Water Resour Manage (2012) 26:4449–4466
DOI 10.1007/s11269-012-0156-4

Spatiotemporal Surface-Groundwater Interaction Simulation in South Florida

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Received: 20 February 2011 / Accepted: 18 September 2012 /
Published online: 9 October 2012

Abstract South Florida ecosystem is dictated by a large wetland, karst hydrogeology and extended coastal boundary with the Atlantic Ocean. The risks related to the ecosystem include: disruption of groundwater flow as a result of frequent sinkhole formation; flooding in urban areas as a result of the shallow water table; saltwater intrusion from the ocean; and excessive nutrient load to surficial water bodies and subsequently eutrophication because of the intensive utilization of wetlands for nutrient removal. Attempts to understand eco-hydrological processes primarily focus on extensive monitoring and use of distributed hydrological models. However, the relatively flat nature of the region and also the extended coastal boundary with the ocean, makes watershed-based approaches less realistic. A regional spatiotemporal groundwater level modeling approach was attempted using a Dynamic Factor Analysis (DFA) method. The daily water levels of 13 monitoring well sites from major hydrogeologic regions and different land uses were used to conduct the DFA analysis, and six dynamic factors were identified using minimum Akaike Information Criterion (AIC). Further exploratory analysis to relate the dynamic factors with physically attributable explanatory variables has helped to identify five of the major factors that govern the groundwater dynamics in south Florida. Three of the factors were attributable to the Lake Kissimmee water level in the north, Caloosahatchee River water level in the west, and Hillsboro canal in the east. The other two factors identified were the regional averaged rainfall and soil moisture. The spatiotemporal simulation involved interpolation of the loadings of the dynamic factors using an inverse distance weighted method and convoluting with the dynamic factors. The result has shown a good fit with the maximum RMSE of 0.12 m. Retrieval of rainfall, soil moisture, and surface water level from satellite imagery makes spatiotemporal modeling of the groundwater level achievable.

Keywords Groundwater · South Florida · Akaike Information Criterion · Spatiotemporal modeling · Dynamic factor analysis

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1 Introduction

Surface-groundwater interaction in southern Florida is dictated by a wetland ecosystem, karst surficial aquifer, and the coastal boundary with the Atlantic Ocean (Gunderson 2001). The wetland ecosystem interacts with the stream flow retaining flood during the wet season and discharging subsurface water to the streams during the dry season. The karst hydrogeology dictates direction of groundwater flow as well as the efficiency of nutrient removal vis a vis the dissolution of limestone and hence formation of sinkholes (Genereux and Slater 1999). The coastal boundary with the Atlantic Ocean poses saltwater intrusion, especially when groundwater head drops.

Apparently any subsurface water management in the SF should take into account: the risks associated with ecological failure because of the connectivity of groundwater to the wetlands at times of drought; the risk of contamination by saltwater in the coastal areas where there is very thin vadose zone and over pumping of groundwater; flooding of urban areas from groundwater surge because of the flat terrain and shallow water table; and the risks associated with the use of STAs in the karst areas where nutrient attenuation could not be achieved.

Recognizing such risks, South Florida Water Management District (SFWMD) uses over 1854 networked stations as a tool to monitor the eco-hydrology of the region. Harvey et al. (2004) reported the logistical challenge to monitor connectivity of groundwater fed micro-ecosystems attributed to the large expanse of the wetland. The karst hydrogeology setting of the district increases the complexity of monitoring because of the dynamic property of the hydraulic conductivity potentially causing flow directional changes (anisotropy), (Genereux and Slater 1999). Evidently, real-time analysis and synthesis of the groundwater hydrology specifically spatiotemporal modeling of surface-groundwater interaction at regional scale is vital for decision making. Such analysis would not be met using watershed based distributed hydrological models because of the absence of clearly delineated watershed boundary (indiscernible from the flat topography) with no flow dividing lines, except for the Kissimmee River basin that constitutes less than 25 % of the land mass. In addition, the watershed based models are computationally expensive for operational prediction in karst hydrogeology region, as in SF, because of the dynamic nature of the hydrogeological factors which raise parameterization uncertainty whenever changes occur. Operational modeling and prediction in Karst areas require low input models such as transfer functions that demand minimum parameterization (Denic' and Jukic' 2003; Jukic' and Denic' 2004).

In this study, a regional scale spatiotemporal model capable of simulating the daily groundwater level was developed making use of existing data. The regional scale spatiotemporal model is intended to be linked with point scale groundwater operational prediction for regional groundwater level forecasting. The model will be ultimately used to identify hot spots of groundwater drop/rise and also as a predictor for soluble phosphorus load. The point scale prediction was already developed for major hydrogeological regions from which the model presupposes to use (Chebud and Melesse 2011). Therefore, the specific objectives of the study were to:

- analyze the factors that influence regional groundwater level dynamics in South Florida,
- develop a regional scale spatiotemporal groundwater modeling approach
- develop regional scale operational prediction of groundwater dynamics.

2 Factor Analysis

Water table fluctuation in karst regions is affected by precipitation (Park and Parker 2008; Knotters and Bierkens 2001), air pressure changes and Moon's tide (Ma'rkus et al. 1999), the soil moisture (Hoogland et al. 2010), surface water level (Ritter and Mun'oz-Carpena 2006; Genereux and Slater 1999). The effects of some of the variables are measureable and categorized as explanatory while the background effects of other hidden variables are assumed as latent (Ma'rkus et al. 1999). The latent factors could also represent unidentified explanatory factors (Zurr et al. 2003), or lack of proper parameterization. The concept helps to reduce a complex interplay of factors to a minimum number through factor reduction method (Aggarwal 1998).

For explanatory variables reduction, Ramsey and Shaffer (2002) suggested sequential forward/backward stepwise regression methods imposing Akaike's Information Criteria (AIC) or the Baye's Information Criterion (BIC). The AIC and BIC inform the log-likelihood of a model penalizing it for every addition of a parameter as indicated on Eqs. (1) and (2) (Claeskens and Hjort 2008). The difference in the two criteria is that in the case of BIC, penalization increases with the increased number of data and hence it is stricter than AIC. The penalization is used to avoid complication from increased number of parameters.

$$AIC = 2\ln(\theta) - 2length(\theta) \tag{1}$$

$$BIC = 2\ln(\theta) - \log(n)\ length(\theta) \tag{2}$$

where θ is the parameter and n is the number of data, length is the number of components in vector θ.

Another factor reduction method is a multivariate principal component analysis (PCA) that trade off with 'factor analysis' method (Davis 2002). The PCA identifies the eigen structure of factors using Singular Value Decomposition approach (SVD) and retain the factors that give the maximum efficiency (highest content of the explainable variance) and discards less informative ones. The method could theoretically identify latent factors with prior knowledge of explanatory variables and factor loadings. However, variables such as groundwater fluctuation would be affected by the lag factors failing to meet independence assumption of factor analysis using PCA (Ma'rkus et al. 1999).

Lopes et al. (2008), Zurr and Pierce (2004) and Zurr et al. (2003) reported effectiveness of a dynamic factor analysis method to identify the latent factors and explanatory variables from a time series of the response variables. The method is reported to have flexibility and capture any patterns such as periodic, non-periodic and multiple jumps of time series response variables (Zurr et al. 2003). The method masks the seasonal elements in the model and hence the representation ultimately captures all season simulation (http://www.brodgar.com/index.htm). The DFA was used as a tool for spatiotemporal dynamic forecasting of groundwater fluctuation (Hoogland et al. 2010). Ritter and Mun'oz-Carpena (2006) reported employment of dynamic factor analysis for prediction of surface groundwater interaction in the Agricultural areas, north of Everglades National Park.

