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ORIGINAL PAPER

Validation of daily surface water depth model of the Greater Everglades based on real-time stage monitoring and aerial ground elevation survey

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Abstract As part of the Everglades Depth Estimation Network (EDEN) project, this paper describes validation of raster-based daily surface water depth models of the Greater Everglades in Florida developed using real-time stage data and elevation data obtained from a survey with an aerial height finder. Daily median stage data obtained at over 200 locations were interpolated using the multiquadric radial basis function. Surface water depth was obtained by subtracting a digital elevation model from the interpolated stage raster. The model was validated with 751 independent field measurements of surface water depth between 1999 and 2004. Correlations between prediction error and both density of the monitoring gages and distance from a major linear geographic feature, such as a canal, were weak, suggesting that the error does not depend on these features. South Florida has distinct dry and wet seasons and the study area is dominated by sawgrass and wet prairie. Seasonality and ground vegetation type significantly affect prediction error. Correlation between observed and predicted water depth was high for all combination of season and vegetation type (0.83–0.96). Model validation using an equivalence test provided evidence of equivalence between predicted and observed water depths in dry season prairie-dominated and wet season sawgrass-dominated areas with the strict test and in dry season sawgrass-dominated areas with the liberal test, but not in wet season prairie-dominated areas. Equivalence between observed and predicted water depth for both dry season sawgrass- and wet season prairie-dominated areas were confirmed with the strict test after further model calibrations using linear regressions.

Keywords Everglades · Digital elevation model · Multiquadric · Radial basis function · Vegetation map

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Introduction

Because hydrology plays a central role in maintaining wetland ecosystems, hydrologic information is essential for understanding, predicting changes in, and managing wetland biotic communities. In the Florida Everglades, there have been numerous efforts to measure and link daily and seasonal fluctuations in surface water depths to biotic communities (Busch et al. 1998; David 1996; Ross et al. 2003; Loucks 2005). Repeated field measurement is a traditional way to obtain such information, but it is labor intensive and does not provide information on the spatial variability of water depth across a large area. Taking systematic field measurements of surface water depth across space and time is difficult since the Everglades is comprised of remote and inaccessible areas. Alternatively, hydrologic models are frequently used in ecological research in the Everglades (Walters et al. 1992; Curnutt et al. 2000; Immanuel et al. 2005). A 3.2 km resolution daily basis water level simulation model for 1965–2000 that used rainfall data as input and accounted for loss to evapotranspiration, net flow to and from surrounding areas, and volume addition and removal by canals has previously been developed (MacVicar et al. 1983; South Florida Water Management District 2005). More recently, several government agencies including Big Cypress National Preserve (BCNP), Everglades National Park (ENP), the South Florida Water Management District (SFWMD), and the U.S. Geological Survey (USGS), have placed over 200 real-time stage monitoring gages throughout the Everglades to automatically measure stage and radio-transmit the data. The Everglades Depth Estimation Network (EDEN) is a collaborative project between these government agencies, scientists in south Florida, and the University of Florida to develop a finer-resolution raster-based daily surface water depth model using real-time stage data and an elevation survey. The entire project has several phases: gathering stage data from owner agencies, creation of a Digital Elevation Model (DEM) based on a recent elevation survey, stage interpolation, creation of water depth models, and development of a server for daily data estimation and delivery to the user community.

The DEM, created at the USGS Eastern Science Center, is based on elevation data obtained with a helicopter-based instrument, the airborne height finder, because the study area comprises remote and environmentally sensitive areas, making ground or airboat surveys infeasible (Desmond 2003; Johns and Price 2007). With an airborne GPS platform and surveyor's plumb bob, the system is able to penetrate vegetation to measure the topographic surface. Mean vertical accuracy of the airborne height finder as compared to the National Geographic Survey was 3.3 cm and the data were confirmed to meet 15 cm vertical accuracy specification. Over 46,000 elevation data points were collected throughout the Greater Everglades area at approximately 400 m intervals in a grid pattern. The DEM was generated by anisotropic ordinary kriging, which was the best performing method compared to radial basis function (RBF) and topogrid, for each of seven sub-areas (Johns and Price 2007). Cross-validation root mean square error (RMSE) of prediction by this method ranged 8.87–16.17 cm depending on the sub-area in the Greater Everglades.

Palaseanu and Pearlstine (2008) investigated an appropriate stage interpolation method for this purpose using data from three representative days. Geostatistical interpolation such as kriging is frequently used in hydrologic models (Vieux 2001; Ramesh et al. 2005), but was considered to be unsuitable because: (1) spatial correlation throughout the entire area was extremely weak as a result of interrupted hydrological connections by canals and levees, (2) the number of stage monitoring gages in sub-areas was small, and (3) kriging assumptions of local stationarity in the variance and variogram, that is an invariant stochastic process across the space, were not met. Palaseanu and Pearlstine (2008) applied a multiquadric RBF for stage interpolations because the method has previously proved to be useful for hydrologic models (Hardy 1971, 1990; Strack 1989; Strack and Jankovic 1999). Through model comparisons, Palaseanu and Pearlstine (2008) found that the method is superior to other interpolation methods, including inverse distance weighting and spline, in representing boundary conditions and smooth continuity in the marsh. They examined stage predictions for representative days; however, accuracy of predicted surface water depth across space and time was not explored.

