

Effects of the spatial distribution of best management practices for watershed wide nutrient load reduction

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ABSTRACT

Excessive nutrient loads represent a major source of water pollution globally. Best Management Practices (BMPs) are typically implemented in agricultural and urban landscapes to reduce nutrient losses at individual parcels. However, the effectiveness of BMPs in reducing nutrient loads at regional watershed domains remains an open question. This study aims to evaluate the effectiveness of parcel-based agricultural and urban BMP implementations in reducing watershed-wide phosphorus (P) and nitrogen (N) loads. The Lake Okeechobee watershed in Florida (USA), covering 10,600 km² of mixed agricultural and urban land-use/land-cover, is used as a case study. Hydrological and nutrient transport processes were simulated using the Watershed Assessment Model (WAM). The model was calibrated and validated for river discharge and nutrients for each of the six sub-watersheds, with R² values ranging from 0.43 to 0.80 for flows and 0.24 to 0.85 for nutrients. Four what-if scenarios were simulated representing different regional BMP implementations: No BMPs implemented, current conditions (1032 km² area influenced), maximum potential scenario (5923 km² area influenced), and optimal BMP placement. Simulations indicated that currently implemented BMPs could be reducing P loads from 482 to 468 tons/year (3%) and N loads from 4384 to 3796 tons/year (13%). Implementation of all potential BMPs could reduce P to 307 tons/year (36%) and N to 3036 tons/year (31%). Dividing the watershed into subwatersheds illustrated that BMPs in Taylor Creek-Nubbin Slough (50% agriculture) have the potential to reduce P by 55%, and in Upper Kissimmee (23.5% urban) BMPs have the potential to reduce N by 42%. In addition, optimal BMP spatial distributions in each subwatershed could reduce P loads and N loads by 10% and 4%, respectively, providing a cost-effective solution to nutrient pollution mitigation. Our simulations suggest that other strategies would be needed to further reduce P and N, especially in subwatersheds that have low BMPs reduction potential.

1. Introduction

Nutrient loading from nonpoint sources has been a major cause of aquatic environment degradation in watersheds around the globe (Xu et al., 2013; Robinson and Melack, 2013). Excessive nutrient loads, primarily phosphorus (P) and nitrogen (N) in different organic and inorganic forms, to streams and lakes negatively impact the environment by causing algal blooms, oxygen deficiency, and biodiversity deterioration (Carpenter et al., 1998; Lamba et al., 2016). In addition,

large nutrient loading causes eutrophication, which is the most common type of impairment of surface waters in the United States (U.S. EPA, 1990). Thus, conservation programs proposed by the U.S. Clean Water Act, widely known as best management practices (BMPs), have been widely implemented in impaired watersheds to reduce nutrient loads from nonpoint sources (Gaddis et al., 2014; Shen et al., 2015; Sharpley et al., 2015; Osmond et al., 2012; Khare et al., 2021; Dai et al., 2018).

Lake Okeechobee, the largest hydrologically regulated lake in the US by surface area (1732 km²), plays a crucial role in South Florida,

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supplying water for consumption to five municipalities and two Native American communities, irrigation water for the Lake Okeechobee Service Area and Everglades Agricultural Area, environmental flows for the Everglades National Park, as well as freshwater for the St. Lucie and Caloosahatchee estuaries (Paudel et al., 2020). Lake Okeechobee is a nutrient impaired lake as per the Florida Department of Environmental Protection (FDEP; Faridmarandi et al., 2020). The main source of P and N has been nonpoint agricultural runoff from fertilizers, animal waste, and legacy nutrients stored in soils (Boggess et al., 1995; Hiscock et al., 2003; Ma et al., 2020).

BMPs, in the context of this paper are defined as parcel-based activities and technologies that are implemented to reduce nutrient loads into drainage waters (Bottcher et al., 1995; Khare et al., 2019a, 2019b). BMPs have been widely used to address hydrology and water quality issues in both agricultural and urban areas (Liu et al., 2017). BMPs effectiveness to reduce watershed-wide nutrient loads have been widely evaluated. Some studies evaluated the impacts of different BMPs implementation scenarios (types and locations) on P loads in agricultural watersheds (Gaddis et al., 2014; Dong et al., 2018; Pokhrel and Paudel, 2019; Hanief and Laursen, 2019; Khare et al., 2020), while other studies have also considered N load reductions in addition to P in agricultural watersheds (Chaubey et al., 2010; Himanshu et al., 2019; Risal and Parajuli, 2022). However, evaluating the impacts of BMPs in urban watersheds, addressing the potential of a regional combination of BMPs to minimize nutrient loads, and determining the optimal spatial distribution (location and type) of BMPs, are critical considerations in the management of impaired watersheds in need of further research. Effectiveness of various BMP scenarios on nutrient load reductions in a section of the northern Lake Okeechobee Watershed was already evaluated using the Watershed Assessment Model (WAM; Corrales et al., 2017; Khare et al., 2021; Khare et al., 2019a, 2019b), but effects of current and potential portfolios of BMPs throughout the entire watershed on total P and N loads to the lake remain an open question. Moreover, previous studies in Lake Okeechobee Watershed focused on phosphorus, which is critical to mitigate detrimental effects to freshwater bodies. However, nitrogen reduction needs to also be considered simultaneously to improve water quality in the lake, in particular in relationship to cyanobacteria algal blooms (Paerl et al., 2020; Vermeylen et al., 2022; Rosen et al., 2017; Medina et al., 2020; Dang et al., 2023). In summary, BMP effects on nutrient loads have been addressed, though few studies have considered both nitrogen and phosphorus or determined the maximum potential of a watershed to reduce nutrients.

This study evaluated the effectiveness of BMPs in mixed agricultural and urban watersheds in reducing P and N loads to a eutrophic lake. The physically-based hydrologic-water quality WAM model was utilized to simulate hydrology and nutrient dynamics in Lake Okeechobee's watersheds. Then, the model was used to evaluate the effects of four different scenarios of watershed-wide BMPs distribution: current conditions, no BMPs implemented in the watershed, BMPs implemented in every potential location, and optimal spatial distributions of BMPs. In addition, uncertainties in BMP removal efficiencies were considered. The ultimate goal of this study is to guide future research and the implementation of an optimal placement and performance expected for a portfolio of BMPs in order to reduce the net watershed contribution of nutrient loads to a receiving water body.

2. Materials and methods

2.1. Case study area: Lake Okeechobee Watershed

This study focused on the northern Lake Okeechobee Watershed, the primary source of water and nutrients to the lake. Even though the lake also receives some drainage from the south, east and west sides, these contributions account for only 6% of the flow, facilitated through a complex system of pumped back flows that were excluded from this study (Abtew et al., 2007). The Lake Okeechobee Watershed covers an

area of 10,600 km², which is characterized by various types of agricultural crops, natural vegetation, multiple open water bodies, and considerable area of medium density residential, though the relative combination of land-use/land-cover (LULC) varies by sub-watershed (Fig. 2). Lake Okeechobee Watershed has exported large nutrient loads over the last eight decades to Lake Okeechobee, which led to the designation of Lake Okeechobee as an impaired waterbody for P. Thus, a total maximum daily load (TMDL) of P loads to Lake Okeechobee has been identified by the FDEP to achieve a target restoration goal of 40 ppb in the pelagic zone of the lake. The TMDL of P loads is 140 tons per year, including 105 tons from watershed runoff and 35 tons from atmospheric deposition (FDEP, 2001). The Kissimmee River represents the largest source of flow (56%), P loads (34%), and N loads (46%) to Lake Okeechobee (Tarabih and Arias, 2021; Zhang and Welch, 2018; James and Zhang, 2008; Bertolotti et al., 2014; Welch et al., 2019). The Upper Kissimmee is the northernmost sub-watershed of the Lake Okeechobee Watershed (Fig. 1), and it is also the largest, covering an area of almost 4162 km². The Lower Kissimmee sub-watershed covers an area of 1737 km² and the Taylor Creek/Nubbin Slough (here referred to as Taylor/Nubbin) sub-watershed occupies an area of 800 km². The Fisheating Creek sub-watershed covers an area of 1285 km² and is unique in that the discharge to Lake Okeechobee has no control structure at the sub-watershed mouth. Lake Istokpoga sub-watershed spans an area of 1595 km² that discharges to the Indian Prairie sub-watershed, which covers an area of 1119 km² on its southern edge. The Indian Prairie releases most of its water and nutrients directly to Lake Okeechobee, while also discharging a portion of its water to the Kissimmee River, which ultimately flows into Lake Okeechobee.