The dynamic factor analysis formulates the response variable as a combination of the effects of latent variables and explanatory variables as indicated on Eqs. (3) and (4) after Ritter and Mun'oz-Carpena (2006).

$$Y_j(t) = \sum_{i=1}^{I} \lambda_{i,j}\rho_i(t) + \mu_j + \sum_{k=1}^{K} \omega_{k,j}\psi_k(t) + \varepsilon_j(t) \tag{3}$$

$$\rho_i(t) = \rho_i(t-1) + \varphi_i(t) \tag{4}$$

where Y(t) is the j^{th} response variable at site j and time t; ρ_i (t) is the i^{th} unknown trend at time t; $\lambda_{i,j}$ represents the unknown factor loadings; μ_j is the trend parameter, $\omega_{k,j}$ is a regression parameter; ψ_k is the k^{th} explanatory variable; ε_j and φ_i are the observation error and systemic error terms that are independent, normally distributed, and each of them with zero mean but unknown covariance matrix.

In order to use DFA on surface-groundwater interaction, prior knowledge of the explanatory variables would simplify the model uncertainty. The most common explanatory variables for the groundwater fluctuation includes rainfall (Park and Parker 2008), surface-water level (Genereux and Slater 1999) and pedosphere soil moisture (Hoogland et al. 2010; Visser et al. 2005). The unidentified hydrologic and climatic variables as well as the dynamic karst aquifer properties could be captured by the latent factors.

3 Dynamic Factor Analysis and Spatial Structure

A peculiar application of dynamic factor analysis is to understand the common trends of a large area that influence the response variable and their loadings. An important aspect of common regional factors versus their loadings is the possibility of incorporating the spatial structure into the later for a spatiotemporal dynamic modeling. Gamerman (2010), and Lopes et al. (2008) suggested implicit framing of the spatial structure into the loading 'λ_t' as indicated in Eq. (5), while the common dynamic factors 'ρ_t' in Eq. (5) capture the temporal changes.

$$\begin{gathered} \lambda_j \sim N\left(\beta_j, \sigma_j{}^2 \Omega_j\right) \\ \lambda_t(x) = \lambda_{t-1}(x) + w_t(x) \end{gathered} \tag{5}$$

where $\lambda_{j,}$ the loading from Eq. (4), is independent and distance-based Gaussian Random field; β_j is an N-dimensional mean vector; Ω_j is given by a correlation function f(Is_l-s_kI) which could be exponential, spherical etc.; t is time; and x is a coordinate point.

Other methods that exploit the spatial relationship of the loading factors for spatiotemporal dynamic formulation include geostatistical approach (Hoogland et al. 2010; Visser et al. 2005; Knotters and Bierkens 2001), Bayesian methods (Diggle and Edith 2010; Lopes et al. 2008), Neural and Networks (Nayak et al. 2006). Amongst the methods, using Bayesian method is comparatively less advantageous for the intensity of computation whereas the geostatistical approach is the most commonly used (Hoogland et al. 2010).

4 Study Area

The study was conducted over the geographical boundary of SFWMD that distinctively constitutes the largest wetland, and extended coastal boundary with the Atlantic Ocean. The direction of ground water flow (though dynamic with the management) was found generally from North to South, South East, and South west (Fig. 1a) similar to the surface water flow. The contour lines are mean groundwater level ranging from 0 to 42 m.a.s.l. from South to Northern. The surficial aquifers of the SFWMD could be broadly categorized as the Biscayne aquifer and the undifferentiated aquifer system (Randazzo and Jones 1997). The same report indicates the Biscayne aquifer covers the south eastern part of the district (Fig. 1b) namely the Miami Dade, Broward, southern Palm Beach and eastern Marone counties. The lithographic layering

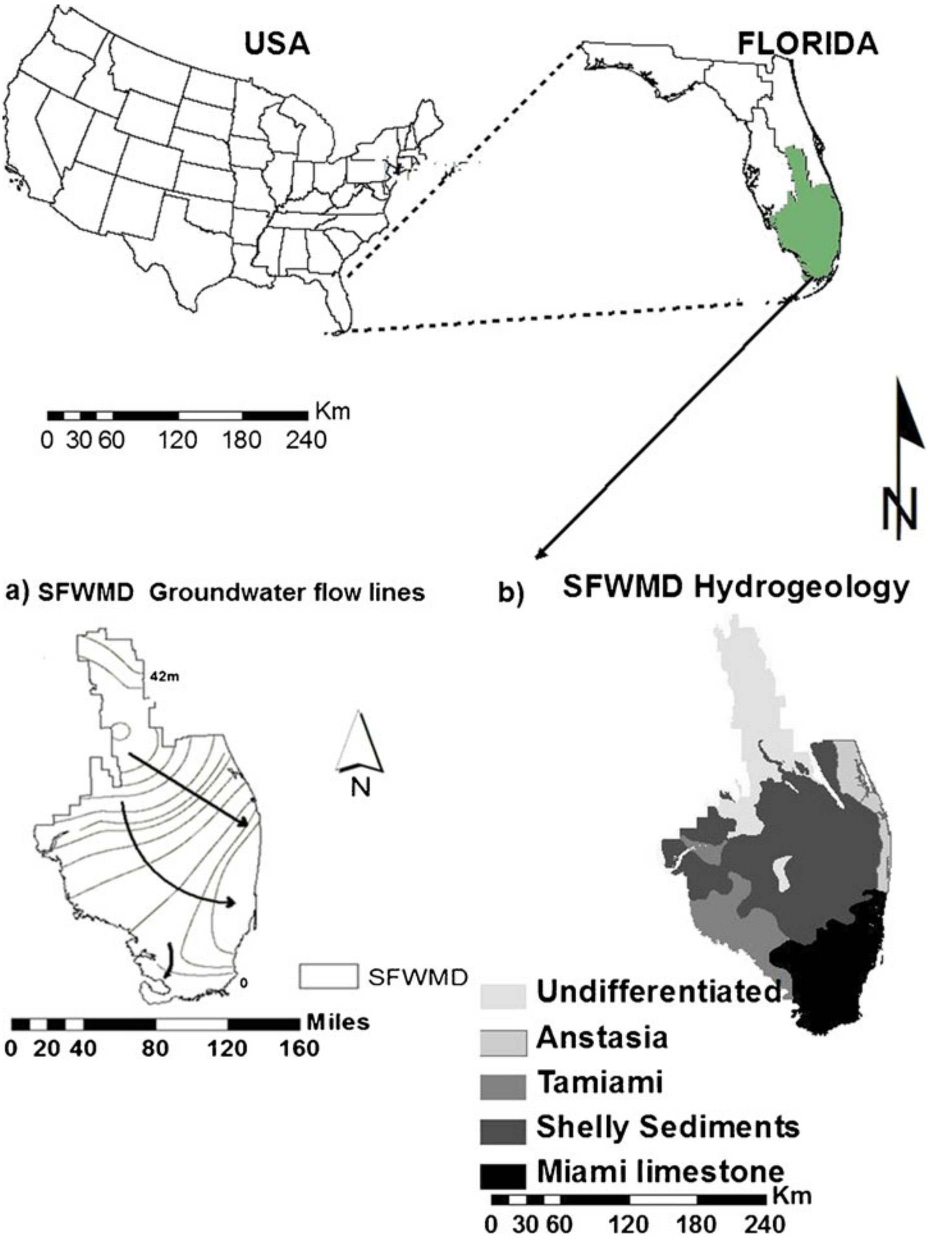


Fig. 1 **a**) Direction of groundwater flow in SFWMD for the month of July, **b**) Hydrogeological units of SFWMD

