Rapid spatio-temporal pumping volume estimation from electricity consumption big data

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Abstract: Land subsidence due to groundwater over-exploitation is a serious problem worldwide. Acquiring total pumping volumes to assess the stresses imposed that lead to subsidence is often difficult to quantify because groundwater extraction is often an unregulated water source. Consequently, pumping volumes represent a critical step for water resource managers to develop a strategic plan for mitigating land subsidence. In this investigation, we develop a time-dependent spatial regression (TSR) model to estimate monthly pumping volume over a ten-year period based on electricity consumption data. The estimated pumped volume is simplified as the spatial function of the electricity consumption and the electric power used by the water pump. Results show that the TSR approach can reduce the errors by 38% over linear regression models. The TSR model is applied to the Choshui alluvial fan in west-central Taiwan, where hundreds of thousands of unregulated pumping wells exist. The results show that groundwater peak extraction across the region occurs from January to May. Monthly pumping volume, and rainfall information are available to provide a better understanding of seasonal patterns and long-term changes of subsidence. Thus, the temporal regional subsidence patterns are found to respond to variations in pumping volume and rainfall.

Keyword: Groundwater, Pumping, Electricity consumption, Time-dependent spatial regression.

INTRODUCTION

Land subsidence caused by groundwater overexploitation is a serious global problem (Higgins, 2016). Subsidence areas identified revealed that subsidence has preferentially occurred in alluvial basins or coastal plains where urban or agricultural areas (Herrera-García *et al*., 2021). Acquiring total pumping volumes to assess the stresses imposed that lead to subsidence is often difficult to quantify because groundwater extraction is often an unregulated water source. The accuracy for the estimation of the quantity of groundwater withdrawal significantly influences regional groundwater resource management (Shao *et al*., 2014) and the amount of land subsidence that occurs from the lowering of the water levels. Tsanis & Apostolaki (2009) presented an estimation of the annual groundwater withdrawal rate based on a water balance approach using surface and groundwater hydrological components. Water budget components and groundwater levels made it possible to understand large-scale regional groundwater systems (Zhou & Li, 2011; Konikow, & Neuzil, 2007). Rodell *et al*., (2009) used terrestrial water storage-change observations from the GRACE satellite and simulated soil-water variations to estimate groundwater withdrawal.

Electric power consumption records from pumping wells is another feasible means of providing an estimate of groundwater usage (Hurr& Litke 1989). Total monthly pumped volume can be estimated on the basis of electric power consumption. However, data for electric power consumption records is required for every well in order to use this approach. These data must include, at a minimum, well location, power consumption records and pump power requirements. Many factors can affect spatio-temporal pumping volume estimation, including well design, pump power, and hydraulic conductivity (Chu *et al*., 2020). Following an empirical formulation, regression coefficients are quantified on the basis of well design, pump power, and hydraulic conductivity and then applied to the Choshui River alluvial fan in west-central Taiwan. The complexity of this systems makes the process of acquiring an accurate calibration extremely challenging due to the various pump designs and large hydrogeological data requirements for model development. The time-dependent spatial regression (TSR) method can be used in this investigation to model the spatial distribution of pumping volumes based on the spatial distribution of electric-power consumption and electric power requirements of the water pumps. Each time step, the TSR explicitly considers spatially-dependent models to overcome the spatial variability of data mapping (Ali *et al*., 2020). In addition, the regression parameter which depends on well characteristics *e.g*. well depth, well diameter, and aquifer hydraulic conductivity at site locations, is the function of a spatial location. Thus, applying TSR for modeling will provide a more robust goodness of fit to reduce spatial uncertainty.

The aim of the study is to (1) estimate the spatio-temporal pattern of pumping volume for each well, and determine areal and total volume of pumping,

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(2) simplify the model calibration process, and (3) provide understanding about the temporal relation between pumping, rainfall and land subsidence. This study applies the TSR approach to estimates total groundwater pumpage in the study area. The estimation of the spatiotemporal distribution of groundwater pumping volume is applied using electric power consumption and pump power data. After acquiring the groundwater pumping volume, the temporal analysis of the rainfall, and groundwater pumpage are used to explore the temporal patterns of land subsidence.

