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Middle-term metropolitan water availability index assessment based on synergistic potential of multi-sensor data

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Middle-term metropolitan water availability index assessment based on synergistic potential of multi-sensor data

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Abstract. The impact of recent drought and water pollution episodes results in an acute need to project future water availability to assist water managers in water utility infrastructure management within many metropolitan regions. Separate drought and water quality indices previously developed might not be sufficient for the purpose of such an assessment. This paper describes the development of the “Metropolitan Water Availability Index (MWAI)” and its potential applications in assessing the middle-term water availability at the watershed scale in a fast growing metropolitan region – the Manatee County near Tampa Bay, Florida, U.S.A. The MWAI framework is based on a statistical approach that seeks to reflect the continuous spatial and temporal variations of both water quantity and quality using a simple numerical index. Such a trend analysis will surely result in the final MWAI values for regional water management systems within a specified range. By using remote sensing technologies and data processing techniques, continuous monitoring of spatial and temporal distributions of key water availability variables, such as evapotranspiration (ET) and precipitation, is made achievable. These remote sensing technologies can be ground-based (e.g., radar estimates of rainfall), or based on remote sensing data gathered by aircraft or satellites. Using a middle term historical record, the MWAI was applied to the Manatee County water supplies. The findings clearly indicate that only eight out of twelve months in 2008 had positive MWAI values during the year. Such numerical findings are consistent with the observational evidence of statewide drought events in 2006-2008, which implies the time delay between the ending of severe drought period and the recovery of water availability in MWAI. It is expected that this forward-looking novel water availability forecasting platform will help provide a linkage in methodology between strategic planning, master planning, and the plant operation and adaptations in response to the MWAI implications.

Keywords: Water sustainability, remote sensing, drought management, water supply, risk assessment.

1 INTRODUCTION

Regional water supply utilities commonly obtain their water from three primary sources: 1) surface water bodies (canal, lake, or river); 2) groundwater aquifers; and/or 3) desalination plants that treat seawater and/or brackish water. Yet global climate change will influence many environmental conditions including temperature, precipitation, surface radiation, humidity, soil moisture and sea level, as well as significantly impact regional-scale hydrologic processes such as evapotranspiration (ET), runoff, groundwater flow and
The quantity and quality of water available for drinking and other domestic usage will likely be affected by changes in these processes. Recent extreme hydroclimatic events in the U.S. alone include the droughts in the Maryland-Chesapeake Bay area in 2001 through September 2002; Lake Mead in Las Vegas in 2000 through 2004; the Peace River and Lake Okeechobee in South Florida in 2006; and Lake Lanier in Atlanta, Georgia in 2007 that affected the water resources distribution in three states - Alabama, Florida and Georgia. Alternative water supply for irrigation was made possible through wastewater reclamation and stormwater reuse in many states. To many water utility managers and water agency planners, today’s challenge is to identify an effective way to sustain adequate water supply and water quality compliance in response to the changing hydroclimatic conditions. This requires timely assessment and forecasting of water availability for the efficient operation of drinking water, stormwater and wastewater infrastructures collectively using an index approach. Such a need is paramount for the increased frequency and magnitude of prolonged drought occurrence in a time of climate change and for the increased domestic and industrial water consumption of the 21st century.

The earlier drought index derivations mostly relied on a point measurement of the temperature and precipitation information. The occurrence of droughts in several regions has led to studies on their impact, mostly on water availability or water shortage in regard to public needs [1], and to seek new methods for quantitative assessment of regional extent and drought severity. Current drought measurement mostly relies on biophysical parameters such as vegetation indices (VIs), land surface temperature (LST), soil moisture, albedo, precipitation, and ET using remotely sensed data [2]-[11]. In the last two decades, several satellite-derived indices have specifically been developed as indicators of plant water content, or water stress. Their development and application allow timely assessment of water budget and its spatial distributions over a large contiguous area. For example, the indices based on remotely sensed data of microwave, visible and near-infrared wavelengths were used to estimate changes in vegetation, surface soil moisture, and ET in a study of vegetation biomass, phenology, and net primary productivity [12]-[19]. Ground-based radar stations, such as NEXRAD (Next-Generation Radar) consisting of 158 high-resolution Doppler weather radars operated by the National Weather Service (NWS), can provide quantitative information of the spatial and temporal precipitation distributions [20]-[23]. Some of recent drought monitoring models were developed with the aid of satellite remote sensing imageries in relation to those VIs and LST using a combination of LST from thermal band data versus VIs from visible and near infrared data [11],[24]. To assess the relationship between vegetation vigor and moisture availability, several more remote sensing-based drought indices were developed [22]. Some early drought indices, like the Keetch-Byram Drought Index (KBDI), are also being further modified to include the El Niño/Southern Oscillation (ENSO) information for assessment of the impacts of global climate change [26]-[27]. Impacts of these recent drought events are significant but difficult to measure by a traditional drought index because of the extent and magnitude associated with both water quantity and quality simultaneously. Numerous interpretations of water quality were addressed by using water quality indices in the literature [28]. Many river water quality monitoring exercises and assessments examined separate stretches of freshwater in terms of their chemical, biological and nutrient constituents and overall aesthetic condition [29]-[32].

Satellite remote sensing is also useful to monitor inland water quality through the use of correlations between broad-band reflectance and other properties of the water column such as Secchi disk depth, Chlorophyll-a (Chl-a) concentrations, temperature, dissolved organic matter (DOM), biochemical oxygen demand (BOD), and chemical oxygen demand (COD) [33]-[44]. Chen et al. [45] further developed empirical functions with multiple spectral parameters from the LANDSAT 7 Enhanced Thematic Mapper (ETM+) data on water quality in a subtropical reservoir with the aid of parallel genetic algorithms based on an extended concept of genetic programming [46]. The optimal relationship among remotely sensed imageries and
Chl-a was acquired through the use of a parallel genetic algorithm. Although the LANDSAT Thematic Mapper\textsuperscript{TM} sensor provides the longest continuous dataset of high-spatial resolution and is able to present a synoptic monitoring of water quality problems, its quantitative use is still a difficult task \cite{47}. LANDSAT 7 ETM+ and the Hyperion instrument on the Earth Observing-1 satellite obtain visual images of the surface of the Earth at a higher spatial resolution than MODIS. Both can be analyzed to track changes in water quality over time. Overall, these advances in remote sensing make the inclusion of water quality impacts as an integral part of MWAI possible, such as the inclusion of the trophic state based on chlorophyll-a (chl-a) concentrations and turbidity levels.

