From a water utility perspective, we can see that the City receives water from reservoirs that are all located outside the city boundary. There are water filtration plants and wastewater treatment plants (located within or near the City) that supply and treat water for the City and its five surrounding counties (Figure 4). Besides the three reservoirs, the region also receives water from the Susquehanna River that flows through the states of New York, Pennsylvania, and Maryland, making it the longest trans-boundary river on the east coast of the United States. Even though water is not regularly drawn from the river (except for the time of persistent rainfall deficit, which last occurred in 2002), studies suggest that this river may be utilized as a continuous source in the future (BC-DPW 2020).

The City is also currently under a consent decree with the U.S. EPA to comply with the Clean Water Act, which requires upgrading its aging wastewater infrastructure and eliminating sanitary sewer overflow into roads, streams, and rivers. There has also been a series of severe flood events in the region (as shown in Figure 4) in recent years. Among the flood victims, low-income non-white populations have been disproportionately impacted (Figure 4 left and middle) and many such communities have yet to recover from their losses. Figure 4 (right) also shows that the low-income non-white neighborhoods have a lower potential of runoff reduction due to tree cover compared to middle- to high-income communities with a majority white population (based on American Community Survey Data 2018; U.S. EPA EnviroAtlas i-Tree Model for Baltimore, MD 2017). Baltimore's water system is one of the oldest in the nation, and challenges in its upkeep and evolution have included severe budgetary limitations, major socio-economic challenges, and climate change. Hence, the inclusion of social equity principles to ensure equitable access to and distribution of services and benefits is considered one of the key objectives of our presented ReUWS framework.

Future Challenges

Figure 5 shows potential future mean daily precipitation and mean daily maximum temperature in the region based on downscaled, bias-corrected general circulation models. The ensembles are generated based on 32 CMIP5 model simulations with RCP 4.5 (Joshi et al. 2020). These simulations suggest that the regions experiencing higher precipitation are also expected to get warmer in the coming years. Based on the trends of these simulations (Tamaddun et al. 2019a & b), one can also extrapolate that the climate conditions of the region are expected to become more severe with frequent flood events and long-term droughts.

The Baltimore City Department of Public Works has already invested in a range of projects to reduce surcharging to avoid sanitary sewer overflow, which is responsible for major nutrient loading into Baltimore's surrounding rivers and streams and causes severe water quality concerns. Increased pipe size and installation of bypass and backwater valves are examples of gray strategies that are being implemented in the sanitary sewer system and water treatment plants in Baltimore. In conjunction with these gray measures, strategic use of green infrastructure may produce significant improvement in dealing with surcharging and associated water-related issues. Hence, we can use the ReUWS framework to provide alternative supply sources, reduce runoff and flood risks, mitigate heat island effect, and improve water quality by maximizing GGI potentials