2.2. Watershed assessment model (WAM)

WAM is a spatially distributed, physically-based hydrologic/water quality model designed to handle the unique hydrologic conditions of Florida (e.g., canals that experience periodic flow reversals, abundance of wetlands, high-ground water table, and operations of water control structures; Khare et al., 2019a, 2019b; Shin et al., 2023). A detail description of the model is presented in SWET (2018), but here we synthesized information on some of its key features related to our study. WAM simulates water and constituents through the watershed in three phases. Phase 1 is the source cell simulation where WAM overlays LULC, soil, rainfall, and wastewater service areas for each cell in the watershed to identify the unique combinations of these inputs. Then, WAM uses the Basin Unique Cell Shell submodule to simulate daily surface and groundwater flows and constituent concentrations leaving every grid cell in the watershed. Phase 2 represents the source cell to hydrologic features routing where runoff flow and constituents are routed through the encountered landscape to the closest reach using the Basin Land Area to Stream Routing (BLASROUTE) submodule. A unit hydrograph is applied to the flows and loads leaving each source cell to distribute the delivery of water to the associated outflow reach. In the final phase, stream routing collects all side flows (surface runoff and groundwater percolation) to each individual stream and routes the flow hydrodynamically through the stream network using the BLASROUTE submodule. Stream routing is applied using a modified linear reservoir routing technique for solving the uniform channel flow equations utilizing the Manning's equation. Water quality constituents are attenuated overland and in-stream using Eqs. 1 and 2, respectively:

$$C = (C_0 - C_b) * e^{(-a^*(q-b)^*d)} + C_b \quad (1)$$

$$C = (C_0 - C_b) * e^{\left(-a^*\frac{x}{k}\right)} + C_b \quad (2)$$

where C represents the concentration reaching the stream (ppm), C_0 indicates concentration leaving the source cell (ppm), C_b represents the background concentration (ppm), a and b are attenuation parameters, q

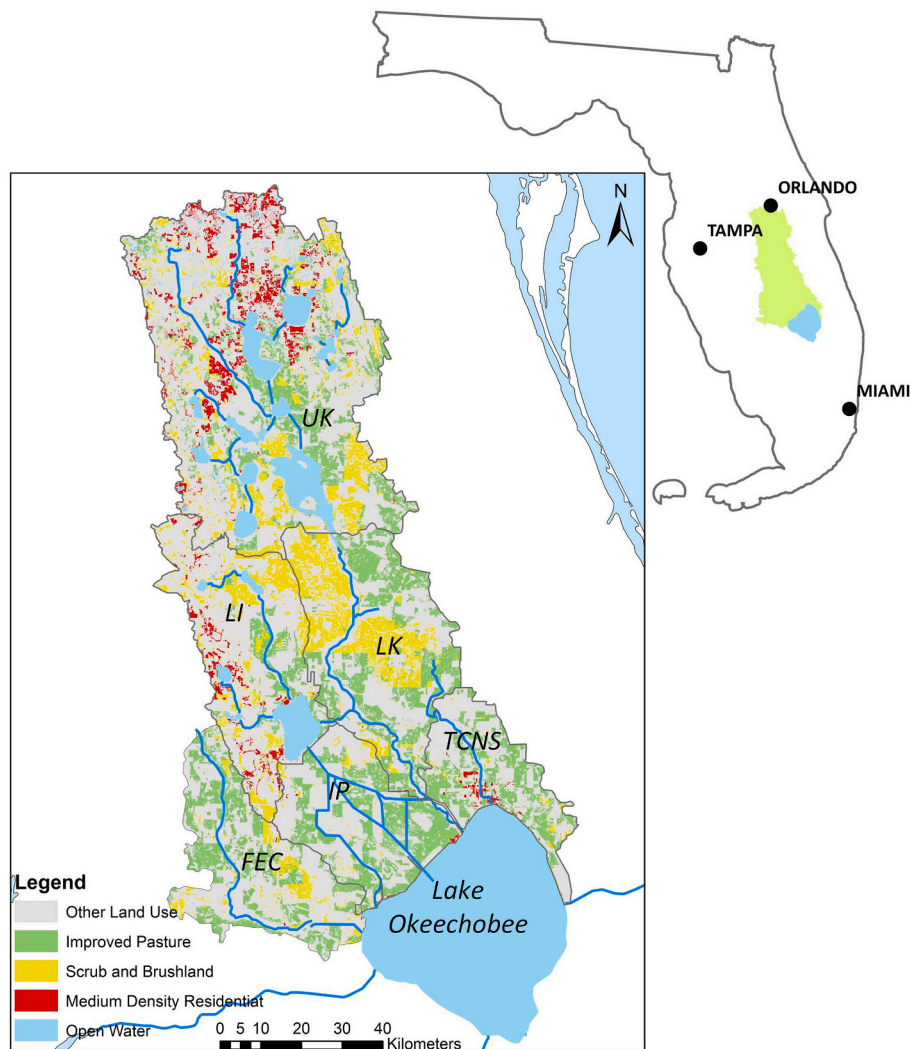


Fig. 1. The six northern Lake Okeechobee sub-watershed boundaries as analyzed in this study with the dominant land-uses in the watershed. UK: Upper Kissimmee, LK: Lower Kissimmee, LI: Lake Istokpoga, FEC: Fisheating Creek, IP: Indian Prairie, and TCNS: Taylor Creek/Nubbin Slough. Upper right side map represents the location of Lake Okeechobee and its watershed within the State of Florida.

indicates flow rate leaving the source cell ($\text{m}^3 \text{s}^{-1} \text{ha}^{-1}$), d represents the flow distance (m), τ represents time interval, and R is hydraulic radius of stream.

WAM simulates daily water quantity constituents such as water stage, depth, velocity, and flow, as well as water quality constituents such as soluble nitrate, soluble ammonia, soluble organic nitrogen, soluble phosphorus, sediment ammonia, sediment organic nitrogen, sediment phosphorus, total suspended solids, and biological oxygen demand. WAM is calibrated in two steps: 1) hydrologic and hydraulic calibration, in which WAM's global parameters are changed to minimize deviation between flow simulations and observations at the watershed outlet; 2) constituent concentration calibration, where constituent routing parameters are fine-tuned to minimize departures of simulated constituent concentrations from related measurements at the watershed outlet.

The WAM application used in this study was originally developed as a result of FDEP's Lake Okeechobee Basin Management Action Plan (BMAP; [SWET, 2015](#)), though we extended the simulation period to 1995–2018 and recalibrated/validated the model. We simulated each sub-watershed separately because simulating the entire Lake Okeechobee Watershed requires heavy computational resources. Yet, for inter-dependent subwatersheds (Upper-Lower Kissimmee and Lake Istokpoga-Indian Prairie), boundary conditions were incorporated from the

upstream sub-watershed into the downstream simulations. The model was recalibrated by dividing the study period into two separate periods: calibration period (1995–2006) and validation period (2007–2018). The model was calibrated and validated for both hydrology (i.e., flow) and nutrients (i.e., total phosphorus and total nitrogen). The hydrologic calibration was performed by fine-tuning the Potential Evapotranspiration Adjustment parameters to override the amount of potential evapotranspiration estimated with the Priestley-Taylor method (default option in WAM). The nutrient concentration calibration was performed by modifying the constituent global attenuation parameters to enhance the simulated concentrations of phosphorus and nitrogen. The calibration procedure was performed manually by modifying one or more parameters and run the model to evaluate the targeted output (i.e., flow, P, and N). Hydrologic and nutrient simulation performance in each sub-watershed was evaluated utilizing three statistical evaluation metrics: coefficient of determination (R^2), Nash Sutcliffe coefficient (NS), and Percent BIAS (PBIAS). A brief description of each metric is provided in the Supplementary Materials, and for a more detailed description the reader can refer to [Moriassi et al. \(2015\)](#).

2.3. Data sources

WAM requires different spatially distributed GIS-based data

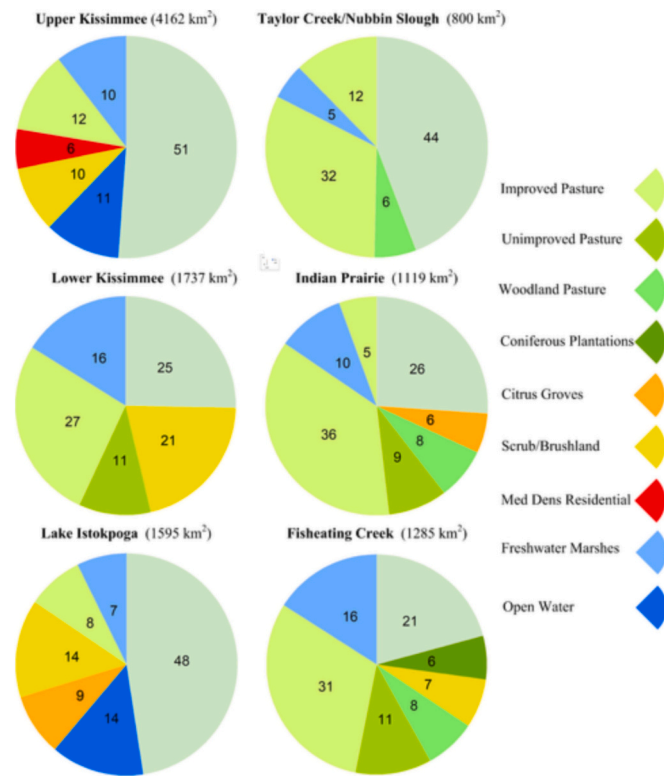


Fig. 2. Dominant land-use/land-cover categories in each of the six northern Lake Okeechobee sub-watersheds. Numbers indicate the percentage of area coverage for each LULC category, relative to the total area of the sub-watershed.

including topography, LULC, and soil data (Fig. 3). In addition, WAM requires different time series data incorporating rainfall, water flow, and nutrient data. A continuous elevation raster that covers the entire study area was obtained from the South Florida Water Management District (SFWMD). This raster has 15 m by 15 m grid cells that were resampled to one-hectare grid cells. LULC data are used to define source cell characteristics, and these were obtained from a composite of best-available data as of November 2016 created from current LULC datasets developed by the different water management districts. Soil type information was extracted from the U.S. Department of Agriculture, Natural

Resource Conservation Service published SSURGO data for 2013–2015. Daily rainfall data were synthesized for 35 gauge stations spatially distributed over the entire watershed (Fig. S1) from SFWMD's data portal (DBHYDRO). Daily water flow data were synthesized at main water control structures from DBHYDRO also (Fig. S2). Different nutrient indicators were synthesized at each water quality sampling site in the watershed from DBHYDRO, including orthophosphate, total phosphorus, nitrate, nitrite, Kjeldahl nitrogen, and total nitrogen collected at a bi-weekly basis. Existing BMPs were obtained from FDACS, representing projects implemented in the watershed by the FDACS BMP program as per 2016. BMP projects were then incorporated into the LULC map as input to the model.