constitutes up to 6 m thick organic soils, 14 m Pamlico sand layer, 14 m thick Miami limestone, 150 m thick Forthompson formation, 40 m thick layer Ansatsia formation and 20 m thick Key Largo formation in consecutive order from top to bottom. Other part of the district is dominated by the undifferentiated formation whose Lithographic layering is similar to the Biscayne aquifer except that the top layer is alluvium unlike the organic soils of Biscayne and also absence of the Key Largo formation. The geographical exposition of the lithographic units in SFWMD is dominated by Miami limestone, Tamiami formation, Undifferentiated and the Anstasia formations as shown in (Fig. 1b). The Miami limestone extends in the Eastern and south eastern part while the Tamimai formation covers the western and south western. The northern part is a clastic sandy unidentified formation. The Anstasia formation, the smallest in proportion, covers the north eastern part of the district.

The land use of the district is categorically proportioned as 60 % wetland, 20 % pastureland, 10 % cropland, 6 % forest land, 1 % urban, and the rest 3 % are other environmental service areas (Chebud et al. 2011).

5 Methodology

A stratified sampling was proposed at the outset to select groundwater wells from the three major hydrogeological units splitting by soil type and four major land uses. The selection was made from sites which were at least 5 miles from canals to avoid daily influences of the canal operation. About 13 wells (Table 1 and Fig. 2) were selected from the intersection of a given hydrogeological unit, soil type, and land use using the Geographic Information Systems tool- ArcGIS analyst.

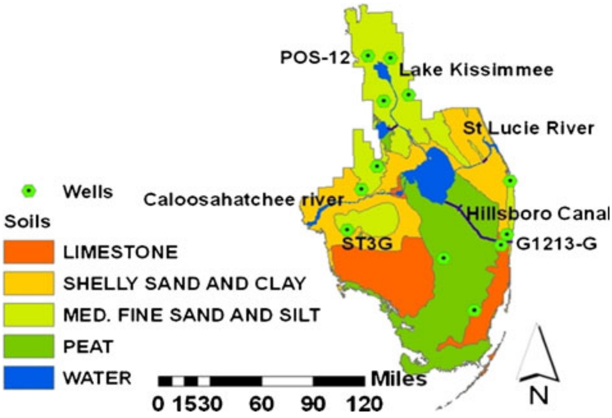
The DFA was conducted for the normalized daily groundwater level from the 13 wells using Eq. (3). A coupled statistical package of R was used accordingly as suggested by Zurr et al. (2003). Upon the DFA analysis, a search for the relationship of the identified factors against explanatory factors was made to give the identified factors a physical meaning and help for the development of a unified spatiotemporal model.

As a preliminary analysis of the explanatory factor search, the relationship of groundwater fluctuation with rainfall, canal water level, and soil moisture were observed for three stations (ST3G, POS-12, G1213-G, Fig. 1a), situated in three different hydrogeologic units. Daily rainfall as well as daily canal water level readings were obtained from the nearest station of each well site (Fig. 1b). The data sets of groundwater level, rainfall and canal water level were taken from the SFWMD DBHYDRO data base. The daily soil moisture data for multiple depths below surface (10 cm, 40 cm and 100 cm) were obtained from the NOAA-Global Land Data Assimilation System (GLDAS) website. The soil moisture is available at 0.125^{o} for the USA from the National Land Data Assimilation System (NLDAS).

Table 1 Sampling distribution of wells

	Miami limestone			Tamiami formation			Undifferentiated		
	Peat	Sandy	Bare	peat	Sandy	bare	peat	Sandy	bare
Urban		1	1		1	1	1	1	
Forest				1		1			
Crops				1				1	
Scrub/Range		1						1	1

Fig. 2 Rivers, canals, lakes and well sites



Backward and forward stepwise regression method was applied for each groundwater monitoring station to identify potential exploratory variables using the AIC Criterion. Upon parameterizing rainfall and soil moisture by their respective regional average and normalizing the nearest canal/river water levels, a curve fitting method was used to analyze patterns of the explanatory variables and dynamic factor trends. Finally, invoking a spatial structure into the loading through interpolation using Inverse Distance Weighted (IDW) method, a regional groundwater level was developed at daily scale.

6 Analysis

Using Eq. (3), which offers several model types depending on the experimental design, a framework was chosen assuming all factors are latent. So the component of explanatory variable in Eq. (3) was substituted by latent factor and formulated the model as:

Response variable (groundwater level) = m common trends + noise (6)

Applying the assumption, $m>1$, the model served for factor analysis on smaller data sets (~20 events) as suggested in (http://www.brodgar.com/index.htm). The DFA analysis was employed on each month separately in 2004 for which complete data was available for the majority of the wells. The minimum AIC as well as the RMSE of the model was employed as a criterion to determine the number of common factors 'm' for the regional groundwater fluctuation.

The DFA analysis was done using normalized groundwater level data series from the 13 wells selected. The normalization is required expecting different units of the dynamic

Table 2 AIC values of the DFA

m	Jan.	Feb.	March	April	May	June	July	Aug.	Sep.	Oct.	Nov.	Dec.
1	187	612	827	634	851	692	650	886	882	590	331	928
2	178	711	685	506	546	567	563	730	698	439	221	794
3	171	584	574	366	454	487	509	657	619	327	167	730
4	230	542	470	322	359	450	471	615	544	229	37	651
5	243	520	464	373	359	407	452	634	516	205	26	599
6	142	492	437	311	347	361	402	538	507	189	5	563
7	195	493	447	366	370	497	400	681	520	271	61	578