Consequently, it is necessary to incorporate the quantity and quality information of all viable source water available for water supply into the same metrics for comparison in order to address the water availability issue for a given region. The main scientific questions remaining are: 1) how do we combine both impacts cohesively? and 2) how can remote sensing technologies aid in such an assessment? This paper aims to develop such an index, which we term the Metropolitan Water Availability Index (MWAI), in the context of Total Water Management (TWM) to assess the integrated status of both quantity and quality of available potable water sources using integrated remote sensing technologies. The TWM approach integrates the functions of all components of the built and natural water cycles, and holistically evaluates the interactions of major water availability components within an entire water system. Hence, major MWAI attributes should at least include: 1) an index that must reflect the short-term developing water quantity and quality conditions; 2) an index that should be without seasonal influence (i.e., the index should be able to indicate a drought and/or contamination event irrespective of season); and 3) an index that should consider water sources from non-traditional water resources including reclaimed water. With both quantitative and qualitative information included, such a trend analysis may result in final MWAI values which will range from -1 to +1 for regional water management and decision making. This paper describes the development of MWAI, and further elaborates application potential with a case study based on a set of decadal-scale data at an urban region with the aid of remote sensing technologies.

2 METHODOLOGY OF MWAI

2.1 Theoretical framework

In principle, the MWAI is a combination of two assessment factors in water quantity and water quality weighted by two coefficients – the weighting factors. Although the water quantity and quality information can be theoretically related to the index value through various algebraic expressions in decision analysis, a linear weighted average of quantitative and qualitative impacts is the simplest form for the easy implementation in a metropolitan region \cite{48}:

$$Q = f(w_1, w_2, Q_1, Q_2) = w_1 Q_1 + w_2 Q_2 \quad (1)$$

where \(w_1\) and \(w_2\) are the weighting factors, and \(Q_1\) and \(Q_2\) are the water quantity and quality impacts, respectively. In order to unify the information of fresh water availability, the sum of the two weighting factors should be one.

The intrinsically dependent relations between water quantity and water quality in most cases make the computation a difficult task. However, widely applied water resources management objectives and associated engineering practices could lend a common basis to parameterize the quantity and quality variables. It is recognized, however, that these variables are location-specific depending on water infrastructure assets, water resources functionality, and management objectives, for which further studies are warranted. The following Eqs. are expressed for the purpose of demonstration, in which only seven water quality parameters are
considered. Using integrated remote sensing and in-situ observations, \( Q_1 \) and \( Q_2 \), are derived either from the application of spatially averaged pixel values of satellite images or some point measurements with respect to a specific quantity or quality parameter of interest within a particular time period. They can be defined in greater detail as follows [48]:

\[
Q_1 = w_{11} R_1 + w_{12} R_2 + w_{13} R_3 = w_{11} (P_n + G_n \pm T_a - ET_n - R_n \pm \Delta S_n) + w_{12} R_2 + w_{13} (R_{31} + R_{32}) \tag{2}
\]

\[
Q_2 = w_{21} T + w_{22} CHL + w_{23} Phos + w_{24} Cl_p + w_{25} Sul_p + w_{26} Cl_a + w_{27} Sul_a \tag{3}
\]

where \( w_{ij} \) and \( w_{ij} \) are the weighting factors defined for \( Q_1 \) in Eq. (2) and \( w_{ij} \), \( w_{2j} \), \( w_{2j} \), \( w_{2j} \), \( w_{2j} \), \( w_{2j} \), and \( w_{2j} \) are the weighting factors defined for \( Q_2 \) in Eq. (3) corresponding to different water quality parameters. Conceptually, \( R_1 \) is the contribution from the availability of source water in the terrestrial system, including those from surface and fresh groundwater systems. \( R_2 \) is the contribution from the availability of source water produced by seawater/brackish water desalination. \( R_3 \) is the contribution from water reuse in which \( R_{31} \) and \( R_{32} \) are the contributions from the reclaimed wastewater and from the reused stormwater, respectively. Whenever there is a downtime of a water management facility, a safety factor may be applied in \( R_2 \) or \( R_3 \) individually.

In computation, the sum of the three weighting factors in Eq. (2) should be equal to one. Within the first parenthesis of Eq. (2), which represents the watershed-based water budget consideration in the context of fresh water availability, the parameters \( P_n, G_n, ET_n, R_n, T_n \), and \( \Delta S_n \) are normalized to a middle term average of precipitation, groundwater aquifers, ET, river runoff, transboundary inputs/outputs, and soil moisture. Although the formulation here tries to be all-inclusive with respect to a hydrological cycle, it is not always necessary to take all components into account in a single assessment and the selection of each actually depends on the data availability in applications. For example, the inclusion of ET in a humid and cold region, such as the Pacific Northwest region in the US, may be ignored. For this reason, the use of MWAI is system- and region-specific and is more for temporal comparison at a given single area rather than spatial comparison between regions. In decision sciences, by the same token, the summation of these two weighting factors should be equal to one in Eq. (3); the \( T \), \( CHL \), and \( Phos \) are the concentrations of turbidity, chl-a, and phosphorus in a surface water body, respectively. \( Cl \) and \( Sul \) are chloride and sulfate concentrations in groundwater, respectively. Subscripts “p” and “a” associated with chloride and sulfate concentrations represent production wells and aquifer storage and recovery (ASR) wells, respectively. If necessary, this Eq. may be expanded to include other water quality parameters, such as heavy metals.

In Eqs. (2) and (3), all of the terms involved are dimensionless after carrying out normalization to avoid any bias embedded in different unit associated with a differing component in the hydrological cycle. For example, \( P_n = (P_{jk} - P_{min})/(P_{max} - P_{min}) \) is the normalization of precipitation in a particular month \( j \) in a specific year \( k \) that is compared against the minimum value of precipitation in the year considered. The base, that is the difference between the maximum and minimum precipitation in that year, is therefore used as the denominator to normalize the precipitation making the value of \( P_n \) fall into the range between 0 and 1.

Trend analysis on a short-term, middle term, or long-term basis may further affect the evaluation of the water availability statistically. Therefore, when taking historical time periods into account for the present MWAI prediction, normalized \( Q_1 \) and \( Q_2 \), which are designed to avoid any comparative bias between \( Q_1 \) and \( Q_2 \) in totality, can be derived based on Eqs. (4) and (5) below [48]:

\[
\]
\[ \Delta Q_{1j} = \frac{Q_{1ijk} - \left( \sum_{j=1}^{p} \sum_{i=1}^{N} Q_{1ijk} \right) / (pN)}{3\sigma_{Q_{1ijk}}} \]  
(For water quantity) \hspace{1cm} (4)

\[ \Delta Q_{2j} = \frac{\left( \sum_{j=1}^{p} \sum_{i=1}^{N} Q_{2ijk} \right) / (pN) - Q_{2ijk}}{3\sigma_{Q_{2ijk}}} \]  
(For water quality) \hspace{1cm} (5)

