Spatial variability, distribution and uncertainty assessment of soil phosphorus in a south Florida wetland

S. Grunwald, K. R. Reddy, S. Newman and W. F. DeBusk

Soil and Water Science Department, University of Florida, Gainesville, FL 32611-0290, U.S.A.
South Florida Water Management District, West Palm Beach, FL 33416-4680, U.S.A.

SUMMARY

Phosphorus enrichment has been of major concern in the Greater Everglades (GE) ecosystem since the early 1980s. Our objectives were to estimate spatio-temporal patterns of soil total phosphorus (TP) in Water Conservation Area 2A (WCA-2A) in the GE ecosystem and to compare two different geostatistical methods: ordinary kriging (OK) and conditional sequential Gaussian simulation (CSGS), addressing spatial variability, continuity and uncertainty of TP estimations.

Overall, TP estimated with OK and CSGS were higher in 1998 than in 1990. Both methods generated spatial patterns of TP in 1998 which showed a spatial expansion of the phosphorus enrichment identified in the 1990 dataset. Cross-validation using OK produced a mean prediction error of −10.71 (1990) and −6.07 (1998). CSGS modeled the spatial uncertainty of TP estimations explicitly with 50 generated realizations. Uncertainty was modeled using the E-type mean of TP, which ranged from 216 to 2100 mg kg⁻¹ in 1990 and 325.2 to 3660 mg kg⁻¹ in 1998. Standard deviations ranged from 0 to 550 mg kg⁻¹ maximum.

To evaluate TP exceeding a threshold of 450 TP mg kg⁻¹, which represents natural historic wetland conditions, we produced probability maps. Results suggested a distinctly higher retention of TP using CSGS when compared to the OK generated probability maps. Spatial probability patterns are valuable to guide the restoration process of this wetland.

Jackknifing was used to estimate the bias of the descriptive statistics and semivariance. The total number of samples was robust enough to produce stable variograms; however, jackknifing suggested that more samples at closer distances from each other should be collected to reduce the uncertainty of the semivariance and to address short-range spatial variability. Copyright © 2004 John Wiley & Sons, Ltd.

KEY WORDS: spatial variability; spatial distribution; phosphorus; stochastic simulation; kriging; jackknifing

1. INTRODUCTION

Wetlands in the Greater Everglades ecosystem have been impacted by phosphorus (P) input from adjacent agricultural and urban land uses for many years. Since wetland soils are potentially a source or a sink for nutrients, it is important to quantify their influence on overlying water quality in order to understand their importance in overall ecosystem nutrient budgets.

*Correspondence to: S. Grunwald, Soil and Water Science Department, University of Florida, 2169 McCarty Hall, P.O. Box 110290, Gainesville, FL 32611-0290, U.S.A.
E-mail: SGRunwald@mail.ifas.ufl.edu

Copyright © 2004 John Wiley & Sons, Ltd.

Received 28 August 2003
Revised 20 January 2004
Historically, the wetland areas of the Everglades were a phosphorus-limited marsh environment, in which sawgrass (*Cladium jamaicense*) thrived, aided by natural fires during dry cycles that served to eliminate encroaching woody species. Both dissolved materials (mineral nutrients, organic matter, metals and pesticides) and particulate materials (detritus, soils) are transported through canals, wetlands, creeks and groundwater from the Everglades Agricultural Area (EAA) through three Water Conservation Areas (WCAs) southward into the pristine Everglades National Park (ENP). Water Conservation Area-2 (WCA-2) is the smallest of the WCAs with a size of 44,700 ha (DeBusk et al., 1994). It receives the majority of its water (59 percent) from surface water inflow, which includes drainage from the EAA and outflow from WCA-1. Prior to drainage, WCA-2 was part of the extensive ridge and slough landscape (Sklar et al., 2002). The most noticeable impact is observed in the northeastern and western part of WCA-2A, where 10,000 ha of cattail (*Typha spp.*) have appeared since the 1970s (Koch and Reddy, 1992; Jensen et al., 1995). This change is thought to be primarily due to the ability of cattail to outcompete sawgrass under increased nutrient loads (Davis, 1991; Koch and Reddy, 1992; Rutchev and Vlachok, 1999).

