



A 24-Year Spatial Analysis on Lake Powell Located in Page, Arizona Analyzing Water Levels Through Supervised Classification, Change Detection, and Vector-Based Manipulation to Assess Impact on our Livelihood and Ecosystem

GGR335H5 - Fall 2022 - Group 11

December 4, 2022

Ashutosh Sharma¹, Jessica Bhinder², Lana Maljevic³, Shahzaib Saleem⁴ and Shreya Tanguturi⁵

¹ 1006477894; ashutosh.sharma@mail.utoronto.ca

² 1005387715; jessica.bhinder@mail.utoronto.ca

³ 1007295730; lana.maljevic@mail.utoronto.ca

⁴ 1006027826; shahzaib.saleem@mail.utoronto.ca

⁵ 1005102906; shreya.tanguturi@mail.utoronto.ca

Abstract

With improvements in technology, the generation of hydropower has become accessible and efficient. Lake Powell generates hydropower for its seven neighboring American states and helps approximately 6 million people in powering their homes, businesses and industries. However, as global warming and climate change continue to alter our natural systems, there has been a steady decline in Lake Powell's ability to provide hydropower over the last two decades. With remote sensing tools such as supervised classification and change detection we are able to conclude that Lake Powell is experiencing drought and thus has decreased in size and water level since 1998. Therefore, Lake Powell is at risk of losing its ability to provide hydropower which will impact those who are dependent on this lake for its energy.

Keywords: GIS; Remote Sensing; Lake Powell; Change Detection Analysis; Supervised Classification; Vector-Based Manipulation

1. Introduction

Water systems are an integral part of our lives. Water systems, such as lakes, provide various benefits to our physical environment as well as to those residing in proximity to these systems. Lakes help sustain biodiversity, provide access to clean and fresh water, and improve the economy by providing the medium for trading via ports and harbors (Rutledge et al., 2022). In addition to providing clean water, lakes play an important role in generating hydropower. Hydropower is a type of renewable energy that is created from flowing water. In hydropower plants, water is released through a dam from an elevated height, and with its strong force, the water spins the blades of a turbine as it flows downwards (The National Renewable Energy Laboratory, 2014). The turbine is attached to a generator which creates electricity. This generated electricity is used to power homes, businesses, and industries. Since this process does not consist of any pollutants and chemicals, hydropower is a clean, efficient and convenient method of obtaining electricity. With newer technologies, dams are able to control how much water should be released to generate a specified amount of electricity, which helps in the management of water and the electricity produced from it (Stokstad, 2013). Recently, countries around the world have begun generating hydropower to generate their homes, businesses, and industries. In fact, approximately 17% of the world's electrical energy comes from hydropower (Vliet et al., 2016). In the United States of America, Lake Powell - situated between the states of Utah and Arizona - provides hydropower to seven states and approximately 6 million people (Wheeler et al., 2022). Currently, it provides hydropower to Wyoming, Arizona, California, New Mexico, Utah, Nevada, and Colorado (Wheeler et al., 2022). At its full capacity, Lake Powell was capable of generating approximately 1,320 megawatts, however, there has been a decline in the generation of hydropower due to a possible drought crisis (Yeung, 2022). Droughts often occur due to global warming and climate change which cause deficiency in precipitation and increased evaporation (Wang et al., 2020). As we continue to lose hydropower, there are negative side effects inflicted on the ecosystem, agriculture, water resources, and our energy supply (Stokstad, 2021). With more than 6 million people dependent on Lake Powell, it is important to increase production rather than deter from it. Fortunately, geographic information systems and remote sensing applications allow us to monitor the size of lakes - using satellite imagery - and allow us to use other supplementary data such as weather analysis to draw conclusions in changes that need to be made and assist us in understanding what creates favorable conditions to promote hydropower. In this study, we aim to investigate whether the size of Lake Powell has increased or decreased in water levels throughout the years and whether it is at risk of losing the ability to provide hydropower to Americans.

2. Methodology

2.1. Site Selection

Our study is focused on Lake Powell, situated in the United States of America. This site was chosen as our area of study since it is a large body of water amidst a desert in the USA.