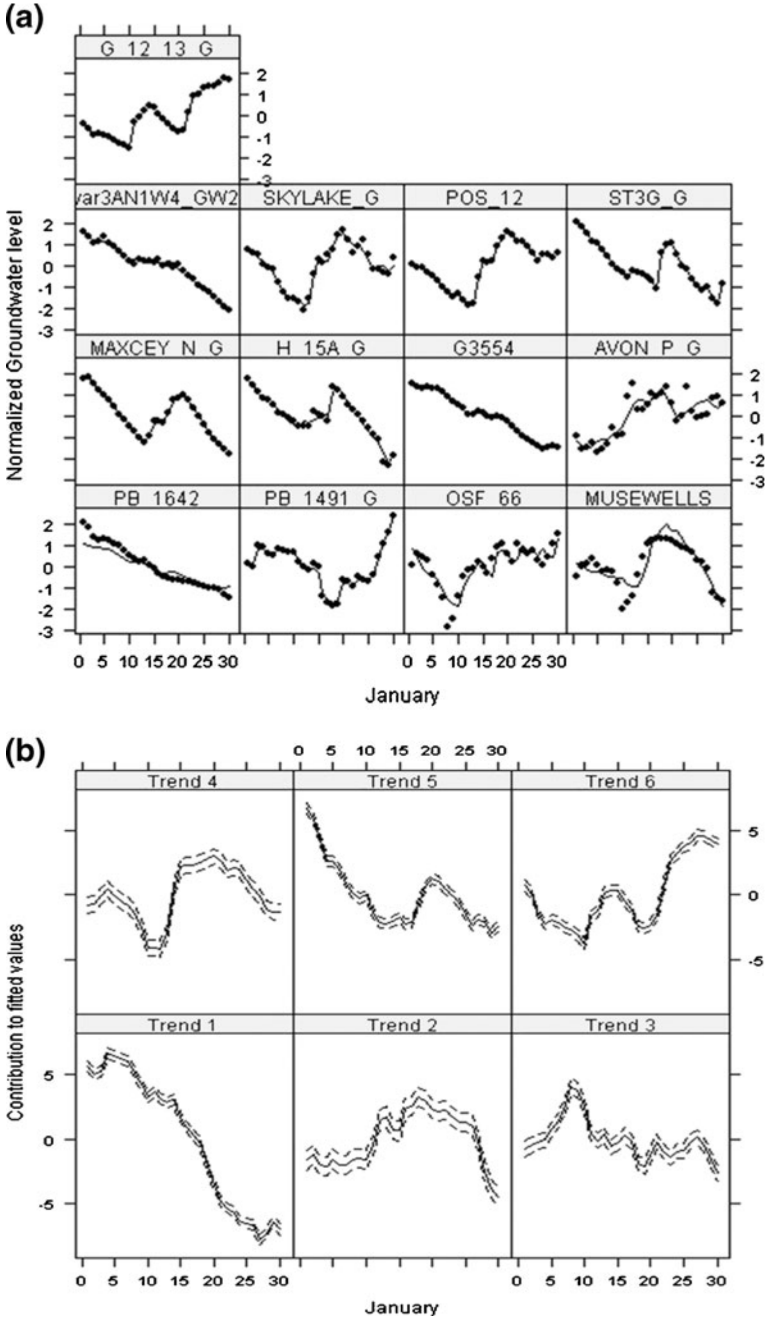


Fig. 3 **a** Simulated and observed groundwater level, January 2004. **b** Dynamic trends (factors), January 2004

factors, for instance rainfall (mm), soil moisture (kg/m^2) and water level (m). Also the normalization removed the local trend μ_j from Eq. (3), and reduce the complication which could rather be added on the output. The analysis was conducted using the averaged daily

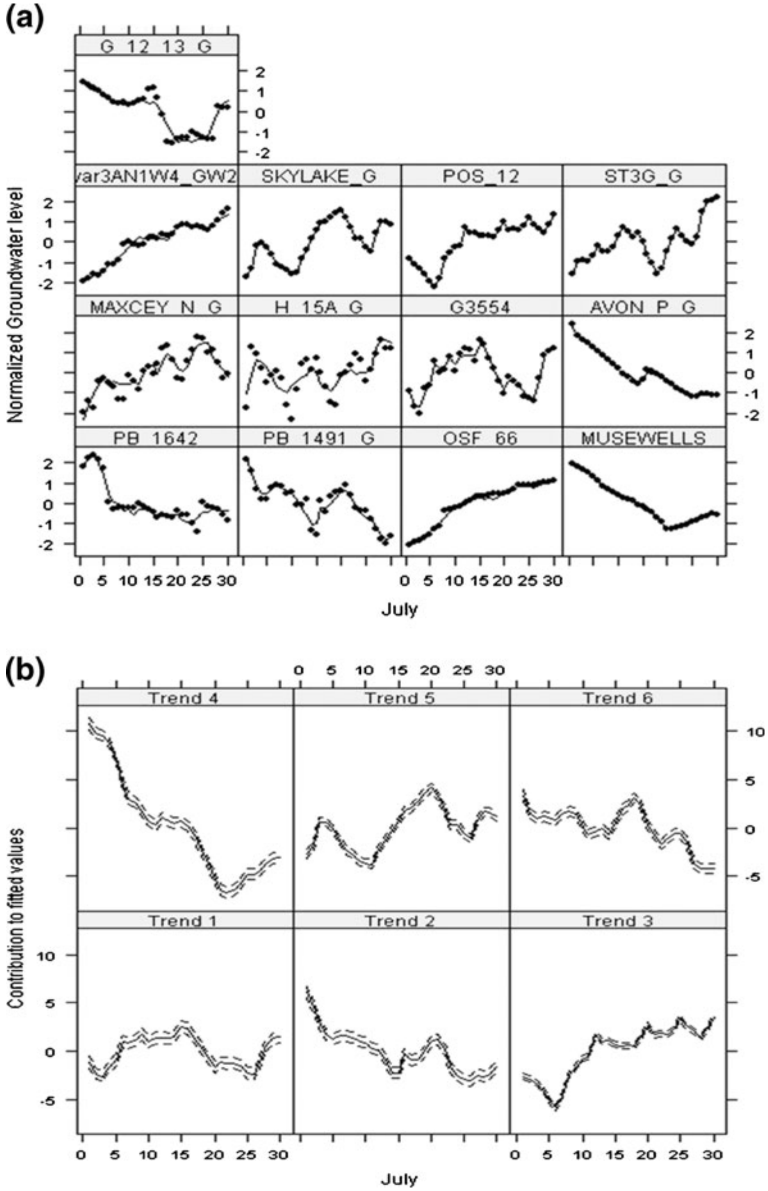


Fig. 4 **a** Simulated and observed groundwater level, July 2004. **b** Dynamic trends (factors), July 2004

data from 2004 to 2009 in iterative fashion increasing the number of common factors mentioned in Eq. (3) starting from 1. The analysis of the DFA for each month showed that minimum AIC was achieved when dynamic common factors are six (Table 2).

The analysis was further conducted for 2004, a year with complete dataset. The common dynamic factors were fixed this time to 6 and analysis was made each month using normalized daily data. The DFA analysis extracts a fit of the observed and simulated groundwater levels (Figs. 3a and 4a) and the six dynamic trends (Figs. 3b and 4b). In this

Table 3 RMSE values at each well site for January and July 2004

Stations	RMSE		Ground water level (m.a.s.l)		
	January	July	Minimum	Maximum	Mean
PB_1642	0.02	0.04	1.69	2.62	2.27
PB_1491_G	0.06	0.04	0.02	2.54	1.17
OSF_66	0.06	0.02	14.17	16.89	15.81
MUSEWELLS	0.04	0.01	11.13	13.52	12.70
MAXCEY_N_G	0.02	0.08	20.13	33.01	27.22
H_15A_G	0.03	0.12	18.20	19.60	18.99
G3554	0	0.04	1.18	1.96	1.59
AVON_P_G	0.07	0.01	42.22	43.38	42.75
var3AN1W4_GW2	0.01	0.03	3.07	4.19	3.67
SKYLAKE_G	0.03	0	13.28	18.35	15.42
POS_12	0.01	0	19.03	21.06	20.14
ST3G_G	0.04	0	8.09	9.62	8.98
G_12_13_G	0	0.05	−1.28	0.99	0.00

paper, only outputs for the month of January and July are presented with the intention to represent dry and wet seasons. The maximum RMSE was only 0.12 m for the month of July showing a good fit of the observed and simulated (Table 3).

Associated with the six identified factors are their loadings that have similar meaning to a weight factor. The retrievability of the loadings at each observation point in space (Tables 4 and 5) offers an opportunity to introduce the spatial structure through interpolation in the regional spatiotemporal simulation process. The loadings on Tables 4 and 5, related to the January and July dynamic trends indicated in Figs. 3b and 4b, are derived on condition of minimum AIC.