Biological response models of the Everglades are often sensitive to small changes in hydrology, particularly during low-water conditions. Input of inappropriate hydrologic predictions may result in erroneous inferences about biological responses. Validation is essential for understanding the limitations, accuracy, and precision of the models being used (Gentil and Blake 1981; Mayer and Butler 1993; Rykiel 1996). Validation of a spatial–temporal model is difficult because prediction error may be associated with both spatial and temporal heterogeneities such as ground cover type, other geographic features, and seasonality. For example, the Everglades has distinct dry (October–May) and wet (June–September) seasons and the ground is a mosaic of different vegetation types. Functional connections between hydrology and vegetation affect water levels (Gunderson 1989; Olmsted and Armentano 1997; Busch et al. 1998). Additionally, the area is divided by canals and levees which are managed for flood control and water storage, so hydrologic connectivity is interrupted. Inclusion of such linear landscape features in hydrologic models is a challenge (Duke et al. 2003). All these attributes can be sources of prediction error.

Advances in GIS and statistical software allow us to readily create spatially explicit environmental models which are frequently used as inputs to ecological models and simulations in support of ecosystem management. As accuracy is a central question in using such models as inputs, users should be aware of the uncertainty contained in the models. The objective of this study is to validate the daily surface water depth model created by the interpolated stage surface using multiquadric RBF and the DEM based on aerial height finder measurements. We examine potential spatial and temporal error sources including density of stage gages, proximity to a canal, seasonality, and land cover type based on a vegetation map created by manual stereoscopic analysis of 1:24000 color infrared aerial photographs (Rutchey et al. 2005), and further calibrate the model. Although correlation between predictions and observations, mean square error of prediction (MSE), or lack of significant difference between predictions and observations are frequently used as means for model validation, these do not verify model validity, that is, high correlation, low MSE, and lack of significant difference do not imply equivalence. In recent years, model validations have shifted to more rigorous methods to test equivalence between predictions and observations (Robinson and Froese 2004; Robinson et al. 2005). We used a paired *t*-test for equivalence (Wellek 2003) as a basis for model validation.

The goal of the EDEN project is to support scientific research and resource management by making near-real time hydrologic data of the Greater Everglades publicly available through a website (US Army Corps of Engineers 2006) (http://sofia.usgs.gov/eden). These data not only provide information on the distribution and dynamics of surface water depth, but also are useful for deriving other hydrologic properties such as hydroperiod, recession rate, and volume, which are important for ecological consequences and management decision making. The results of this study provide model accuracy information to the users and input to further elaborate the model.

Study area

The project area of EDEN comprises the fresh water domain of the Greater Everglades including Water Conservation Areas (WCA), ENP, and BCNP. Coastal zones were excluded from the project boundary because of their distinctly different hydrologic processes and hydraulic forces such as tidal and wind effects on surface water flow. In this study, we focus only on a northern part of the modeled area, referred to as WCA 3 (Fig. 1) because of data availability for model validation. Historically, Sawgrass (*Cladium jamaicense*) is the dominant vegetation cover comprising 70% of the area (Loveless 1959) (Fig. 2). In sawgrass-dominated marshes, surface water depth fluctuates greatly throughout the year and hydroperiod and mean water depth increase with sawgrass density (Ross et al. 2003). The central to southwestern portion of the study area is a mosaic of sawgrass and wet prairie (Fig. 2). Wet prairie marshes are composed of grasses and low growing plants including beaksedge (*Rhynchospora tracyi*), spikerush (*Eleocharis cellulose*), and maidencane (*Panicum hemitomon*) (Loveless 1959). Wet prairie marshes occur in poorly drained areas and are characterized by a relatively longer hydroperiod and higher mean water depth (Ross et al. 2003). Vegetation density and type are also associated with soil conditions. Ross et al. (2003) showed that the soil depth decreases in the order of dense sawgrass, sparse sawgrass, and spikerush in Shark Slough. The study area is divided by canals and hydrologic connectivity between the divided areas is interrupted (Fig. 1).

Methods

Surface water depth model and validation data

We used radio-transmitted hourly water stage measurements at 207 water stage monitoring gages between October 1999 and September 2004. The vertical datum was unified to NAVD 88. To minimize the effects of inaccuracies in the data due to instrument malfunctions, the daily median stage value at