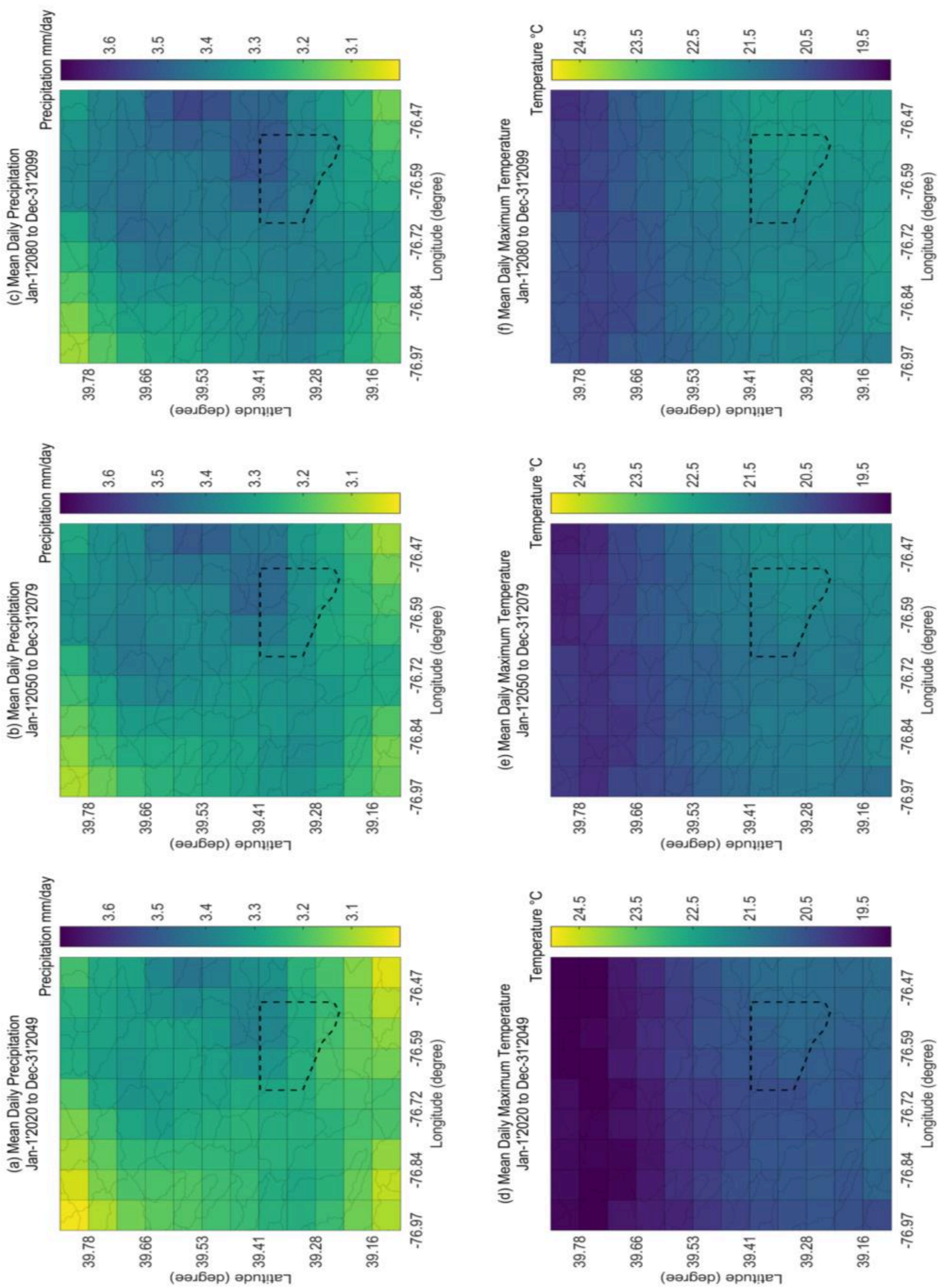

Figure 5: (1st row) Mean daily precipitation (mm/day) and (2nd row) mean daily maximum temperature (°C) from 2020 to 2049, 2050 to 2079, and 2080 to 2099, at 1/16 degree spatial resolution grid cell based on downscaled and bias-corrected GCMs (the average is calculated based on 32 CMIP5 model simulations) using RCP 4.5 (630 ppm of CO_2 concentration). Warmer (cooler) color suggests lower (higher) precipitation and higher (lower) temperature. The black dotted line represents the boundary of Baltimore City.

Application of ReUWS

The use of low impact development approaches such as rainwater harvesting, vegetative swales, rain gardens, and increased urban tree canopy can reduce runoff generation and nutrient loading. Such strategies may also lower groundwater tables resulting in reduced sewer infiltration. Harvesting and repurposing (followed by effective and equitable distribution) of stormwater can also reduce dependence on the reservoir supply. Such multi-purpose strategies could be quite useful for Baltimore as it faces a potential increase in periodic water supply scarcity, floods, and economic hurdles among many communities.

The ReUWS framework and its nested-modeling structure can be used to evaluate available GGI strategies and their overall benefits. For example, RHESSys and i-Tree Hydro+ (which includes i-Tree CoolAir) can be used to estimate groundwater tables, soil saturation levels, runoff production, and heat island effects, which are all relevant to the Baltimore City water system. The produced runoff can be fed through HEC-RAS to estimate potential flood magnitude and frequency impacts. SWMM and i-Tree Hydro+ can be used to evaluate storm sewer surcharging and water quality impacts. These models, at the lower-level, can simulate local hydro-geophysical processes to help define potentials of various GGI strategies, e.g., strategies specific to urban areas of Baltimore City with its upstream contributing watersheds. Mid-level models can address many trans-boundary issues in terms of water allocation, usage, and disposal. The developed DSS tools can work as a common platform among community members, stakeholders, and modelers to engage and work towards unified goals and practices.