Table 4 Loadings (weights) of each trend for the month of January

Stations	Trend 1	Trend 2	Trend 3	Trend 4	Trend 5	Trend 6
PB_1642	0.144	0.035	0.104	−0.047	0.187	0.09
PB_1491_G	−0.01	−0.404	−0.002	−0.07	−0.036	0.001
OSF_66	−0.009	−0.017	−0.539	0.032	0.017	0.03
MUSEWELLS	0.056	0.163	0.046	0.392	0.013	0.038
MAXCEY_N_G	−0.001	0.056	0.063	0.14	0.345	−0.052
H_15A_G	0.063	0.17	−0.052	0.095	0.241	−0.071
G3554	0.147	−0.015	0.016	0.04	0.105	−0.038
AVON_P_G	−0.025	0.128	−0.299	−0.077	−0.238	−0.069
var3AN1W4_GW2	0.154	0.109	0.051	0.035	0.143	0.012
SKYLAKE_G	−0.062	−0.053	−0.166	0.314	0.162	−0.043
POS_12	−0.138	−0.08	−0.132	0.264	0.107	−0.09
ST3G_G	0.025	0.034	−0.12	0.019	0.307	−0.107
G_12_13_G	0.013	−0.008	−0.141	0.002	−0.119	0.292

Table 5 Loadings (weights) of each trend for the month of July

Stations	Trend 1	Trend 2	Trend 3	Trend 4	Trend 5	Trend 6
PB_1642	−0.246	0.006	0.022	0.204	0.036	−0.083
PB_1491_G	−0.119	0.358	−0.046	−0.098	−0.099	0.196
OSF_66	0.098	−0.076	0.129	−0.083	0.016	−0.032
MUSEWELLS	−0.002	0.029	−0.066	0.149	−0.067	−0.056
MAXCEY_N_G	−0.165	−0.38	−0.053	−0.08	0.02	0.163
H_15A_G	−0.045	−0.1	−0.012	0.108	0.151	−0.369
G3554	0.587	0.014	0.018	0	0.043	−0.077
AVON_P_G	−0.027	0.141	−0.078	0.086	0.021	0.078
var3AN1W4_GW2	0.124	−0.004	0.112	−0.095	0.057	−0.101
SKYLAKE_G	0.088	−0.058	0.001	−0.001	0.429	−0.019
POS_12	0.033	0.013	0.403	0.009	0	0.019
ST3G_G	0.164	0.046	−0.005	−0.017	−0.036	−0.48
G_12_13_G	0.234	−0.001	0.052	0.211	−0.007	−0.136

Explaining the dynamic factors in terms of the physically known variables is the key aspect of the development of a generic spatiotemporal model. Most physically known variables of the water budget that dictate groundwater level include soil moisture, rainfall and surface water level (Ritter and Mun'oz-Carpena 2006). Assumption was made that evapotranspiration is embedded in the soil moisture storage estimation and hence it is an already reduced factor. Accordingly, exploratory factor analysis was done in a stepwise regression of monthly averaged groundwater level against monthly averaged values of rainfall, soil moisture, and canal water level. Factor selection was on the basis of the condition of AIC (Table 6).

The relationship of the dynamic factors obtained from DFA and possible explanatory variables was established fitting normalized and parameterized time series of regional average rainfall, regional average soil moisture and surface water level. Results showed that the three dynamic factors were found related to three surface water bodies namely: the Lake Kissimmee water level in the north (Fig. 5a and b); the Caloosahatchee River water level in the west (Fig. 5e and f); and the Hillsboro canal water level in the east (Fig. 5i and j) that drains from Lake Okeechobee to the east coastal area. The two other factors identified from the DFA were explainable by the regional averaged rainfall (Fig. 5m and n), and regional averaged soil moisture (Fig. 5q and r). The curve fitting of the dynamic factors against the explanatory variables show similar trends at all seasons. Only one factor was found unexplainable (Fig. 5u and v) and assumed as latent factor (Zurr et al. 2003). From the point of view of the water balance approach, water abstraction would partially explain the latent factor, though not tested for lack of data.

Table 6 AIC values of the stepwise regression

Hydrogeology	Station	Rain	$\theta_{10\ cm}$	$\theta_{40\ cm}$	$\theta_{100\ cm}$	Stage	AIC (a)
Tamiami formation,	ST3G				X	X	−101.2
Miami limestone	G2131_G	X				X	−28.94
Undifferentiated,	POS12	X	X		X	X	−84.27

Fig. 5 **a** Factor 1 Fit - July, **b** Factor 1 fit - January, **c** Factor 1 Loading - January, **d** Factor 1 loading - July, **e** Factor 2 fit - January, **f** Factor 2 fit - July, **g** Factor 2 Loading - January, **h** Factor 2 Loading - July, **i** Factor 3 fit - January, **j** Factor 3 - July, **k** Factor 3 Loading - January, **l** Factor 3 loading - July, **m** Factor 4 fit - January, **n** Factor 4 fit - July, **o** Factor 4 Loading - January, **p** Factor 4 Loading - July, **q** Factor 5 fit - January, **r** Factor 5 fit - July, **s** Factor 5 loading - January, **t** Factor 5 Loading, **u** Factor 6 fit - January, **v** Factor 6 fit - July, **w** Factor 6 loading - January, **x** Factor 6 Loading - July

The spatial association of the loadings to the explanatory factors was also found in agreement with the exploratory factor analysis. The analysis showed a localized higher weight in the north as shown in Fig. 5c and d, attributable to factor 1 (Lake Kissimmee water level); higher weight in the south, Fig. 5g and h, attributable to factor 2 (Caloosahatchee River water level); and discernible higher local weight in the east, Fig. 5k and l, attributable to factor 3 (the Hillsboro canal water level). The effect of factor 4 (rainfall average) is spatially variable and event dependent, and hence assumes the loading spatial variability accordingly as shown in Fig. 5o and p. The effect of factor 5 (soil moisture) in most part of the region is observed shifting with seasonal changes as shown in Fig. 5s and t.

The dynamicity and spatiotemporal implicit nature of the loadings was observed from the changes over the seasons confirming the applicability of Eq. (5) after Gamerman (2010). The increased loading of the soil moisture from east (Miami limestone area) to west as observed on Fig. 5s and t suggests the lagging effect of the overlying clayey soil on recharge. The higher loading of most factors in the extreme southern part supports the fact that the area is under high water table over most seasons of the year.

