Use of a Bayesian network as a decision support tool for watershed management: A case study in a highly managed river-dominated estuary

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Research Article

Keywords: salinity, nutrient loads, chlorophyll a, color, light attenuation

Posted Date: August 9th, 2022

DOI: https://doi.org/10.21203/rs.3.rs-1921586/v1

Additional Declarations: No competing interests reported.

Version of Record: A version of this preprint was published at Environmental Monitoring and Assessment on May 26th, 2023. See the published version at https://doi.org/10.1007/s10661-023-11273-y.

Abstract

Decision making in water resource management has many dimensions including water supply, flood protection, and meeting ecological needs; therefore, is complex, full of uncertainties, and often contentious due to competing needs and distrust among stakeholders. It benefits from robust tools for supporting the decision-making process and for communicating with stakeholders. This paper presents a Bayesian Network (BN) modeling framework for analyzing various management interventions regulating freshwater discharges to an estuary. This BN was constructed using empirical data from monitoring the Caloosahatchee River Estuary in south Florida from 2008–2021 as a case study to illustrate the potential advantages of the BN approach. Results from three different management scenarios and their implications on down-estuary conditions as they affected eastern oysters (*Crassostrea virginica*) and seagrass (*Halodule wrightii*) are presented and discussed. Finally, the directions for future applications of the BN modeling framework to support management in similar systems are offered.

Introduction

Bayes Theorem describes the probability of an event occurrence based on previous knowledge of the conditions associated with the event. More importantly, it provides a mathematical rule for combining prior probabilities with new information to produce posterior probabilities. Published in 1761, the Theorem was at first ignored but later taken up (as Laplace's rule) and began to dominate statistical thinking only to be eclipsed in the 1920s when the ideas of Pearson, Fisher, and Neyman were integrated into what is now termed the classical "frequentist approach' for significance testing through calculation of *p* values (Newman, 2008; McGrayne, 2011). Ironically, the lay public often misinterprets *p* values from frequentist statistics as the probability that a given hypothesis is true even though it never calculates that probability. Several attempts were made to resurrect Bayesianism, particularly following the publication of refinements to algorithms governing the propagation of conditional probabilities in the 1980s (Fenton & Neil, 2018). A turning point occurred in 1986 when Pearl (1986) demonstrated how probabilistic knowledge could be represented and manipulated in graphical forms, later termed Bayesian belief networks or simply Bayesian networks (BNs). Yet, the mathematics dealing with conditional probabilities remained an impediment to more widespread use. Courses in Bayesian statistics were and continue to be only infrequently taught as a complement to or as a replacement for the classical frequentist approach (Huegh, 2020).

A second turning point occurred in 1992 when computer technologies and new software became increasingly available to calculate conditional probabilities enabling investigators to build BNs without an in-depth knowledge of all the underlying algorithms (Fenton & Neil, 2018). This led to a rapid expansion in the use of BNs in a variety of different disciplines including medicine (Arora et al., 2019), law (Kadane & Schum, 1996), ecology (McCann et al., 2006) and, in particular, risk assessment and decision analysis (Fenton & Neil, 2018). Because BNs can easily integrate many different types of information (e.g., both qualitative and quantitative data, other model outputs, expert opinion, or a combination of any of these) into a single integrated model they are highly flexible and are particularly useful when dealing with limited data sets. Equally important, communicating model results probabilistically using a directed graph that depicts hierarchal dependencies is more easily understood by non-technical decision makers (i.e., elected officials) and the public leading to greater confidence in its output, which is crucial in today's climate of growing skepticism and reluctance to trust government scientists.

For these same reasons and because of the other advantages they offer, BNs have also been increasingly applied to water management (Forio et al., 2015, McDonald et al., 2015, for review, see Phan et al., 2016). Reckhow (1999) reviewed the pros and cons of employing models of differing complexity for water management and made a case for use of probabilistic models because they require fewer resources, suffer less error propagation, but also because they are useful as decision support tools (DST). Others warn that process-based models can often be overparameterized when system-specific data are limiting and often must rely on default values (Borsuk et al., 2003). Unlike process-based models, there are no "hidden" variables in BNs and probabilistic output explicitly conveys inherent uncertainty avoiding false precision, which is rampant in other models.

This paper presents a Bayesian network constructed using field-collected data from monitoring the Caloosahatchee River Estuary (CRE), which has been the subject of numerous restoration efforts most recently as part of the Comprehensive Everglades Restoration Plan (CERP). The BN focuses on the conditions within what would typically be the mesohaline portion of the estuary but, due to altered inflows, has been subject to extreme salinity fluctuations. This BN can be contrasted directly with a previous modeling effort of the same system (and the St. Lucie Estuary on Florida's east coast). That effort employed multiple oyster and seagrass models comprised of twenty-two separate simulation equations containing forty-six coefficients integrated within an estuarine hydrodynamic model ultimately driven by output from a complex regional-scale hydrologic model (Buzzelli et al., 2015). The agency responsible for watershed management, the South Florida Water Management District (SFWMD) relies heavily on the products from these types of models and on traditional, some might say dated, decision trees in managing the system (e.g., Lake Okeechobee Regulation Schedule Part D: Establish Allowable Lake Okeechobee Releases to Tide). Often these decisions are very contentious, due to the competing needs for water by various sectors within the larger watershed and the prevailing public perception that flows from the lake are the major cause of eutrophication in receiving waters. They, therefore, receive considerable media attention (Wink, 2016; Gillis, 2021; Gillis & Williams, 2021). Although the need for complex models both in terms of the number of estimated parameters and code cannot be avoided for a system this large and complicated, the goal of this case study is to illustrate the potential advantages of the BN approach for decision making and engaging the public in this and other comparable large-scale projects.

Material And Methods

Study site

The first step in developing a BN is generating a conceptual model of how the system works identifying relevant variables as well as endpoints of concern to the public and decision-makers (Fig. 1).

The CRE is located on the southwest coast of Florida (Fig. 2). The river was first extended eastward and artificially connected to Lake Okeechobee and its large watershed, with a combined drainage area of over 1 million ha, in 1884 (Jones, 1948). The lake receives water and nutrient loads from several tributary systems each with different land uses (including intensive agricultural, sod, dairy operation, among others; Welch et al., 2019). A combination lock and dam structure, designated S-77, was constructed in 1937 to control discharge from the lake (Fig. 2). Two additional structures (S-78 and S-79) were later constructed along the Caloosahatchee River. The furthest downstream structure, the Franklin Lock and Dam or S-79) was added in 1966 and marks the beginning of the CRE. The lake serves as a reservoir where stage is controlled to provide water for agriculture and drinking water, but also for flood control. During the wet season, Lake Okeechobee levels rise until water must be released to tide through the Caloosahatchee (and to a lesser extent the C-44 canal to St. Lucie) to reduce environmental impacts on the lake's littoral ones and to relieve pressure on the dike surrounding the lake (particularly prior to the passage of hurricanes); flows to CRE are, thus, higher than historical flows prior to its artificial connection to the lake. During the dry season, water is released from the lake down the river primarily to provide water for irrigation, urban water supply and minimum flows to the estuary to meet ecological needs.

The C-43 Basin lies between the lake and the estuary with an area of over 240,000 ha (Fig. 2). Although there are plans are to increase storage capacity within the basin, currently there is little storage and discharges, though regulated by S-79, are rain dependent. Land use in the C-43 Basin also includes agriculture (e.g., sugarcane, citrus etc.), sod, improved and unimproved pastures, woodland pastures, range lands and some urban areas. Downstream of S-79 the Tidal Basin with an area of over 100,000 ha has been heavily urbanized. The cities of Cape Coral and Fort Myers, with an extensive network of canals, allow considerable runoff to enter the estuary (Fig. 2).