METHOD

The extracted volume of groundwater (V) is estimated from the flow rate (Q) and operating time (t). Operating time is estimated based on Energy = power × time, where electricity consumption (E) and electric power (P) required by the water pump are used to estimate the pumped volume. The pumped volume can be estimated based on electric consumption, pump power, power efficiency and flow rate.

$$V = Q * t = Q * E/(\varepsilon_w P), \tag{1}$$

where V is the extracted volume of pumping, Q is the volumetric pumping rate (Q in units of volume/time), and E is the electricity consumption. Power efficiency ε_w is assumed is assumed to be constant (.98) for all pumping wells in this study. In the original development of this model (Chu *et al*., 2020), the pump efficiency expressed in Eq. 1 is derived from an empirical relation developed from field conditions that include the pipe diameter, the pump power, well characteristics, aquifer hydraulic conductivity, and electricity consumption. Thus, Eq. 1 is applied for each individual well that is monitored in this investigation. The details of these parameters and their application are discussed more fully in Chu *et al*., 2020.

The estimated pumped volume is simplified as a regression function of the electricity consumption (E) and electric power (P) of water pump.

$$V = f(E, P), \tag{2}$$

Furthermore, a regression expression identifies the relation between pumping volume and electricity consumption. Equation (2) is used to estimate the total pumped volume at observation *i* at time *t*, which can be expressed as:

$$V_{t,i} = \beta_1 E_{t,i} + \beta_2 P_i + \beta_0 + \varepsilon_i, \tag{3}$$

where β_0 is the intercept, and β_1 and β_2 are the slope of the linear regression parameters, and ε_i is the residual of the regression model.

A TSR model that explains the regional variation is the specification combining and modeling spatial relationships each time step (Brunsdon *et al*., 1998; Chu *et al*., 2021). In each time step, Equation (4) is further extended to allow for a spatially varying function for estimating pumped volume at time *t* as:

$$V_{t,i} = \beta_1(x_i, y_i) E_{t,i} + \beta_2(x_i, y_i) P_i + \beta_0(x_i, y_i) + \varepsilon_i, \tag{4}$$

where $\beta_1(x_i, y_i)$ and $\beta_2(x_i, y_i)$ varies with the spatial coordinates (x_i, y_i) at observation *i* and is the slope of the spatial regression parameters. $\beta_0(x_i, y_i)$ is the intercept at observation *i* of the spatial regression parameters in the system.

The estimated parameter matrix $\hat{\boldsymbol{\beta}}\ (x_i, y_i)$ is derived from:

$$\hat{\boldsymbol{\beta}}\ (x_i, y_i) = [\boldsymbol{X}^T \mathrm{W}(x_i, y_i) \boldsymbol{X}]^{-1} \boldsymbol{X}^T \mathrm{W}(x_i, y_i) \boldsymbol{Y}, \tag{5}$$

where $\hat{\boldsymbol{\beta}}\ (x_i, y_i) = \left(\hat{\beta}_0(x_i, y_i), \hat{\beta}_1(x_i, y_i)\right)^{\mathrm{T}}$;

$\boldsymbol{Y} = (V_1, \ldots, V_n)^{\mathrm{T}}$; $\boldsymbol{X} = \begin{bmatrix} 1 & E_{t,1} & P_1 \\ \vdots & \vdots & \vdots \\ 1 & E_{t,n} & P_n \end{bmatrix}$; $\mathrm{W}(x_i, y_i)$ is a spatial weight matrix, which is formulated from the Gaussian and Euclidean distance functions. The Gaussian decay-based function commonly used as a kernel is defined as $e^{-(D_{ij}/h)^2}$, where h is the non-negative bandwidth. The parameter D_{ij} is the distance between the observed points i and j in the space domain, which is defined as $D_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$. Based on the monthly time-varying electricity consumption and electric power, the TSR model can then by applied to estimate pumping volume.

The model was used to estimate (1) monthly pumping volume within the overall study area for each well based on Eq 3 and 4; (2) areal pumping volume calculated from a 200 m grided area was aggregated using the average function; and (3) overall monthly average pumping volume (a time series) in the study area was provided for further temporal analysis of rainfall and land subsidence.

STUDY AREA AND MATERIAL

The study area lies within the Choshui River alluvial fan, which encompasses an area of 1800 km^2 in Changhua and Yunlin Counties (Figure **1**). The study area in the mid-fan area includes the townships of Huwei, Tuku and Yuanchang in Yunlin and covers an area of approximately 190 km^2 and encompasses the area of greatest land subsidence in Taiwan. The Taiwan High Speed Rail line is constructed through the subsidence area. Chinghua county to the north is separated from Yunlin county to the south by the Choshui River, which bisects the alluvial fan and flows from east to west. The western boundary is represented by the South China Sea and the eastern boundary is represented by the headwaters of the Choshui River, which lie about 100 meter above sea level. The bedrock in the upper (eastern) watershed of Choshui River is composed of slate, metamorphic quartzite, shale, sandstone, and mudstone, which creates sediments of the Choshui River alluvial fan (Liu *et al*., 2004). Excessive exploitation of groundwater in Changhua and Yunlin counties has resulted in land subsidence and is creating a potential hazard for infrastructures including the high-speed rail that extends from the northeast to the southern part of the study area (Ali *et al*., 2020).