Hence, in addition to the already taken gray measures by the City as discussed earlier, strategic and equitable use of coupled green infrastructure, with the added participatory functionality provided by the ReUWS framework, may produce significant improvement in dealing with several intersecting water security challenges including sustainable supply of water, mitigation of flood threats, and improvement of water quality. By ensuring stakeholder engagement and community participation throughout the project initiation to implementation phases, ReUWS can help provide equitable services to different population groups under future conditions influenced by hydro-climatic, socio-economic, and regulatory changes.

CONCLUSIONS

This study presented a resilient urban water system (i.e., ReUWS) framework to achieve a GGI-based urban water system with the capacity to change and develop over time under uncertainties from hydro-climatic variability, socio-economic trends, and regulatory reforms. Principles drawn from engineering design, ecosystem science, and social equity concepts help to formulate this interdisciplinary and community-oriented approach. We demonstrate the use of ReUWS to develop a water management system that integrates technological advancement, eco-hydrological dynamics, and stakeholder participation at different stages of design and implementation. This framework allows for an evaluation of alternative pathways in achieving resilient water systems and outlines the processes of deriving meaningful findings from the major interacting sectors within a dynamic water system. The nested-modeling framework may facilitate converting the decision-making process from intuitive actions to evidence-based effective and acceptable solutions. We expect that by adopting this framework, by blending advanced engineering paradigms, maximizing ecosystem service potentials, and establishing social equity principles, in future studies, we will engage a wide range of stakeholders to identify and apply GGI alternatives that promote urban water system resilience.

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Analysis of Suspended Material in Lake Mead Using Remote Sensing Indices

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ABSTRACT

The effective management of suspended solids and their accompanying contaminants in water bodies requires information on the sources of sediments. Clear water reflects small amounts of solar irradiance, while water loaded with suspended materials (SM) has the potential of reflecting large amounts of sunlight. This study focused on the analysis of SM in Lake Mead, which lies on the Colorado River, using remote sensing spectral indices. Landsat 7 Enhanced Thematic Mapper (ETM+) satellite images were used to determine the spectral indices such as normalized suspended material index (NSMI), normalized difference suspended sediment index (NDSSI), and band ratio (BR). This paper established relationship between the satellite image and ground truth data obtained from United States Geological Survey (USGS) data. A map of spatial distribution of suspended sediments in Lake Mead was produced. The map showed that high suspended sediments were generally identified at the entry points of Lake Mead, with lower suspended sediments being concentrated at the basins of the lake. Results also showed that an increase in suspended sediment concentration (SSC) produces a corresponding increase in NSMI values. An exponential relationship between SSC and NSMI values, with coefficient of determination (R^2) of approximately 0.96, was developed in this study.

Keywords: coefficient, determination, ground truth data, remote sensing spectral indices, suspended sediment concentration.

INTRODUCTION

Lakes serve as an important water source for transportation, agriculture, industry, and recreation. The water quality of a number of lakes around the world has deteriorated to the extent that they lose their serviceability (Song et al., 2011; Vedwan et al., 2008). One important parameter that affects the quality of these water resources is suspended material. The knowledge of suspended matter is valuable in the water quality management effort. This is because suspended matter is linked to the intrusion of pollutants and heavy metals in the waterbody (Usali and Ismail 2010).

Remote sensing is an effective means for water quality monitoring and management. Remote sensing has been employed in monitoring water quality parameters such as suspended sediments, chlorophyll-a, turbidity, and surface water temperature (Gholizadeh et al., 2016; Usali and Ismail 2010). Remote sensing applications have been found to be effective, less costly, and valuable tools in the management and monitoring of water quality, compared with in-situ measurements (Usali and Ismail 2010; Gholizadeh et al., 2016). Concentration of suspended materials is influenced by a number of factors such as particle size, shape, and color which in turn has an impact on the spectral properties of water. A clear water exhibits peak reflectance in the blue range of the visible spectrum. As sediments accumulate in water, the reflectance of water increases in the visible spectrum (Montalvo 2010).

