted from: <http://resources.arcgis.com/en/help/main/10.1/index.html#//0031000000q900000>
0.

The Atlas website. Extracted from: <http://atlas.lsu.edu/>.

The CMU website. Weighting function. Extracted from:
<http://www.cs.cmu.edu/~schneide/tut5/node12.html>.

The Esri website. Extracted from:
<http://www.esri.com/news/arcuser/1012/empirical-byesian-kriging.html>.

The National Land Cover Database website. Extracted from:
<http://www.mrlc.gov/nlcd2011.php>.

The NCSU Libraries website. DOQQs. Extracted from:
<http://www.lib.ncsu.edu/gis/doqq.html>.

The SONRIS website. SONRIS Interactive Maps. Extracted from:
<http://sonris-www.dnr.state.la.us/gis/agsweb/IE/JSViewer/index.html?TemplateID=181>.

The SONRIS website. Extracted from: <http://sonris.com>.

The USGS website. Extracted from: <http://groundwaterwatch.usgs.gov/>.

The USGS websites. Faults. Extracted from:
<http://earthquake.usgs.gov/hazards/qfaults/>.

The website of Murphy Lab. Back-propagation neural network. Extracted from:
http://murphylab.web.cmu.edu/publications/boland/boland_node17.html.

The website of OECD Glossary of Statistics Terms. Frequency ratio. Extracted from:
<http://stats.oecd.org/glossary/detail.asp?ID=1066>.

The website of State University of Campinas. Weights of evidence method. Extracted from: <http://www.ige.unicamp.br/wofe/documentation/wofeintr.htm>.

The website of TRE. DInSAR. Extracted from:
<http://treuropa.com/technique/insar-evolution/>.

Urs Wegmuller, Tazio Strozzi, and Gabriele Bitelli. Validation of ERS differential SAR interferometry for Land subsidence mapping: the Bologna case study. Geoscience and Remote Sensing Symposium, 1999. IGARSS '99 Proceedings. IEEE 1999 International (Volume:2).

WANG Chong chang, LV You, SONG Ying. Researches on mining subsidence disaster management GIS `s system. 2012 International Conference on Systems and Informatics (ICSAI 2012), 19-20 May 2012.

Wei-Chia Hung, Cheinway Hwang, Yi-An Chen, Chung-Pai Chang, Jiun-Yee Yen, Andrew Hooper, Chin-Yi Yang. Surface deformation from persistent scatterers SAR interferometry and fusion with leveling data: A case study over the Choushui River Alluvial Fan, Taiwan. Remote Sensing of Environment, 2011. 115, 957–967.

Yanqing Xu and Lei Wang. GIS based analysis of obesity and the built environment in the US. Cartographic and Geographic Information Science, 2015. Vol 42, No. 1, 9-21.

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