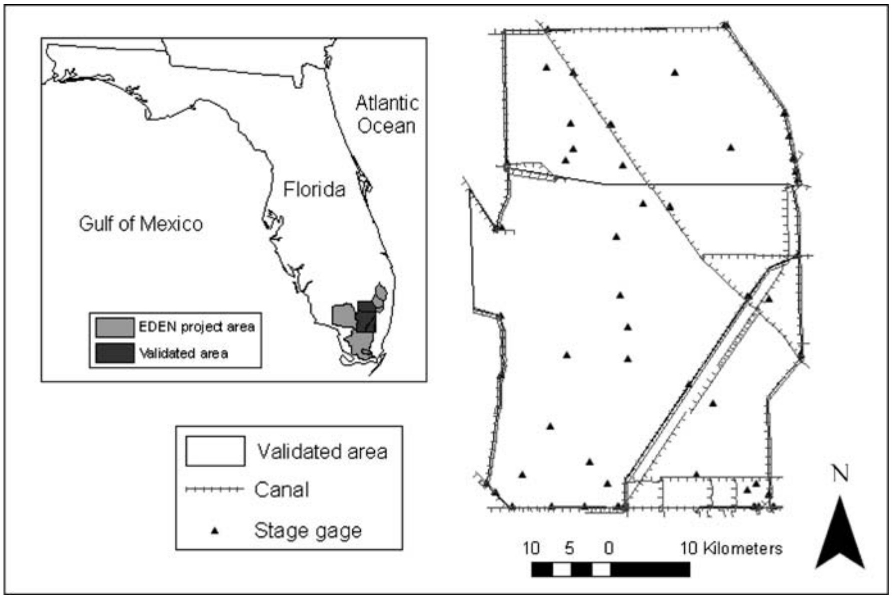


Fig. 1 Map of the study area (highlighted in the entire Florida map in the *upper left*) and location of the real-time stage monitoring gages

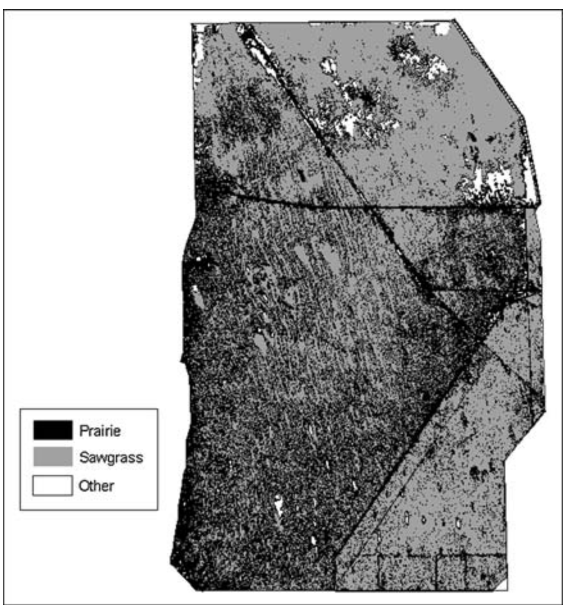


Fig. 2 Land cover map of the study area created from aerial photographs. Original map provided by K. Rutchey of SFWMD (Rutchey et al. 2005) was modified by aggregating areas that are non-prairie and non-sawgrass

each gage was used and apparently erroneous daily values that are extremely different from previous records were eliminated. Since continuous water flow in the Greater Everglades is interrupted by canals and levees, we simulated boundary conditions by linearly interpolating gage data along canals and these values were re-sampled every 200 m. Daily median stage data including re-sampled values along canals were interpolated using multiquadric RBF with an anisotropic neighborhood search in eight cardinal directions (Palaseanu and Pearlstine 2008). RBF is an exact interpolation method in which the interpolated surface passes directly through data values. The radial basis function is a special case of the basis function,

$$f(r) = \sum_{i=1}^{n} w_i h_j(r)$$

where w_i is a weight parameter, and $h_j(r)$ is the multiquadric function,

$$h(r) = \sqrt{r^2 + \varphi^2}$$

where $\varphi = |s_i - s_o|$, the Euclidian distance between the predicted location (s_o) and each known data location (s_i), and r is a smoothing parameter. The sum can also be considered as a single-layer neural network called a radial basis function network. Weight parameters, w_i, were determined so that predicted values at each location exactly matched data values (Johnston et al. 2003). Palaseanu and Pearlstine (2008) compared a number of smoothing parameters that tied to the scale of the problem, the data distribution, and density of data, and suggested that a smoothing parameter equal to the minimum distance between data points had resulted in minimum cross-validation error (Hardy 1977; Franke

1982; Golberg et al. 1996; Rippa 1999; Ferreira et al. 2005). We implemented the interpolation using ArcGIS 9.1 Geostatistical Analyst extension.

Daily water depth surfaces were created by subtracting the DEM from the daily stage surface for each day. The model's spatial resolution was 400 m to match the spatial resolution of the DEM. Obeyselera and Rutchey (1997) reported that the area-perimeter relationship changes beyond a spatial resolution of 100 m and that important features disappear beyond 700 m resolution in the Everglades landscape. Our project resolution is not optimal for capturing detailed ground features, but was considered to be within the reasonable range (<700 m) for application to regional biological modeling.

The validation water depth data consist of 751 measurements which were taken between April 1999 and September 2004 on 70 different days at different locations throughout the study area and are independent of the radio-transmitted stage data. Modeled water depth surfaces for corresponding dates were created and predicted values at locations of validation measurements were extracted.