Studies have employed various remote sensing spectral indices in determining the suspended sediments distribution of water bodies. Montalvo (2010) developed and used a spectral index called Normalized Suspended Material Index (NSMI) to identify SM by using Landsat 7 Enhanced Thematic Mapper (ETM+) satellite data in a coast of Cabo Rojo in the South West of the island of Puerto Rico. Results obtained from the NSMI were compared to other indices such as Normalized Difference Suspended Sediment Index (NDSSI) and a Band Ratio (BR). This study, however, did not have any field or ground truth data to assess the accuracy of the indices. Another study by Malahlela (2019) investigated the spatio-temporal performance of spectral indices including NSMI, Water-Sediment Ratio Index (WSRI), Normalized Difference Vegetation index (NDVI), and Enhanced Green Ratio Index (EGRI) for mapping suspended sediments in Spring Grove Dam, Midmar Dam, Nagle Dam, Albert Falls Dam and the Inanda Dam located in South Africa using Landsat 8 Operational Land Imager (OLI) satellite data. The study showed that NSMI was the most effective index for mapping of suspended solids.

Landsat 7 ETM+ bands cover various wavelengths to study land and water surface. Clear water is exhibits peak reflectance in the blue band with wavelength of 0.45-0.52μm as outlined in Young et al. (2017). Clear water is known to reflect very little solar irradiance while transmitting most of it in the visible spectrum in the spectral curve of water. The amount of suspended sediment in water is proportional to the reflectance of water. Increase in the sediment of water increases the reflectance through the visible spectrum (Arisanty and Saputra 2017; Montalvo 2010).

The objectives of the study were to examine the suspended material or sediment distribution in Lake Mead using remote sensing indices namely NSMI, NDSSI, and BR and to develop a regression model between the NSMI and ground truth data. Landsat 7 ETM+ data was used to achieve these objectives.

This paper is structured into different sections. The next section provides literature review section, which is followed by a section describing the study area. The subsequent section presents the methodology employed in carrying out the study, this includes data collection and image processing. This is followed by results and discussion section. The last section provides the conclusion drawn from the study.

LITERATURE REVIEW

This section provides an overview of various studies in the area of water quality, remote sensing applications, and remote sensing spectral indices.

Water quality. The water quality of freshwater bodies such as lakes, rivers and streams are continually impaired by pollutants from agricultural, human settlements, and industries. The impairment is worsening with rapid population growth and urbanization (Khan et al., 2018). The water quality of more than half of water systems worldwide has been left deteriorated due to human activities. This is causing threats to the environmental ecosystem and public health (Bonansea et al., 2018; Hasab et al., 2020).

The water quality of a waterbody is determined by various indicators or parameters which includes physical, chemical, and bacteriological parameters. These parameters play a pivotal role in assessing water quality (Gholizadeh, et al., 2016; Khan et al., 2018). Information about these water parameters are necessary to aid in decision making with regards to the use of water (Elhag et al., 2019). Total suspended solids (TSS), pH, electrical conductivity (EC), and dissolved oxygen (DO) are some examples of physical indicators. Chemical indicators include cations such as Magnesium (Mg^{2+}) and Sodium (Na^{+}) and anions such as Chloride (Cl^{-}) and Fluoride (F^{-}). Total coliforms and Escherichia coli (E. coli) are some examples of bacteriological indicators (Khan et al., 2018). This research, however, focuses on the suspended sediment solids, a physical water quality indicator which affects the optical clarity of water (Pavelsky and Smith 2009). The effective management of the water quality measuring indicators is necessary to ensure restoration of water quality and to improve on the environmental sustainability as well as the overall safety and health of humans (Hasab et al., 2020).

Various studies have looked at the water quality monitoring through model development. Models were developed for the estimation of salinity and water quality in lakes in several studies including Bosten Lake in China (Rusuli et al., 2015); Urmia Lake in Iran (Sattari et al., 2020); and Mahabad Reservoir in Iran (Nazari-Sharabian, et al., 2019). Models have also been developed for salinity or suspended sediment estimation in rivers including Colorado River (Venkatesan et al., 2011a; 2011b); Mississippi River (Melesse et al., 2011); and Dez River in Iran (Babaei et al., 2019).