The unconsolidated fan deposits consist of four aquifers that are composed of gravel and coarse sand deposits and separated by three finer grained (but locally discontinuous) confining units composed mainly of silts and clays. These aquifers are thickest in the east and become thinner toward the coast in the west where the aquitards tend to dominate. The aquitards are most prevalent in the distal-fan and mid-fan areas and gradually diminish in thickness toward the east. The proximal-fan represents the major recharge area of the aquifer system (Jang *et al*., 2008; Yu and Chu, 2010). Geologic materials are not uniformly distributed. Clay-containing sediments are more likely to compact with head reductions than sand and gravel formations; thus, land subsidence from groundwater pumping is more prone to occur in the western part of the study area.

The period of study extends from Jan, 2007 to April, 2017. Figure **1** shows the location of the study area (*i.e*. Tuku, Huwei and Yuanchang), pumping wells, rainfall and GPS stations. A total of 30,407 pumping wells are located in the study area. Electricity consumption and electric power of all wells are collected. Moreover, in-situ pumping volumes, electric-power consumption and electric power requirements of the pumping wells are acquired at 58 wells that have been identified as control points, and at 5 wells that are used for model RMSE validation on April, 2015. After the calibration, the model was applied for estimation from Jan, 2007 to April, 2017.

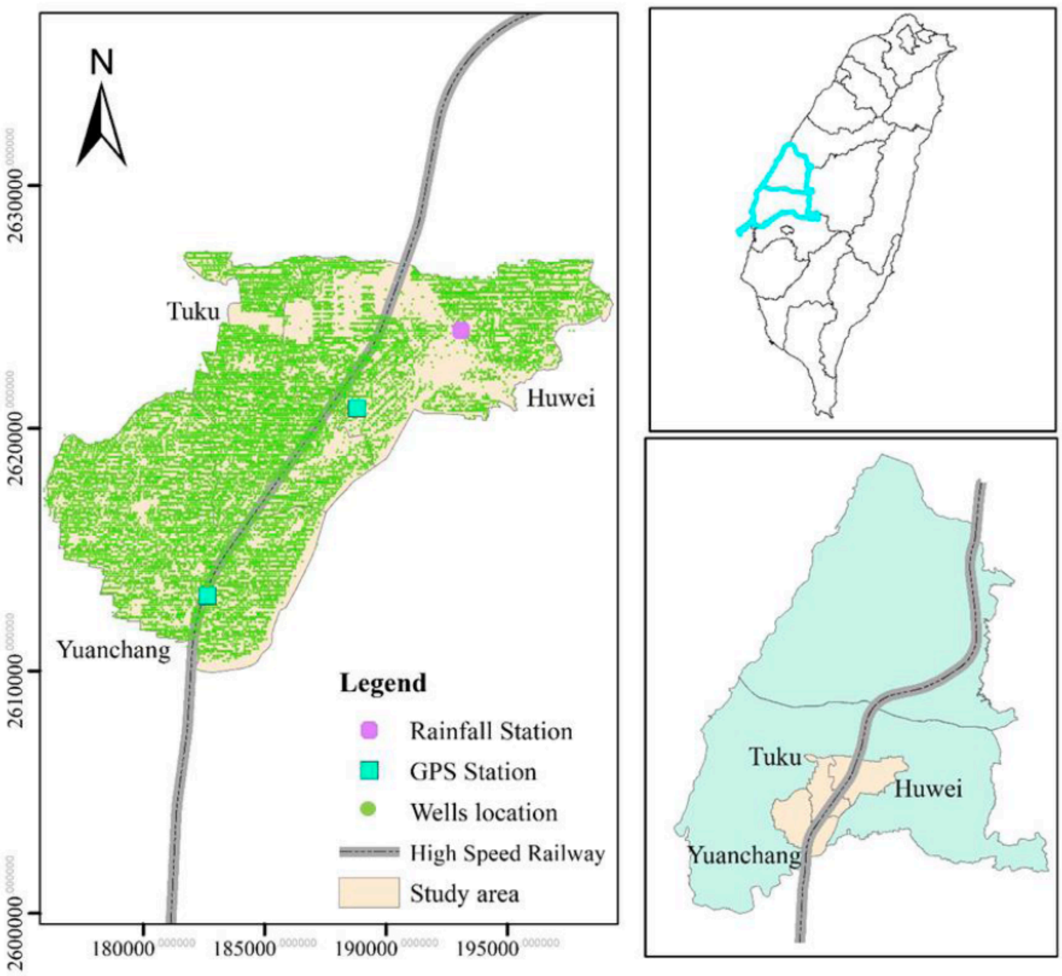

Figure 1: Location of study area (*i.e*. Tuku, Huwei and Yuanchang), pumping well locations (green points), high speed railway, rainfall and GPS stations.