Equivalence testing for model validation

Among a number of previously proposed methods of equivalence testing (McBride 1999), we used a paired *t*-test for equivalence for model validation because it is the uniformly most powerful invariant test under the assumption of normal distribution (Wellek 2003; Robinson and Froese 2004). An equivalence test reverses the usual null hypothesis of non-difference. A paired *t*-test is typically conducted to determine whether two paired sets of observations significantly differ from each other. The test statistic is

$$t_d = \frac{\bar{d} - \delta_0}{\sqrt{\frac{s_d^2}{n}}}$$

where $\bar{d}$ is the mean of the sample differences (d as defined by predicted minus observed values), δ_0 is the population mean difference (usually zero for a null hypothesis of no difference), s_d^2 is the estimated variance of the differences, and n is the number of samples. Then, d has the central t distribution under the condition, $\mu_1 = \mu_2$.

The paired *t*-test for equivalence uses the critical value C as a threshold distance from the mean. If the value $|t_d|$ is above this threshold C, the predicted and observed distributions are said to be dissimilar. The critical value C is the α-quantile of $F\ (1,\ n-1,\ \lambda)$, i.e., F distribution with degrees of freedom $1,\ n-1$, and non-centrality parameter of λ, where $\lambda = n \times \varepsilon^2$, where ε is relative to the sampled standard deviation (SD) of difference, s_d (epsilon). For our study, the null and alternative hypotheses are:

$H_0 : \delta_0 \neq 0$, and

$H_1 : \delta_0 = 0$

The null hypothesis of dissimilarity is rejected if the test statistic (t_d) is smaller than C. We used an α level of 0.05 and 25% and 50% of SD for epsilon where the former is for strict and the latter is for liberal tests (Wellek 2003).

Identifying error sources and model calibration

We suspected that there are four major factors which may affect prediction accuracy: (1) density of stage gages, (2) proximity to a canal, (3) seasonality (dry or wet), and (4) dominant vegetation type. Higher prediction accuracy (smaller absolute d, hereafter denoted as $|d|$) was anticipated at locations with a larger number of stage gages. We created a density map of stage gages, and using the validation data, we examined the correlation between density and $|d|$. Since canals divide hydrological connectivity throughout the area and canals have deeper water compared to marshes, we suspected that interpolation may result in higher prediction (larger d) in marsh closest to canals. Proximity of each validation point to a canal was computed and the correlation between proximity to canals and d was examined.

Particular seasonality and dominant vegetation type may cause systematic prediction error, such as overall lower or higher surface water depth predictions. Moreover, these factors may interact to affect prediction accuracy. The effect of season and dominant vegetation was tested with ANOVA *F*-tests. We used a GIS vegetation map, provided by K. Rutchey of the South Florida Water Management District (Rutchey et al. 2005), to identify the dominant vegetation type, either sawgrass or wet prairie, at each validation point (Fig. 2). This map, based on aerial photographs flown in September 1994 and June 1995, was the finest-resolution and most recent available vegetation map of the validation site that was assessed to have 89.7% accuracy; however, with major hurricanes in south Florida, land cover might have altered and the accuracy of the map for our validation period (1999–2004) might be lower than the original accuracy. To minimize effects of transition between two dominant land cover types, we avoided water depth measurements taken at marginal areas. Validation data were also classified by seasonality: dry season (November–May) or wet season (June–October). Identified influential factors were used to calibrate the water depth surface model using regression and the calibrated water depth model was further validated using equivalence testing. We used an α level of 0.05 for all tests.

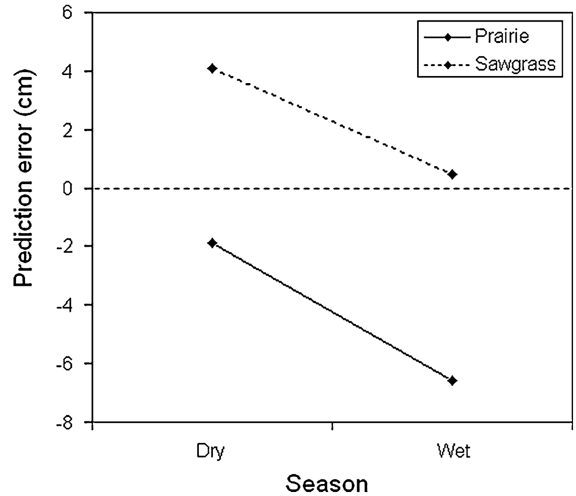


Fig. 3 Mean response plot of prediction error (*d*) by season and dominant vegetation type

Result

Overall mean difference ($\bar{d}$) between measured (W_{obs}) and predicted (W_{pred}) water depths ($W_{pred} - W_{obs}$) was close to zero ($\bar{d} = 0.29$ cm) but the standard deviation was large (SD = 14.28). This suggests that overall, our prediction was unbiased but large variability in prediction accuracy exists. A very small correlation between $|d|$ and density of stage gages ($r = -0.03$) indicates that prediction accuracy does not depend on this attribute. Mean distance between validation points and canals was 4,510 m (SD = 3,276; range 117–13,466). Correlation between d and proximity to a canal was weakly positive ($r = 0.13$). This did not support our suspicion that the model predicts higher water depth near canals, that is, negative correlation between d and proximity to a canal.