Phosphorus inputs from the EAA and other non-point sources into the WCAs have been estimated to be about 347 Mg P yr⁻¹, and rainfall inputs to these areas have been about 272 Mg P yr⁻¹. Loading rates from the EAA and rainfall were 0.25 g P m⁻² yr⁻¹ for WCA-2A in the early 1990s (SWIM, 1992). Reddy et al. (1999) reported total phosphorus (TP) along a nutrient-enriched transect in WCA-2A ranging from 1608 mg kg⁻¹ (impacted site) to 486 mg kg⁻¹ (less impacted site) measured in the detrital layer and 1461 mg kg⁻¹ (impacted site) to 484 mg kg⁻¹ (less impacted site) measured in the topsoil (0–10 cm depth).

Reddy et al. (1999) pinpointed that water column nutrient concentrations in wetlands change rapidly (hours to days) and can be highly variable. Water column nutrients are in direct contact with the microbial communities associated with periphyton mats and plant detritus in the water column, and changes in composition and activities of these communities and materials may provide an indication of recent (< 3 years) impacts from added nutrients. The top wetland soil profile (0 to 10 cm depth) represents the accumulated nutrients over 10 to 15 years in nutrient-impacted (high-productivity) wetlands and 50 to 100 years in nutrient-unimpacted (low productivity) wetlands. The lower wetland profile (10 to 30 cm depth) represents the long-time range component resulting from nutrient loading of 10 to 15 years in impacted and 50 to 100 years in unimpacted wetlands (Reddy et al., 1999). Since the spatial and temporal variability of water and detritus P is high, we decided to focus on the topsoil layer in this study. This pool represents the accumulated nutrient loading of about 10 to 15 years.

Previous studies were able to quantify spatial autocorrelation of soil P (Newman et al., 1997; DeBusk et al., 2001). DeBusk et al. (2001) compared the spatial extent and patterns of soil P enrichment in WCA-2A at two different time periods (1990 and 1998). The authors used ordinary block kriging to estimate P patterns using 300 m blocks and indicator kriging to describe the risk of measured P exceeding a pre-selected threshold value. Although estimated maps were presented, information about prediction errors and assessment of spatial uncertainty were not explicitly addressed.

Our objectives were to estimate spatio–temporal patterns of soil phosphorus in WCA-2A in south Florida and to compare two different geostatistical methods addressing spatial variability, continuity and uncertainty of estimations. Criteria to evaluate the methods were prediction error, the uncertainty of model predictions and suitability for risk assessment. Results are intended to support the ongoing restoration effort in the Greater Everglades ecosystem.
2. METHODOLOGY

2.1. Study area and dataset

Our study area was WCA-2A in south Florida, which is part of the Greater Everglades ecosystem. Soils are Histosols formed by high biomass production of emergent marsh vegetation in conjunction with low biodegradation rates in the predominantly anaerobic soil environment. We used two different datasets to assess spatio-temporal patterns of soil TP in WCA-2A: Both datasets were collected by the Wetland Biogeochemistry Laboratory (WBL), Soil and Water Science Department, University of Florida, 74 sites in July, 1990 and 56 sites in October, 1998. For a detailed description of the WBL datasets refer to Reddy et al. (1998).