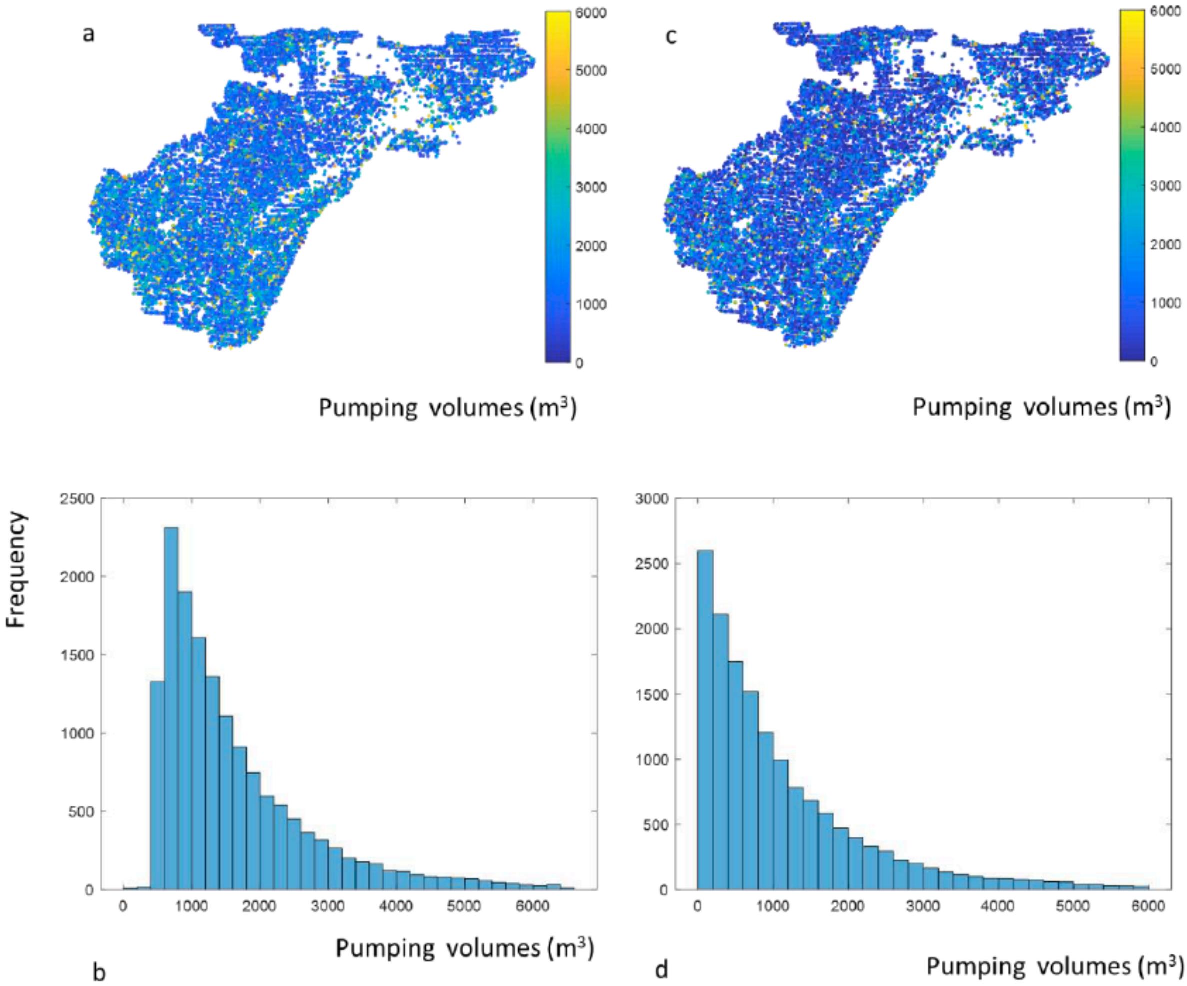

Figure 2: Spatial patterns and histograms of estimated pumping volumes from linear regression (**a**, **b**) and TSR approaches (**c**, **d**) on April, 2015.