2.4. Best management practices

Agricultural nonpoint sources are the major contributor of nutrients to Lake Okeechobee, thus addressing techniques to reduce these sources is crucial to mitigate nutrient levels in the lake (FDEP, 2020; Bottcher et al., 1995). The Florida Department of Agricultural and Consumer Sciences (FDACS) develops and adopts BMPs for agricultural commodity. Typical categories of FDACS agricultural BMPs include nutrient management, water resource protection, and irrigation management. Nutrient management practices minimize the impact of fertilizers and animal waste on water resources by considering their sources, application rates, and timing. Water resource protection practices consist of increasing buffers and setbacks to reduce and prevent nutrients from entering waterbodies. Irrigation management aims to reduce water and nutrient losses from agricultural practices by addressing irrigation methods and scheduling. The majority of urban BMPs in the Lake Okeechobee Watershed utilize stormwater structural retention and detention strategies (i.e., wet detention pond, dry detention pond, and constructed wetlands) that store water temporarily or permanently before discharging runoff to nearby water bodies. Other projects in the watershed include different stormwater structural and non-structural strategies, incorporating physical separation to capture and remove nutrient source (e.g., baffle boxes) and chemical processes that remove nutrient bound in the settlings generated by coagulation (e.g., alum injection system). Table 1 summarizes the type of BMPs included in this study. We considered agricultural BMPs that are approved and implemented by the state, including water retention, fertility management, animal density management, and drainage/water control structure BMPs. We included stormwater retention, and spray fields among others to be implemented in urban lands. WAM simulates each BMP based on

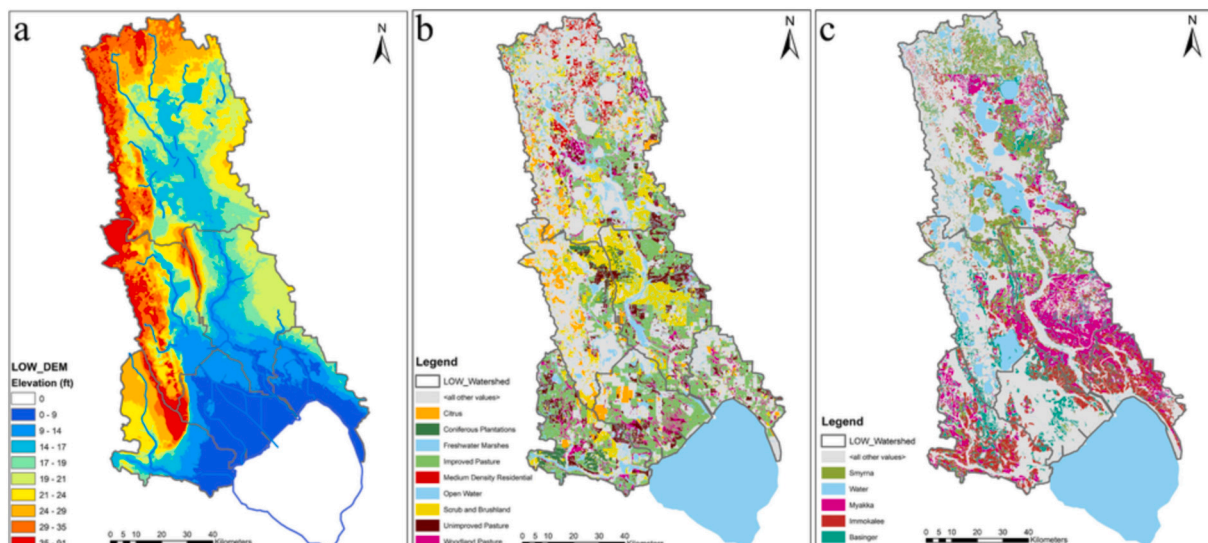


Fig. 3. Lake Okeechobee Watershed digital elevation model, LULC map, and soil type map that were used as inputs to WAM model.

Table 1

Current implemented BMPs (Cu) vs. high-efficiency BMPs for TP removal (P) vs. high-efficiency BMPs for TN removal (N) and their percentage occupied area in each sub-watershed. Information from the Florida Department of Agriculture and Costumer Service BMP program.

Sub-watershed	Upper Kissimmee			Lower Kissimmee			Taylor/Nubbin			Lake Istokpoga			Indian Prairie			Fisheating Creek		
	Cu	P	N	Cu	P	N	Cu	P	N	Cu	P	N	Cu	P	N	Cu	P	N
Drainage and water control structures		7		4	17	4	1	11	1	1	3	1	1	16	1		19	
Drainage improvements							1	1	1									
Water control structures							15	19	19				6	10	10	1	1	1
Irrigation improvements/fertigation	1	1	1	1	1	1				4	4	4	5	5	5	1	1	1
Well and trough							1	1	1									
Dairy improvements								2	2									
Retention BMP		15	12		28	27		32	32		8	8		38	38		31	31
Fertility and low animal density BMP			7			13			11			3			16			19
Retention and fertility BMP			3		2	3		2	3			9		2	8			1
Fertility BMP					2						3						6	
Non-clear cut BMP						2						3						6
Fencing										1	1	1						
Retention and water BMP								2			9			6			1	
Wet retention								1	1									
Residential to sprayfield	11	12	13			2					4	9						1
Storm retention BMP		6	6		2			8	5		7	2					1	
Offsite sewage treatment and fertility/storm retention BMP		1	1															
Offsite sewage disposal										1								
Well or pipeline									2									

its characteristics through parameterizing the LULC where this BMP is implemented; for instance, nutrient management BMPs are simulated by reducing the fertilizer application rate. Retention/detention ponds are simulated such that surface runoff is routed to and through the retention/detention pond by maintaining a complete water balance within the pond incorporating an allowance for percolation to groundwater, rainfall, and evaporation. Then, attenuation coefficients are modified properly to account for the flow to groundwater, based on the surface water flow passing through the retention/detention pond. However, BMPs that cannot be mechanistically simulated are accounted for by applying a user-defined nutrient reduction percentage at the source cell (e.g., fencing, edge of the field chemical treatment). While the concept of incorporating time-varying BMP reduction variables has been recently explored (Shen et al., 2023a, 2023b), it has only been tested in a limited number of BMPs within a small watershed with an area 2000 times smaller and 15 times less BMPs than our study watershed. Consequently, we assumed that BMP reduction factors remain constant for a given BMP throughout the entire simulation, with values synthesized from SWET (2019). Because BMPs affect nutrient loads at the source cell level, each BMP only affects a single land-use polygon it overlays.

2.5. Scenario description

WAM was used to simulate four different scenarios to evaluate the effects of spatial BMP distribution on P and N loadings to Lake Okeechobee.

1. Current BMP scenario: Implemented BMPs were incorporated into WAM simulations for the period 1995–2018. This scenario represents implemented projects until 2016 and were extracted from the FDACS database (FDEP, 2020). The existing scenario was used to calibrate the model.
2. No BMP scenario: All the implemented BMPs were removed, and the model was run for the study period (1995–2018). The No-BMP scenario was used as the reference scenario to evaluate the cumulative effects of the other scenarios.
3. Max potential scenario: All suitable BMPs were implemented in the LULC polygons where no BMPs are included yet. For every base parcel/polygon with a distinct LULC, the BMP with the highest efficiency (i.e., maximum nutrient reduction factor) associated with this LULC category was implemented, regardless of the cost. A list of

the selected high efficiency BMPs is provided in the Supplementary Material (Table S2). This scenario evaluated the potential of the commonly used -yet not implemented- BMP technologies to remove nutrients from the watershed.

4. Optimal scenario: We employed a simulation-optimization technique to derive a set of optimal scenarios aimed at minimizing nutrient loads. WAM was coupled with AquaNutriOpt, an integer linear programming optimization model (Khanal et al., 2023). This integration facilitated the identification of optimal solutions for BMP location and type, strategically minimizing P and N loads at the outlet of each subwatershed while adhering to budgetary constraints. The water network of each subwatershed was derived from WAM configurations and served as a fundamental input for the optimization model. Each node corresponds to a catchment identified in WAM (i.e., finest spatial units within a subwatershed drainage network), where the dominant LULC is identified as the primary contributor to nutrient loads within that catchment. Subsequently, candidate BMPs were identified, each having specific nutrient reduction capabilities applicable to the identified dominant LULC. P and N loads at each catchment node were obtained from the current BMP scenario. The objective function seeks to minimize the total load of the specified nutrient, denoted by Z at the sub-watershed outlet, denoted by L (Eq. 1). The flow-conservation non-linear constraint must be generated at each node j for each nutrient m as expressed by Eq. 2, wherein the total aggregated nutrient load $m \in M$ is defined as the summation of all loads entering the catchment from its upstream reaches and the amount of nutrient m generated within this specific catchment

$\left(\sum_{i \in N_j^-} f_{ijm} + p_{jm} \right)$. The implemented BMP reduction factor, if appli-

cable, is denoted as $\left(1 - \sum_{t \in T_j} \alpha_{tm} x_{jt} \right)$ where α_{tm} indicates reduction rate of technology $t \in T$ on nutrient $m \in M$, and x_{jt} is a binary variable that equals 1 if technology $t \in T$ is implemented in node $j \in N$, and 0 otherwise. The right-hand side of the flow-conservation in Eq. 2 shows the total load exiting the catchment, which must at least be equivalent to the remaining load within the catchment. The initial cost of BMP installations was integrated into the model as a constraint (Eq. 3) While Eq. 2–3 presented the main constraints of the optimization model, there are also some additional technical constraints that have not been provided details for here, including bounding constraints on each nutrient type load, splitting constraints

for nodes with multiple outgoing reaches, and implementation restrictions of BMPs at certain catchments.

$$\min \sum_{i \in N^-} f_{iLZ} \quad (1)$$

$$\left(1 - \sum_{i \in T_j} \alpha_{im} x_{ji}\right) \left(\sum_{i \in N_j^-} f_{ijm} + p_{jm}\right) \leq \sum_{i \in N} f_{jim} \quad (2)$$

$$\sum_{i \in N} \sum_{t \in T_i} c_{it} x_{it} \leq B \quad (3)$$

where N^- represents the set of all upstream nodes, N represents the set of all nodes, c_{it} indicates the cost of implementing BMP $t \in T$ in node $i \in N$, and B is the available budget.