Remote sensing applications. Remote sensing satellite images have been applied extensively in a study of water quality and land surface characteristics. Remote sensing has been applied for estimating soil moisture (Ahmad et al, 2010; Puri et al., 2011a; Stephen et al, 2010), analyzing groundwater changes (Rahaman et al., 2019), urban flooding studies (Kandissounon et al., 2018), land surface emissivity (Stephen et al., 2009), and wetlands monitoring (Puri et al., 2011b). Satellite data has been actively employed in the water quality monitoring efforts. Some of these data include Landsat 8 OLI, Landsat 7 ETM+, Landsat 5 Thematic Mapper (TM), RapidEye images, Pleiades-1A, SPOT-6 images, Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) images, and Sentinel-2A/B Multispectral Instruments (MSI), the Moderate Resolution Imaging Spectroradiometer (MODIS) onboard Aqua (Alparslan et al., 2007; Hasab et al., 2020; He et al., 2008; Isidro et al., 2018; Montalvo 2010; Pavelsky and Smith 2009; Son et al., 2014; Zhang et al., 2020). Studies have developed reliable empirical relationships between Landsat satellite data and ground measurements of water quality (Alparslan et al., 2007). In a study to establish a relationship between reflectance and TSS, a model was developed between these two variables. This model produces a R^2 value of 65% indicating moderately strong relationship between Landsat 7 ETM images and TSS (Isidro et al., 2018). A similar study conducted by Alparslan et al. (2007) using RapidEye, Pleiades-1A, and SPOT-6 images developed a relationship between pixel reflectance values and water quality parameters including chlorophyll-a, suspended solid matter (SSM), secchi disk and total phosphate. This produced a R^2 value of 99.99% between the satellite data and the water quality parameters. Pavelsky et al. (2009) used extensive field data set for Peace-Athabasca Delta (PAD) in Canada to establish positive relationships between in situ SSC and remotely sensed visible or near-infrared reflectance in SPOT and ASTER satellite data.

Remote sensing spectral indices. This subsection provides a brief description of the remote sensing spectral indices. Detailed description of three indices used in this study is provided in the methodology section of this document.

The NSMI was developed on the principle that clean water has a peak reflectance in the blue range, while the presence of suspended material promotes an increase of reflectance in the whole visible spectrum, especially in the range of green and red, where clear water tends to absorb radiation (Montalvo 2010). NSMI was found to be the most sensitive index to suspended sediments compared with other indices such as the WSRI, NDVI, and EGRI in a study to assess the sensitivity of spectral indices for mapping suspended sediments conducted by Malahlela (2019). Although the NSMI was found to be successful in distinguishing between clear water and suspended material in a study done in Cabo Rojo in Puerto Rico, it was unable to identify SM in shallow areas such as coral reefs and swamps (Montalvo 2010). NDSSI has also been used in various studies relating to suspended sediments. NDSSI has been found to have the capability to estimate and map spatial distribution of SSC in water bodies (Hossain, et al., 2010). Montalvo (2010) compared results of NDSSI to NSMI and concluded that both indices showed similar patterns, an indication that NDSSI has the potential to distinguish between clear water and suspended sediments. The BR is another index that was used to determine suspended sediment. In this index, the reflectance in the blue and green bands were utilized. The equation utilizes the green band because sediment increases the reflectance of the green range of the spectrum, while clear water has peak reflectance in the blue range. The NSMI was able to detect suspended material while NDSSI and BR were only able to detect suspended sediment in water bodies (Montalvo 2010).

STUDY AREA

In this research, Lake Mead water surface is analyzed for water quality remote sensing. The map of Lake Mead is shown in Figure 1. It is the largest reservoir, in terms of water capacity, in the United States. The Lake was formed after Hoover Dam was constructed in the 1930s (Edalat and Stephen 2019). The Lake is made of four connected basins namely the Gregg, Temple, Virgin, and Boulder basins. The Lake receives flow from the Colorado River, the Las Vegas Wash, the Muddy River, and the Virgin River as seen in Figure 1 (Edalat and Stephen 2019). About 97% of the inflow to Lake Mead comes from the Colorado River, with the remainder coming primarily from the Las Vegas Wash, the Virgin and Muddy Rivers. Flow in the Las Vegas Wash has more than doubled over the past 30 years, as a result of the rapid population growth in Las Vegas (Edalat and Stephen 2019; Li et al., 2010).