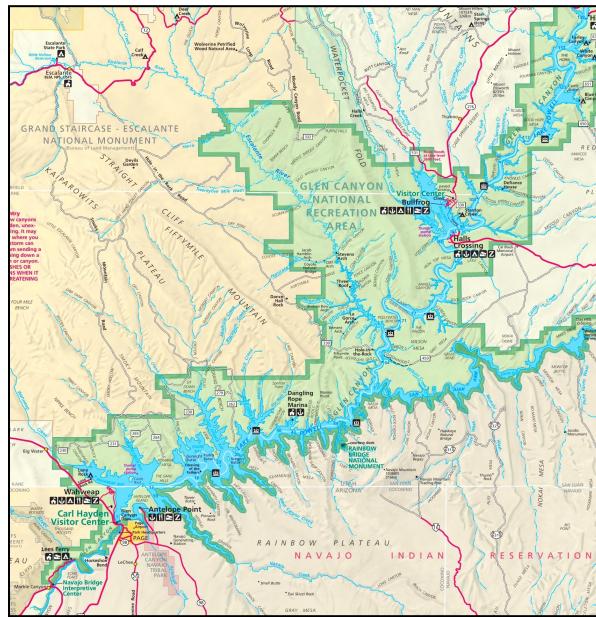


Figure 1. Map indicating the precise location of Lake Powell in the United States of America.

As seen in Figure 1, the precise location of Lake Powell is 37.0683° N, 111.2433° W, and it borders between the states of Utah and Arizona. This study aims to investigate whether the size of Lake Powell has increased or decreased throughout the years. To investigate this, we will analyze the land covers and calculate areas of water classes to determine whether there has been a change in the size of the lake.

2.2. Flowchart Creation

Prior to starting the analysis, we created a flowchart as a plan to help us organize our processing steps. This included the data collection, the methods used, as well as the expected results.