RESULTS

Validation and Comparisons

The RMSE of pumping volume on April, 2015 is 437.8 m^3 when the function is used as a linear regression (Eq 3). The regression coefficients β_1 and β_2 are identified by linear regression to be 8.9 (m^3/deg) and -116.6 (m^3/HP), respectively, while β_0 is calculated to be 512.2 (m^3). However, the RMSE can be reduced by about 38% (to 167.7 m^3) by using the TSR approach (Eq 4). Figure **2** shows the spatial patterns and histograms of estimated pumping volume from the linear regression and the TSR modeling approaches on April, 2015. The estimated volume from linear regression is slightly larger than that calculated via the TSR model. However, the small estimated pumping volume from the TSR model is larger than that calculated via the linear regression. Figure **3** shows the spatial mapping of estimated pumping volume from the original model (Chu *et al*., 2020), and the TSR approach (this paper) for comparison on April, 2007, 2008 and 2010. The spatial patterns from each method are similar but express different details. The estimated pumping volumes from the TSR method are less than the original approach, especially in the north-east part of the study area. The TSR model may be more correct because our new model considers simplified hydrogeologic properties in the field.

Pumping Vs Rainfall and Subsidence

Figure **4** shows the estimated total pumping volumes, land subsidence and total rainfall from 2007 to 2017. Figure **4a** shows the estimated total pumping volumes based on the previous (original) study (Chu *et al*., 2020, the red color) and the TSR method from this study (the blue color). When compared to the original model, the maximum difference is about 10.6% when compared to the original approach (both peak values are similar) at the peak pumping volume. Our approach considering spatial regression can be applied effectively. In this study, this detailed field investigations that include the pipe diameter, well characteristics, and aquifer hydraulic conductivity can be ignored. Figure **4b** shows the variance in monthly