where \( \Delta Q_{1j} \) and \( \Delta Q_{2j} \) are the translated value of \( Q_1 \) and \( Q_2 \), respectively, for pixel \( i \) of a quantitative component in time period \( j \) (e.g., \( j \) could be a particular year of concern) in which \( p \) is the total number of years; \( \bar{Q}_{1ijk} = \left( \sum_{j=1}^{p} \sum_{i=1}^{N} Q_{1ijk} \right) / (pN) \) and \( \bar{Q}_{2ijk} = \left( \sum_{j=1}^{p} \sum_{i=1}^{N} Q_{2ijk} \right) / (pN) \) are the spatially averaged values of \( Q_{1ijk} \) and \( Q_{2ijk} \), respectively, and \( \sigma_{Q_{1ijk}} \) and \( \sigma_{Q_{2ijk}} \) are the standard deviations of \( Q_{1ijk} \) and \( Q_{2ijk} \), respectively, for pixel \( i \) in time period \( j \) in a multi-year time frame in which the historical data is available. \( k \), in this context, is defined as an intermediate subscript to help sum over the relevant time series data from the first year to the \( k \)th year. If a monthly MWAI is to be taken into account, subscript \( k \) is defined accounting for monthly effect in the sense that relevant monthly values in all previous years collectively affect the current monthly MWAI in the current year (e.g., \( k \)th year). When dealing with Eqs. (4) and (5), the spatial average should be carried out at first before running the time series data for MWAI derivation. \( N \) is the total number of remote sensing image pixels under consideration spatially in an environmental system that could be a watershed, a reservoir, a lake, etc. Should the remote sensing images not be available, \( N \) stands for the total number of in-situ point measurements. The purpose of choosing 3 standard deviations from the mean is to capture the largest possible statistical variances over the time series in order to form a comparative basis in the denominator. So the standard deviation should be the average of \( N \) pixels, not the deviation for an individual pixel. When assessing the quantity of source water available for use, the MWAI follows the principle of the more-the-better; yet this is only seldom possible in most occasions for the assessment of the quality of the water. For example, the less-the-better principle is not true for some water quality parameters like dissolved oxygen (DO). Yet DO is not a factor of concern in this study. For this reason, the average value \( \bar{Q}_{2ijk} \), in the numerator of Eq. (5), needs to move to the front implying the less-the-better principle. For operational simplicity, the period \( j \) in Eqs. (4)-(5) can be on a weekly or monthly basis, while keeping on a changing and moving time window for improved forecasting accuracy by capturing periods of relatively homogeneous hydrologic sample population, or even on specific designed periods conforming to water management objectives of a specific region.

Finally, if the spatial analysis is feasible with the aid of remote sensing and/or sensor networks, the pixel-based metrics for the MWAI (dimensionless) may be evaluated area-wide by simultaneously taking all pixel values or point measurements into account by integration. Hence, the MWAI for the \( j \)th month in the \( k \)th year can be finally defined as follows [48]:

\[ \text{MWAI}_{j} = w_{1} \Delta Q_{1j} + w_{2} \Delta Q_{2j} \]  
(6)

A typical range of the MWAI is between -1 and +1. The physical implication of such MWAI values lies in their perspective realization of where we are in terms of water availability status relative to the historical trend, which makes MWAI an effective vehicle as to what decision associated with adaptive infrastructure management strategies we have to make in the next step. It is analogous to the NASDAQ-100 index in financial markets to be used as a physical trading floor to conduct trading in the next step. This definition reflects the fact that extreme events that deviate from the mean by three or more standard deviations, whether they are
positive or negative, could not be managed by the MWAI. To represent a large geographic area, aggregated values may be selected based on the actual basin-wide condition. The normalization of $\Delta Q_1$ and $\Delta Q_2$ sets up a basis for application across geographic areas or through time at a given location. This mathematical treatment allows the use of integrated remote sensing and in-situ sensor networks to accumulate the spatiotemporal water information. In decision analysis, however, the interactions between $\Delta Q_1$ (quantity) and $\Delta Q_2$ (quality) can possibly become important and nonlinear terms may warrant full integration of the two variables in Eq. (6).

### 2.2 Determination of weighting factors

The principal criteria in preliminary screening are designed to examine the relative impacts of water quantity and water quality changes. Thus, the first criterion focuses on the quantitative assessment. With the availability and limitation of monitoring data in most terrestrial fresh water systems, precipitation, stream flow, soil moisture and ET are collectively considered as four major quantitative components of water quantity assessment. The reason for including the stream flow is due to the absence of groundwater in the metrics although, in most cases, stream flow is a second tier hydrologic process in response to precipitation, soil moisture, ET, topography, etc. The water quality variability is represented by any constitutes of concern, such as turbidity and chl-a in most of the fresh water systems, which respectively indicate the impacts from particulate and nutrient contents in the source water. These two gross water quality parameters are indicative of the difficulties in water treatment for drinking water supplies, as well as the suitability for potential industrial and agricultural uses. On some occasions, heavy metals could be an integral part of the qualitative assessment, however.

Determination of the weighting factors of the gross water quantity and water quality is carried out using the Analytic Hierarchy Process (AHP), one of the Multiple Attribute Decision Making (MADM) methods, which has found widespread applications in multiple criteria decision-making for complex systems of many levels of priority identification [49]. To determine the weighting factors within the water quantity or quality domain, respectively, pair-wise comparison in the AHP may trigger the evaluation of the relative importance between these components of concern associated with each layer. For example, the pair-wise comparison between turbidity and chl-a concentrations may be considered based on the potential risk in compliance with water quality standards. If nutrient management is of primary concern in the watershed, chl-a concentrations should have a higher impact than the others and thus greater weighting factor in calculation of the water quality impact $Q_2$ in Eq. (2). The second criterion is related to the pair-wise comparison among the types of source water. By comparing the overall contribution of different source water, if the reclaimed wastewater plays a critical role in water supply relative to the others, the fresh water may have lower impact than the others and a lower weighting factor in the quantitative analysis as well.

### 3 THE STUDY AREA AND DATABASE

#### 3.1 Watershed delineation and water infrastructure system

Manatee County is located in the Southern Water Use Caution Area (SWUCA) due to the depletion of the Upper Floridian Aquifer. The entire western portion of the County is designated as part of the Most Impacted Area (MIA) within the Eastern Tampa Bay Water Use Caution Area relative to the SWUCA (see Fig. 1). A major source of Manatee County’s water is a 332-Km$^2$ (82,000-acre) watershed (i.e., Lake Manatee Watershed) that drains into the man-made Lake Manatee Reservoir. The lake has a total volume of 0.21 billion m$^3$ (7.5 billion gallons) and will cover 7.3 Km$^2$ (1,800 acres) when full. The County has the Lake
Manatee Water Treatment Plant (WTP) that receives the surface water from the Lake Manatee and two wellfields including East County Wellfield I (ECWF I) and the Mosaic Phosphate Wellfield (MPWF). The annual withdrawal from the lake is limited to 0.14 million m$^3$/day (34.9 million gallons per day, MGD) on average. Two well fields, Duette Park I (ECWF I) and MPWF supply source water at a rate of 0.05 and 0.008 million m$^3$ (13.5 and 2 million gallons) per day, respectively. Manatee County purchased 83 km$^2$ (20,500 acres) of land to protect the Duette Park well field. In addition, aquifer storage and recovery (ASR) wells have been in operation at the WTP since 1986. Treated drinking water is injected through ASR wells into the Floridian Aquifer for storage during periods of low demand and high stream flows. In addition, six ASR wells can provide 180 days of emergency capacity at a rate of 0.038 million m$^3$/day (10 MGD). The water treatment plant can treat 0.2 million m$^3$/day (54 MGD) of the lake water and 0.11 million m$^3$/day (30 MGD) of the groundwater.