In addition, to evaluate the uncertainty associated with BMP efficiencies, a different set of simulations was carried out, in which for currently implemented BMPs, the default efficiency was doubled and also halved.

3. Results and discussion

3.1. Model performance evaluation

The northern Lake Okeechobee model was recalibrated for the period (1995–2006) and was validated for the period (2007–2018) for streamflow and nutrient loads (Table 2). Monthly streamflows, TP and TN loads were evaluated at the outlet of each subwatershed, and for subwatersheds with multiple outlets (i.e., Taylor/Nubbin and Indian Prairie), the sum of flows and loads were used for calibration and validation. Sample calibration time series for Lower Kissimmee are presented in Fig. 4, and for the other subwatersheds in Figs. S3–S7 in the Supplementary Materials. In terms of streamflow, the model performance was

good in Indian Prairie, and Taylor/Nubbin ($R^2 > 0.74$), satisfactory in the Lower Kissimmee, Fisheating Creek, and Lake Istokpoga ($R^2 = 0.56$ – 0.67), and not satisfactory in the Upper Kissimmee ($R^2 = 0.43$). This performance below expectation in the Upper Kissimmee is primarily because there are several human-operated water control structures in this watershed. Nutrient loads are heavily dependent on streamflow; thus, the model's nutrient performance followed similar trends according to subwatershed as the flow performance. The model performance was good for TP in the Lower Kissimmee ($R^2 = 0.56$ – 0.73) and Indian Prairie ($R^2 = 0.66$ – 0.78) and even better for TN ($R^2 = 0.64$ – 0.72 in lower Kissimmee, and $R^2 = 0.79$ – 0.85 in Indian Prairie). In addition, the model performance was good for TP ($R^2 = 0.63$ – 0.79) and TN ($R^2 = 0.62$ – 0.67) in Fisheating Creek. The model performance was satisfactory in Lake Istokpoga and Taylor/Nubbin for TP ($R^2 = 0.35$ – 0.65) and for TN ($R^2 = 0.36$ – 0.71). The model poorly simulated TP and TN in Upper Kissimmee ($R^2 = 0.28$ – 0.36 and 0.24 – 0.39 , respectively) which was expected given the poor performance for flow simulations. It is noteworthy to highlight the negative values of PBIAS linked to TP loads in most subwatersheds, particularly during the validation period. These values suggest an overestimation of simulated TP loads compared to observed values. In the case of Lake Istokpoga, the elevated PBIAS is attributed to a lack of observations. Conversely, in Upper Kissimmee, Taylor/Nubbin, and Fisheating Creek, the negative PBIAS in TP loads correlates with negative PBIAS in flows. However, in Indian Prairie, the negative PBIAS in TP, despite a positive PBIAS in flows, may be associated with ongoing BMP projects in the subwatershed that were not accounted for in the model.

Overall, estimates of nutrient loads with the recalibrated WAM model provided a realistic representation of past observed loads (Fig. 5). For instance, our simulations resulted in average annual TP and TN loads from the Upper Kissimmee of 79 and 1209 tons/year, respectively, compared to 87 and 1346 tons/year reported by SFWMD for the same period (1995–2018) based on monitoring data (Zhang and Welch, 2018;

Table 2

Performance evaluation statistics for flow, TP load, and TN load calibration (1995–2006) and validation (2007–2018) for the six northern Lake Okeechobee subwatersheds (Upper Kissimmee, Lower Kissimmee, Taylor/Nubbin, Indian Prairie, Lake Istokpoga, and Fisheating Creek).

		Calibration (1995–2006)			Validation (2007–2018)		
		Nash Sutcliffe (NS)	Coefficient of determination (R^2)	Percent BIAS (PBIAS)	Nash Sutcliffe (NS)	Coefficient of determination (R^2)	Percent BIAS (PBIAS)
Upper Kissimmee	Flow	0.42	0.43	10.47	0.42	0.43	−4.08
	TP load	0.34	0.36	19.43	0.20	0.28	−13.85
	TN load	0.33	0.39	25.20	0.24	0.24	4.70
	load						
Lower Kissimmee	Flow	0.62	0.65	10.53	0.66	0.67	−1.45
	TP load	0.52	0.56	13.71	0.69	0.73	2.62
	TN load	0.61	0.64	13.38	0.72	0.72	−0.84
	load						
Taylor/Nubbin	Flow	0.74	0.74	1.11	0.68	0.74	−13.95
	TP load	0.38	0.44	22.39	0.34	0.65	−49.89
	TN load	0.26	0.42	−2.93	0.59	0.66	−11.78
	load						
Indian Prairie	Flow	0.76	0.78	1.90	0.72	0.80	20.77
	TP load	0.45	0.66	−33.85	0.57	0.78	−42.78
	TN load	0.74	0.79	15.03	0.73	0.85	26.35
	load						
Lake Istokpoga	Flow	0.63	0.63	−1.62	0.55	0.60	25.99
	TP load	0.46	0.50	−24.42	0.23	0.35	−13.96
	TN load	0.71	0.71	5.24	0.32	0.36	20.63
	load						
Fisheating Creek	Flow	0.51	0.56	−0.87	0.49	0.59	−13.37
	TP load	0.62	0.63	−8.81	0.76	0.79	−15.72
	TN load	0.59	0.62	−6.37	0.60	0.67	−20.92
	load						

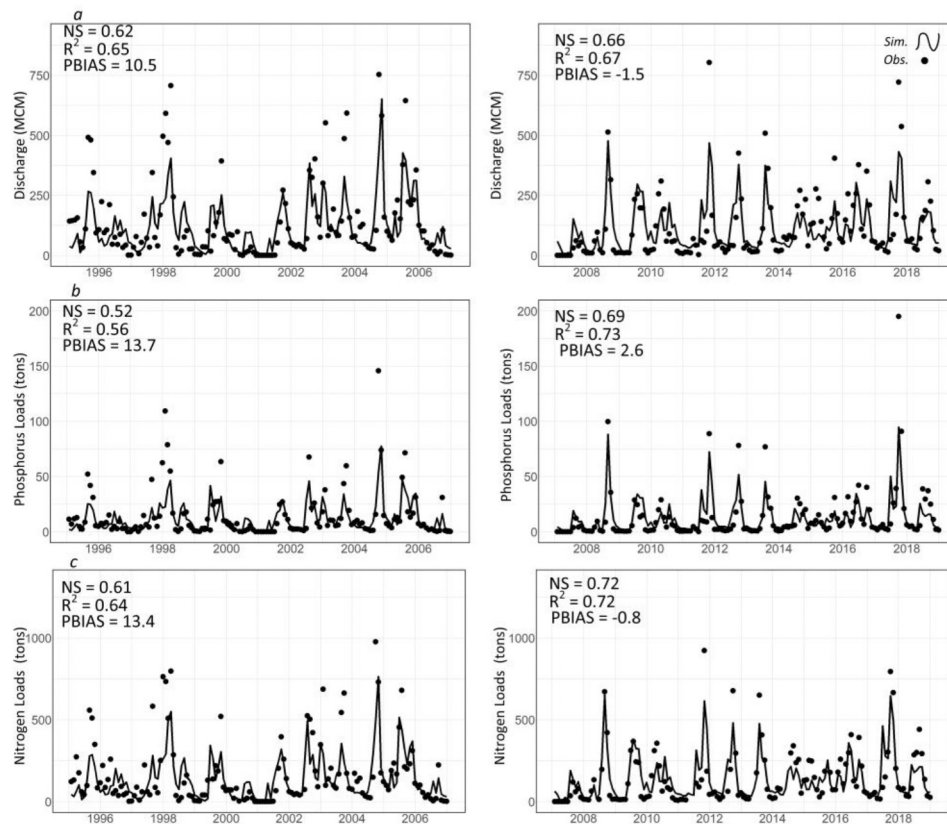


Fig. 4. Simulated vs. observed (a) water flows, (b) TP loads, and (c) TN loads at the outlet of Lower Kissimmee at structure S65E (the closest to Lake Okeechobee) for the calibration period (1995–2006; left panels) and for the validation period (2007–2018; right panels). Similar results for all other subwatersheds are presented in Figs. S3–S7 in the Supplementary Materials.