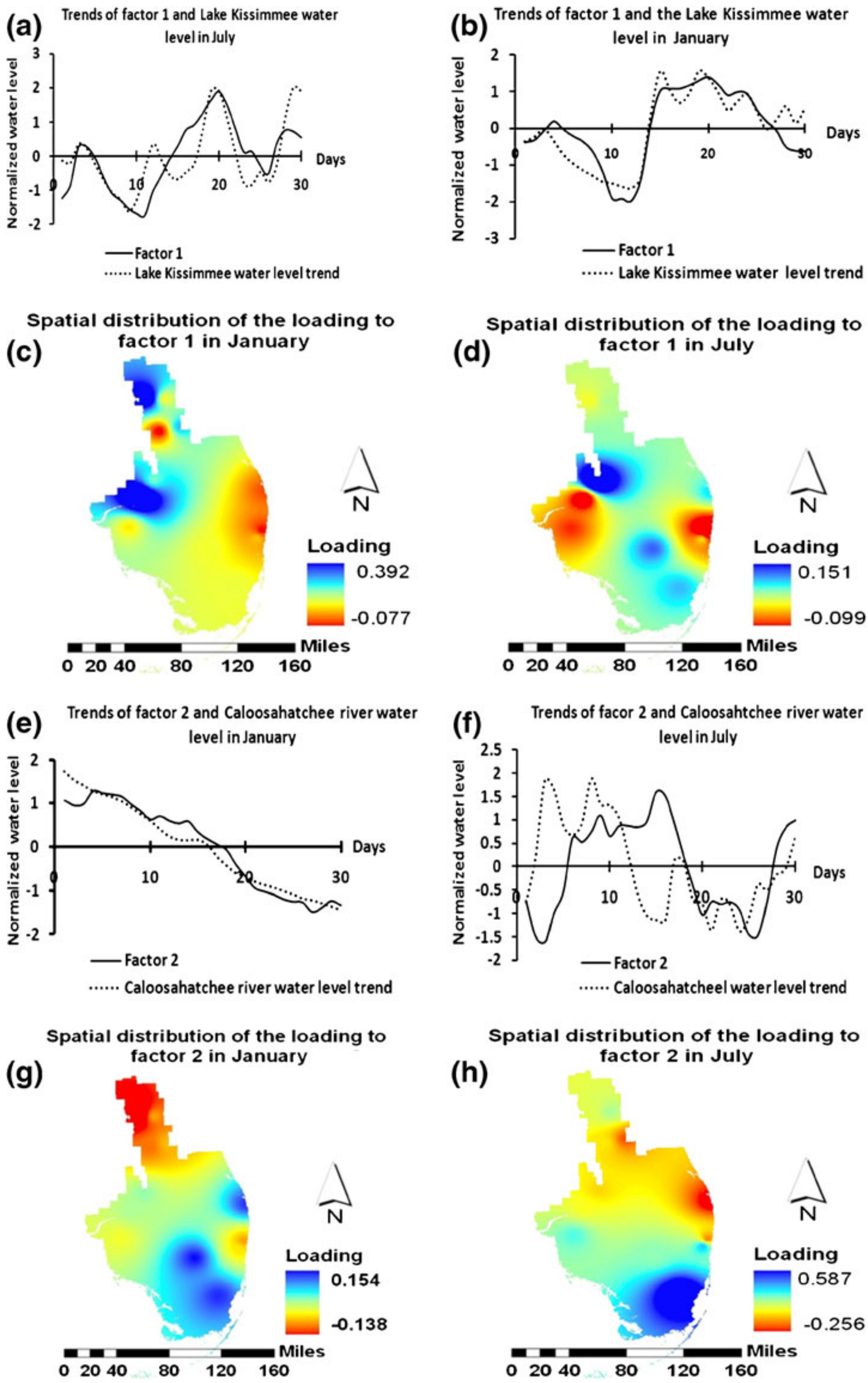
7 Simulated Groundwater Level

Convolving the dynamic factors with the spatially interpolated loadings, a regional scale spatiotemporal groundwater level was simulated. Cases were observed for four arbitrary dates of January 15, January 30, July 15 and July 30 as shown in Fig. 6a, b, c and d, respectively, all from year 2004. The results show those highest water levels in the east, west and northern part, seemingly a result of the management effect. The lowest drop of groundwater level below the monthly average, on January 30 (drier month), was −60.42 cm in the east coast as shown in Fig. 6b. The pattern could be traced for each day of the drier months and observe risks of oceanic water intrusion during the dry season. Similarly, the maximum groundwater rise on July 30 2004 (Fig. 6d) was 67 cm above the monthly average and such trends could be traced for the wettest months to oversee flooding risks. The validation conducted on three wells, not included in the simulation, show that the maximum RMSE is 17 cm.

8 Conclusion and Recommendation

The spatiotemporal model was developed extracting dynamic factors and their respective loadings from time series observations of groundwater level using a dynamic factor analysis (DFA) method. The DFA served to extract common latent factors at regional scale together with their loadings in which the latter allow incorporation of the spatial structure for a spatiotemporal modeling of groundwater levels.

The results of the analysis showed that the surface ground-water interaction in the SFWMD is governed by regional averaged rainfall, regional averaged soil moisture, Lake Kissimmee water level in the north, Caloosahatchee River in the west and Hillsboro canal water level in the East. A regional water level was simulated using a combination of the factors and interpolated


(a)
Trends of factor 1 and Lake Kissimmee water level in July
Normalized water level
Days
Factor 1
Lake Kissimmee water level trend
(b)
Trends of factor 1 and the Lake Kissimmee water level in January
Normalized water level
Days
Factor 1
Lake Kissimmee water level trend
(c)
Spatial distribution of the loading to factor 1 in January
N
Loading
0.392
-0.077
Miles
0 20 40 80 120 160
(d)
Spatial distribution of the loading to factor 1 in July
N
Loading
0.151
-0.099
Miles
0 20 40 80 120 160
(e)
Trends of factor 2 and Caloosahatchee river water level in January
Normalized water level
Days
Factor 2
Caloosahatchee river water level trend
(f)
Trends of facor 2 and Caloosahtchee river water level in July
Normalized water level
Days
Factor 2
Caloosahatcheel water level trend
(g)
Spatial distribution of the loading to factor 2 in January
N
Loading
0.154
-0.138
Miles
0 20 40 80 120 160
(h)
Spatial distribution of the loading to factor 2 in July
N
Loading
0.587
-0.256
Miles
0 20 40 80 120 160