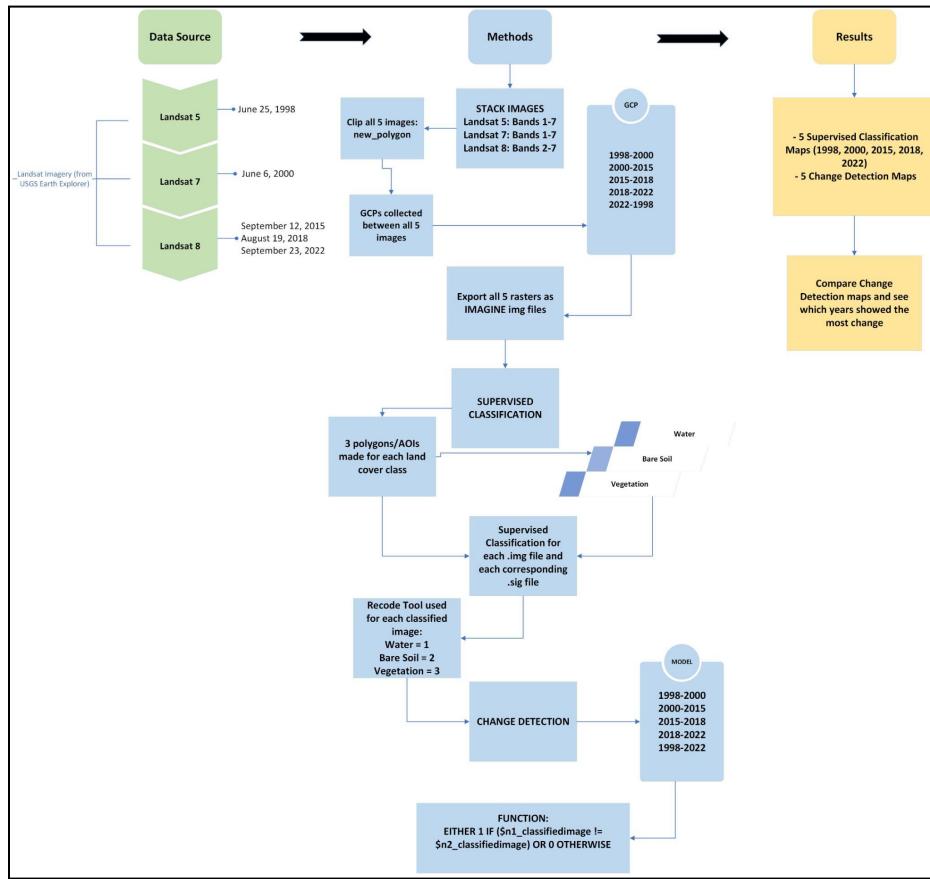


Figure 2. Flowchart displaying the data source, methods and results of this study.

Figure 2 shows the time period of our study, how we have acquired the data, the methods we implemented as well as the results obtained. In the next section, we will be going into depth about the analysis and how we have met our expectations. These steps include: creating composite images, collecting ground control points, conducting supervised classification and conducting change detection.

2.3. Data Collection

As part of our research, we gathered satellite imagery from the USGS Earth Explorer website over a 24-year period, specifically looking at years 1998, 2000, 2015, 2018 and 2022. To ensure more accurate results, we collected images with 0-30% cloud cover, such that virtually nothing was obstructing the observation site. Initially, we intended to collect data from the same time of year, focusing on summer months such as June and July; however, to ensure that we have the desired geographical location and no cloud cover, our time period has been extended from June to September over the years. To allow a better comparison, we chose to conduct our analysis over a longer time frame, which meant that the data

obtained came from different Landsat satellites. The data was collected from the Landsat 5 (Thematic Mapper) satellite on June 25, 1998, the Landsat 7 (Enhanced Thematic Mapper Plus) satellite on June 6, 2000, and the Landsat 8 (Operational Land Imager/Thermal Infrared Sensor) satellite on September 12, 2015, August 19, 2018, and September 23, 2022 (shown in green in Figure 2). In addition to the cloud cover requirement, we also chose Landsat Collection 2 Level-2 images for greater accuracy when taking ground control points.

2.4. Processing of the Data

2.4.1. Composite images and Ground Control Points

Since the data came from different satellite sensors, the resolution and bands used by each sensor differed. We first created composite images for each year by stacking the bands according to the satellite sensor after importing the Landsat imagery into ArcGIS Pro. By stacking bands 1-7 for Landsat 5 and 7, and bands 2-7 for Landsat 8, we created True Color Composite images with band combination RGB=321. To simplify our analysis, we clipped the image to a smaller area focusing specifically on the lake by creating a new polygon, while also including the other land cover classes like Bare Soil and Vegetation. We then collected Ground Control Points (hereon referred to as GCPs) between 1998-2000, 2000-2015, 2015-2018, 2018-2022, and 2022-1998 to determine the difference between the water land cover class over a 24-year period. To ensure consistency across years, we collected 15 points, with 2 points each for the Bare Soil and Vegetation land covers, and the rest of the points focused on the lake. Looking at the imagery, we could see a difference in the edges of the lake gradually disappearing over time, so the GCPs were collected as such, by concentrating half of the points inside the lake, and the other half for the lake's edges and streams.

2.4.2. Supervised Classification

Supervised classification is the process of selecting training sites of known land cover classes, which are then applied to the entire image. Upon collecting all of the GCPs, we exported all 5 images as Imagine image rasters and switched to ERDAS Imagine software to continue our analysis. To perform supervised classification on all of our images, we first defined the Areas of Interest (hereon referred to as AOIs), which specify the various land covers present in each image. This was accomplished by drawing polygons around the Areas of Interest: *water, bare soil, and vegetation*. To ensure that ERDAS correctly identified the classes, we created three polygons for each land cover class around different parts of the image and merged them into three classes. After classifying the AOIs, they were added to the signature

editor and saved as a .sig file. This is when we begin the supervised classification process, with both the previously created .sig file and the image being classified as inputs. We were able to run the classification and get an output that ERDAS could open by setting the output to an .img file and the parametric rule to Minimum Distance. This process was applied to all the years of study that we chose (shown in blue in Figure 2). To ensure consistency across all classified images, we used the recode tool to assign a number to each land cover type: Water: 1, Bare Soil: 2, and Vegetation: 3.