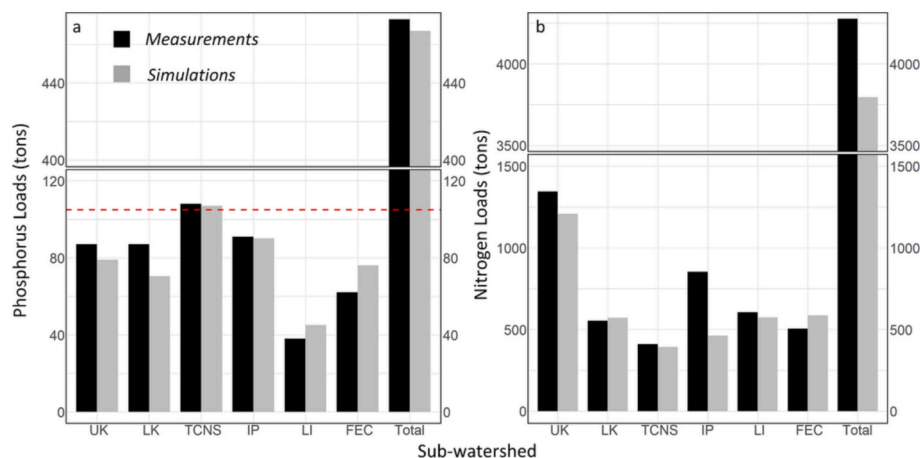


Fig. 5. Simulated (grey bars) vs. measured (black bars) (a) TP load and (b) TN load contribution of each subwatershed as well as the entire watershed to Lake Okeechobee. The red horizontal line in (a) indicates the (105 tons) related to the TP Total Maximum Daily Load criteria for the watershed. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

James and Zhang, 2008; Bertolotti et al., 2014; Welch et al., 2019). A comparison of the total annual simulated TP and TN loads versus values reported by the SFWMD based on observations for the same period (1995–2018) can be found in Table S3 in the Supplementary Materials. Based on the simulated vs. measured average annual TP and TN loads for the study period (1995–2018; Fig. 5), the model could be used to evaluate the effects of different BMP scenarios as those scenarios would focus on the percentage of annual average TP and TN change associated with the different scenarios.

3.2. BMP spatial distribution analysis

The Upper Kissimmee currently has BMPs implemented in locations that influence 12.5% of the subwatershed, most of which are urban areas (Fig. 6a). Yet, 33.7% of the Upper Kissimmee area has in fact the potential to implement BMPs (24% agriculture, and 9% urban; Fig. 6b) whereas the rest area of the watershed includes LULC categories that are not appropriate for potential BMP implementation as defined in this study. The Lower Kissimmee has BMPs influencing 6% of the

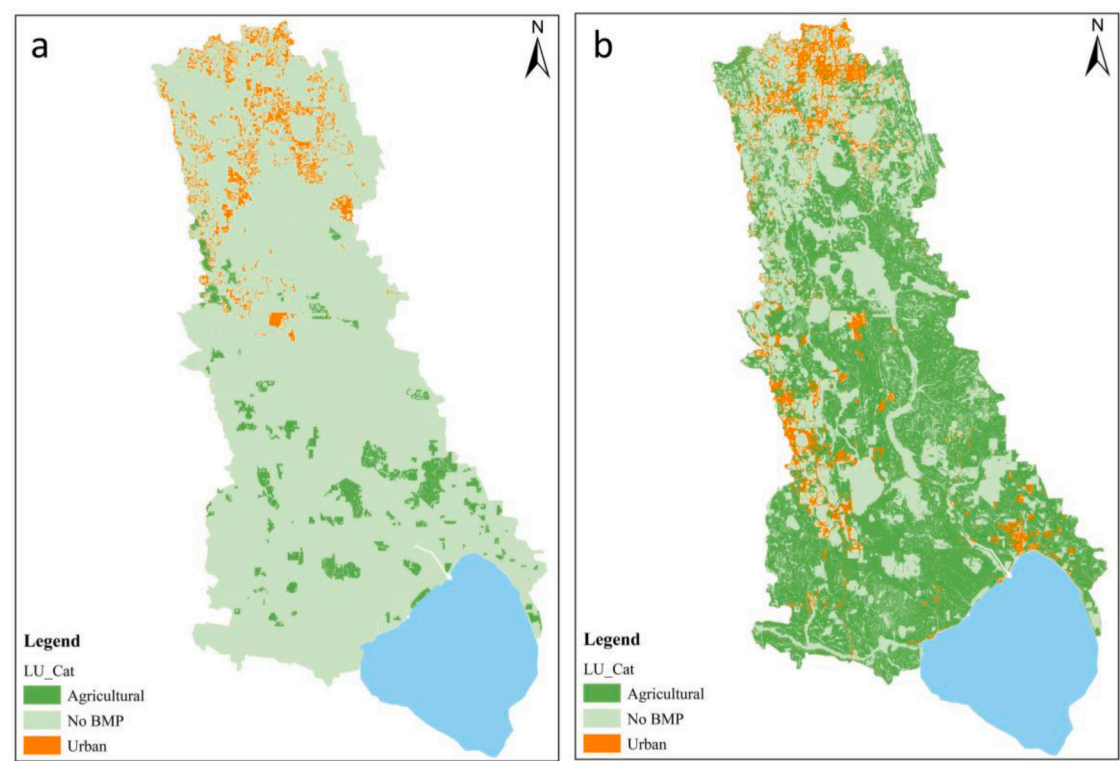


Fig. 6. Northern Lake Okeechobee land parcels with (a) currently implemented BMPs and (b) all potential for BMP implementation.

subwatershed area, most of which are pastures. Overall, the Lower Kissimmee still has 48.6% of its area where BMPs could be potentially implemented, mainly in agriculture lands. The Taylor/Nubbin has 17.7% of its area influenced by implemented BMPs mainly associated with agricultural activities (Fig. 6a). If all potential BMPs were implemented in the Taylor/Nubbin, they would affect 64.6% of the

subwatershed, mainly in agriculture, yet 8% of which is urban (Fig. 6b). The Indian Prairie has BMPs targeting 11.7% of the subwatershed, most of which in agriculture lands, though the Indian Prairie has the potential to have BMPs in 68.3% of its area, mainly affecting agriculture. The Lake Istokpoga subwatershed has BMPs implemented in locations affecting 6.4% of the area, however, if all potential BMPs were implemented in

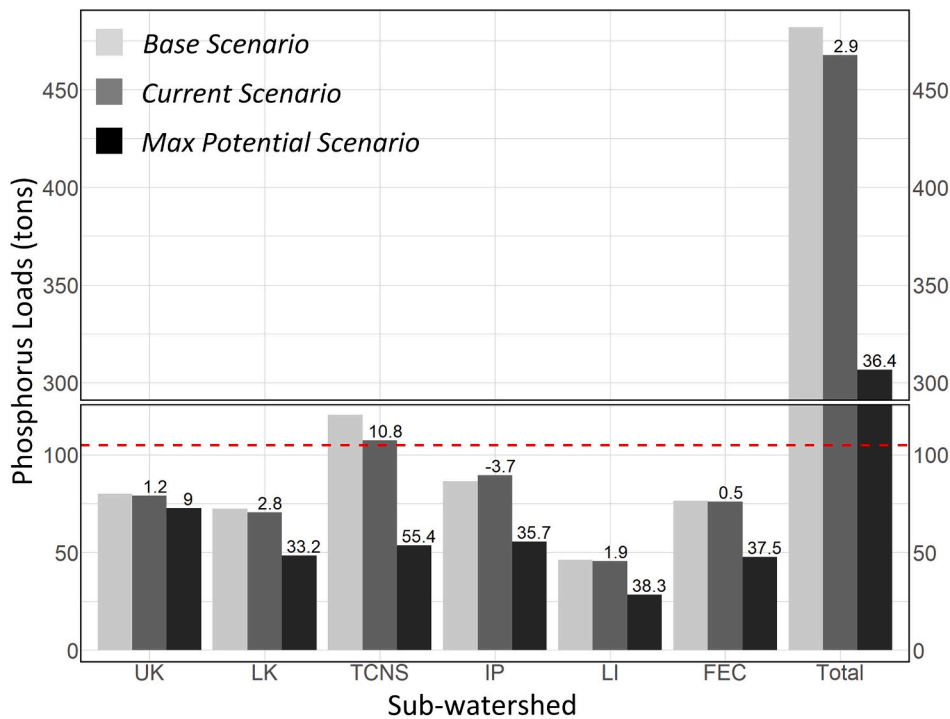


Fig. 7. No BMP (light grey) vs. current (dark grey) vs. maximum potential (black) scenario effects on phosphorus loads in the northern Lake Okeechobee sub-watersheds. P reduction (%) relative to no BMP scenario is illustrated above the associated scenario (+X% for reduction and -Y% for increase).

Lake Istokpoga, they would influence 39.1% of its area distributed as 26% in agriculture and 13% in urban. The Fisheating Creek has BMPs that only affect 2.6% of the subwatershed. Yet, 59.7% of the Fisheating Creek has the potential to have BMPs, mainly in agricultural lands. Overall, BMPs have been widely implemented in the northern Lake Okeechobee Watershed, especially in Taylor/Nubbin, Upper Kissimmee, and Indian Prairie, though large portions of the region still have the potential to implement BMPs that could further reduce nutrient loads to Lake Okeechobee.

3.3. Effect of BMP regional distribution on phosphorus loads

We evaluated the effect that different allocations of BMPs through the watershed could play on total nutrient load exports. This was carried out through the comparison of four simulation scenarios: No BMP (reference scenario), the current condition scenario (existing BMPs), the maximum potential scenario (BMPs implemented wherever possible), and the optimal configuration scenario. The total simulated phosphorus loads from the six northern Lake Okeechobee subwatersheds were 482 tons/year for the no BMP scenario, where Taylor/Nubbin was the major contributor with 120 tons/year. Overall, implementation of the existing BMPs should be reducing P loads to Lake Okeechobee to 468 tons/year, a 3% total reduction (Fig. 7). This total reduction, however, is not evenly distributed spatially: The existing BMPs implemented in the Taylor/Nubbin have performed well, with a 13 tons/year (11% of P loads in Taylor/Nubbin) reduction in P loads compared to the no BMP scenario (Fig. 7), whereas current BMP implementation in the other five subwatersheds has probably not reduced P loads to Lake Okeechobee in a significant matter. Surprisingly, the Indian Prairie has experienced increases in TP loads of ~3% which might be associated with low efficiency of the implemented BMPs in the sub-watershed. Doubling the efficiency of implemented BMPs would not significantly improve P reductions except in the Taylor/Nubbin (7% extra reduction than the current condition), while lowering the efficiency to its half would not worsen the P loads except for the Taylor/Nubbin (−5% increase in P loads compared to the current scenario; Fig. S8).