The Tidal Basin receives input from numerous unregulated rivers and creeks including Orange River, Telegraph Creek, Daughtrey Creek, Trout Creek, Popash Creek, Powell Creek, Hancock Creek, Billy Creek, and Whiskey Creek. During unusually dry years flows down the river are lower than historic flows, due to increased water supply demand in the basin.

Discharge from the lake combined with runoff from the C-43 Basin can result in discharges up to 818 m^3/sec or 28,900 cfs (cubic feet per second; note, the SFWMD operates and communicates flows in terms of cfs or acre feet per unit time and, for consistency, those units will be used here) through S-79. These discharges have been repeatedly shown to be the dominant influence on the water quality of the estuary (Fig. 1, Chamberlain & Doering, 1998; ERD, 2003; Janicki Environmental, Inc., 2003, Doering et al., 2006, Rumbold & Doering, 2020). Concentrations of nutrients and other constituents have been shown to be dependent on flow rate and source of water (Rumbold & Doering, 2020). Although Lake Okeechobee contributions to S-79 flows and loads can be as important or more important than C-43 Basin inputs during certain periods, generally the latter dominates on an annual basis (Doering & Chamberlain, 1999; Rumbold & Doering, 2020; Kahn & Betts, 2021); this despite the prevailing perception by the public and elected officials that Lake Okeechobee discharges are the major source of the problems in the estuary.

The tidal creeks and river inputs to the Tidal Basin are generally ungagged, however, early monitoring studies revealed Orange River and Telegraph Creek to have the most significant volumetric inputs as well as nutrient loading to the estuary, particularly during the wet season (i.e., that is after S-79, ERD, 2002; for review, see Knight et al., 2005). While long-term average (i.e., 1997–2020) flow and nutrient loads from the lake are much greater than those estimated to come from the Tidal Basin, the lake's inputs decreased in 2020 resulting in a relatively greater influence of the tidal inputs; however, the combined flows and loads from S-79 still dominated (Kahn & Betts, 2021). During the dry season, when there is no discharge from S-79, the Caloosahatchee may have a negative net flow into tidal creeks and rivers.

The first report that the artificial connection and freshwater flows from Lake Okeechobee was having an adverse effect on biological resources by altering the salinity, color and clarity and dissolved oxygen content in the estuary was in 1954 (Murdock, 1954). The first report that nutrient loading to the estuary was exceeding its assimilative capacity was in the early 1980s (DeGrove, 1981). More recent reviews of these adverse effects from altered quantity and quality of inputs (Fig. 1) include Barnes et al. (2006), FDEP (2009), Douglas et al. (2020), and MacFarland et al. (2022). Multiple efforts are underway by different agencies to improve the timing, quantity and quality of water discharged to the estuary to restore lost seagrass meadows, oyster reefs and other biological resources in the CRE.

Restoration targets

Mixing of freshwater discharge with seawater from the Gulf of Mexico results in a gradient in salinity and other constituents such as nutrients and color along the estuary that is dependent on flow rate (Fig. 1), tidal forcing and distance from the mouth of the estuary. This, in turn, affects the distribution and abundance of biological resources along the estuary. Restoration targets, particularly resource-based targets are, therefore, locational or segment dependent. Various organisms considered valued ecosystem components (VECs) have been targeted to assess salinity conditions and restoration activities in different segments along the estuary. These include, among others, *Vallisneria americana* (tape grass) in the upper estuary and more salt-tolerant species like *Halodule wrightii* (shoal grass) and the eastern oyster (*Crassostrea virginica*) in the lower estuary (Fig. 1; Barnes et al., 2006; Douglas et al., 2020; Kahn & Betts, 2022; MacFarland et al., 2022).

Based on numerous previous studies (e.g., Doering et al., 2002; Mazzotti et al., 2007; Volety et al., 2016), flow rates at S-79 of 750 cfs to 2,100 cfs have been established as targets as part of CERP to generate salinity envelopes along the estuary that would be optimal for the VECs, including minimum flows for up-estuary tape grass and maximum flows to prevent damage to down-estuary seagrasses and oysters (Fig. 1; for review, see RECOVER, 2020). However, as evident by recent efforts to update the Lake Okeechobee System Operating Manual (LOSOM), the need for occasional high-volume flows to tide will continue for some years into the future.

As mentioned previously, nutrient loading associated with these freshwater discharges, particularly of nitrogen, has also been identified as causing increased chlorophyll a (Chl a), as a proxy for phytoplankton blooms in the estuary (DeGrove, 1981; Doering et al., 2006). The assimilative capacity of the estuary to accept nitrogen was recently estimated as a basis for a Total Maximum Daily Load (TMDL) analysis by the Florida Department of Environmental Protection (FDEP) using two coupled models, one for the watershed (HSPF) linked to a hydrodynamic model (EFDC; FDEP, 2009). The TMDL assessed the influence that nitrogen had in stimulating phytoplankton blooms, which, in turn, was thought to reduce the percentage of photosynthetically active radiation (PAR; along with color and turbidity) reaching seagrass (Fig. 1). The resulting TMDL called for 23% reduction in total nitrogen (TN) loading or annual load not to exceed 9,086,094 lbs (i.e., 4121 Tons per year or on average 343 tons per month; FDEP, 2009).

In 2011, FDEP adopted a rule to establish numeric nutrient concentration (NNC) criteria for several coastal waterbodies that were to be based on data observed from 1999 (or in certain regions from 2003) through 2007 to gauge whether water quality conditions were worsening (characterized as hold-the-line criteria). NNC were established for total phosphorus (TP) and Chl a for the Lower Caloosahatchee River Estuary as 0.040 mg/L TP and 5.6 μg/L Chl a as long-term averages (F.A.C. 62-302.53). The Technical Advisory Committee for Charlotte Harbor National Estuary Program also recommended a NNC for TN concentration in the Tidal Caloosahatchee (which includes up-estuary segments and so may not be appropriate for the lower segment) as 1.09 mg/L (Janicki Environmental Inc., 2011).

As indicated by its selection for the basis of the TMDL, light availability to seagrasses is an important consideration for the health of the CRE. The problem is that as light attenuation increases, the depth at which the seagrass can survive decreases. However, a recent study evaluating the principal components causing light attenuation in the estuary (e.g., color, chl a and TSS) found the relationship between Chl a and light attenuation (Kd, 1/m) to be statistically significant only in the lower estuary with an R^2 of only 0.08 (Rumbold & Doering, 2020). Instead, color was found to be the dominant factor in all segments of the estuary (with an R^2 of 0.31 in the lower estuary; TSS was a significant contributor only in the upper estuary; Rumbold & Doering, 2020). This finding was in agreement with previous optical models in this estuary (for review, see Chen & Doering, 2016). As mentioned earlier, increased color in water discharged from the lake was reported as early as 1954 (Murdock, 1954) and the problem appears to have worsened (Doering, 2006). However, because of their strong correlation, it is difficult to separate changes in color concentration (possibly due to land use changes, rapid drainage and runoff of colored dissolved organic matter, CDOM) from increasing tends in flow over time (Corbett, 2007). Several different light attenuation targets have been offered to support seagrass recovery in the estuary dependent on the distance from the mouth (i.e., segment), seagrass species and its light requirements (Doering, 2006; Corbett & Hale, 2006; Mazzotti et al., 2007). The dominant seagrass species in the lower estuary, *Halodule wrightii*, is reported to require between 20–30% of incident light (Doering, 2006; Mazzotti et al., 2007). The CERP target for light attenuation to recover viable seagrass coverage in the lower estuary to a depth of at least 1 m (deep edge of bed, DEB) is a Kd of < 1.6 1/m assuming a requirement of 20% of incident light (Doering, 2006; RECOVER, 2007) or < 1.39 1/m assuming 25% of incident light (note, the down-estuary target for San Carlos Bay is < 0.69 1/m for a DEB at 2 m).