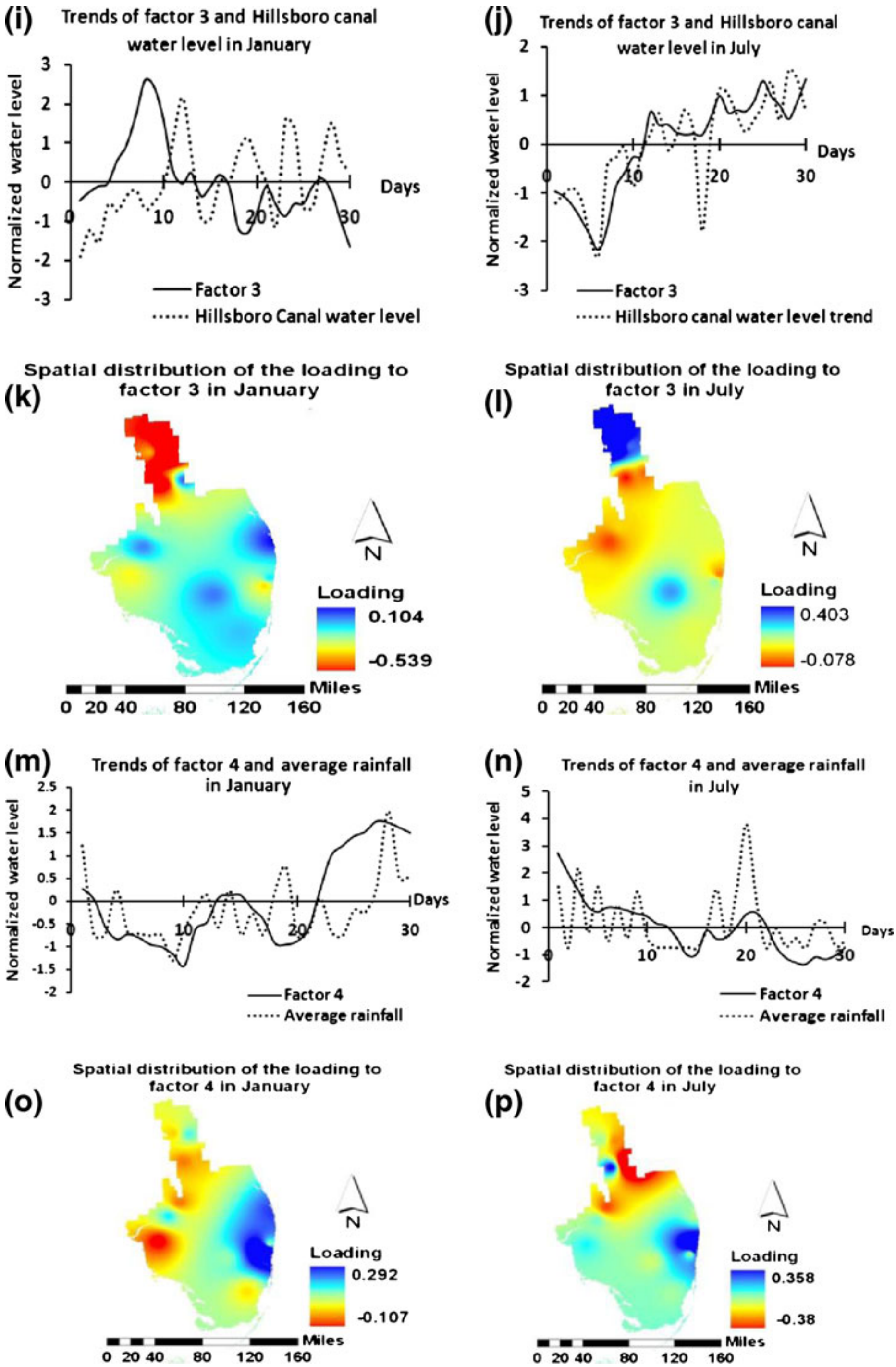


Fig. 5 (continued)

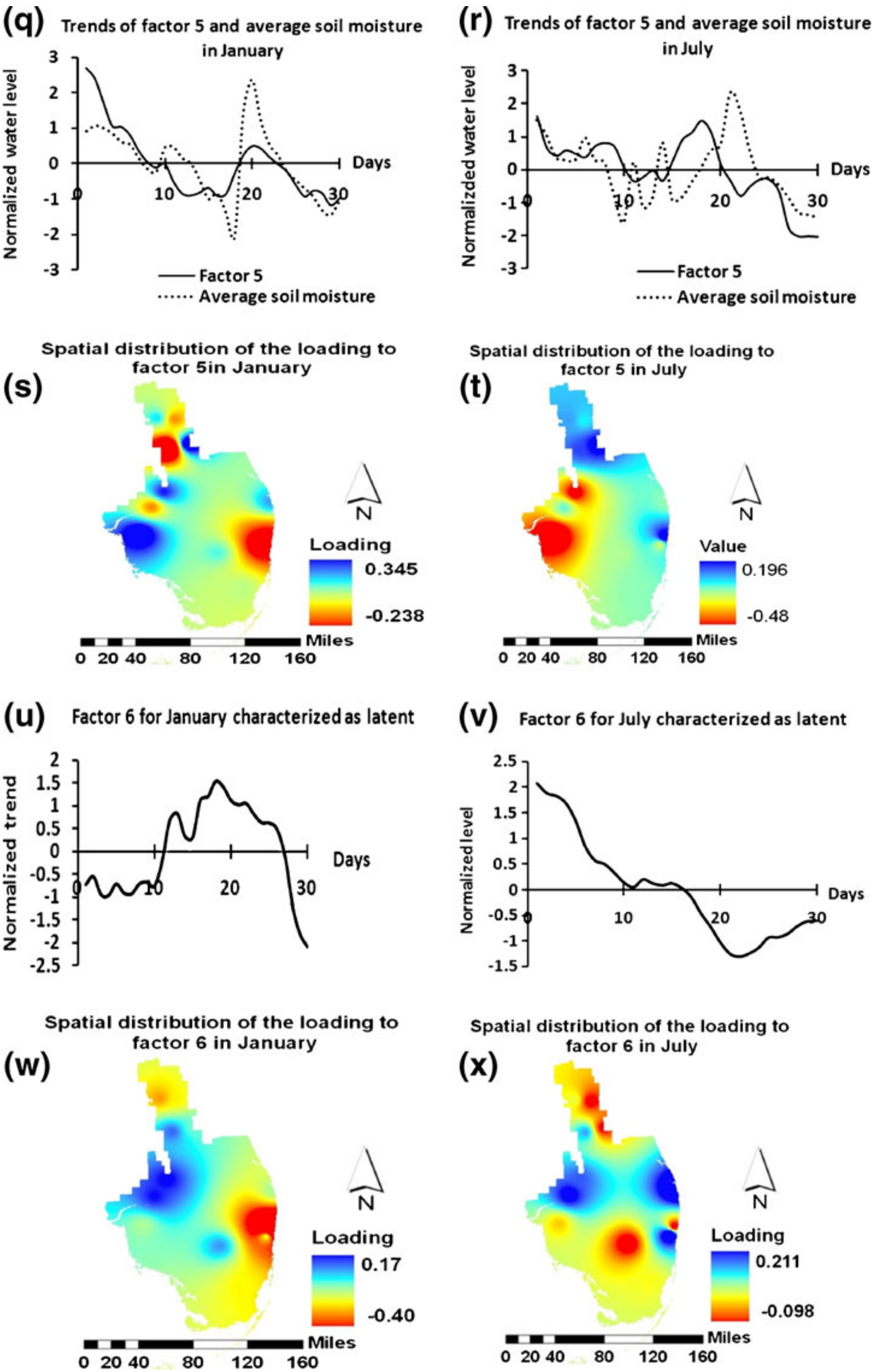


Fig. 5 (continued)

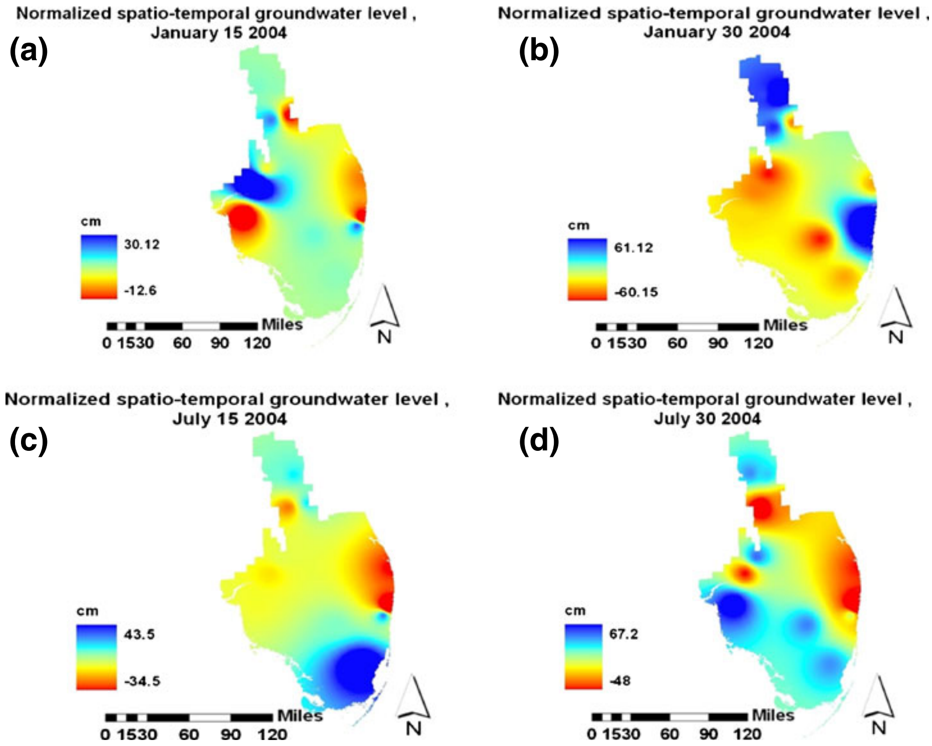


Fig. 6 Simulated groundwater level. **a**15 Jan 2004, **b** 30 Jan 2004, **c** 15 July 2004, **d** July 30 2004

loadings at regional level. Further study into the inclusion of water extraction as part of the explanatory variables should help for groundwater level management.