Implementation of all potential BMPs throughout the six subwatersheds could reduce P loads to Lake Okeechobee to 307 tons/year, a 175 tons/year (36%) reduction compared to the no BMP

scenario. The maximum potential P load reduction for the Taylor/Nubbin was as high as 67 tons/year (55% of P loads in the sub-watershed) compared to the no BMP scenario (Fig. 7). This significant reduction in P loads in Taylor/Nubbin was associated with BMPs implementations targeting three land-uses contributing the most TP loads in the sub-watershed (i.e., abandoned dairies, dairy boundary pasture, and improved pasture; Fig. S9). The maximum potential P reductions for Lake Istokpoga, Fisheating Creek, Indian Prairie, and Lower Kissimmee were 17.7 tons/year (38%), 28.6 tons/year (37%), 30.9 tons/year (36%), and 24 tons/year (33%), respectively (Fig. 7). These P reductions affected land areas just north of the lake which are currently considered as hot spots which might have a positive impact on water quality in this region (Fig. 8). The maximum potential P reduction for the Upper Kissimmee was 7.2 tons/year (9%). Optimal spatial distribution of BMPs was implemented in the six sub-watersheds, separately (Fig. 9a) where BMPs were allocated across the watershed with a substantial area of BMPs implemented in hot spot regions (Fig. 8a). Optimal BMP implementations resulting in P load reduction of 8.7 tons/year (8%) in TCNS, 6 tons/year (13%) in Lake Istokpoga, 20.7 tons/year (27%) in Fisheating Creek, 10.5 tons/year (8%) in Indian Prairie, 5.6 tons/year (4%) in Lower Kissimmee, and 9.2 tons/year (12%) in Upper Kissimmee associated with an initial implementation cost of US\$ 2 million in each subwatershed.

3.4. Effect of BMP Regional distribution on Nitrogen Loads

The total simulated nitrogen load from the northern Lake Okeechobee Watershed was 4384 tons/year for the no BMP scenario, with the Upper Kissimmee contributing 1789 tons/year (Fig. 10). We estimated that N loads were reduced to 3796 tons/year, a 13% reduction, with the current BMP implementation through the watershed. The simulations indicated that the existing BMPs implemented in the Upper Kissimmee have performed well in mitigating N loads, with a 581 tons/year reduction (32% of N loads in the subwatershed) compared to the no BMP scenario (Fig. 10). Urban BMPs, especially low and medium density residential to sprayfield, that were implemented in considerable area of the Upper Kissimmee have significantly reduced N loads in the watershed. However, for the other sub-watersheds, BMPs probably have not performed as well for N, with maximum reduction of 2% for a given

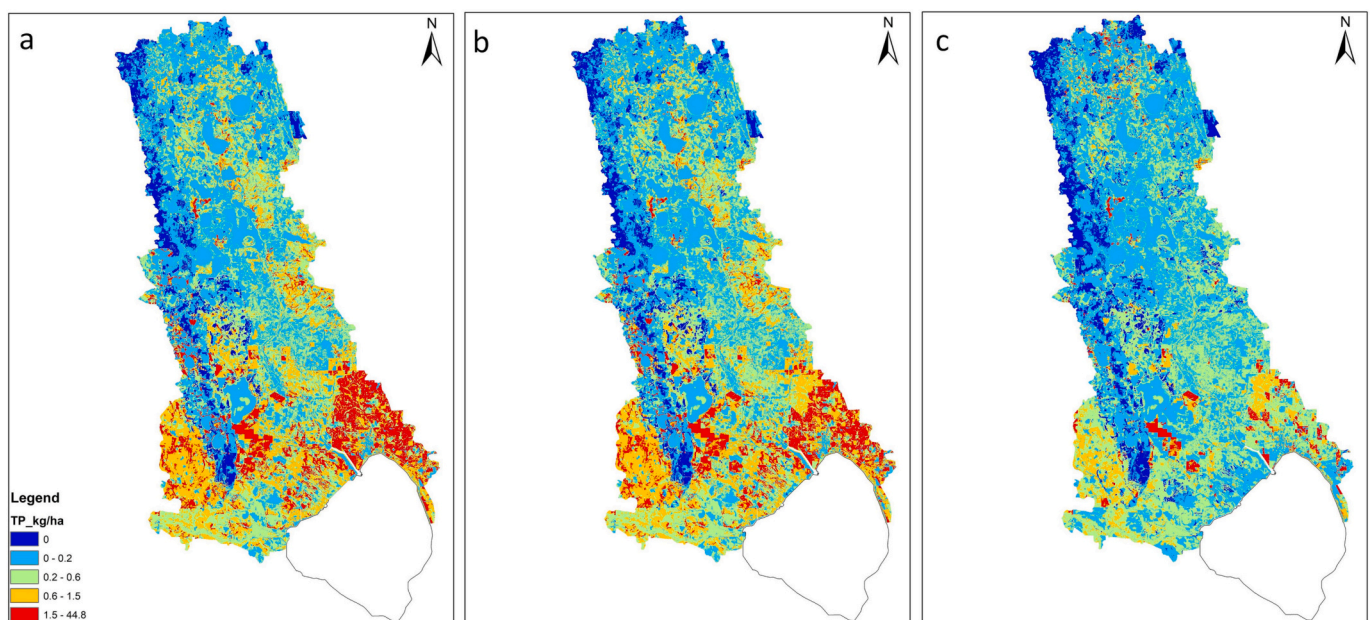


Fig. 8. Unattenuated phosphorus average load per unit area (kg/ha) in the northern Lake Okeechobee Watershed for the no BMP scenario (a), the current condition scenario (b), and the maximum potential scenario (c).

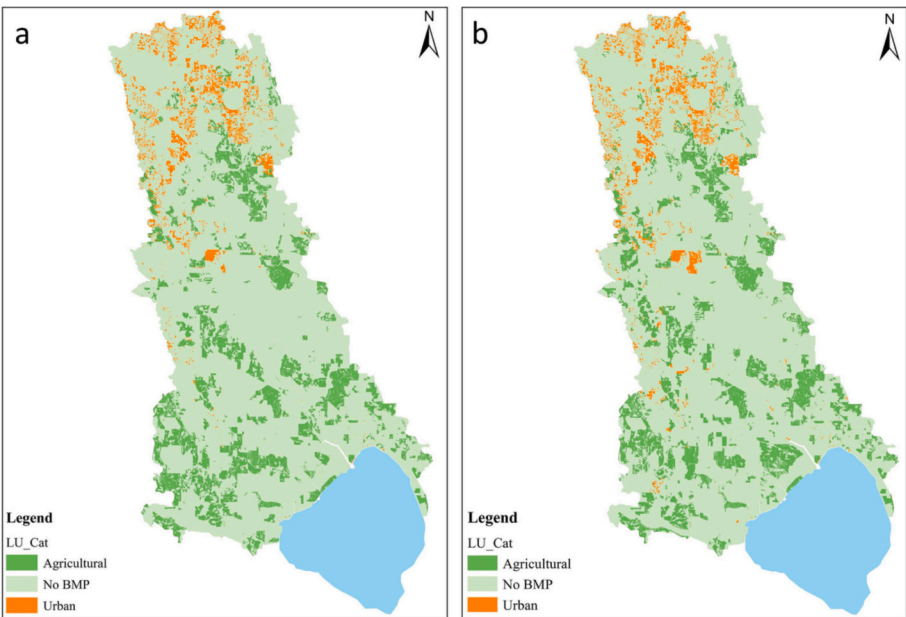


Fig. 9. Optimal distribution of land parcels where agricultural (dark green) and urban (orange) nutrient management BMPs should be installed for (a) P loads minimization, and (b) N loads minimization. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

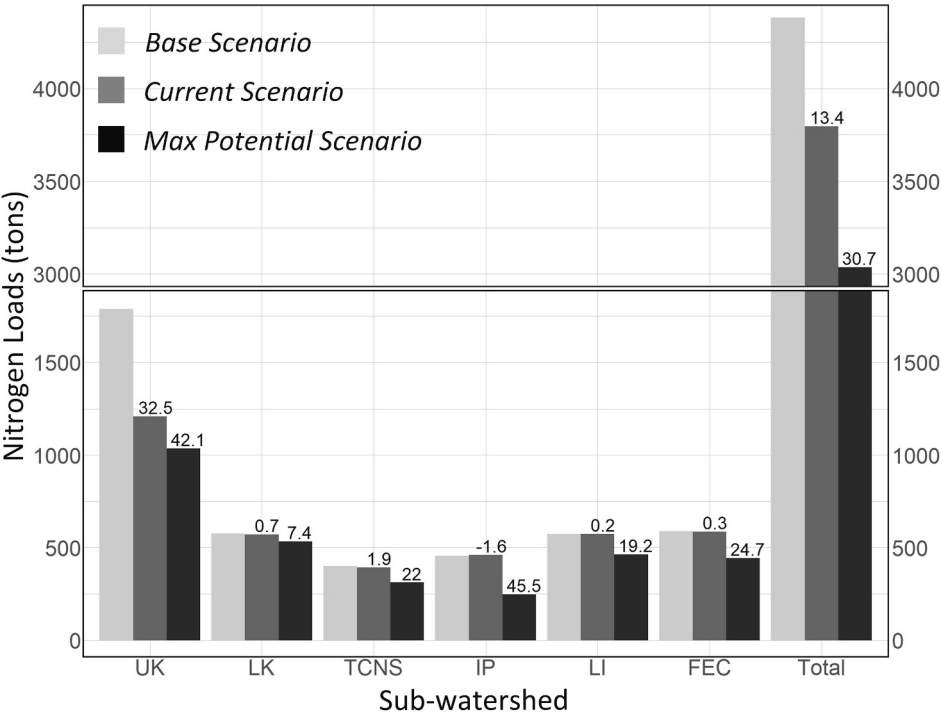


Fig. 10. Impacts of no BMP vs. current vs. maximum potential scenarios on nitrogen loads in the northern Lake Okeechobee sub-watersheds. N reduction (%) relative to no BMP scenario is illustrated above the associated scenario (positive indicates reduction and negative indicates increase).

subwatershed. Surprisingly, the Indian Prairie sub-watershed has experienced an increase in N loads of -1% which might be associated with low efficiency of the implemented BMPs in the subwatershed. If the efficiency of every single implemented BMP was doubled, that would reduce N loads in upper Kissimmee by 7% compared to the current condition among minor reductions in the watershed. Meanwhile, reducing BMP efficiencies to 50% of their original levels would not significantly impact the performance of the BMPs compared to the current condition (Fig. S8).