BN model

The next step is to use the conceptual model as a framework for constructing the BN (for additional guidance, see Rickhow, 1999; Borsuk et al., 2004; Fenton & Neil, 2018). Relevant variables from the conceptual model are represented in a directed graph as nodes with an arrow from one node to another to represent causal dependence between the corresponding variables. A node that has no incoming arrows is said to be a parent node, which typically represents initial forcing functions. Intermediate and response variables are termed child nodes because they have incoming arrows that indicate dependency. Each node (variable) has a finite set of possible outcomes or “states” (i.e., bins) that the variable can exhibit representing either continuous or discrete (e.g., categorical, Boolean, ranked or ordinal) distributions. Continuous variables can be described as distributions, mathematical expressions or discretized into bins. The likelihood that a particular state is manifested is defined by probabilities based on 1) observed frequencies in historical data, 2) probabilistic output from another model, or, 3) relative likelihood elicited from scientific experts. Because the system used in this case study is monitored extensively and because it represents the least controversial data source to the public (as opposed to simulation or expert opinion), monitoring data was used as fully as possible for this BN. Parent nodes are described using marginal or unconditional probability distributions represented in node probability tables. For this BN, distributions of flows from the three sources were determined from historic data (Fig. 3, see below for details on data sources). Child nodes are conditional on every possible combination of their parent nodes and represented by conditional probability tables (CPTs). This conditional dependence is where the chain rule becomes important to calculate the joint probability based on all the connected nodes (for details, see Reckhow, 1999; Fenton & Neil, 2018). For example, in this case study, Chl a concentration in the estuary was conditional on combinations of TN and TP concentrations (Table 1), which, in turn, were dependent on flows and loads entering the estuary (Fig. 1). Careful consideration must be given to discretizing continuous variables because CPTs quickly become unwieldy with increasing node states. For this reason, it is also important to minimize the number of parent nodes linked to a child node. Increasing the number of nodes (variables) and linkages also runs the risk that the BN will become too complex and may overwhelm the intended audience. Hence, the goal of discretizing is to represent the influences of the variables on the endpoint with the fewest discrete states necessary.

If a model does become too large it may need to be decomposed into smaller component models termed object-oriented BNs (OOBNs, for details, see Fenton & Neil, 2018). It is also important to recognize that conditional independence (lack of arrows) is not the same as complete independence, as many of the variables are interrelated but only the most influential relationships (key dependencies or linkages) are modeled. Empirical datasets like those used in this BN can be discretized using several different methods: the equal-interval or equal-frequency method (Chen & Pollino, 2012), Jenk's Optimization or "natural breaks" method for clustering numerical data (Jenks & Caspall, 1971) or, where available, ranges or bins can be defined based on management objectives or targets. In the present study, flows and intermediate variables were discretized based on a combination of Jenks optimization method and restoration targets described above.

AgenaRisk 10, a commercially available software program (Agena Ltd., for details, see Fenton & Neil, 2018), was used for constructing the BN in the present study; however, numerous software packages have been used to develop BNs for aquatic sciences (for listings, see McDonald et al., 2015).

Data sets

Average daily freshwater discharge from Lake Okeechobee at S-77 and to the estuary at S-79 were obtained from SFWMD's data portal (https://www.sfwmd.gov/science-data/dbhydro) for the period of November 2007 through July 2021 and processed using Microsoft Access. Flows at S-79 represent contributions from both the lake and the C-43 Basin; the latter was calculated by subtracting S-77 flows from S-79. Occasionally S-77 flows were negative during times of back-pumping to the lake (thus, no downstream contribution). Furthermore, flows from S-79 were sometimes less than S-77 representing periods of withdrawals from the river for irrigation within the C-43 Basin.

Flows from the Tidal Basin were determined based on discharges monitored by USGS at the following tributaries: Telegraph Creek (022929176), Orange River (02293055), Popash Creek (02293090), and Whiskey Creek (02293230) (all available from https://waterdata.usgs.gov/nwis/). These flows were monitored by the USGS from November 2007 through April 2013 but then discontinued until monitoring was resumed in September 2018 and continues as of this writing. Available data was collected through July 2021 resulting in over 98 months of flow data with a gap of approximately five and half years. Accordingly, this same period was also used as the basis for delimiting the period of record for all other input variables.

Nutrient loads in discharges from S-77 and S-79 were calculated using flows described above and nutrient concentrations observed during monthly water quality monitoring at these structures by SFWMD (Project Code CRFW); also downloaded from their web data portal (DBHYDRO). Loads at S-77 represent loads coming out of the lake. Loads at S-79 minus loads at S-77 represent loads added from the C-43 Basin. Nutrient concentrations at these two structures have previously been shown to differ depending on the dominant source of water and flow rate (Rumbold & Doering, 2020). Loads from the Tidal Basin were based on flows (described above) and water quality monitoring by the Lee County Environmental Laboratory within Orange River (40-32GR), Whiskey Creek (WHISGR10), Telegraph Creek (29-8GR), and Popash Creek (23-5GR). Loads were calculated based on a daily time step using linear interpolation between concentrations observed between monthly grab samples. These flows and loads should be considered an underestimate, however, given the many canals and unnamed creeks discharging downstream of S-79 (Fig. 2). Daily flow was averaged and daily nutrient load summed over the 30 days prior to each sampling event for water quality in the lower estuary (described below). This 30-day lag period is thought to approximate the hydraulic residence time under most conditions and, therefore, yielded higher correlations between load or flows and downstream concentrations, particularly salinity, in previous studies (Doering & Chamberlain, 1999; Rumbold & Doering, 2020). For this BN, nutrient concentrations could have been expressed as a continuous function conditional on flow; however, the daily time step calculation (rather than monthly) and summing of loads (particularly from the tributaries in the Tidal Basin) was deemed an unnecessary complexity and not shown in the BN. As discussed below, future BNs of this system may want to include these nodes as efforts to reduce nutrients in discharges from the lake and C-43 Basin progress.

Down-estuary conditions were assessed based on water quality monitoring data collected in the estuary by SFWMD at their station CES07 (Fig. 2, available at https://www.sfwmd.gov/science-data/dbhydro) and by Lee County Environmental Laboratory at their station CES10SUR (Fig. 2; available on http://leegis.leegov.com/surfwater/). These two monitoring sites are located approximately 3 km apart in what is typically the mesohaline segment of the estuary, which is the focus of the present study. Typically, sampling dates for the two independent monitoring programs haphazardly fell one to two weeks apart; however, all individual data values were used and aligned with average flows and total loads over the previous 30 days. Using all values was deemed preferable over the potential bias resulting from low sampling frequency that can sometimes miss concentration peaks. Response variables downloaded from these sites included: salinity, TP (mg/L), TN (mg/L, or Total Kjeldahl nitrogen summed with nitrate- + nitrite-N), Chl a corrected (ug/L), light attenuation or PAR (Kd, 1/m) and color (PCU). With one exception frequencies of different conditions used to populate CPTs were based on empirical data collected during these monitoring programs. The exception was PAR which was monitored routinely by SFWMD only after 2014 and only intermittently by Lee County throughout the period that resulted in a more limited data set that did not happen to occur during extremes (i.e., bins) of color and Chl a. Where Kd information was lacking during those extremes in Chl a and color, the Kd was judged to be > 1.39 1/m with a 100% frequency.