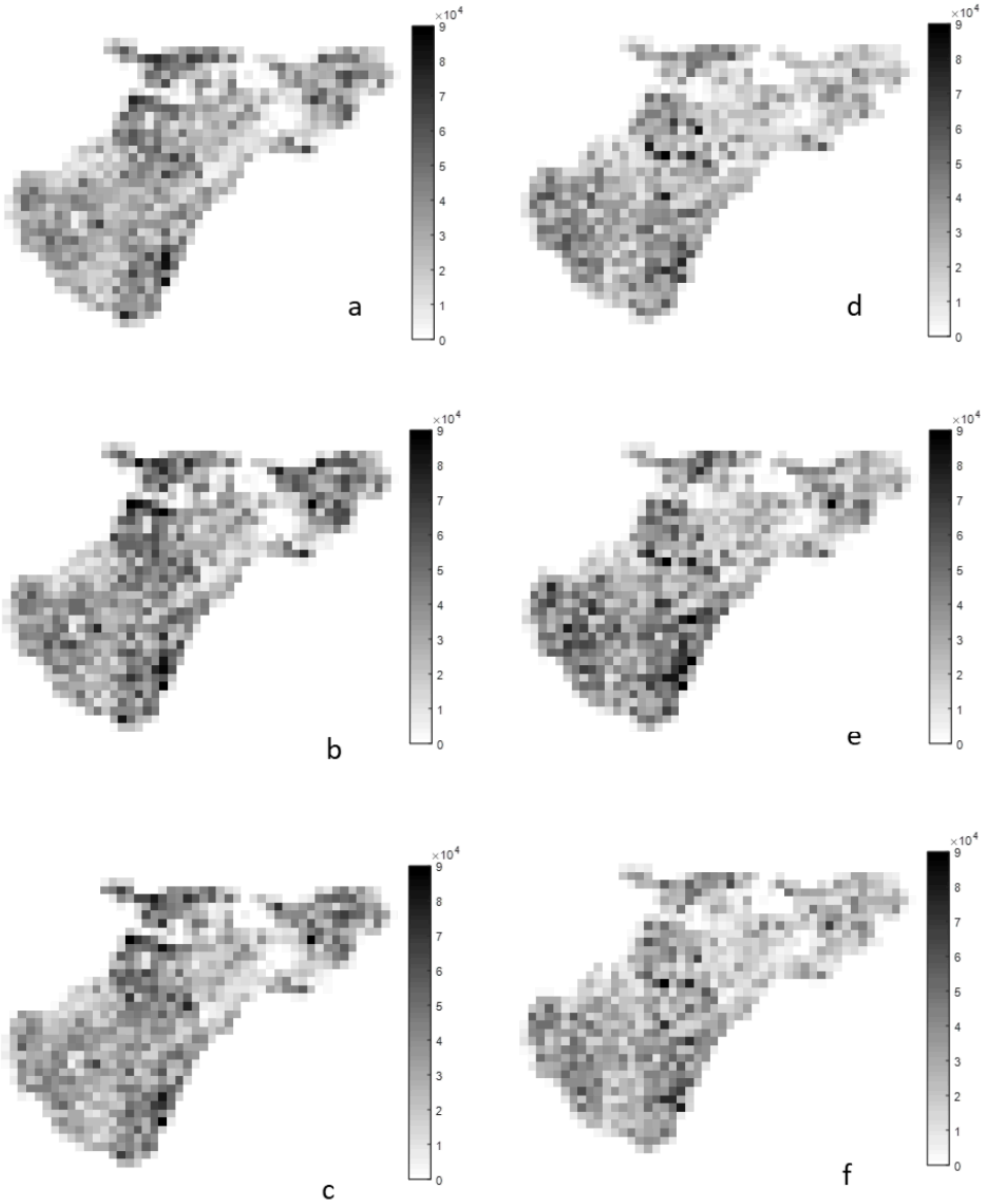

Figure 3: Spatial aggregation map of estimated pumping volume from the original (**a**, **b**, **c**) and TSR approaches (**d**, **e**, **f**) on April, 2007, 2008 and 2010.

rainfall distribution from 2007 to 2017 as recorded from the weather station in the study area. Results show that pumping continues throughout the year regardless of rainfall and subsidence continues to occur in the study area, especially in 2007, 2008, 2011, and 2015. Subsidence occurs in the study area because of excessive groundwater pumping and drought conditions persisting during the investigation period. Figure **4c** shows the subsidence series from 2007 to 2017 at Kezhuang (the blue) and TuKu (the red). The results show that subsidence is more severe at TuKu than at Kezhuang because subsidence is highly related the total pumping volumes. Figure **5** shows the estimated average monthly pumping volumes, subsidence and rainfall from 2007 to 2017. The high pumping volumes (Figure **5a**) occur in February, March and April, whereas the low ones occur in July to December. Therefore, the high subsidence rates (Figure **5b**) occur from January to May, and especially in February and March. The greatest monthly rainfall rates occur from June to September (Figure **5c**). The results show a strong correlation between the pumped volume, rainfall and subsidence. The high subsidence rates occur in the months with the lowest rainfall and highest pumping rate. The monthly groundwater withdrawal for irrigation varies from 8.2 million m^3 to 33.0 million m^3 in the study area. Farmers regularly and seasonally pump water for irrigation in the majority of the areas, and they need a large quantity of groundwater for irrigation during the spring and in the dry season.