ANOVA F-test results showed that season and dominant vegetation do not interact significantly to affect prediction error ($P = 0.63$); however both season ($P < 0.01$) and dominant vegetation ($P < 0.01$) independently affect prediction error, suggesting that the seasonal effect on prediction error was consistent across different dominant vegetation types and vise versa (Fig. 3). On average, d was 6.55 cm higher in sawgrass-dominated areas as compared to prairie-dominated areas. Likewise, d was 4.15 cm higher in the dry season as compared to the wet season. A summary of W_{obs}, W_{pred}, and d by season and dominant vegetation is shown in Table 1. Equivalence testing was conducted for each combination of season and vegetation type including dry season-prairie, dry season-sawgrass, wet season-prairie, and wet season-sawgrass. Although correlation (r) between W_{obs} and W_{pred} was high for all combinations of season and vegetation type (0.83–0.96), the null-hypothesis of dissimilarity between W_{obs} and W_{pred} was rejected with the strict test only for dry season-prairie and wet season-sawgrass (Table 1; Fig. 4). On average, the model predicted water depth higher by 4.1 cm in dry season-sawgrass areas, while it predicted water depth lower by 6.6 cm in wet season-prairie areas. With the liberal test, the null-hypothesis was rejected for dry season-sawgrass in addition to dry season-prairie and wet season-sawgrass. For dry season-sawgrass and wet season-prairie, for which the null-hypothesis of dissimilarity was not rejected with the strict test, we calibrated predictions using linear regression (Table 2). Figure 5 illustrates that d centered on zero once linear regression was added to the multiquadric RBF interpolation. With equivalence testing after calibration, the null-hypothesis of dissimilarity between W_{obs} and W_{pred} was rejected for both dry season-sawgrass and wet-season prairie, confirming equivalence between W_{obs} and W_{pred}.

Discussion

Equivalence testing can be a rigorous method for model validation. Despite the high correlation between W_{obs} and W_{pred} in dry season-sawgrass ($r = 0.84$) and

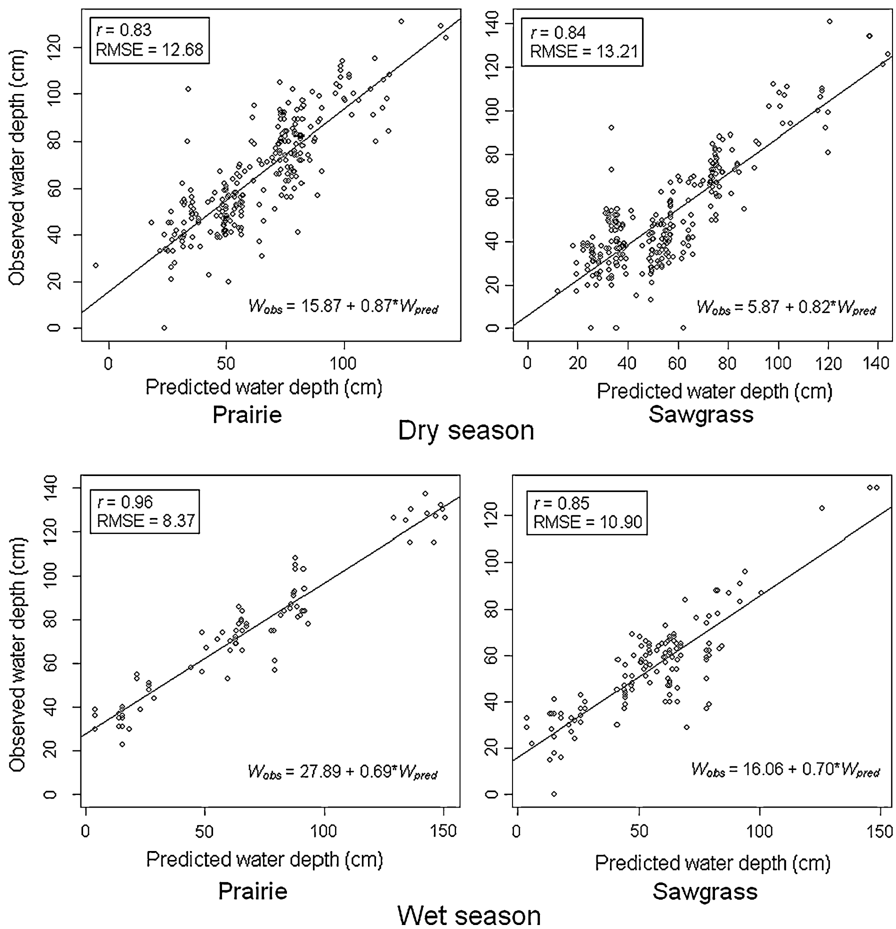
Table 1 Mean and standard deviation (SD) of observed and predicted water depths and prediction error (d) by season and dominant vegetation type and the results of equivalence testing

Season	Dominant vegetation	N	Observed		Predicted		d		t_d	
			Mean	SD	Mean	SD	Mean	SD		
Dry	Prairie	256	65.63	22.74	63.73	24.21	−1.89	13.72	−2.20	*
	Sawgrass	282	51.12	24.13	55.20	24.64	4.08	13.92	4.92	**
Wet	Prairie	78	75.01	29.04	68.42	40.39	−6.59	15.07	−3.86	
	Sawgrass	135	53.81	20.93	54.30	25.74	0.49	13.39	0.42	*