Lake Mead is joined by the Virgin River water at its extreme north. The Las Vegas Wash joins the Lake at the extreme western part of the Lake. The Wash includes runoff from the Las Vegas Metropolitan area, discharges from nonpoint sources, groundwater discharges and wastewater effluents from wastewater treatment plants (WWTPs) in Las Vegas and Henderson (Bai and Acharya 2017; Edalat and Stephen 2019). Lake Mead is the source of water to more than 25 million people in the Southwest of the United States including Nevada and Arizona. People depend on water from Lake Mead for household use, power generation, municipal, industrial, and agriculture purposes (Edalat and Stephen 2019; Sierks et al., 2020). It is therefore important to understand issues relating to sediment concentration which impact the quality of water and subsequently affect human and aquatic life as they are exposed to the Lake. Lake sedimentation is a key issue in the sustainable management of water supply systems. Accumulation of sediments is a likely phenomenon in Lakes and would therefore need to be addressed since it impacts the quality of water (Edalat and Stephen 2019). About 6.6 million cubic meters of sediment slug which eroded from the Las Vegas Wash within approximately 25 years was deposited in Las Vegas Bay in Lake Mead (Whitney et al., 2015).

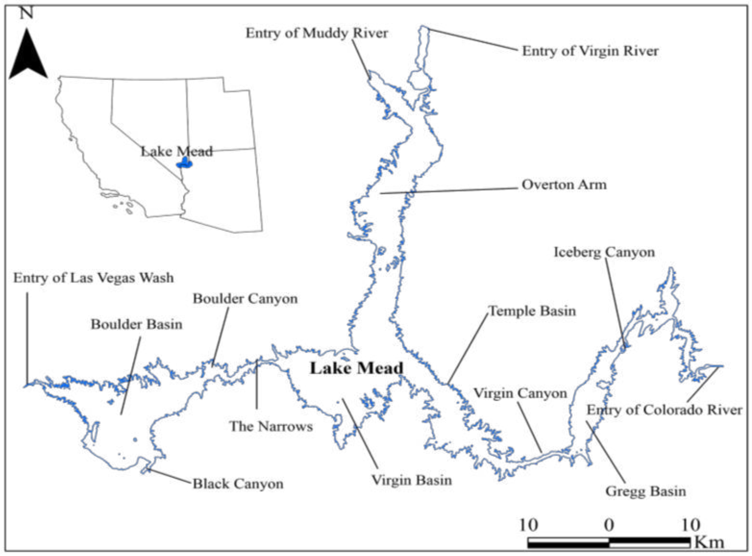

Figure 1: Detailed map description of the study area (Adopted from National Park Service 2020)

MATERIALS AND METHODOLOGY

This section describes the data collection as well as the approach employed in executing the work. The section includes data collection of Landsat 7 ETM+ images, USGS sediment data, US States and Lake Mead boundaries. The section also provides the description of image processing techniques adopted for the study. The data collection and the image processing techniques are further elaborated in the subsequent subsections.

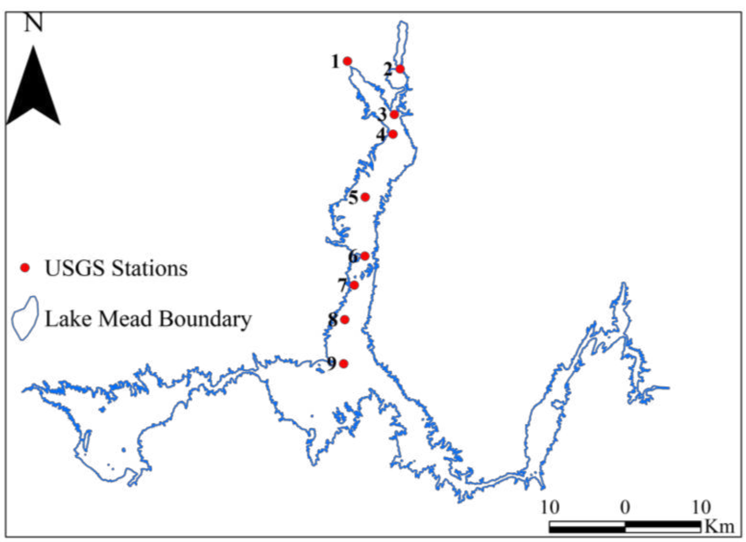

Figure 2: USGS Sampling stations along the Lake Mead