According to the Manatee County Final Water Supply Facilities Work Plan[50], the potable water demand is estimated to rise from 0.17 million m$^3$/day (45.5 MGD) in 2006 to 0.23 million m$^3$/day (61.9 MGD) in 2030. The current permitted capacity is 0.20 million m$^3$/day (53.9 MGD) which can barely meet the projected water demand until about the year 2014. The imbalance between the projected water demand and the current capacity requires a total of approximately 0.03 million m$^3$/day (9.1 MGD) of new water supply to become available for the 2030 planning period. One option is water saving such as limiting the use of potable water for landscape irrigation. The other option is to increase drinking water supply and continue to develop environmentally sustainable, highly reliable and drought-resistant water supply systems. For this management option, a number of viable water supply alternatives are available for consideration within the next 25 years: 1) more agricultural re-use of reclaimed wastewater to reduce water withdrawal from the Upper Floridian Aquifer, and thus to increase groundwater allocation for the County beyond the permitted pumping rate of 0.008 million m$^3$/day (2.17 MGD), 2) the inclusion of a few new wellfields with transferable water use permits throughout the County, 3) the regionalization plan in 2017 with neighboring counties proposes a centralized water supply system from where Manatee County may receive a certain level of wholesale water flow annually, 4) construction of a desalination plant at the Port Manatee site, and 5) stormwater reuse by storing the runoff at swamps and or any impoundments to gain permit or credit transfer with varying reservoir size, shape and historical flows (e.g., candidate sites at present include Tatum reservoir and Lake Parrish reservoir).

Fig. 1 The Lake Manatee watershed and study area.
3.2 Availability of monitoring data

Quantitatively, three hydrological parameters, consisting of rainfall, ET and water storage in Lake Manatee, are included in this analysis to illustrate the hydrological setting of MWAI. The variations of water levels in Lake Manatee may reflect the changing status of stream flow and part of the base flow in the watershed. Qualitatively, chemical differences between native groundwater and surface water will stimulate different reactions. Mixing and mineral reactions which impact on the chemical changes of dissimilar types of water at sites located in a karstic, confined carbonate aquifer in south Florida can be envisaged by reviewing similar case studies with similar site features [47]. The major effect on water quality within a certain distance of the injection well following injection of finished water could be carbonate dissolution and sulfide mineral oxidation. Although trace metals have been detected during the recovery operation of drinking water at the Collier County Manatee Road ASR facilities in Florida, it will not be an issue after several cycles of operation [52]. Hence, this study picked up chloride and sulfate as the representative parameters for water quality assessment in both production and ASR wells. In regard to the lake water quality, excess levels of nitrogen (N) and phosphorus (P) in the influent can lead to significant water quality problems, which include eutrophication, harmful algal blooms, hypoxia, and can affect wildlife habitat. Hence, phosphate, chlorophyll-a, turbidity were also included in the MWAI calculations in our study. Table 1 lists all parameters being used in our MWAI calculations. Table 2 summarizes the data or image types, sources, and the time span of the data. In most cases, the data available from 2002 to 2008 are sufficient to fully support the calculations of the MWAI in 2008; but a few of them, such as production wells and ASR wells, have missing attribute values. We were not able to pursue some approaches, such as the valued tolerance and MLEM2 approaches, to handle missing attribute values in data sets [51]. Given the fact that the MWAI is defined as a spatially and temporally integrative assessment tool with a flexible tolerance towards missing data, the varying length of data sets may still be assimilated collectively to support the MWAI calculations in a value between -1 and +1 according to Eqs. (1)-(6).

Table 1. Summary of parameters used in MWAI calculations.

<table>
<thead>
<tr>
<th>Sources of water</th>
<th>Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lake Manatee</td>
<td>Water storage, phosphate, chlorophyll-a, turbidity</td>
</tr>
<tr>
<td>ASR wells</td>
<td>Sulfate, chloride</td>
</tr>
<tr>
<td>Production wells</td>
<td>Sulfate, chloride</td>
</tr>
<tr>
<td>Lake Manatee Watershed</td>
<td>Monthly rainfall, ET</td>
</tr>
</tbody>
</table>

Table 2. Summary of data type, sources, and length of data.

<table>
<thead>
<tr>
<th>Data or Image</th>
<th>Type</th>
<th>Time span</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rainfall</td>
<td>Monthly average, 24-hr total rainfall (mm/day)</td>
<td>1998 - 2008</td>
<td>SWFWMD (temporal NEXRAD-based precipitation data) (<a href="http://www.swfwmd.state.fl.us">http://www.swfwmd.state.fl.us</a>), NOAA (spatial NEXRAD-based data) (<a href="http://water.weather.gov">http://water.weather.gov</a>)</td>
</tr>
<tr>
<td>Estimated Soil Moisture</td>
<td>Monthly Average</td>
<td>2003 - 2008</td>
<td>MODIS NDVI and MODIS LST Data Obtained from the Warehouse Inventory Search Tool (WIST) at <a href="https://wist.echo.nasa.gov/api/">https://wist.echo.nasa.gov/api/</a></td>
</tr>
</tbody>
</table>
Within this context, the NOAA Geostationary Operational Environmental Satellite (GOES) and US Geological Survey (USGS) LANDSAT satellites support the estimation of “ET”. In Florida, USGS worked on producing retrospective potential and reference evapotranspiration (RET) estimates throughout Florida at a 2-km and daily resolution, which uses a combination of satellite (NOAA GOES) and land-based (weather stations) methods to compute ET. The overall effort may provide gridded estimates of solar radiation, net radiation, potential ET, reference ET, and actual ET at a (2 km x 2km) grid scale and a daily time scale from 2002 to 2008 for the entire state of Florida, which should support our MWAI calculations smoothly [53].