The maximum potential N load reductions were not as high as for P reductions. Further implementation of BMPs in the six sub-watersheds could reduce nitrogen to 3036 tons/year, a 1348 tons/year reduction (31% of N loads in the watershed) compared to the no BMP scenario (Fig. 10). The Indian Prairie and Upper Kissimmee ranked first and second with maximum potential reductions of 207.1 tons/year (46%) and 754 tons/year (42%) of N loads in the subwatershed compared to the no BMP scenario, respectively (Fig. 10). In addition, the maximum potential reduction of N loads for the Fisheating Creek, Taylor/Nubbin,

and Lake Istokpoga were 145 tons/year (25%), 88 tons/year (22%), and 111 tons/year (19%), respectively. Surprisingly, the maximum potential N reduction for the Lower Kissimmee sub-watershed was only 43 tons/year (7%). N reductions were evenly distributed across the northern Lake Okeechobee Watershed, though hot N spots closest to the lake were affected the most, and despite the significant N reductions in the Upper Kissimmee, there are still N hotspots in the sub-watershed (Fig. 11). Optimal spatial distribution of BMPs was independently implemented in each of the six subwatersheds (Fig. 9b) where BMPs were distributed across the watershed with a substantial area of BMPs implemented in hot spot regions (Fig. 11a). Optimal BMP implementations resulting in N load reduction of 11 tons/year (3%) in TCNS, 52 tons/year (9%) in Lake Istokpoga, 61 tons/year (10%) in Fisheating Creek, 36 tons/year (3%) in Indian Prairie, 14 tons/year (1%) in Lower Kissimmee, and 67 tons/year (6%) in Upper Kissimmee associated with US\$ 2 million initial implementation budget in each subwatershed.

3.5. Comparison to previous studies in Lake Okeechobee Watershed

FDEP published the Lake Okeechobee BMAP in December 2014, which contains strategies to reduce pollutant discharges through various means. The BMAP details existing and expected projects to improve Lake Okeechobee water quality and establishes a monitoring plan to evaluate water quality improvements. The BMAP is designed to be implemented in a phased approach to achieve the watershed runoff part of the Lake Okeechobee total maximum daily load (TMDL) of 105 tons/year. This initiative targets a P load reduction of 455.6 tons/year from the northern Lake Okeechobee Watershed based on the 5-year average of 2014–2018. Our study concluded that the potential BMPs in the northern Lake Okeechobee Watershed could reduce P loads from 482 to 307 tons/year (a reduction of 175 tons/year). BMAP assigned the reduction required from each sub-watershed based on the contribution of this sub-watershed into P loading to Lake Okeechobee for 2014–2018, and our results addressed the reduction that could be achieved in each sub-watershed with BMP implementations. A complete comparison is synthesized in Table 3. Overall, Upper Kissimmee and Lower Kissimmee showed lower potential to reduce P loads than anticipated BMAP reductions, though Taylor/Nubbin and Fisheating Creek showed higher potential to reduce P loads than anticipated BMAP reductions. Our

Table 3

BMAP required P reductions vs. maximum potential P reductions according to our results and actual P reductions according to BMAP vs. actual P reductions associated with BMP implementations according to our results.

Subwatershed	BMAP's required P reduction	Maximum potential reduction in P according to this study	Actual P reductions through 2019 according to BMAP	Actual P reductions associated with BMP implementation
Upper Kissimmee	90.5 tons/year, 16%	7 tons/year, 4%	16.4 tons/year	0.9 tons/year
Lower Kissimmee	125.9 tons/year, 23%	24 tons/year, 14%	5.6 tons/year	2.1 tons/year
Lake Istokpoga	47.7 tons/year, 8.7%	18 tons/year, 10%	2.5 tons/year	0.9 tons/year
Indian Prairie	102.5 tons/year, 19%	31 tons/year, 18%	20.5 tons/year	−3.2 tons/year
Taylor /Nubbin	113.6 tons/year, 21%	67 tons/year, 38%	23.3 tons/year	13 tons/year
Fisheating Creek	72.4 tons/year, 13%	29 tons/year, 16%	14.4 tons/year	0.4 tons/year

results indicated lower P load reductions than BMAP's P reductions through June 2019 from all the sub-watersheds, but only Taylor/Nubbin illustrated significant P reduction with 13 tons/year. This is probably because our study focused only on parcel-scale BMPs, while regional scale BMAP projects also include Dispersed Water Management (DWM), Wetland Restoration (WR), and Stormwater Treatment Areas (STAs; FDEP, 2020). These alternatives occupy large areas and a different modeling framework (not included in our study) would be needed to also consider them.

Previous studies have evaluated BMP-related nutrient reductions in Lake Okeechobee's watershed, yet our study has led to important improvements to this body of knowledge (Table 4). Our study presented the effects of various BMPs implementation in each of the six northern Lake Okeechobee sub-watersheds separately as well as their cumulative effects on P and N loads to Lake Okeechobee. WAM simulations

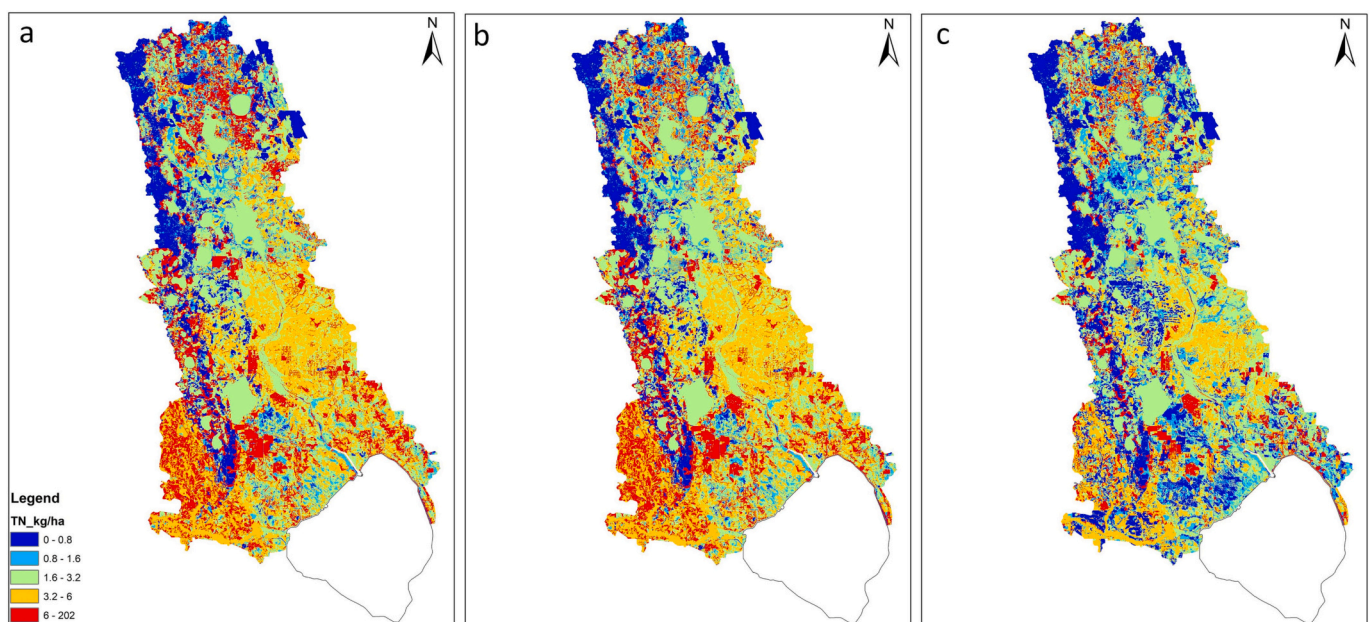


Fig. 11. Unattenuated TN average loading per unit area (kg/ha) in the northern Lake Okeechobee Watershed for the no BMP scenario (a), the current condition scenario (b), and the maximum potential scenario (c).

Table 4

Summary of previous studies focused on nutrient reduction objectives in Lake Okeechobee's watershed.