Management and Optimization Scenarios

The scenarios used in the case study were set within the system's observed variability in freshwater discharges, loads and conditions observed in the CRE from 2008–2021. The BN was constructed using results from the 98 months of monitoring (coinciding with flow monitoring at the down-estuary tributaries) and was considered general conditions. Three management scenarios were run to explore down-estuary conditions under different flow regimes. The first management scenario assessed system response under extremely wet conditions, i.e., high flows from all sources. This is timely considering the Draft Lake Okeechobee System Operating Manual (LOSOM) under review by the United States Army Corps of Engineers at the time of this writing projects increased frequency of releases at S-79 in the range of 2100 cfs to 2600 cfs and > 6500 cfs, depending on lake stage (12 January 2022 Project Delivery Team Meeting). The second management alternative minimized flows from the lake (i.e., 0 cfs to 350 cfs) during wet conditions when runoff from the C-43 and Tidal Basins was high as a possible future scenario when managers have the option to move water from the lake south, which is a goal of CERP. This scenario is also similar to the scenario modeled by Busselli et al. (2015). The third scenario assessed system response under extremely dry conditions, i.e., little or no flows from all sources. Stakeholders and elected officials on Florida's east coast have argued strenuously for no releases from the lake to the St. Lucie Estuary; however, resource managers on the west coast recognize that flows from the lake are necessary under dry conditions to maintain favorable salinities in the upper estuary, at least until more storage is available in the local basins (for review, see RECOVER, 2020).

Results And Discussion

General conditions over the monitoring period

The BN analysis of the variable hydrologic conditions over the entire 98-month monitoring period (i.e., when viewed in total) showed flows from the upstream watershed (i.e., S-79 structure) exceeded upper restoration target flow rate (i.e., 2,100 cfs) 32% of the time (Fig. 3; recognizing these values represented 30-d moving average flows which may dampen the extremes relative to the target based on 14-d moving average). The dilution effect from this freshwater discharge resulted in damaging or stressful salinities in the lower estuary for oysters and shoal grass 23% and 37% the time, respectively (Fig. 3). Yet, flows fell below the minimum target established for tape grass in the upper estuary (i.e., 750 cfs) almost 40% of the time. This minimum flow target was revised from 450 cfs to 750 cfs only recently in 2020 (RECOVER, 2020), so this failure rate in regulated flow should not be surprising. The new minimum flow target for tape grass was achieved almost 28% of the time. Under these general conditions, TN loads to the estuary were below their TMDL target 95% of the time (i.e., if annual load was averaged over 12 months). This is in agreement with estimates from SFWMD that annual TN loads exceeded the TMDL only twice since 2008 (in 2014 and 2018; Zheng et al., 2016; Khan & Betts, 2021). Flows from the Tidal Basin were most often less than 200 cfs (73.5% of the time) and contributed less than 10% of the TN load to the estuary as compared to loads from S-79 and the upper watersheds. Over the entire monitoring period, TN concentrations in the lower estuary were below the CHNEP restoration target for TN (of 1.09 ug/L) almost 88% of the time. Interestingly, the BN analyses indicated that during the monitoring period, Chl a concentrations were below the FDEP NNC (< 5.6 ug/L) 86% of the time. This is despite TP concentrations exceeding its NNC (0.04 mg/L) 83% of the time. It is noteworthy that this NNC is much lower than the median TP concentration generally found in this region of the estuary which typically fell within the middle bracket (Doering et al., 2006; Rumbold & Doering, 2020), possibly indicating this hold-the-line criterion should be revisited by FDEP. Finally, light attenuation (Kd 1/m), conditional on color and Chl a, resulted in PAR reaching shoal grass growing at 1 m or deeper 63% of the time throughout the monitoring period.

Species distributions are not defined by average or general conditions over the long term but, instead, by critical threshold limits in environmental conditions to which the organism can only survive for short periods, if exceeded. Damaging conditions, even if it occurs only once every few years, can devastate oyster reefs and seagrass meadows. Accordingly, the BN was run under low and high discharge scenarios to examine how the CRE responded to extreme wet and dry periods.

Wet conditions

The problem for biological resources in the lower CRE tends to be a result of too much freshwater rather than too little. During wet periods when managers allowed discharge from the lake even though runoff from the C-43 and Tidal Basins were high, the frequency of observing salinities damaging or stressful to oysters and seagrass increased by 46% (from 23–69%) and 52% (from 37–89%), respectively (Fig. 4). This is in agreement with Chamberlain & Doering (1998) who reported that freshwater flows > 4500 cfs at S-79 lowered salinity to point of being damaging to seagrasses even further down-estuary in San Carlos Bay. It is noteworthy that with the increased loads of TN associated with these freshwater discharges the frequency of exceeding the TMDL increased by 95% (from 5–100% of the time) and the frequency of exceeding the NNC for TN and TP increased by 72% (from 12–84%) and 15% (83–98%), respectively. Yet this did not result in much change in Chl a (86.3–86.8%) as might have been expected. This was likely due, in part, to a flushing or 'wash out' effect at these extreme flows (Doering et al., 2006). Chl a concentration thought to be associated with mild to obvious phytoplankton blooms (> 9 ug/L; Phlips & Badylak, 1996; Mathews, 2013) was a relatively infrequent event over the monitoring period as a whole (4.3%) and even during periods of high flows and nutrient loads (10.1%; Fig.s 3 and 4). Thus, nutrient enrichment and phytoplankton blooms do not appear to be a frequent problem in this segment of the estuary. Nonetheless, phytoplankton blooms, including those of the toxic cyanobacteria, *Microcystis* (Williams et al., 2007) have occurred in the upper, oligohaline region of this estuary sometimes resulting in sags in dissolved oxygen when blooms crashed (Doering et al., 2006; Mathews, 2013); thus, nutrient reductions are warranted.

Although phytoplankton was not a significant factor causing reduced light for shoal grass under high flows, the frequency of observing color > 37 PCU increased by 62% (from 37.1–93.3%) likely due to increased concentrations of CDOM. This increase in color was associated with frequency of light attenuation > 1.39 1/m increasing by 44% (36.5–80.5%). This clearly shows what others have reported from stepwise multivariate regressions (i.e., optical models) that nutrient targets to reduce phytoplankton shading (which was the basis of the TN TMDL) have a low probability of success in increasing light penetration for seagrass (Chen & Doering, 2016; Rumbold & Doering, 2020).

Reduced flows from Lake Okeechobee during wet conditions (i.e., sending the water south scenario)

The BN was updated to assess conditions in the estuary when local runoff was high from both the C-43 and Tidal Basins, but managers were able to minimize flows from the lake (i.e., it either had storage capacity or inflows from central Florida were not elevated). This would be analogous to the CERP goal of moving water south and increasing available storage to reduce flows to tide. Under this scenario, targeted flows continued to be exceeded 100% of the time, because the C-43 Basin was still discharging (note, extreme discharge rates from this basin > 4500 cfs occurred only when the lake was also discharging), and, while the frequency was reduced, salinities damaging to oysters and seagrass continued to occur 19% of the time; down only 5% from 24% under high flows from all sources (Fig. 5). It is interesting to note that the modeling effort by Buzzelli et al. (2015) found only a 2.3% increase in the average salinity of this segment of the estuary during the wet season under their best management scenario of moving water south. Under minimal flows from the lake, nutrient loads reaching the estuary would be reduced but would still exceed the TMDL 64% of the time and light conditions would remain poor much of the time due to the elevated color (and CDOM) in the runoff from the local basins (Fig. 5). These findings may come as a surprise to those stakeholders that believe water discharged from the lake is the sole source of problems in the estuary.