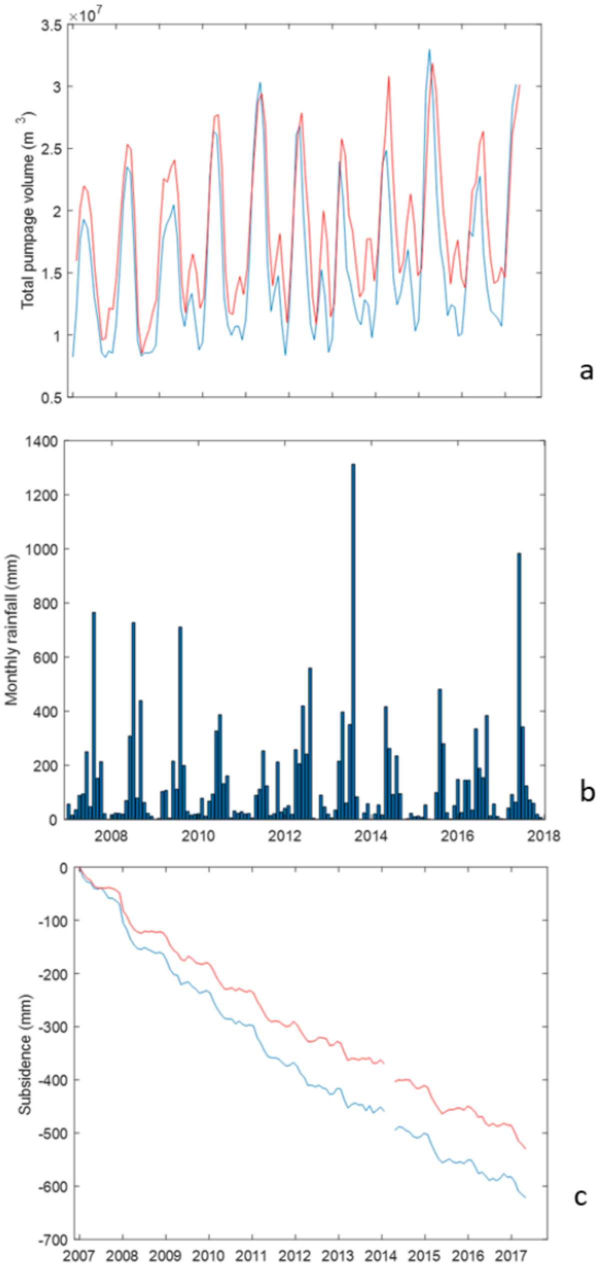

Figure 4: a. Total pumping volume (red: original; blue: TSR model in this study), **b**. Rainfall time series, and c. GPS subsidence data in two stations (blue: Tuku; red: Kezhuang) from Jan, 2007 to April, 2017 (no data at Feb and Mar, 2014).

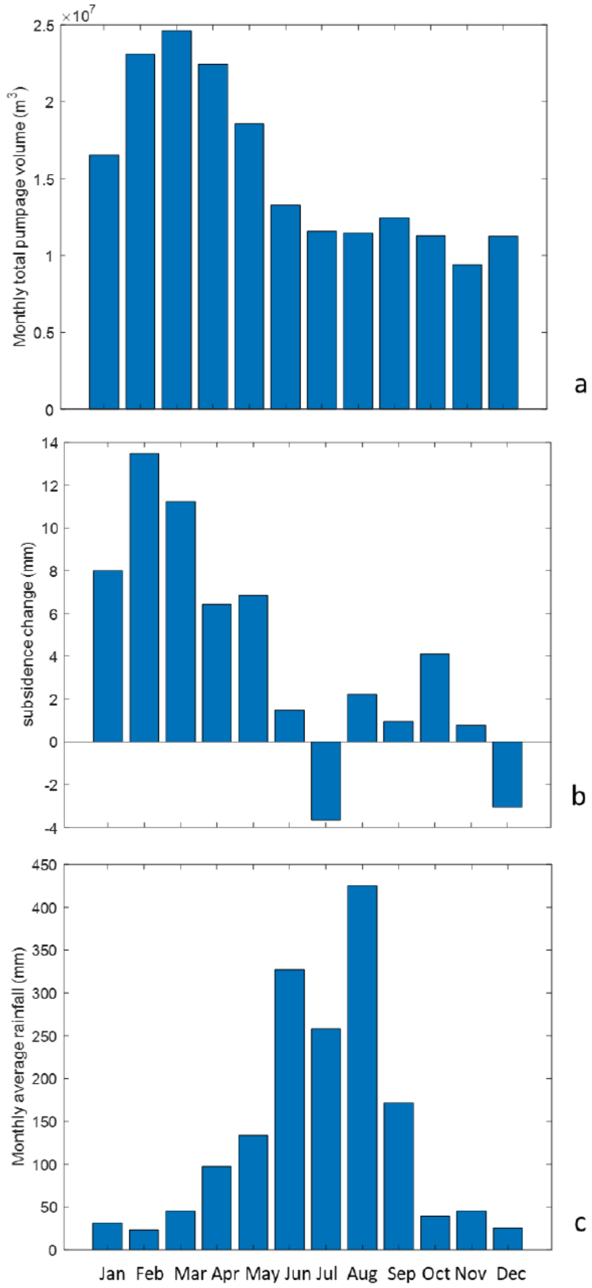

Figure 5: Monthly averages during the period from Jan, 2007 to April, 2017 for **a**. pumping volumes, **b**. subsidence, and **c**. rainfall at Tuku.