2.2. Spatial analyses

We used the ISATIS software (Geovariances Inc. & Ecole des Mines De Paris http://www.geovariances.fr) to conduct the geostatistical analysis and ArcGIS software (Environmental Systems Research Institute, Redlands, CA) for visualization of model output. Ordinary kriging and CSGS were used to estimate TP across the study site using two soil TP datasets collected at different time periods. Kriging and stochastic simulation are geostatistical methods which are commonly used to create continuous maps. The two methods have opposing goals–kriging aims at local accuracy through minimizing a covariance-based error variance, while simulation aims at reproducing spatial structure through a covariance model. Kriging produces one output map. In contrast, stochastic simulation generates multiple realizations of the spatial distribution of (soil) attribute values and it uses differences among simulated maps as a measure of uncertainty. Therefore, kriging is preferred for local estimation, whereas simulation is increasingly preferred for assessment of spatial uncertainty and reproduction of global statistics, risk assessment, flow modeling, and water quality simulation modeling (Desbarat, 1996; Vanderborght et al., 1997; Loague and Kyriakidis, 1997; Goovaerts, 1997). The latter ones require knowledge about the uncertainty of environmental attribute values at many locations simultaneously (multiple-point or spatial uncertainty).

Since there is no ‘best’ a priori estimation method for all situations that is the ‘best’ model to assess spatial uncertainty, different algorithms need to be applied to the data and their respective performances have to be compared before drawing conclusions. This article compares two different geostatistical methods: (i) ordinary kriging (OK), described by Goovaerts (1997) and Webster and Oliver (2001), and (ii) conditional sequential Gaussian simulation (CSGS), described by Chilès and Delfiner (1999) and Lantuéjoul (2002) to estimate soil P and evaluate the uncertainty of estimations.

Least-square interpolation algorithms such as kriging tend to smooth out local details of the spatial variation of the attribute, with small values typically overestimated and large values underestimated (Isaaks and Srivastava, 1989). This is a serious shortcoming if large pollutant concentrations are of interest. Unlike kriging, stochastic simulation does not aim at minimizing a local error variance but focuses on the reproduction of statistics such as the sample histogram or the semivariogram model in addition to honoring of data values. The output results, i.e. a set of alternative realizations, provide a visual and quantitative measure of the spatial uncertainty. A probability distribution (cdf) for attributes at a particular location can be built for a set of multiple realizations of the joint distribution of attribute values in space (Goovaerts, 1997). CSGS is a stochastic simulation method for the generation of partial realizations using normal random functions. The method uses the Gaussian model type and is ergodic, which means that simulations have a sample mean close to the theoretical mean ($m$) and a sample covariance close to the theoretical covariance $C(h)$. This implies that all simulations...
are drawn from the realizations of a random function that is ergodic in the mean value and the covariance (second-order ergodicity) (Chiles and Delfiner, 1999). Conditioning is the operation that ensures that simulation values match values at sample points. Chiles and Delfiner (1999) disaggregated the conditional simulation $T(x)$ into:

$$T(x) = Z'(x) + [S(x) - S'(x)]$$

(1)

conditional simulation = kriging estimator + simulation of kriging error

CSGS provides a measure of local uncertainty because each conditional cdf relates to a single spatial location $x$. Stochastic simulation was employed successfully by Carlson and Ociensky (1998), Holmes et al. (2000), Goovaerts (2001), Kyriakidis and Journel (2001) and Lapen et al. (2001) using a variety of different environmental datasets.

A sensitivity analysis was conducted to optimize the search neighborhood for simulations using the following criteria: (i) the reproduction of the sample histogram and (ii) the semivariogram parameters (range, sill and nugget). Best results were obtained using a maximum dilation radius for the search neighborhood of $x$: 9 pixels and $y$: 9 pixels, which equals a dilation radius of 4500 m. We constrained the estimation of target values to a maximum of 20 data nodes and 10 simulated nodes within the search neighborhood. We used 500 m pixels to estimate TP based on OK and CSGS. Fifty realizations were generated for each of the datasets (WBL 1990 and 1998).