On the other hand, the National Weather Service (NWS)'s 158 radars, known as WSR-88D (Weather Surveillance Radar-1988 Doppler) or NEXRAD, have analyses of spatial coverage of heavy rainfall to illustrate the fundamental advantages of radar over rain gauge networks for rainfall estimation. NEXRAD precipitation data products (e.g., Level II and Level III through National Climate Data Center and Stages I, II, III or The Multisensor Precipitation Estimator (MPE) through River Forecast Centers) were used recently to analyze statistical characteristics of extreme precipitation events [12]. Within our study region, the rainfall data from 1999 to Sept. 2007 were generated based on the raw NEXRAD radar data of hourly digital precipitation array (DPA) through a NWS-authorized commercial data vendor, WSI, with approximately 2 km x 2 km grid size resolution every 15 minutes. They were calibrated by the in-situ rain gauge record. After Sept. 2007, the Level I raw NEXRAD radar data were used to process the rainfall information with a similar calibration procedure.

There are a number of different passive and active remote sensing techniques for measuring soil moisture with a variety of data assimilation methods. In-situ measurements of soil moisture provide groundtruthing values. Highly complex non-linear functions via genetic programming (GP) for estimating the surface soil moisture were constructed [54]. Millions of GP-based models were created and measured during the evolutionary process for screening. The better the fitness value, the better the model. Within this study, many GP-derived models were rejected due to either over-fitting or poor fitness and less complex-structured models may have a better chance to survive in final selection. Only the top thirty models with the highest level of fitting were selected for further evaluation by the software applied. Amongst these top thirty models, the GP model finally selected should perform well on both validation (unseen) and calibration datasets. The best GP-derived model of soil moisture was selected based on the R² and the t-score statistics calculated from the corresponding unseen dataset.

MODIS Monthly Normalized Difference Vegetation Index (NDVI) and MODIS Monthly Land Surface Temperature (LST) data were obtained from the Warehouse Inventory Search Tool (WIST) [53]. The soil moisture model was created as a graphical model in Erdas Imagine.
9.2 raster processor to calculate soil moisture spatially based on the NDVI and LST MODIS images. Both datasets must be post-processed with the MODIS Reprojection Tool (MRT) into GeoTIFF file format with geographical projection. The digital numbers (DN) of both datasets were used as inputs.

4 RESULTS AND DISCUSSION

4.1 Data analysis

Temporal and spatial variations of both quantity and quality of the source water have to be investigated collectively for the characterization of the MWAI. If remote sensing data are available, spatial averages at each time period need to be calculated at first in support of the subsequent time series analyses. Fig. 2 shows time-series data of ET, rainfall, and Lake Manatee Reservoir volume from 1998 to 2008. In this context, these ET estimates are spatial averages on a daily basis based on the GOES remote sensing images. Inflow is the sum of discharge volume plus the change in lake volume for that day. The lake exchange volume is defined as the sum of discharge volume plus the increase in lake volume for day and the monthly average values show a very consistent trend as does the rainfall. If we only look at the lake water volume, then the higher the rainfall, the higher the lake volume. Overall, seasonal patterns are apparent in all of these three parameters although rainfall has diminished to a historically low level in the last three years. Figs. 3(a) and 3(b) demonstrate two episodes of ET extremes in 2008 for the purpose of illustration. These drought periods were coincident with low rainfall record whilst the ET values remained stable over the entire study period. The GP model derived as below:

\[
\text{Soil moisture} = \frac{L1}{0.19} \quad (7)
\]

where \( L1 = \cos(L2); \) \( L2 = \sin(L3); \) \( L3 = \sqrt{L4}; \) \( L4 = L5 + V(1); \) \( L5 = L6 \times V(0); \)
\( L6 = L7 + 0.3032015562057495; \) \( L7 = L8 + V(1); \) \( L8 = \cos(L9); \) \( L9 = \sin(L10); \) \( L10 = L11 + V(1); \)
\( L11 = L12 \times V(0); \) \( L12 = L13 + 0.3974273204803467; \) \( L13 = L14 + V(1); \) \( L14 = \cos(L15); \)
\( L15 = \sin(L16); \) and \( L16 = V(0). \) The \( V(0) \) in above is Vegetation Indices 16-Day L3 Global 1km MODIS satellite images and \( V(1) \) is Land Surface Temperature/Emissivity 8-Day L3 Global 1km MODIS satellite images.

Forty-nine points of in situ soil moisture data were collected from a densely monitored Tampa Bay watershed study area, and were used to calibrate the GP model for soil moisture estimation. MODIS AQUA monthly NDVIs and MODIS LST were used as independent input parameters to calibrate soil moisture models. It produced an \( R^2 \) value of 0.45. A map of soil moisture of the Lake Manatee Reservoir Watershed in August 2008 is presented in Fig. 4 for the purpose of demonstration. The NEXRAD radar images of watershed-wide rainfall measurements are shown in Fig. 5. Fig. 6 shows decadal-scale variations of water quality in groundwater production and ASR wells. While the chloride concentrations remained stable over that time period, large changes in sulfate concentrations were evident in ASR-recovered groundwater. Fig. 7 exhibits time-series variations of surface water quality in Lake Manatee. The water quality parameters exhibited annual cyclic patterns. Within the annual variations, the phosphate and Chl-a concentrations showed an overall increase in the 1990s in the lake. As a result of lake eutrophication, algal bloom events occurred twice during the study period.

4.2 MWAI calculations

The Atlantic Multidecadal Oscillation (AMO), which is based on long term changes in the temperature of the surface of the North Atlantic Ocean, is a source of changes in river flow patterns in Florida. The AMO has a multi-decadal frequency. Under its impact, several
distinct types of river patterns were identified within Florida. It had been observed that the river flow rates varied significantly between AMO warm (i.e., from 1939 to 1968) and cold phases (i.e., from 1969 to 1993) in this region. The 2008 MWA1 was calculated. The monthly average dataset of 11 years from 1998 to 2008, which reflects the trend in the beginning of a new warm phase, were collected and used for $\Delta Q_1$ and $\Delta Q_2$ calculation based on Eqs. (4)-(5).

Fig. 2. Time-series data of ET, rainfall, and water storage in Lake Manatee.
Fig. 3(a). Map of high range ET of the Lake Manatee Watershed on May 12, 2008.

Fig. 3(b). Map of low range ET of the Lake Manatee Watershed on January 18, 2008.

Fig. 4. Map of soil moisture of the Lake Manatee Watershed in August, 2008.
Fig. 5. High range 24-hour rainfall of the Lake Manatee Watershed on June 22, 2008.