Dry conditions

When the BN was revised to focus on dry conditions with little to no freshwater discharge from any of the sources, nutrient loading was found to be much reduced with the TMDL being met 100% of the time and targeted concentrations of TN and Chl a achieved much of time (Fig. 6). Alternatively, TP concentration continued to exceed its NNC frequently. Minimum flows targeted for maintaining salinity favorable for tape grass in the upper estuary were never met. This finding would seem to confirm the consensus of local resource managers that minimal flows from the lake are necessary at certain times to maintain low salinities in the upper estuary for tape grass and other oligohaline biota, given the current storage availability in the C-43 and Tidal Basins. Yet, response variables in the lower estuary all showed improvement relative to general conditions with color < 37 PCU 99% of the time, Chl a < 5.6 ug/L 93% of the time and resulting light attenuation < 1.39 1/m almost 89% of the time. Under these conditions the frequency of observing low salinity in the damaging or stressful ranges for oysters and shoal grass fell to 0%; however, the frequency of salinity > 30 increased and, if prolonged, could allow marine predators and parasites to become stressful to the oysters. These high salinities would be optimal for shoal grass 100% of the time, which would also benefit from improved light conditions allowing meadows to grow deeper (Fig. 6).

This run of the BN clearly illustrates conflicts among restoration goals for tape grass in the upper estuary and, to a lesser extent, even between oysters and shoal grass in the lower estuary.

BN as a decision support tool

This case study demonstrated how complex linkages between management interventions and various ecological outcomes could be formalized in a concise, transparent BN that could serve both as DST and as a tool for communicating decision rationale to the public. Like many other large-scale ecological restoration projects, conceptual models were and continue to be used extensively in South Florida restoration efforts. Ogden et al. (2005) characterized conceptual models, as used in the Everglades restoration program, as non-quantitative planning tools for communicating among scientists and policymakers.

As shown here, BNs are capable of going a step further and quantitatively evaluating various management interventions and, thus, are better suited as a DST. Although not shown here, the ability of BNs to combine output from other models with empirical data as well as expert opinion would likely be extremely valuable.

This relatively simple BN was also shown to be capable of taking a systems approach to assessing the impacts of multiple stressors (e.g., flow impacts on salinity, nutrients, and color) on multiple ecological endpoints (e.g., shoal grass and oysters in the lower estuary and even provide a condition index for tape grass in the upper estuary) as opposed to having to rely on multiple, independent models (cf. Buzzelli et al., 2015 that used multiple different models that focused almost entirely on salinity). This capability is essential to reveal significant interactions between restoration goals, sometimes competing, i.e., goal conflicts (e.g., flows needed by the tape grass in the upper-estuary and shoal grass and oysters in the lower estuary), or identify opportunities for synergies (e.g., flows and resulting salinity for oysters and salinity and light conditions for shoal grass). Understanding these interactions is essential in arriving at sound management actions.

Examining the monitoring data based on frequency distributions (or probabilities) rather than estimates of central tendency and dispersion (i.e., mean ± 1SD) more accurately conveyed the system conditions (particularly time under damaging conditions) and would likely be more easily interpretable by non-technical stakeholders. Focusing on the relative change between alternative scenarios and, thus, on effect size, would also be an advantage over relying on p values. In today's climate of austerity measures, it is essential to have public support to increase the likelihood of turning restoration initiatives into reality. This requires a decision support tool such as a BN that people can understand and that offers opportunities for participation in the decision-making process (Maguire, 2003; cf. Buzzelli et al., 2015). This would likely also engender more confidence in the output. Other desirable characteristics of DSTs include ease of use and a robust user interface. The BN constructed in this case study was easily updated when any number of variables were adjusted and required almost no run time compared to complex process models. It could easily be employed in a multi-stakeholder workshop that would allow decision-makers and stakeholders to work collaboratively in assessing restoration goals and potential benefits and risks of management alternatives.

Future modeling efforts

The period of record and datasets available for this case study were limited by the intermittent monitoring of flow at tributaries in the Tidal Basin. The node representing flows from this basin could have been replaced by the output from the model developed by Wan and Konyha (2015) that is used by others (e.g., Buzzelli et al., 2015; Kahn & Betts, 2021). This BN did not model seasonal variations; however, it could easily have been expanded to evaluate seasonal effects on precipitation and discharge, seasonal variations in life histories (presence of early reproductive stages in the water column or just settled), as well temperature extremes known to act as a synergistic stressor. This BN could easily have also been extended to consider other segments of the estuary including the oligohaline segment where there is great concern about the loss of tape grass. As mentioned previously, phytoplankton blooms including toxic cyanobacteria occur in the oligohaline segment. In the future, a BN could be constructed to assess the influential factors associated with these blooms similar to what has been done in other systems (e.g., Rigosi et al., 2015; Moe et al., 2016; Shan et al., 2019). A future BN might also disentangle flows from nutrient loads and concentrations and model the effect of basin management action plans to accomplish TMDLs recently established in the C-43 Basin, as has been done in other systems (e.g., Borsuk et al., 2003; Ames & Lall, 2008; Qian & Miltner, 2015). As mentioned previously, if the BN becomes too large or complicated it may be decomposed into smaller (but linked) component models termed object-oriented BN (OOBNs; Fenton & Neil, 2018).

Bayesian networks, of course, also have applications for supporting decision making in the ongoing ecological restoration of the wider Everglades basin.

Conclusions

This BN revealed flows from the upstream watershed exceeded upper restoration targeted flows 32% of the time under general conditions. This resulted in damaging or stressful salinities in the lower estuary for oysters and shoal grass 23% and 37% of the time, respectively; this increased to 69% and 89% of the time, respectively under wet conditions. If managers did not allow high flows from Lake Okeechobee during periods of high runoff from the local basins, the frequency of damaging or stressful conditions was reduced but not curtailed. When updated to reflect dry conditions with little to no freshwater inputs to the estuary, the BN showed both oysters and shoal grass benefitting from increased salinities at the expense of tape grass in the oligohaline, upper estuary. This case study conveyed complex linkages between the different management actions and various ecological outcomes in a transparent manner that would be well suited for communication between scientists, stakeholders, and decision makers. Moreover, because of its capability and ease of use in quantifying the consequences of these actions, the BN has the potential to serve as a robust decision support tool for collaboratively determining the best approaches for implementing restoration and water management initiatives.

Declarations

Funding: The author did not receive support from any organization for the submitted work.

Availability of data and material: All data used in the study are available from the sources identified in the paper: https://www.sfwmd.gov/science-data/dbhydro; https://waterdata.usgs.gov/nwis; http://leegis.leegov.com/surfwater/

Compliance with Ethical Standards

All authors have read, understood, and have complied as applicable with the statement on "Ethical responsibilities of Authors" as found in the Instructions for Authors and are aware that with minor exceptions, no changes can be made to authorship once the paper is submitted

Conflict of interest: The author declares that he has no conflict of interest.

Financial interests: The author has received research support from SFWMD in the past.

Research involving human participants and/or animals: This research did not involve humans or animals

Informed consent: Not applicable

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Tables

Table 1 is available in the Supplementary Files section.