Risk analysis which relies only on one semivariogram model implies that it accurately represents spatial variation at the site and assumes that the range of uncertainty of subsurface interpretations is completely defined by the process. However, the results derived from one single semivariogram and subsequent kriging can be misleading; depending on the parameters used to define the semivariogram, the same data can yield different results. Even stochastic simulation techniques are incapable of accounting for all the uncertainty, if only a single deterministic semivariogram model is utilized. To address the uncertainty of semivariogram modeling, jackknifing was used (McKay et al., 1979; Wingle, 1997). To demonstrate this technique, consider a sample comprised of 100 scores. The first sub-sample is identical to the entire sample except for the first score, the second sub-sample is identical to the entire sample except for the second score, and so forth. Jackknifing thus produces as many sub-samples as individuals. For each sub-sample, the statistics of interest are then computed (e.g. mean, semivariance $\gamma$). The standard deviation of these values resembles the standard error.

Jackknifing and cross-validation are similar in respect of omitting one (or more) samples. The major difference is that cross-validation is used to estimate the prediction error while the jackknife is used to estimate the bias of a statistics. We used jackknifing to create subsets omitting one sample at a time and then compute (i) mean, standard deviation and percentiles and (ii) semivariances. By repeating this procedure for every sample in the dataset, a series of $n$ (number of samples) experimental semivariograms was calculated. For each lag distance there were $n$ times $\gamma$ values. Using these values, 95 percent confidence limits were determined for the jackknifed mean $\gamma$ at a particular lag. Jackknifing is well suited to compare the subset statistics to statistics of the entire dataset in order to estimate the bias of the latter (Wingle, 1997).

3. RESULTS AND DISCUSSION

The descriptive statistics for the datasets are summarized in Table 1. The mean of TP was smaller in 1990 when compared to 1998. Because the distribution of values were skewed the median provides a
Table 1. Summary descriptive statistics for soil TP measured at depth 0–10 cm

<table>
<thead>
<tr>
<th></th>
<th>WBL 1990</th>
<th>WBL 1998</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of sites</td>
<td>74</td>
<td>56</td>
</tr>
<tr>
<td>Minimum (mg kg(^{-1}))</td>
<td>217.0</td>
<td>328.0</td>
</tr>
<tr>
<td>Maximum (mg kg(^{-1}))</td>
<td>2100.4</td>
<td>3676.0</td>
</tr>
<tr>
<td>Mean (mg kg(^{-1}))</td>
<td>660.8 ± 47.3(^{1})</td>
<td>860.1 ± 79.1(^{1})</td>
</tr>
<tr>
<td>Median (mg kg(^{-1}))</td>
<td>513.8</td>
<td>860.1</td>
</tr>
<tr>
<td>Std. dev. (mg kg(^{-1}))</td>
<td>406.7</td>
<td>594.8</td>
</tr>
<tr>
<td>Skewness (-)</td>
<td>1.801</td>
<td>2.493</td>
</tr>
</tbody>
</table>

\(^{1}\)Standard error of mean (SE).

Figure 1. Labels show measured TP in mg kg\(^{-1}\) in 1990 and 1998. Selection of sampling sites in 1998 was based on sampling sites in 1990.

A better measure to compare the WBL 1990 dataset with a median of 515.8 mg kg\(^{-1}\) to the WBL 1998 dataset with a median of 860.1 mg kg\(^{-1}\), which was very much higher. The maximum measured TP in both datasets was relatively high. To put our measured TP values into perspective we compared them to other datasets collected in the WCAs. Newman et al. (1997) measured mean TP of 544 mg kg\(^{-1}\) (standard error of mean (SE): 41.0 mg kg\(^{-1}\)) in WCA-1 in September 1991. In the nutrient-enriched cattail zone in WCA-1 they found a mean TP of 1028 mg kg\(^{-1}\) (SE: 93) and 368 mg kg\(^{-1}\) (SE: 13) in the interior zone. Nutrient-enriched water is routed from WCA-1 into WCA-2 impacting the latter one.
The spatial distribution of measured TP in 1990 and 1998 is shown in Figure 1. Observations indicate a larger impact close to the control structures S-7 and S-10. Maximum TP and average TP was higher in 1998 when compared to 1990 (Table 1; Figure 1). Figure 2 shows the semivariograms of TP for both time periods. Interactive fitting was used to generate model (fitted) semivariograms. Spherical variogram models were selected for both datasets. The nugget and sill values were very similar in 1990 and 1998. The range was higher in 1998, with 7549 m, when compared to 6500 m in 1990.