(a) Middle term time series

(b) Short-term time series

Fig. 6. Time series data of chloride and sulfate data in production and ASR wells.
4.2.1 MWAI quantitative index

The Quantitative Index ($Q_1$) of MWAI refers to the quantity of available water such as rainfall, lake inflow, and soil moisture. Lost water such as ET and runoff are considered as negative water availability. The $Q_1$ represents the quantitative component of water in a specific month ‘relative’ to the same month in all previous years of consideration. In this study, due to the smaller size of datasets available in terms of water quantity as compared to the counterpart of water quality data, only the monthly historical data from 2002 to 2008 with respect to both quantity and quality can be considered simultaneously. The first step in MWAI calculation is to normalize value of each parameter of each month in 2008 based on the data from 2002 to 2008. These normalized values represent the magnitude of the parameters compared to the dataset of the same month from 2002 to 2008. Table 3 presents a set of $Q_1$ (2008) including rainfall, ET, soil moisture, and lake exchange volume based on such an arrangement. For instance, the normalized value of ET in February 2008 (normalized to 2008) in Table 3 shows that ET in Feb. 2008 at the Lake Manatee Watershed had the norm of 1.0. This means that ET in February 2008 was the highest compared to the ET in February of all previous years between 2002 and 2008. Another example is that the normalized value of rainfall in September 2008 was 0.00, meaning that the amount of rainfall in September 2008 is the lowest as compared to all the September rainfall between 2002 and 2008.

Second, the normalized value of each parameter in each month is summed and multiplied by a weighting factor of 1.0 following the Eq. (2) because of no desalination, wastewater reclamation, and stormwater reuse involved. These monthly $Q_1$ (2008) values were the quantitative component index of water availability in Manatee County WTP associated with each month in the year 2008 relative to the same month in all previous years between 2002 and 2008. The average and standard deviation of $Q_1$ between 2002 and 2008 can then be calculated in support of generating $\Delta Q_1$ (2008) following Eq. (4) to address the water quantity component in the context of the MWAI.

4.2.2 MWAI qualitative index

The qualitative component ($Q_2$) of MWAI refers to the quality of water that might be influential in source water supply. Water quality constitutes such as chloride, sulfate, phosphate, chlorophyll-a, and turbidity are commonly used as indicators to justify the quality of source water when using both surface and groundwater as source water. The $Q_2$ represents the quality of water on a monthly basis ‘relative’ to the same month in all previous years in
the case study. Similar to the calculation of $Q_1$, a normalized value of each qualitative constituent was produced based on the historical data between 2002 and 2008 according to Eq. (3). For example, a normalized value of the lake phosphate concentration in May 2008 was 1.00, meaning that the lake water phosphate concentration was the highest in May 2008 as compared to the phosphate concentrations in May within all the previous years between 2002 and 2008. The $\Delta Q_2$ values were then calculated following Eq. (4). Table 4 shows the $Q_2$ and $\Delta Q_2$ values used to further calculate the MWAI for Manatee County in 2008. According to Table 4, there are seven water quality constituents involved so that the value of $1/7$ was used as the weighting factor to connect all seven water quality constituents in the context of MWAI calculation.

Table 3. Summary of $Q_1$ (2008) and $\Delta Q_1$ (2008) of Manatee County.

<table>
<thead>
<tr>
<th>Month</th>
<th>Normalized value of 2008*</th>
<th>Eq.2</th>
<th>Eq.4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jan</td>
<td>1.00</td>
<td>0.68</td>
<td>0.44</td>
</tr>
<tr>
<td>Feb</td>
<td>0.00</td>
<td>1.00</td>
<td>0.34</td>
</tr>
<tr>
<td>Mar</td>
<td>0.44</td>
<td>0.61</td>
<td>0.65</td>
</tr>
<tr>
<td>Apr</td>
<td>0.97</td>
<td>0.38</td>
<td>1.00</td>
</tr>
<tr>
<td>May</td>
<td>0.25</td>
<td>0.78</td>
<td>0.72</td>
</tr>
<tr>
<td>Jun</td>
<td>0.23</td>
<td>0.83</td>
<td>1.00</td>
</tr>
<tr>
<td>Jul</td>
<td>0.28</td>
<td>0.53</td>
<td>0.77</td>
</tr>
<tr>
<td>Aug</td>
<td>0.26</td>
<td>0.40</td>
<td>0.82</td>
</tr>
<tr>
<td>Sep</td>
<td>0.00</td>
<td>1.00</td>
<td>0.49</td>
</tr>
<tr>
<td>Oct</td>
<td>0.36</td>
<td>0.65</td>
<td>0.86</td>
</tr>
<tr>
<td>Nov</td>
<td>0.13</td>
<td>0.68</td>
<td>0.45</td>
</tr>
<tr>
<td>Dec</td>
<td>0.03</td>
<td>1.00</td>
<td>0.75</td>
</tr>
</tbody>
</table>

* normalized value range from 0 to 1.
Table 4. Summary of $Q_2(2008)$ and $\Delta Q_2(2008)$ of Manatee County.

<table>
<thead>
<tr>
<th>Month</th>
<th>Production Wells</th>
<th>ASR Wells</th>
<th>Lake Manatee</th>
<th>Eq.3</th>
<th>Eq.5</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Sulfate</td>
<td>Chloride</td>
<td>Sulfate</td>
<td>Chloride</td>
<td>Chlorophyll-a</td>
</tr>
<tr>
<td>Jan</td>
<td>0.59</td>
<td>0.87</td>
<td>0.00</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Feb</td>
<td>0.88</td>
<td>0.79</td>
<td>0.00</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Mar</td>
<td>0.65</td>
<td>1.00</td>
<td>0.00</td>
<td>1.00</td>
<td>0.87</td>
</tr>
<tr>
<td>Apr</td>
<td>1.00</td>
<td>0.36</td>
<td>0.66</td>
<td>1.00</td>
<td>0.52</td>
</tr>
<tr>
<td>May</td>
<td>0.65</td>
<td>0.14</td>
<td>0.76</td>
<td>0.33</td>
<td>0.37</td>
</tr>
<tr>
<td>Jun</td>
<td>0.53</td>
<td>0.13</td>
<td>1.00</td>
<td>0.55</td>
<td>0.10</td>
</tr>
<tr>
<td>Jul</td>
<td>1.00</td>
<td>0.24</td>
<td>0.37</td>
<td>0.61</td>
<td>0.47</td>
</tr>
<tr>
<td>Aug</td>
<td>0.69</td>
<td>0.00</td>
<td>0.07</td>
<td>0.63</td>
<td>0.59</td>
</tr>
<tr>
<td>Sep</td>
<td>0.56</td>
<td>0.07</td>
<td>0.00</td>
<td>0.82</td>
<td>0.23</td>
</tr>
<tr>
<td>Oct</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.60</td>
<td>1.00</td>
</tr>
<tr>
<td>Nov</td>
<td>0.00</td>
<td>0.10</td>
<td>0.00</td>
<td>0.87</td>
<td>0.92</td>
</tr>
<tr>
<td>Dec</td>
<td>0.23</td>
<td>0.00</td>
<td>0.36</td>
<td>0.36</td>
<td>0.44</td>
</tr>
</tbody>
</table>