* The null hypothesis was rejected with the strict (epsilon = 0.25) and liberal (epsilon = 0.5) tests

** The null hypothesis was rejected with the liberal (epsilon = 0.5) test

Fig. 4 Plots of predicted and observed water depths with linear regression lines by season and dominant vegetation type



wet season-prairie ($r = 0.96$), equivalence was not confirmed with the strict test when the surface water depth model was created only from multiquadric RBF interpolation of stage and DEM. Overall, our model predicted higher water depths than observed in dry season-sawgrass, in which surface water tends to become shallow, and in contrast, it predicted lower water depths than observed in wet season-prairie, in which surface water tends to become deep. However, as we illustrated, the results of the equivalence test varied by the magnitude of the region of similarity employed. With the liberal test, wet season-prairie was the only season-vegetation combination for which the null-hypothesis was not rejected.

Table 2 Mean and standard deviation (SD) of observed and predicted water depths, prediction error (d) and the result of equivalence testing for dry season-sawgrass and wet season-prairie after applying corrections

Season	Dominant vegetation	N	Predicted		d		t_d	
			Mean	SD	Mean	SD		
Dry	Sawgrass	282	75.10	27.87	0.09	8.32	0.0002	*
Wet	Prairie	78	51.13	20.21	0.01	13.19	0.0002	*

* The null hypothesis was rejected with the strict (epsilon = 0.25) test

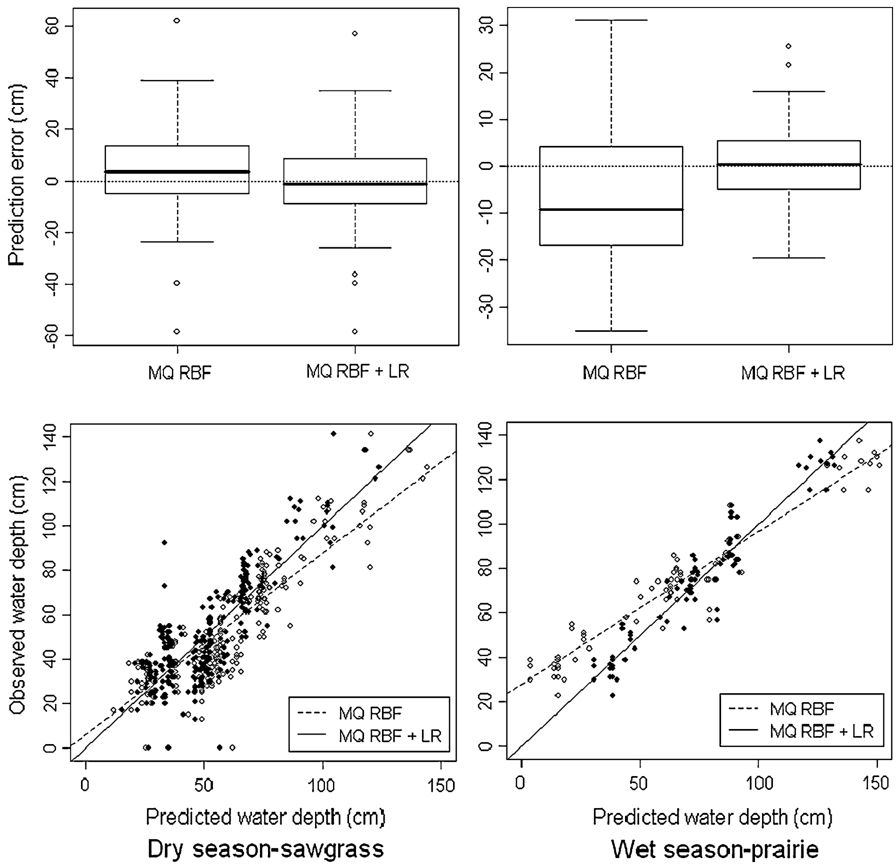


Fig. 5 Box plots to compare prediction error ($W_{pred} - W_{obs}$) with radial basis function multiquadric interpolation only (MQ RBF) and with calibration using linear regression (RBF MQ + LR) (*top*). Plots of predicted and observed water depths with linear regression lines for dry season-sawgrass and wet season-prairie with multiquadric RBF only (*empty-dots* and *dashed-line*) and with calibration using linear regression (*filled-dots* and *solid line*) (*bottom*)

Notably, prediction errors were compounded from two distinct error sources in our proposed model algorithm: interpolation method (multiquadric RBF) and DEM based on surveys with the aerial height finder. The multiquadric RBF interpolates data with neighbors minimizing total curvature of the output surface which tends to result in a smooth surface (Franke 1982). The method is considered to be useful for gradually varying elevation models and hydrologic models because of this property. Since our study area is a mosaic of different land cover types (Fig. 2), infiltration characteristics are different at finer spatial scales depending on the ground type. As it is known that landscape fragmentation affects hydrologic consequences (Ziegler et al. 2004), spatial discontinuities resulting from vegetation mosaics with differing flow resistances may be introducing added spatial variance to water stages that has not yet been accounted for. Our methodology of stage interpolation may be elaborated by accounting for ground type in the model algorithm, for example, by interpolating neighboring data with the same vegetation type for each predicted location or accounting for spatial discontinuity in selecting the neighbors. Errors in the