DISCUSSION

The TSR models developed for this investigation allow for the spatial patterns of pumping volumes to be estimated solely on the basis of electricity consumption and electric pump power requirements. The approach is one of spatial approximation of overall groundwater volumes without extensive model calibration. The model is an effective calibration process for the spatial mapping (Chu *et al*., 2020; Chu *et al*., 2021). Generally, the pumping volume is a critical parameter to evaluate groundwater systems, but is also often elusive because pumping rates are often not regulated or monitored. In this study, the two major variables such as electricity consumption and electric power, were included. Spatial uncertainty, such as well characteristics *e.g*. well depth, well diameter, and aquifer hydraulic conductivity can be conducted by the TSR. Many factors can affect the estimation of pumping volumes, which is shown not to be intuitive. That is, pumping volumes are not strongly tied to climate parameters such as precipitation. For example, Sahoo *et al*. (2017) suggest that precipitation has a stronger influence on seasonal groundwater levels than does irrigation demand. Following an empirical formulation, parameter coefficients of pumping volume estimation are generally quantified on the basis of well design, pump power, and hydraulic head (Chu *et al*., 2020). Specially, hydraulic conductivity of the aquifer being pumping is another major factor. The physical approximation model is used to estimate the volume of available groundwater under steady-state conditions (Bailey *et al*., 2017). Model inputs also include annual rainfall quantity, aquifer extent aquifer hydraulic conductivity, and aquifer depth. The observational data used to characterize the hydrogeology is limited, which includes the hydraulic diffusivity and thickness of the confining layers, the distance from the pumping wells, and length of the recovery cycle. The aim of this investigation was to simplify the regression model for pumping volume estimation without involving the use of hydrogeological parameters. Thus, the major contribution in this study is to consider only two major parameters (electric consumption and pump power). The parameters such as pipe diameter, well characteristics *e.g*. well depth, well diameter, and static head, and aquifer hydraulic conductivity were used for building an empirical formula (Chu *et al*., 2020) but are not needed in the simplified approach developed here. The simplified model can consider the spatial heterogeneity to reduce the uncertainty for the above spatial parameters. The TSR model provides a rapid analysis and understanding of spatial distribution of pumping volumes.

The TSR model explains the local variability of the pumping volumes better than the linear regression model. This improved outcome is achieved by only using electricity consumption and electric pump power requirements. The estimated pumping volume in this study is less than the volume estimated in the original model from Chu *et al*., 2020. However, the trends of total pumping volume are same as the original model. The spatial pattern of pumping is similar in most of the study area. Spatial patterns of pumping volume can be estimated at other study sites if the electricity consumption and electric power requirements of the water pumps are provided. In the future, machine learning or AI methods will be applied for the identification and classification of pumping patterns, for the prediction of time-series and formulation of decision-making rules (Sahoo *et al*., 2017; Guzy & Malinowska, *et al*., 2020).

Land subsidence continues to be a serious and continuous problem in the study area. Pumping based on variations in seasonal demand increases the potential for subsidence during dry seasons (Galloway & Burbey, 2011). To prevent this problem, the most effective way to reduce the impacts of land subsidence in the current study area is to decrease groundwater pumping from January to May.

Limitations include spatial data uncertainty (*e.g*., data missing and geographic masking). Future study will consider the uncertainty analysis of model. A temporal weighted approach will consider estimation of temporal and nonstationary pumping volumes. The real-time calibration will be implemented in the future. Based on the time-varying in-situ input data, the model will be more accurate. Moreover, power efficiency is assumed is assumed to be constant in this study, but it can be a spatial variable. Complexity of real world ensures that the scope of possible distance metrics is far larger than the traditional Euclidean distance. Groundwater network distance or flow-path distance can be considered in the future.

CONCLUSIONS

In this investigation, time-varying spatial regression (TSR) is used to estimate total monthly pumping volume for a portion of the Choshui River alluvial fan in west-central Taiwan on the basis of electricity consumption over a decade. This represents a significant achievement in an area where tens of thousands of unregulated and unmonitored wells are used largely for irrigation and contribute to a significant amount of land subsidence in the area. We have shown that developing a simplified TSR model using pumping volumes based only on electricity consumption and water pump power requirements is a useful and direct way for summarizing the patterns of pumping rates in a region. The study helps describe the spatiotemporal patterns of groundwater pumping volumes that are obtained from electricity consumption and pump power of each well. Our modeling framework can serve as an alternative approach to estimate pumping volumes, especially in regions without any subsurface properties such as aquifer parameters.

Using this model, the point-based and areal pumping volumes can be identified. Considering the sparse availability of investigations, the use of the model represents a powerful solution for future monitoring of estimated groundwater volumes in the areas. Moreover, the temporal analysis of regional pumping, rainfall and subsidence can provide a summary for the temporal subsidence patterns (*i.e*. monthly variations and trends). Seasonal variations in pumping, and rainfall result in water-level changes that subsequently lead to land subsidence. As land subsidence from over-pumping continues to be a problem in the region, the ability to evaluate and identify the relations among rainfall, pumping and subsidence is key to developing a sustainable water-management plan for mitigating land subsidence. This study suggests that the most effective way to ease the impacts of land subsidence is to reduce seasonal pumping in the study area during the dry and agricultural season *e.g*. from January to May.

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