* normalized value range from 0 to 1.
4.3 MWAI trend analysis

This case study shows the MWAI of 2008 based on the retrospective records of seven years of historical data between 2002 and 2008. The weighting factors between water quantity and water quality components in MWAI were assumed to be 1:1 in this case study. Fig. 8 shows the Monthly MWAI values in year 2008 which were derived based on the intercomparison between the current month in 2008 and the same months in all previous years of consideration from 2002 to 2007. It is observed that the lowest MWAI occurred due to the peak of ET in May, 2008, and the highest MWAI appeared in August, 2008 due to the continuous peaks of rainfall in June, July, and August in 2008. As shown in Fig. 6, sulfate concentrations of ASR water were very high between April and June 2008 and resulted in additional negative impact on MWAI. Numerically, if the sulfate concentrations become higher than the historical average, $\Delta Q_2$ would be negative so that the MWAI values would be worsened according to Eq. (5). This concern signifies the importance of taking into account the water quality impacts at production wells and ASR wells. On the other hand, as shown in Fig. 7, relatively higher phosphate concentrations in Lake Manatee during the late spring and early summer time period 2008 induced the increase of chlorophyll-a concentrations in the lake. Because the chlorophyll-a and related biological contaminants in source water could interfere with the drinking water treatment process, the MWAI value decreased for the corresponding period in May, 2008. This consideration also signifies the importance of taking into account the water quality impacts at Lake Manatee. As a consequence, the MWAI, which may collectively address both quantitative and qualitative impacts at the middle term basis, was proved applicable in this study.

![Fig. 8. The Monthly MWAI values in year 2008 which are based on the correlation between the current month in 2008 and the same months in all previous years of consideration.](image)

4.4 MWAI sensitivity analysis

In essence, the MWAI is a tool that indicates the water availability of an area in a specific month or week compared to the historical water availability of the same month or week over a study time period. Yet challenges with characterizing and propagating uncertainty, and validating predictions permeate decision making. The middle term sensitivity of monthly or weekly time windows is therefore the frame of reference that determines how the MWAI will
appear. Besides, on a rolling basis, the data length available for such an evaluation also exhibits a unique sensitivity, which could deter applications of the MWAI. Parameters involved in Eq. (6) provide a mathematical framework that may serve as a basis for concluding to whether either quantity or quality concerns or both will significantly alter the trend. The distribution of weighting factors may also influence the MWAI ranges. The metrics for validation of the sensitivity of the middle term assessment via the MWAI are summarized in Table 5, which is instrumental for describing uncertainties in decision making as a whole. It helps to assess how the current MWAI responds to various changes such as the length of historical datasets, the moving time window, the absence or presence of parameter(s), and even the different distribution of weighting factors within a single scenario.

4.4.1 Scenario 1: time length sensitivity

Since the MWAI depends on the middle term trend of historical datasets, the length of historical data used to calculate the MWAI will certainly affect the actual ranges of the MWAI. Simulation analysis can be made possible on a rolling basis from 2005 to 2008 for MWAI calculation. For example, a January 2005 MWAI may be calculated based on the dataset from January 2002, 2003, 2004, and 2005. A June 2008 MWAI may be calculated based on a longer dataset from June 2002 to June 2008. This changing basis may reveal how the MWAI responds to data sets of varying length. Thus, the monthly MWAI from 2005 to 2008 on a rolling basis is shown in Fig. 9. The 2005 MWAI plot with values between -0.236 and +0.236 has a relatively larger step in each change as compared to the others due to the shorter memory reflected by the smaller historical dataset. The year 2006 was a year with severe drought so that the corresponding MWAI values in 2006 tend to become smaller compared to others. The drought situation was gradually relieved in 2007 resulting in slightly higher MWAI values. Consequently, the 2008 MWAI shows relatively smaller step in each change due to the longer memory in data length. Overall, the positive MWAI values mean that the water availability of that month is above the middle term average of historical water availability level in that particular month over the selected years of interest. To allow further appraisal by the readers, the MWAI values presented in Fig. 9 are provided in Appendix I.

Table 5. Summary of metrics of sensitivity analysis in the case study of Manatee County, Florida.

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>Details</th>
<th>Weighting factors (w1:w2)</th>
<th>Datasets</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scenario 1: Time Length</td>
<td>Length of historical dataset</td>
<td>0.5:0.5</td>
<td>2005 monthly MWAI</td>
</tr>
<tr>
<td>Sensitivity</td>
<td></td>
<td></td>
<td>2006 monthly MWAI</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>2007 monthly MWAI</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>2008 monthly MWAI</td>
</tr>
<tr>
<td>Scenario 2: Time Window</td>
<td>Quarterly and Semi-Annually</td>
<td>0.5:0.5</td>
<td>Three-month average:</td>
</tr>
<tr>
<td>Sensitivity</td>
<td>MWAI</td>
<td></td>
<td>January – March</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>April – June</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>July – Sept.</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Six-month average:</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>May – Oct. (Wet Season)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Nov. – April (Dry Season)</td>
</tr>
<tr>
<td>Scenario 3: Parameter-based</td>
<td>Water Quantity Sensitivity</td>
<td>0.5:0.5</td>
<td>MWAI without Evapotranspiration</td>
</tr>
<tr>
<td>Sensitivity</td>
<td></td>
<td></td>
<td>MWAI without Rainfall</td>
</tr>
</tbody>
</table>
### Scenario 4: Weighting Factor Sensitivity

<table>
<thead>
<tr>
<th>Weighting Factor</th>
<th>Sensitivity</th>
<th>MWAI without Lake Chlorophyll-a data</th>
<th>MWAI without wells’ chloride data</th>
<th>2008 monthly MWAI</th>
</tr>
</thead>
<tbody>
<tr>
<td>w1(water quantity)</td>
<td>w2(water quality)</td>
<td>w1(0.3) : w2(0.7)</td>
<td>w1(0.7) : w2(0.3)</td>
<td></td>
</tr>
</tbody>
</table>

Fig. 9. A summary of monthly MWAI from 2005 to 2008 based on datasets of differing length of time.

#### 4.4.2 Scenario 2: time window sensitivity

In this scenario a time window sensitivity study between the quarterly and the semi-annual MWAI values was set up to assess how the MWAI responds to changes of varying time window. Two general time windows were selected to test the dry-wet seasonal fluctuations in a water year and quarterly variations over a year. In Florida, the dry season normally lasts from November to April, and the wet season from June to October. These two seasons were applied as the semi-annual time window. In the same context, four quarters of consideration herein include Jan – March, April – Jun, July – Sept., and Oct. – Dec. Both of the quarterly and semi-annual MWAI plots can be seen in Figs. 10 and 11, respectively. Obviously, the semi-annual variations only reveal a general trend without regard to monthly fluctuations. This is not lucid enough for decision making in the water utility industry.