Figures

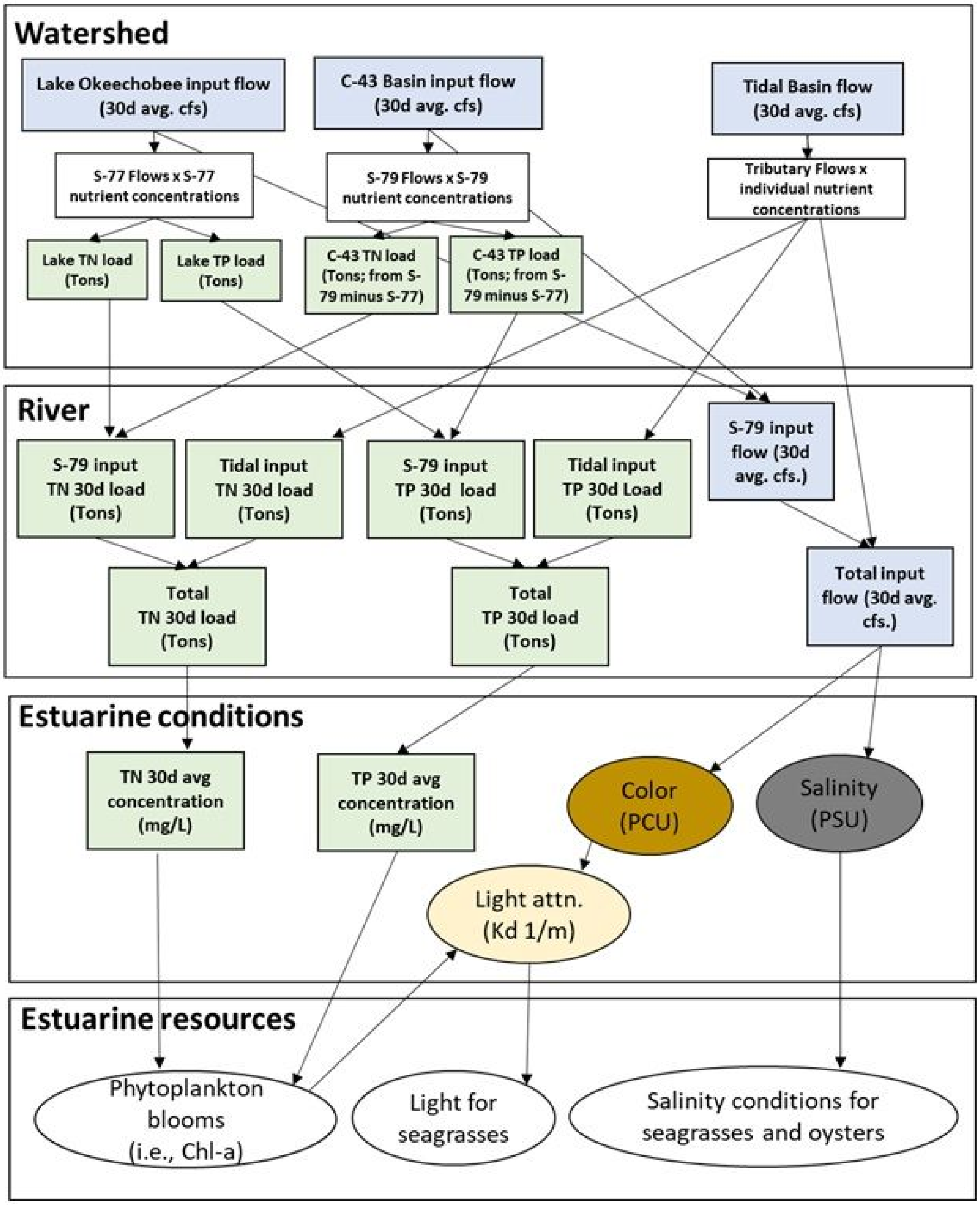

Figure 1

A conceptual model identifying linkages among relevant variables as well as endpoints of concern to the public and decision-makers in this system.

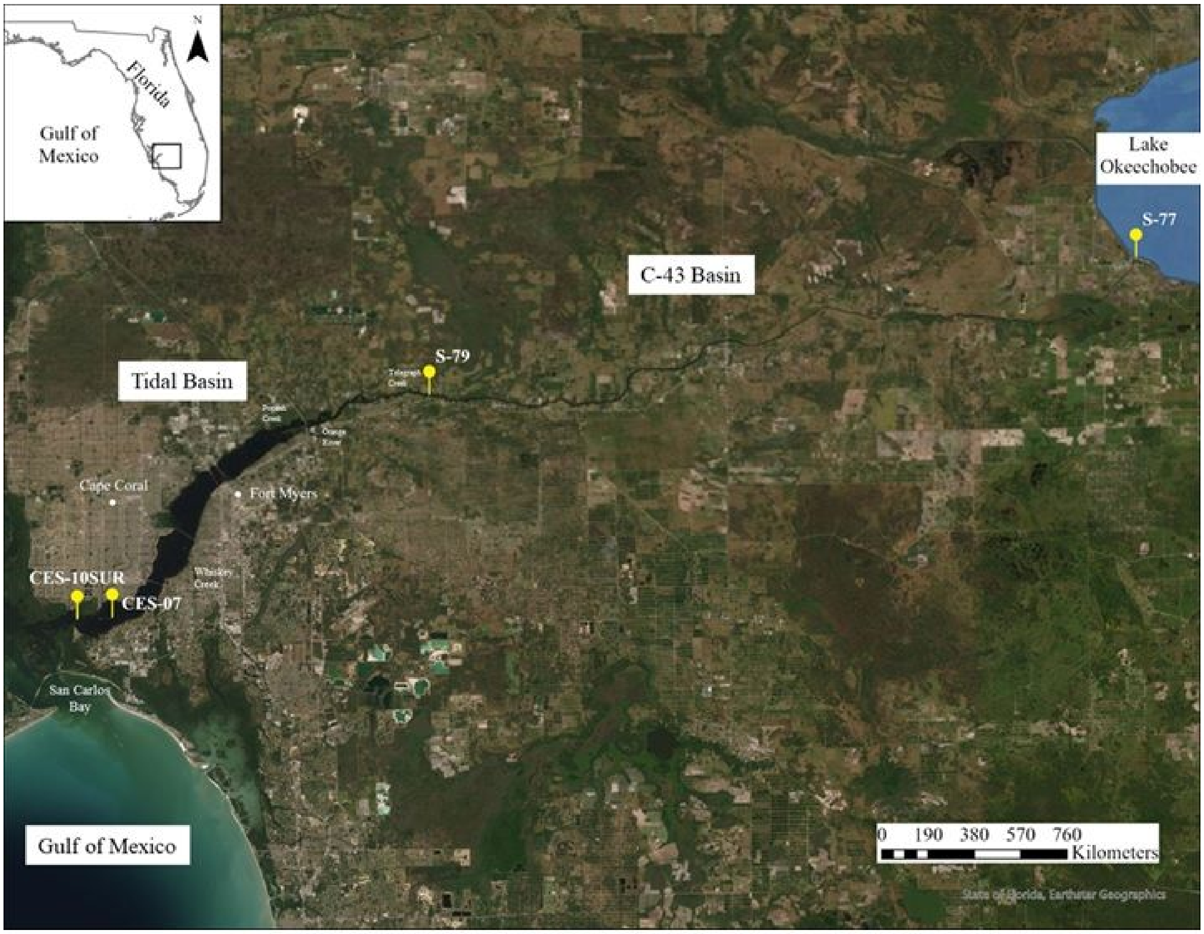

Figure 2

Map of the watershed showing different basins, upstream water control structures and the location of two monitoring sites within the mesohaline segment of the Caloosahatchee River Estuary.