Overall spatial patterns of TP were similar for dataset 1990 using OK and CSGS with larger values close to the P input sources (Figures 3 and 4). However, the OK map was much smoother. The CSGS maps showing the mean of all realisations for 1990 and 1998, respectively, were patchier. Visiting the nodes at random and preparing a different schedule for every realization maximized diversity among realizations. The conditioning to the data was automatic. The kriging variance at a sampling location was assigned zero, ensuring that the only possible drawing was that of the observed value. The maximum TP was relatively high in 1990 and 1998 when compared to other wetland soils in the Greater Everglades ecosystem. For example, Reddy et al. (1999) measured a maximum of 1461 mg TP kg⁻¹ at nutrient-enriched sites. Both the OK and CSGS showed an expansion of the nutrient-enriched zone extending south of control structure S-10. The spatial expansion of the phosphorus-enriched zone represents the degradation of this P-limited wetland ecosystem. Numerous studies in WCA-2A have also shown a steep gradient of P extending south of control structure S-10 (Davis, 1991; DeBusk et al., 1994; Qualls and Richardson, 1995). The elevated TP extending south of S-10 was associated with calcium (Ca) and magnesium (Mg) contents of about 130 000 and 5000 mg kg⁻¹, respectively. In contrast, Ca and Mg were higher, with 200 000 and 8000 mg kg⁻¹, close to control structure S-7 and smallest in the interior of WCA-2A with 16 000 and 2000 mg kg⁻¹ of Ca and Mg, respectively. The chemical precipitation of Ca phosphates and retention of water-column dissolved P by soils are suggested to explain the high retention of TP in the western and eastern parts close to the control structures. Although Ca and Mg phosphates contribute to the retention of P, the organic P pool in these
Figure 3. Total phosphorus estimated with OK for 1990 and 1998 in WCA-2A

Figure 4. Total phosphorus estimated with CSGS for 1990 and 1998 in WCA-2A
soils is expected to exceed 50 per cent of TP (Reddy et al., 1998). The encroachment of cattail close to control structure S-10 might illustrate the high TP spatial patterns of this area. Francois (1990) found that macrophytes such as cattail tend to produce complex lignins (e.g. fulvic acids) as opposed to humic acids associated with algae of the aquatic slough and sawgrass communities within the marsh interior. Such recalcitrant P forms dominate the storage of P in P-enriched areas, while less resistant forms are present in the unenriched interior. Reddy et al. (1998) reported that the high productivity of cattail in WCA-2A leads to more organic matter accumulation in the P impacted zones, suggesting high P storage in the organic pool.

Cross-validation using OK and the TP 1990 dataset resulted in a mean prediction error of $-10.71$, and in 1998 the error was smaller, with $-6.07$. The root mean square error (RMSE) of TP in 1990 was 296.3 and in 1998 higher with 461.9. The prediction standard error for the kriged maps is shown in Figure 5. It is evident that the prediction standard error was greatest for high estimated values of TP. In contrast, the error was smaller for small estimated TP values. The interior of WCA-2A showed lowest prediction standard errors. Similar patterns emerged from maps generated using CSGS. E-type statistics were generated calculating the standard deviation for all 50 realizations in 1990 and 1998, respectively (Figure 6). Because CSGS is conditional, the predictions of TP at sampling locations matched the measured data values, resulting in standard deviations (and variance) of 0 at sampling locations. No cross-validation for the TP maps generated with CSGS was conducted because the method honors data values resulting in a mean prediction error of 0. Standard deviations of TP computed by CSGS were higher in 1998 when compared to 1990. Generally, standard deviations were greatest in the western and eastern parts of WCA-2A close to the control structures.
Figure 6. Standard deviation of TP generated using CSGS in 1990 and 1998

Figure 7. A subset of realizations generated using the TP 1990 dataset

The spatial uncertainty was modeled explicitly using the CSGS method. Figure 7 shows a subset of 10 generated realizations capturing spatial uncertainty. The full range of possible outcomes was represented by multiple generated realizations. This approach is very different from a kriged map, which generates only one output TP map that attempts to minimize the error variance. Addressing the
Figure 8. Maps show estimated TP using the 1990 dataset. Spatial uncertainty was modeled using smallest and largest realizations.