Study	Subwatersheds included	Study Period	Nutrient Considered	Aim of the study
This Study	All six subwatersheds of the Northern Lake Okeechobee Watershed	1995–2018	TP & TN	Evaluated the effectiveness of BMPs in reducing TP and TN loads to Lake Okeechobee.
Khare et al. (2019)	Northern Lake Okeechobee Watershed (cumulative effects).	1998–2007	TP	Evaluated the performance of different nutrient mitigation alternatives to achieve a mean TP concentration of 40 µg/L into the Lake.
Corrales et al. (2017)	Upper Kissimmee & Taylor/Nubbin.	2002–2009	TP	Reducing P loads into the Lake.
Khare et al. (2021)	Taylor/Nubbin.	2003–2013	TP	Investigated the contributions of different sources to P loads into the Lake.
Shin et al. (2023)	Upper Kissimmee, Lower Kissimmee, and Taylor/Nubbin.	Future scenarios based on 2015–2020	TP, TN	Evaluating the impacts of climate change on water quantity and quality of the Northern Lake Okeechobee Watershed.

indicated that P loadings from the northern Lake Okeechobee could be reduced from 482 tons/year to 307 tons/year. As a reference, the Lake Okeechobee TMDL targeted a P loading of 105 tons/year. Khare et al. (2019a, 2019b) concluded that BMPs, DWM, and WR are not sufficient, and they recommended that STAs are also necessary to achieve the Lake Okeechobee TMDL. Corrales et al. (2017) proposed to combine BMPs and advanced wastewater treatment technologies, with a potential phosphorus reduction in the Upper Kissimmee and Taylor/Nubbin subwatersheds by 46% and 32%, respectively. Meanwhile, our study addressed the potential reduction of the northern Lake Okeechobee subwatersheds to reduce P and N loads with only BMP implementations. Upper Kissimmee and Lower Kissimmee illustrated a poor response to BMP implementation in the subwatersheds in agreement with Tarabih and Arias (2021) who found no trends in P loads in the Kissimmee River in the last five decades. In contrast, Taylor/Nubbin illustrated the opposite behavior, where more P loads than anticipated by BMAP could be reduced using only BMPs.

BMP effects on nutrient load reductions have been widely addressed at different watersheds around the globe; however, mitigating impacts of nonpoint sources on water quality in the watershed and the receiving water body is still a challenge. Effects of BMP implementation in agricultural watersheds have been extensively addressed in multiple studies (Pokhrel and Paudel, 2019; Lam et al. 2011; Risal and Parajuli, 2022; Chaubey et al., 2010; Himanshu et al., 2019). Lake Okeechobee Watershed is dominated by agricultural crops, yet Upper Kissimmee and Lake Istokpoga sub-watersheds include considerable portions of urban land. Some studies focused on phosphorus reduction only (Gaddis et al., 2014; Dong et al., 2018; Pokhrel and Paudel, 2019; Hanief and Laursen, 2019), though other studies considered both phosphorus and nitrogen load reductions (Lam et al., 2011; Risal and Parajuli, 2022; Chaubey et al., 2010; Himanshu et al., 2019). Freshwater ecosystems could shift from phosphorus limited to nitrogen limited and/or vice versa associated with N:P mass ratio in the water body (Lewis et al., 2011; Davis

et al., 2015; Domagalski et al., 2021). Thus, we considered both nitrogen and phosphorus load reductions in the watershed to improve water quality in the watershed and the receiving lake.

Optimization algorithms have been integrated with watershed simulation models forming simulation-optimization approaches to adopt the best spatial distribution of an individual BMP or a combination of various BMP types to achieve maximum nutrient reductions and/or minimum cost (Pokhrel and Paudel, 2019; Gaddis et al., 2014; Qiu et al., 2018). Other studies used optimization to identify priority management areas; defined as areas where diffusive pollution mitigation can achieve relatively better water quality improvements (Dong et al., 2018). Linear programming models, unconstrained multi-objective optimization approach, a metamodeling-based optimization approach, integrating LMBP with genetic algorithm (GA), and a NSGA-II based multi-objective optimization were adopted to solve the optimization problems. We used an integer linear programming optimization model to choose the best spatial distribution of BMPs in each of the subwatersheds to minimize P and N loads constrained with an identified budget. Most of the studies that considered simulation-optimization approaches suggested that optimal BMP implementations (types and locations) reduced nutrient loads and/or were substantially more cost-effective than most scenarios proposed by stakeholders. Our results addressed the same behavior where optimal BMP spatial distributions in the watershed were more cost effective than other scenarios. Different structural as well as nonstructural agricultural BMPs have been implemented, to evaluate their effectiveness and cost, include field buffer strip, nutrient management, grazing management practice, litter application rate and timing, litter characteristic, Electric Arc Furnace (EAF) steel slag barriers for tile drains, and EAF steel slag for surface runoff. Urban BMPs include utilizing P-free fertilizers in urban land-uses, and road sweepers. Among these BMPs agricultural buffers, nutrient management, and tillage practice management proved their efficiency (Lam et al., 2011; Risal and Parajuli, 2022; Chaubey et al., 2010; Himanshu et al., 2019; Gaddis et al., 2014; Pokhrel and Paudel, 2019). We considered BMPs that are approved and implemented in the Lake Okeechobee Watershed including water retention, fertility management, animal density management, and drainage and water control structure BMPs for agricultural crops (mainly pastures, and citrus). Urban BMPs considered in the Lake Okeechobee Watershed incorporate stormwater retention, and spray fields. In summary, the study proposed a watershed simulation-optimization framework that could be used to simulate different watershed management scenarios as well as to find optimal solutions to mitigate nutrient impacts in the watershed and the receiving waterbody.

3.6. Limitations

Our study provided an informative guideline for BMP implementation in the case study watershed, yet there are limitations that could be further addressed in future studies. One limitation of this study includes using a static LULC (no change with time) input for the entire simulation period as our watershed modeling tool does not allow the utilization of dynamic land-use changes. Yet, the performance of the WAM model was acceptable for the calibration and validation periods addressing the total P and N loads at the watershed outlet. Our study focused on evaluating effectiveness of BMPs implementations at the watershed scale, but regional nutrient treatment techniques have been addressed in Lake Okeechobee Watershed including DWM, WR, STAs, and reservoirs, thus effectiveness of these projects on flow and nutrient loads should be addressed. Besides, climate change will definitely impact flow and nutrient loads in the watershed (Shin et al., 2023), thus different climate change scenarios, incorporating drought and wet conditions, are recommended to be evaluated. In addition, future LULC changes would affect flow and nutrient loads in the watershed, which could be incorporated into WAM simulations.

4. Conclusions

We simulated hydrology and nutrient load generation from the northern Lake Okeechobee Watershed. Four different scenarios of BMP spatial configuration were evaluated: the no BMP scenario, the current condition scenario (currently implemented BMPs), the maximum potential scenario (All the highest efficiency BMPs implemented wherever possible), and the optimal BMP spatial allocation scenario. In addition, we evaluated the uncertainty associated with BMP efficiency by doubling and halving the default efficiencies, which demonstrated relatively mild effects from individual BMP performance on net nutrient loads at the watershed scale. Current BMP implementation reduced P from 482 tons/year to 468 tons/year, 13 tons/year of that in a single subwatershed (Taylor/Nubbin). Doubling BMP efficiencies would reduce P loads in Taylor/Nubbin by an additional 7%. Further implementation of potential BMPs could reduce P loadings to Lake Okeechobee to 307 tons/year, which will not be enough to achieve Lake Okeechobee's TMDL (105 tons/year). P load reductions by subwatershed illustrated that Taylor/Nubbin BMP implementation would perform well with 38% P reduction, while Upper Kissimmee and Lower Kissimmee, the largest sub-watersheds, showed low P reductions with 4% and 14%, respectively. Thus, other project alternatives should be considered to reduce P loads from those subwatersheds. Current implementation of BMPs reduced nitrogen loads from 4384 tons/year to 3796 tons/year, with BMPs in the Upper Kissimmee –the subwatershed with most urban development– performing the best (581 tons/year N reductions). Doubling BMP efficiencies would reduce another 7% of N loads in the Upper Kissimmee. Further (maximum potential) implementation of BMPs in the watershed would reduce N loadings to Lake Okeechobee to 3036 tons/year. N loads reductions by subwatershed indicated that Upper Kissimmee BMPs performed well with 55% N reduction, while Lower Kissimmee performed the poorest with 7% N reductions. Thus, further N loading reductions would require other alternatives in subwatersheds where BMPs did not perform as good (i.e., Lower Kissimmee and Taylor/Nubbin). In addition, optimal BMP allocations in the different subwatersheds would reduce total P and N loads by 10% and 4%, respectively. Overall, this study evaluated the effectiveness of BMP implementation in the main subwatersheds of Lake Okeechobee and provided an informative guideline on the potential of BMP technologies to reduce nutrient loads to a large eutrophic lake.

CRedit authorship contribution statement

Osama M. Tarabih: Formal analysis, Investigation, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing. **Mauricio E. Arias:** Conceptualization, Funding acquisition, Investigation, Project administration, Supervision, Writing – original draft, Writing – review & editing. **Andres Lora Santos:** Data curation, Formal analysis, Investigation, Validation. **Jiayi Hua:** Formal analysis, Writing – original draft, Writing – review & editing. **Rachael Z. Cooper:** Formal analysis, Writing – review & editing. **Ashim Khanal:** Methodology, Software, Writing – review & editing. **Thanh D. Dang:** Writing – review & editing. **Yogesh P. Khare:** Resources, Software, Writing – review & editing. **Hadi Charkhgard:** Funding acquisition, Software, Supervision, Writing – review & editing. **Mark C. Rains:** Funding acquisition, Supervision, Writing – review & editing. **Qiong Zhang:** Conceptualization, Funding acquisition, Project administration, Supervision, Writing – review & editing.

Declaration of competing interest

Qiong Zhang reports financial support was provided by US Environmental Protection Agency. Mark C. Rains reports a relationship with Florida Department of Environmental Protection that includes: employment. Mark Rains is currently serving as the Chief Science Officer for the State of Florida. The views expressed in this article are his own

and do not necessarily reflect the views of the State of Florida. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.ecoleng.2024.107211>.

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