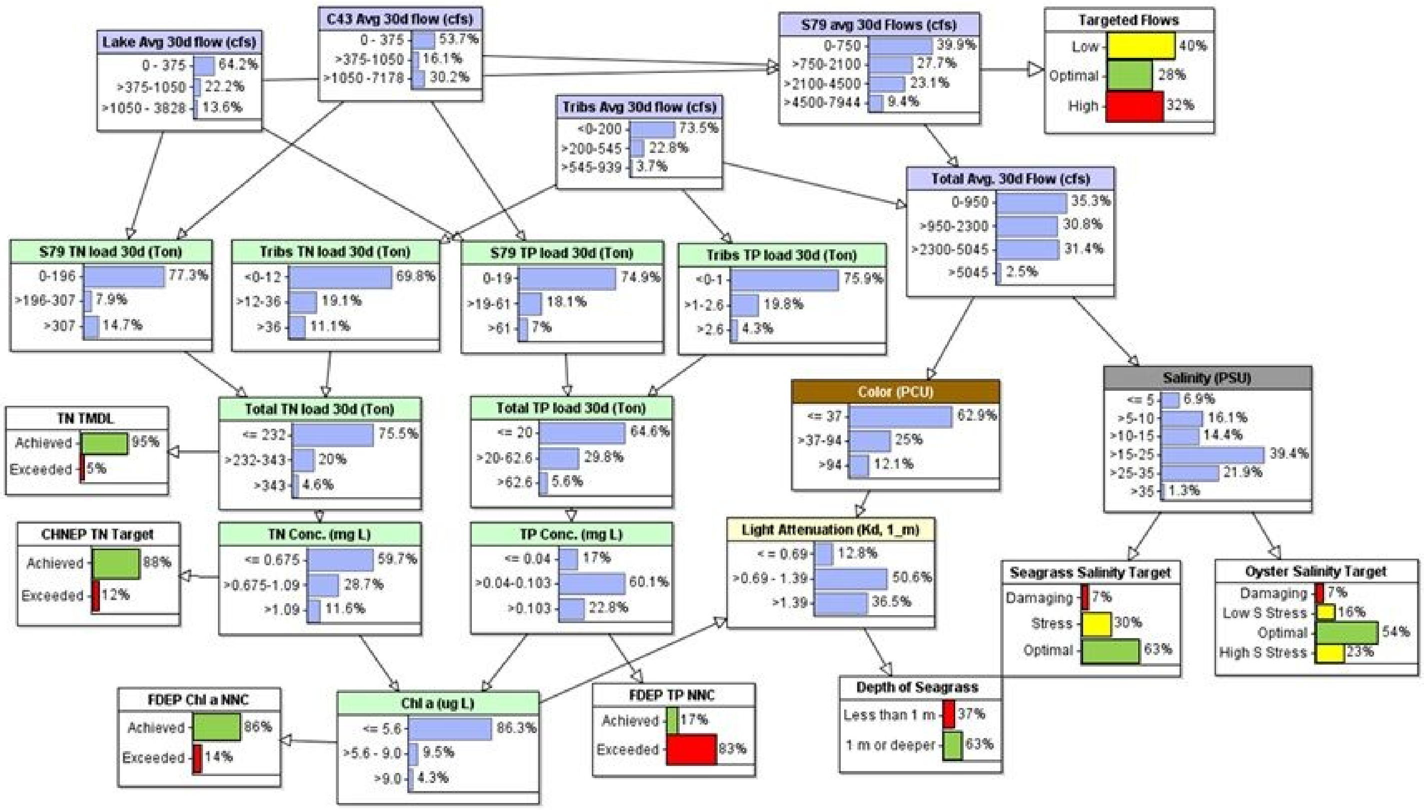

Figure 3

BN describing general conditions over the 98 months of intermittent monitoring of the CRE and upstream watersheds from 2008 - 2021. The length of each bar in the node reflects the conditional probabilities for the occurrence of observations falling within that histogram bin. Response variables were translated into Boolean outcomes based on management objectives (e.g., achieved or exceeded) or as ranked states (e.g., damaging, optimal and stressful conditions) and color coded to increase interpretability.

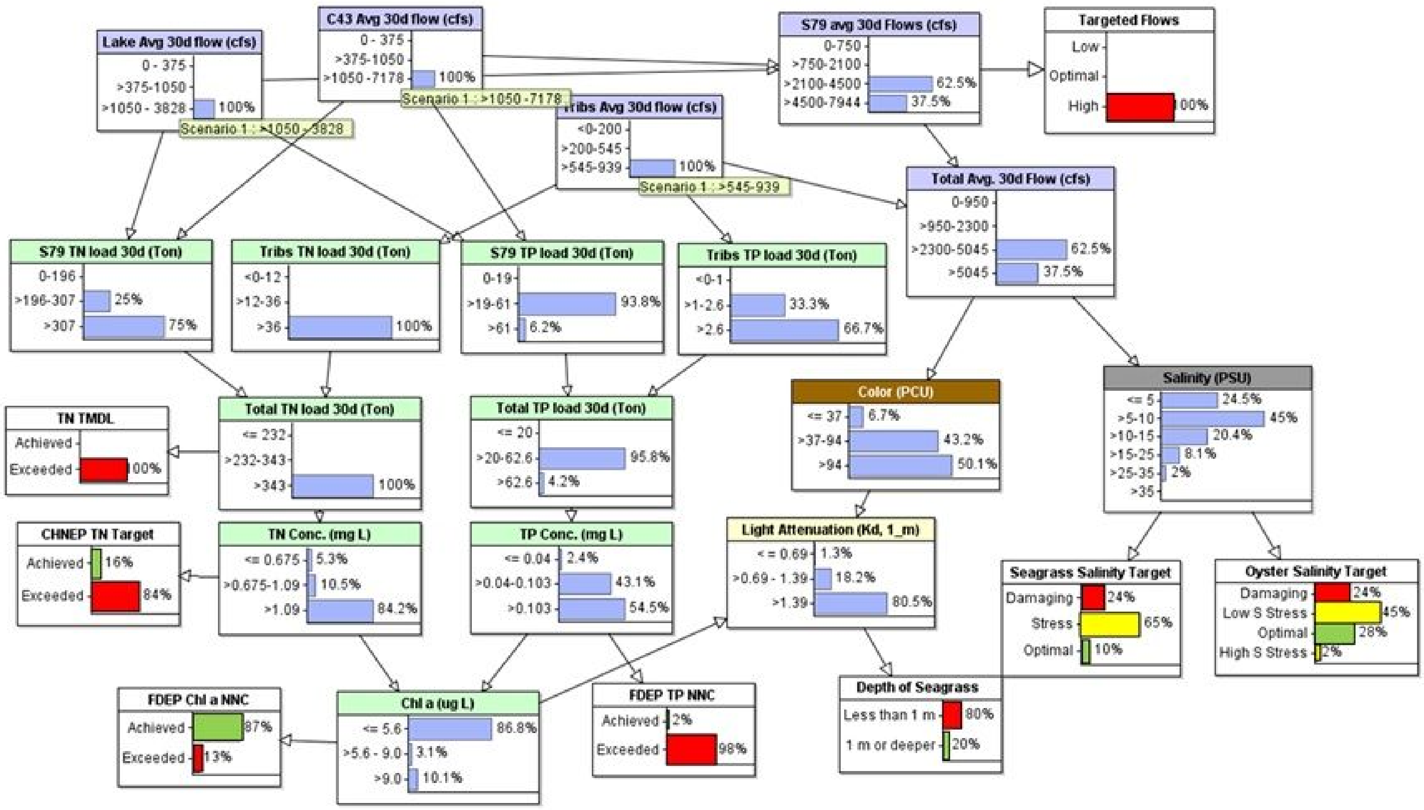

Figure 4

BN updated to focus on wet conditions when managers allowed large-volume discharges from Lake Okeechobee while runoff and discharges from the C-43 and Tidal Basins were also high.