Figure 9. Probabilities exceeding TP 450.0 mg kg\(^{-1}\) using OK.
worst- and best-case conditions (Figure 8) and possible realizations in-between provides a more realistic estimate of actual conditions than a single output map.

A threshold of 450 mg kg$^{-1}$, which represents background or historic natural wetland conditions in the northern Everglades ecosystem (Reddy, personal communication), was used to create probability maps for dataset TP 1990 and 1998 derived form OK and CSGS (Figures 9 and 10). The 450 mg kg$^{-1}$ threshold value is even more conservative than the threshold used by DeBusk et al. (2001).

Probability maps derived from CSGS were much patchier when compared to the OK maps for both time periods. CSGS estimated higher probabilities in the risk class [0.9 to 1.0] with 43 percent of all pixels using the TP 1990 dataset. In contrast, only 29 percent of all pixels derived from OK were grouped into the high-risk class using the TP 1990 data. Probabilities greater than 0.5 accounted for 74 percent of all pixels derived from CSGS and 48 percent of all pixels derived from OK for the TP 1990 dataset. The results can be explained by the fact that OK typically underestimates large values (Isaaks and Srivastava, 1989; Webster and Oliver, 2001). Overall, probabilities to exceed the threshold of 450 mg P kg$^{-1}$ were higher in 1998 when compared to 1990. For 1998 data, CSGS grouped 54.3 percent of all pixels into the high risk class [0.9–1.0]. Only 33.4 percent of all pixels were grouped into the high-risk class using OK. Probabilities greater than 0.5 accounted for 82.3 percent of all pixels (CSGS) and 96.9 percent of all pixels (OK), respectively. The OK and CSGS methods yielded very different probabilities for both datasets. The risk assessment quantifying the amount of soil P exceeding the threshold of 450 mg P kg$^{-1}$ is highly dependent on the selected geostatistical method. Since this study focused on estimating TP at unsampled locations and assessing the risk of elevated TP, CSGS provides an alternative model reproducing standard statistics (e.g. histogram,
Table 2. Comparison between measured and jackknifed statistical parameters (TP 1990) to estimate the bias

<table>
<thead>
<tr>
<th></th>
<th>Sample</th>
<th>Jackknifed</th>
<th>95% Confidence interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>660.77 ± 47.30$^1$</td>
<td>660.86 ± 47.27$^1$</td>
<td></td>
</tr>
<tr>
<td>Std.dev.</td>
<td>406.68</td>
<td>406.64</td>
<td></td>
</tr>
<tr>
<td>Percentile 25</td>
<td>412.97</td>
<td>413.24</td>
<td></td>
</tr>
<tr>
<td>Percentile 50</td>
<td>515.70</td>
<td>515.18</td>
<td></td>
</tr>
<tr>
<td>Percentile 75</td>
<td>732.23</td>
<td>727.81</td>
<td></td>
</tr>
</tbody>
</table>

$^1$Standard error of mean (SE).

mean) while at the same time reproducing spatial variability derived from the sample semivariogram. To explicitly model spatial uncertainty is valuable for future assessment of the spatial distribution and uncertainty of TP in this wetland and other wetland ecosystems.