When the quarterly MWAI values were compared against the monthly MWAI values, it was observed that the two time windows were in concert with each other. For instance, the 2005 quarterly MWAI of Oct.-Dec. was larger than the other years (see Fig. 10). The 2005 monthly MWAI plot also presents the largest values in October and November accordingly (see Fig. 9). While the 2006 monthly MWAI values in July, August, and September are lower than those in the same month of the other years (see Fig. 9), the 2006 quarterly MWAI values in July-Sept. are actually lower than those in July-Sept. quarterly MWAI values of the year 2005, 2006, and 2008 (see Fig. 10). Comparing the MWAI plots in Figs. 10, 11 and 12 as a whole further reveals that the monthly MWAI values are probably more useful than the seasonal and semi-annual MWAI values. However, the finer the time-scale employed, the greater the computational efforts required.
4.4.3 Scenario 3: Target year parameter-based sensitivity

As mentioned, the two major components employed to calculate the MWAI values are the water quantity and water quality each of which contains a series of parameters or constitutes. Thus, parameter-based sensitivity was also set up to examine how well the MWAI values respond to the inclusion or exclusion of specific parameter(s) in the MWAI calculations. This sensitivity analysis was performed based on the dataset from 2002 to 2008 so as to provide the longest possible memory in the system. Dropping ET, rainfall, surface water, chlorophyll-a, or chloride in production out of the MWAI calculations results in the alternative plots in Figs. 12 and 13. Excluding rainfall data caused a decrease of monthly MWAI as shown in Fig. 13. It can be observed that the MWAI values increased when ET is neglected, which is deemed as a logical response. On the other hand, the water quality component can affect water availability in the context of the MWAI calculations too. The absence of a contaminant in groundwater water should increase the water availability. When the chlorophyll-a component was removed, for example, the MWAI values increased holistically from the
baseline (Fig. 13). Similarly, when the production wells’ chloride data were removed, the MWAI values also increased holistically from the baseline as shown in Fig. 13. These sensitivities show that the MWAI can respond to the inclusion or exclusion of particular water quantity and quality parameters or constituents in a logical manner.

Fig. 12. Monthly 2008 MWAI with or without the inclusion of ET or rainfall data.

Fig. 13. Monthly MWAI with or without the inclusion of lake surface water chlorophyll-a or chloride in production wells.
4.4.4 Scenario 4: weighting factor sensitivity

Two weighting factors defined in this study are w1 and w2 in Eq. (6) associated with water quantity and water quality components, respectively. Two additional sets of weighting factors for sensitivity analysis, including (0.3, 0.7) and (0.7, 0.3), were applied to the 2008 MWAI calculations for the purpose of comparison. Fig. 14 shows the impacts of differing weighting factors. Changing weighting factors may increase or decrease the monthly MWAI values over different months depending on whether water quantity or quality was emphasized via the weighting factor distribution. If more weight were taken by water quantity, early spring had the slightly better MWAI values due to the higher rainfall amount received. In contrast, early fall experienced the worse MWAI values due to the presence of lower rainfall.

![Fig. 14. Monthly MWAI based on different sets of weighting factors.](image)

4.5 Threshold analysis

The choice of threshold and the selection of criteria for water management and decision making are subjective. Two different approaches can be collectively adopted for threshold selection. The first is based on physical criteria such as the identification of the flood and drought levels; and the second is based on the status of the water infrastructure. The MWAI falls into the latter category. Within this domain, the process of over- and under-threshold values, the choice of the threshold levels, the verification of the independence of the values, and the stationarity of the process, need to be determined independently within different types of applications.

In general, the threshold levels of “unusual”, “slightly unusual”, and “normal” may be categorized for short-term or middle term operation associated with appropriate numerical ranges. In our case study in Manatee County, Florida, with the aid of a decadal scale historical record, the “normal” status of the MWAI values may be in a range between 0 and 0.3. On the other hand, any MWAI value that is slightly smaller than 0 indicates that the system was receiving a mild impact via either water quantity or water quality, or both. The status of “slightly unusual” might be defined when the MWAI values fall into the range between -0.2 to -0.3. This should trigger a possible managerial action to identify a feasible response or strategy. Any MWAI value below -0.3 in this system might be regarded as
“unusual” and should trigger management actions depending upon the actual needs. However, the actual magnitude of these values will probably be subject to adjustment in individual cases.

5 CONCLUSIONS

Today, satellite coverage and other advances in remote sensing afford higher accuracy and improved quantification of hydrological cycles even on the small watershed scale. This paper proves the concept that the advent of many new sources of multisensor data, such as satellite-derived data (GOES, LANDSAT, MODIS, etc.) and ground level radar-precipitation data (NEXRAD), will provide new opportunities in monitoring, detecting and understanding water resource availability and water quality changes in metropolitan regions. The newly developed MWAI, supported by advanced remote sensing technologies would enable us to realize the spatial and temporal variations of water resources for short-, middle-, and even long-term purposes in various types of metropolitan regions. Yet much more validation work and analytic results are required to ensure that this procedure will perform better than others to make applications more practical and accurate in the future. The potential of using remotely sensed time-series biophysical and chemical states of landscape to characterize soil moisture conditions, ET, and other chemical states should be investigated based on the pros and cons of each type of satellite imageries so as to maximize the beneficial use of integrated multi-sensor remote sensing images. In the remote sensing field, however, there are several fundamental reasons for the perceived difficulty in measuring watershed-scale surface water and energy fluxes as well as the water quality parameters. There is an obvious trade-off when using multi-sensor platforms. New methods to fuse information for the optimal use of sensors over communication channels are in acute need. Therefore, the performance of tracking and path-following of the versatile satellite and in-situ sensors should be investigated under information constraints. This type of research area will lie at the heart of some important applications such as MWAI.

APPENDIX A: The MWAI values presented in Fig. 9.

<table>
<thead>
<tr>
<th>MWAI</th>
<th>2005</th>
<th>2006</th>
<th>2007</th>
<th>2008</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jan</td>
<td>-0.236</td>
<td>-0.147</td>
<td>0.055</td>
<td>0.043</td>
</tr>
<tr>
<td>Feb</td>
<td>-0.236</td>
<td>-0.163</td>
<td>-0.214</td>
<td>-0.300</td>
</tr>
<tr>
<td>Mar</td>
<td>0.000</td>
<td>-0.136</td>
<td>-0.237</td>
<td>-0.213</td>
</tr>
<tr>
<td>Apr</td>
<td>0.236</td>
<td>0.020</td>
<td>-0.103</td>
<td>0.035</td>
</tr>
<tr>
<td>May</td>
<td>0.000</td>
<td>-0.335</td>
<td>-0.372</td>
<td>-0.318</td>
</tr>
<tr>
<td>Jun</td>
<td>0.000</td>
<td>-0.297</td>
<td>-0.031</td>
<td>0.079</td>
</tr>
<tr>
<td>Jul</td>
<td>0.236</td>
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Acknowledgments

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References