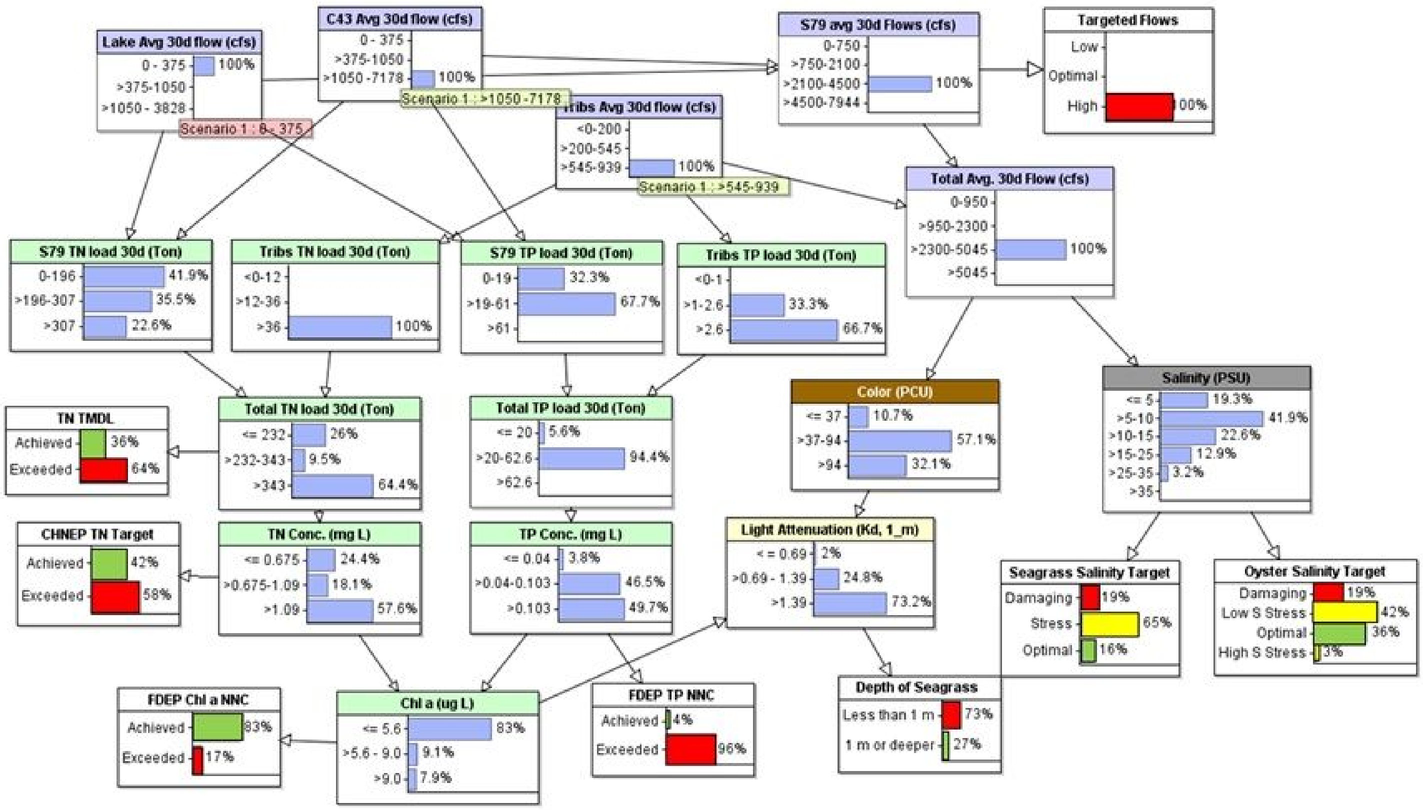

Figure 5

BN updated to focus on wet conditions when runoff from the C-43 and Tidal Basins were high but managers were able to minimize discharge from Lake Okeechobee.

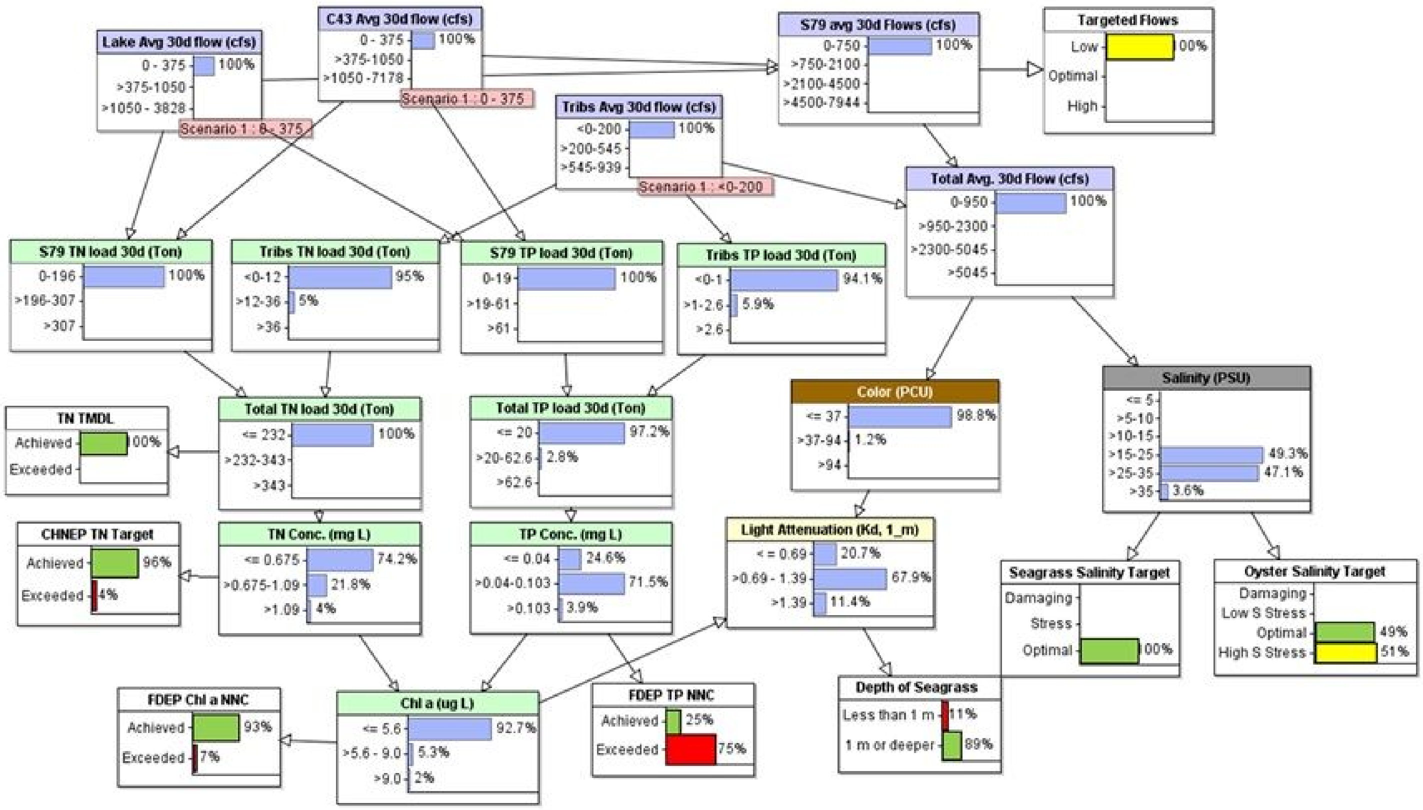

Figure 6

BN updated to focus on dry conditions with little freshwater discharge from any of the main sources.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- RumboldTable1.docx