This is a first time test to understand applicability of the Dynamic Factor Analysis approach for a regional scale spatiotemporal groundwater level model. Workability of the approach is a major achievement for this study. The validation conducted at arbitrary regional points of well sites result shows that a sound agreement exists between the observed groundwater level and the simulated water level with maximum RMSE of 0.12 m. The model in combination with the point scale groundwater prediction model (Chebud and Melesse 2011) would serve for operational prediction and decision making. Employing DFA over SFWMD was also viable for its low computational intensive nature; and efficient for its ease of synthesis of regional spatiotemporal groundwater level through data driven simulation where watershed based approach would not be workable.

The approach will be serving different purposes that need the results of this study as an input. Pragmatically the study serves to inform groundwater status over sinkhole formation areas; flooding risk analysis as a result of the shallow water table in urban areas; saltwater intrusion from the ocean; groundwater nutrient interaction. A case study at micro scale is evidently vital. A spatiotemporal groundwater level (result of this study), for instance, has served as an input for groundwater-phosphorus interaction analysis (Chebud 2012). So, this study recommended a similar case study on groundwater status of karst hydrogeological areas (especially near sinkhole formations) at micro ecological scale.

The DFA analysis indicated that surface water levels and randomly selected wells could serve as a starting point for regional spatiotemporal groundwater level simulation in data scarce areas. It would just require a strategy of using first year data for factor analysis on monthly basis and 2 to 5 years data for validation. On the other hand, most explanatory variables are obtainable from satellite imagery. Rainfall is measured both on the ground as well as using radar; soil moisture is currently available from programs such as GLDAS. Also surface water levels are captured by satellite imagery (TOPIX) in the case of lakes. The economic viability of such inputs from satellite imagery certainly supports the effort.

Last, apart from synthesizing the regional scale water level dynamics, the modeling approach would help for predictions of spatiotemporal groundwater level fluctuation if coupled with the point scale dynamic forecasting as reported by Chebud and Melesse (2011).

Acknowledgments The authors would like to acknowledge the South Florida Water Management District (SFWMD) for making the groundwater and GIS data accessible. Also we would like to acknowledge NASA of the United States of America. The soil moisture data "*used in the study were acquired as part of the mission of NASA's Earth Science Division and archived and distributed by the Goddard Earth Sciences (GES) Data and Information Services Center (DISC).*"

References

Aggarwal YP (1998) Statistical methods concepts, application and computation, 3rd edn. Sterling Publishers Pvt.Ltd, New Delhi, p 387

Chebud YA (2012) Operational prediction of groundwater-phosphorus interaction over surficial aquifers of South Florida. Ph. D Dissertation, Florida International University

Chebud YA, Melesse AM (2011) Operational prediction of groundwater fluctuation in south florida using sequence based Markovian Stochastic Model. Water Resour Manag 25(9):2279–2294. doi:10.1007/s11269-011-9808-z

Chebud Y, Naja GM, Rivero R (2011) Phosphorus run-off assessment in a watershed. J Environ Monit 2011 (13):66. doi:10.1039/c0em00321b

Claeskens G, Hjort NL (2008) Model selection and model averaging: Cambridge series in statistical and probabilistic mathematics. Cambridge University Press, UK, 305

Davis JC (2002) Statistics and data analysis in geology, 3rd edn. John Wiley & Sons, New York, p 638

Denic-Juki' V, Jukic' D (2003) Composite transfer functions for Karst aquifers. J Hydrol 274:80–94

Diggle PJ, Edith G (2010) Second-order analysis of the spatio-temporal distribution of human campylobacteriosis in Preston, Lancashire. In: Atkinson PM, Lloyd CD (eds) GEOENV VII – Geostatistics for Environmental Applications. Springer, Dordrecht, p. 99–106

Gamerman D (2010) In: Gelfand AE, Diggle PJ, Fuentes M, Guttorp P (eds) Dynamic spatial models including spatial time series: handbook of spatial statistics. Chapman & Hall/CRC Boston, USA

Genereux D, Slater E (1999) Water exchange between canals and surrounding aquifer and wetlands in the southern Everglades, USA. J Hydrol 219(1999):153–168

Gunderson LH (2001) South Florida: the reality of change and prospects for sustainability; managing surprising ecosystems in Southern Florida. Ecol Econ 37(2001):371–378

Harvey JW, Krupa SL and Krest JM (2004) Ground water recharge and discharge in the central Everglades. Ground Water-Oceans Issue 42(No. 7):1090–1102

Hoogland T, Heuvelink BMG, Knotters M (2010) Mapping Water-table depths over time to assess desiccation of groundwater-dependent ecosystems in the Netherlands. Wetlands 30(2010):137–147

Jukic' D, Denic-Juki' V (2004) A frequency domain approach to groundwater recharge estimation in Karst. J Hydrol 289:95–110

Knotters M, Bierkens MFP (2001) Predicting water table depths in space and time using a regionalized time series model. Geoderma 103(2001):51–77

Lopes FH, Salzar E, Gamerman D (2008) Spatial dynamic factor analysis. Bayesian Anal 3(4):759–792

Ma'rkus L, Berke O, Kovacs J, Urfer W (1999) Spatial prediction of the intensity of latent effects governing hydrological phenomena. Environmetrics 10(1999):633–654

Nayak PC, Rao SYR, Sudheer KP (2006) Groundwater level forecasting in shallow aquifer using artificial neural network approach. Water Resour Manag 20(2006):77–90

Park E, Parker JC (2008) A simple model for water table fluctuations in response to precipitation. J Hydrol 356(2008):344–349

Ramsey FL, Shafer DW (2002) A statistical Sleuth: A course in methods of data analysis, 2nd edn. DUXBURY; Thomson Learning, California, p 698

Randazzo AF, Jones DS (1997) The geology of Florida. University Press of Florida, Gainesville, p 327

Ritter A, Mun'oz-Carpena R (2006) Dynamic factor modeling of ground and surface water levels in an Agricultural area adjacent to Everglades National Park. J Hydrol 317(2006):340–354

Visser A, Stuurman R, Biierkens FPM (2005) Real-time forecasting of water table depth and soil moisture profiles. Adv Water Resour 29(2006):692–706

Zurr AF, Pierce GJ (2004) Common trends in northeast Atlantic squid time series. J Sea Res 52(2004):57–72

Zurr AF, Fryer RJ, Jolliffe IT, Dekker R, Beukema JJ (2003) Estimating common trends in multivariate time series using dynamic factor ana1lysis. Environmetrics 14(2003):665–685