DEM comprise two major factors: errors associated with the aerial height finder survey and interpolation of the elevation data. Although effects of ground cover type on height finder measurements were not examined, vegetation cover and soil depth might be factors that affect accuracy and precision of the elevation measurement. Observed prediction error associated with ground type (Fig. 3) may be due to errors in height finder measurements associated with different land cover types. Overall, mean prediction error ($\bar{d}$) of surface water depth ranged −6.6 to 4.1 cm. This was within the range of the vertical accuracy of the aerial height finder (Desmond 2003). Johns and Price (2007) reported that cross-validation associated with the DEM within the area ranged from 9 to 11 cm, suggesting that rasterizing point elevation data to the DEM potentially comprises a large portion of the prediction error.

We suspect that the large standard deviation (13–15 cm) in prediction error is attributed to the model scale. Scale impact on model output is a common factor that affects accuracy in raster-based spatial models because a unit of area encompassed by single grid cell is represented by a single value. In our study, field observations of water depth for the validation were made at points while predicted depths are single values for each 400 m × 400 m grid cell. Short of having adequate field observations to report variability within 400 m cells for each unique condition, it becomes incumbent on users of these surfaces for ecological evaluations to recognize that the water depth reported for each cell represents the modeled most likely aggregate value over 400 m. Possible within-cell variability should be recognized. As Obeyselera and Rutchey (1997) reported that most important ground features can be preserved with 100 m spatial resolution in the Everglades landscape, our model prediction may be improved by refining the spatial resolution; however, such detailed elevation surveys across the entire Everglades is cost prohibitive.

Our model is the finest-scale spatially explicit daily hydrologic model for the Greater Everglades that currently exists. While the results of equivalence testing did not confirm validity of our initially proposed model algorithm across different seasons and vegetation types, the results indicated several positive aspects of our model. First, error was not associated with density of gage stations, which suggests there is sufficient geographic coverage of stage monitoring gages throughout the area. Second, accuracy was not associated with proximity to canals, which suggests there is reasonable separation between canal and marsh. Based on our validation results, which indicated high correlation between predicted and observed water depths, our current daily surface water depth model may be suitable to examine correlations between water depth and other ecological attributes; however cautions are needed since degree of error is non-uniform across the landscape; overall higher- or lower-predictions might occur depending on seasonality and ground type. As we demonstrated, errors associated with seasonality and vegetation type can be calibrated using independent calibration data sets using regression models.

In this study, we validated model prediction only in WCA 3, because a vegetation map and sufficient independent data were unavailable for other areas. Extended validation of the model prediction in other modeled areas would be informative for understanding differences in model accuracy across sub-areas. A critical area for validation is ENP, which is different from WCA because water flow and surfaces there are not constrained on the bottom by a levee. It has been proposed that in the park, benchmarks in marsh areas should be placed away from gages, for the specific purpose of continuing validation.

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References

Busch DE, Loftus WF, Bass OL (1998) Long-term hydrologic effects on marsh plant community structure in the southern Everglades. Wetlands 18:230–241

Curnutt JL, Comiskey J, Nott MP, Gross LJ (2000) Landscape-based spatially explicit species index models for Everglades restoration. Ecol Appl 10:1849–1860. doi:10.1890/1051-0761(2000)010[1849:LBSESI]2.0.CO;2

David PG (1996) Changes in plant communities relative to hydrologic conditions of the Florida Everglades. Wetlands 15:15–23

Desmond GB (2003) Measuring and mapping the topography of the Florida Everglades for ecosystem restoration. U.S. Geological Survey Fact Sheet 021-03, 4 pp

Duke GD, Kienzle SW, Johnson DL, Byrne JM (2003) Improving overland flow routine by incorporating ancillary road data into digital elevation models. J Spat Hydrol 3:1–27

Ferreira AJM, Roque CMC, Martins PALS (2005) Analysis of thin isotropic rectangular circular plates with multiquadrics. Strength Mater 27:63–173

Franke R (1982) Scattered data interpolation: tests of some methods. Math Comput 38:181–199. doi:10.2307/2007474

Gentil S, Blake G (1981) Validation of complex ecosystem models. Ecol Modell 14:21–38. doi:10.1016/0304-3800(81)90012-0

Golberg MA, Chen CS, Karur SR (1996) Improved multiquadric approximation for partial differential equations. Eng Anal Bound Elem 18:9–17. doi:10.1016/S0955-7997(96)00033-1

Gunderson LH (1989) Vegetation of the Everglades: determinants of community composition. In: Davis SM, Ogden JC (eds) Everglades: the ecosystem and its restoration. St. Lucie Press, Delray Beach, pp 323–340

Hardy RL (1971) Multiquadric equations of topography and other irregular surfaces. J Geophys 76:1905–1915. doi:10.1029/JB076i008p01905