Jackknifing was used to assess the uncertainty associated with descriptive statistics and the semivariogram which are essential to conduct CSGS. Measured and jackknifed statistical parameters (mean, standard deviation, 25th, 50th and 75th percentiles) used to assess the bias of TP in 1990 are listed in Table 2. All statistical parameters were insensitive; for example, the sample mean of 660.77 mg TP kg$^{-1}$ was very similar to the jackknifed mean of 660.86 mg TP kg$^{-1}$. Only the 75th percentile showed sensitivity with 732.23 mg TP kg$^{-1}$ (sample 75th percentile) and 12.02 mg TP kg$^{-1}$ between the lower and upper bound 95 per cent confidence intervals.

Jackknifed results were different for the TP semivariogram (1990 dataset). The sample mean $\gamma$, jackknifed mean $\gamma$, 95 per cent confidence intervals, minimum and maximum for each lag are shown in Figure 11. The latter ones show the possible range of the modeled semivariogram. In particular, at smaller lags the uncertainty of $\gamma$ was high. The small number of datapairs used to calculate small lag distances can explain this. For example, only 7 datapairs (N) were used to calculate the $\gamma$ at lag 1000 m. For future sampling designs this suggest collecting more samples at closer distances to reduce the uncertainty of $\gamma$ and to address small-range spatial uncertainty. Since the sample and jackknifed means showed similar values the bias was relatively small at most lags. For example, the sample mean at a lag distance 3000 m was 91.789 when compared to the jackknifed mean of 92.399. The lower bound 95 per cent confidence interval for the same lag distance was 91.545 and the upper bound 95 per cent confidence interval was 93.252. The jackknifed minimum and maximum at lag 3000 m were 77.828 and 95.556, respectively, suggesting a small uncertainty for $\gamma$ at this specific lag. In contrast, the uncertainty of $\gamma$ was larger at lags 4000 (N: 91) and 11000 (N: 105) m lag distance. The uncertainty of $\gamma$ was smaller for lag distances 7000 m (N: 251) and 10000 m (N: 252). Our results are beneficial to develop future spatial sampling designs, which should aim to provide a reasonable amount of datapairs for small and large lag distances to reduce bias and minimize the uncertainty of $\gamma$. Jackknifed results for the TP 1998 dataset were very similar, and therefore they are not shown here.
4. CONCLUSIONS

In this study we estimated the spatio-temporal patterns of TP at two different time periods (1990 and 1998) in WCA-2A in south Florida. A comparison between OK and CSGS was conducted to address spatial variability, continuity and uncertainty of estimations. Conditional sequential Gaussian simulation is an alternative geostatistical method, which is well suited for risk assessment because it reproduces sample statistics (e.g. mean, histogram) and the semivariogram, i.e. the spatial structure of the dataset. Additionally, it models the spatial uncertainty explicitly, i.e. it generates multiple realizations, which represent possible estimations of TP across the study site. Since CSGS is conditional it honors data values at observation points, resulting in 0 variance. For risk assessment, CSGS yields more realistic results when compared to OK. Probability maps produced with CSGS suggested a distinctly higher retention of P in WCA-2A when compared to the OK generated TP probability maps. From 1990 to 1998 the probabilities showed an increasing trend based on OK and CSGS, indicating that the storage capacity of P in WCA-2A is decreasing. These findings are of concern. To protect the pristine ENP from human-induced impact is one of the major concerns in the Greater Everglades ecosystem. Realistic risk assessment of P is viable for the preservation of the remaining pristine wetland areas in the Greater Everglades ecosystem. The spatial variability derived from variography and uncertainty derived from jackknifing are valuable to plan future spatial sampling efforts in the WCAs and other wetland ecosystems. The total sample number was robust enough to produce stable variograms; however, jackknifing suggested that more samples at closer distances from each other should be collected to reduce the uncertainty of the semivariance and to address short-range spatial variability.
ACKNOWLEDGEMENT

We acknowledge the release of soil data collected by the Wetland Biogeochemistry Laboratory, Soil and Water Science Department, University of Florida.

This research was supported by the Florida Agricultural Experiment Station and approved for publication as Journal Series No. R-09964.

REFERENCES