Hardy RL (1977) Least squares prediction. Photogramm Eng Remote Sensing 43:475–492

Hardy RL (1990) Theory and applications of the multiquadric-biharmonic method. Comput Math Appl 19:163–208. doi:10.1016/0898-1221(90)90272-L

Immanuel A, Berry MW, Gross LJ, Palmer M, Wang D (2005) A parallel implementation of ALFISH: simulating hydrological compartmentalization effects of fish dynamics in the Florida Everglades. Simul Model Pract Theory 13:55–76. doi:10.1016/j.simpat.2004.09.002

Johns WJ, Price SD (2007) Initial Everglades depth estimation network (EDEN) digital elevation model research and development. U. S. Geological Survey, Open File Report 7007–1304, Reston, Virginia

Johnston K, Ver Hoef JM, Krivoruchko K, Lucas N (2003) Using ArcGIS geostatistical analyst. ESRI Press, Redlands 307 pp

Loucks DP (2005) Modeling and managing the interactions between hydrology, ecology and economics. J Hydrol (Amst) 328:408–416. doi:10.1016/j.jhydrol.2005.12.020

Loveless CM (1959) A study of the vegetation in the Florida Everglades. Ecology 40:1–9. doi:10.2307/1929916

MacVicar TK, VanLent T, Castro A (1983) South Florida water management model-documentation report. South Florida Water Management District, West Palm Beach, Florida, USA

Mayer DG, Butler DG (1993) Statistical validation. Ecol Modell 68:21–32. doi:10.1016/0304-3800(93)90105-2

McBride GB (1999) Equivalence tests can enhance environmental science and management. Aust N Z J Stat 41:19–29. doi:10.1111/1467-842X.00058

Obeyselera J, Rutchey K (1997) Selection of scale for Everglades landscape models. Landscape Ecol 12:7–18. doi:10.1007/BF02698203

Olmsted I, Armentano TV 1997. Vegetation of Shark Slough, Everglades National Park. SFNRC technical report 97-001. South Florida Natural Resources Center, Everglades National Park, Homestead, Florida

Palaseanu M, Pearlstine L (2008) Estimation of water surface elevations for the Everglades, Florida. Comput Geosci 34:815–826. doi:10.1016/j.cageo.2007.08.004

Ramesh SV, Teegavarapu RSV, Chandramouli V (2005) Improved weighting methods, deterministic and stochastic data-driven models for estimation of missing precipitation records. J Hydrol (Amst) 312:191–206. doi:10.1016/j.jhydrol.2005.02.015

Rippa S (1999) An algorithm for selecting a good value for the parameter c in radial basis function interpolation. Adv Comput Math 11:193–210. doi:10.1023/A:1018975909870

Robinson IP, Froese RE (2004) Model validation using equivalence tests. Ecol Modell 176:349–358. doi:10.1016/j.ecolmodel.2004.01.013

Robinson IP, Duursma RA, Marshall JD (2005) A regression-based equivalence test for model validation: shifting the burden of proof. Tree Physiol 25:903–913

Ross MS, Reed DL, Sah JP, Ruiz PL, Lewin MT (2003) Vegetation: environment relationships and water management in Shark Slough, Everglades National Park. Wetlands Ecol Manage 11:291–303. doi:10.1023/B:WETL.0000005541.30283.11

Rutchey K, Vilcheck L, Love M (2005) Development of a vegetation map for water conservation area 3. Technical publication ERA 421, Everglades Division, Watershed Management Department, South Florida Water Management District, West Palm Beach, Florida

Rykiel EJ (1996) Testing ecological models: the meaning of validation. Ecol Modell 90:229–244. doi:10.1016/0304-3800(95)00152-2

South Florida Water Management District (2005) Final documentation for the South Florida water management model. Hydrologic & Environmental Systems Modeling Development, Everglades Restoration, South Florida Water Management District, West Palm Beach, Florida

Strack ODL (1989) Groundwater mechanics. Prentice-Hall, Englewood Cliffs

Strack ODL, Jankovic I (1999) A multi-quadric area-sink for analytic element modeling of groundwater flow. J Hydrol (Amst) 226:188–196. doi:10.1016/S0022-1694(99)00147-X

US Army Corps of Engineers (2006) Everglades depth estimation network: annual status report 2006. U. S. Army Corps of Engineer, Jacksonville, Florida

Vieux BE (2001) Distributed hydrologic modeling using GIS, water science and technology library. Kluwer Academic Publishers, Dordrecht

Walters C, Gunderson L, Holling CS (1992) Experimental policies for water management in the Everglades. Ecol Appl 2:189–202. doi:10.2307/1941775

Wellek S (2003) Testing statistical hypothesis of equivalence. Chapman and Hall, London

Ziegler AD, Giambelluca T, Tran LT, Vama TT, Nullet MA, Fox J, Vien TD, Pinthong J, Maxwell YF, Evett S (2004) Hydrological consequences of landscape fragmentation in mountainous northern Vietnam: evidence of accelerated overland flow generation. J Hydrol (Amst) 287:124–146. doi:10.1016/j.jhydrol.2003.09.027