2.4.3. Statistical Analysis

After conducting the supervised classification to separate the three land covers from the satellite images, we conducted an accuracy assessment analysis in order to quantify how accurately our images were classified compared to real life. This was important as we manually selected the GCPs and in order for our analysis to uphold integrity, we must make sure that our classification reflected the true land cover in that area. This was done through cross referencing the generated points with Google Earth aerial imagery to assess true land cover without satellite images.

Table 1. Accuracy assessment/error matrix table for supervised classification image.

Class Name	Reference Totals	Classified Totals	Number Correct	Producer's Accuracy	User's Accuracy
Bare Soil	13	14	13	100.00%	92.86%
Vegetation	15	14	13	86.67%	92.86%
Water	22	22	22	100.00%	100.00%
Totals	50	50	48	--	--

Table 1 showcases our three land covers, bare soil, vegetation, and water. We were able to accurately determine the water class as the generated points matched the classes producing a 100% producer and user accuracy. The vegetation and bare soil classes were a little lower due to those areas representing a smaller portion on the satellite images. This explains why the producer and user accuracy are below 100%.

Table 2. Classification accuracy percentage and kappa statistics calculated percentages.

Overall Classification Accuracy	Kappa Statistic
96.00%	0.9303

Our main indication of whether or not the supervised classification was done accurately was through the overall classification accuracy percentage. This number is based on the total points correctly classed divided by the total generated points. As seen in Table 1, the analysis correctly identified 48 sites out of the 50 sites generated. This produced an overall accuracy of 96% as seen in Table 2. With this, the kappa coefficient resulted in 0.9303. This means that the classification can be regarded as ‘almost perfect’ due to the number being closer to 1. Therefore, we can conclude that the supervised classification correctly indicates the land cover classes in the images.

2.4.4. Change Detection

Change detection is a process in remote sensing that is used to show the change in an area over a specific time frame. It results in a raster that contains two pixel classes; with white pixels indicating change and black pixels showing no change.

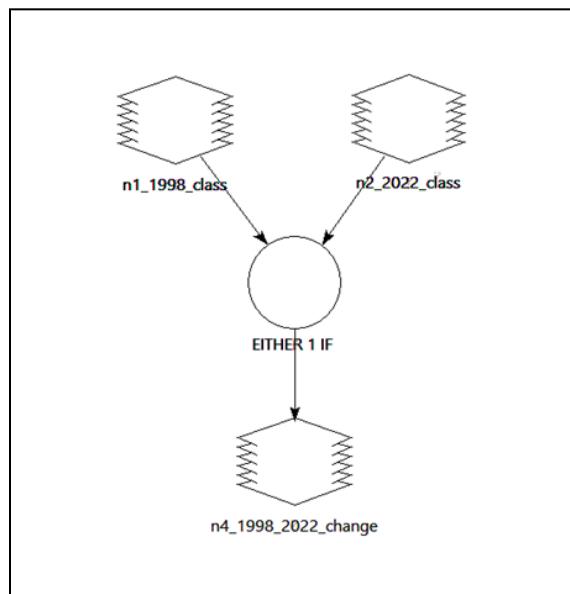


Figure 3. Model maker in ERDAS showing two raster objects as inputs, function and output change map.

With the results from the supervised classification, we conducted a change detection analysis to further solidify our understanding about the changing water class. To demonstrate this, we created five change detection maps, referencing the years 1998-2000, 2000-2015, 2015-2018, 2018-2022, and 1998-2022, and displaying the overall change. This is where ERDAS's model maker (Figure 3) was used to create a model that could be applied for all five maps, along with a formula:

EITHER 1 IF (\$n1_classifiedimage != \$n2_classifiedimage) OR 0 OTHERWISE

The above formula indicates the model to assign the value 1 to areas that experienced change and assign the value 0 otherwise, to create a map that shows the change as white pixels and otherwise as black pixels. By changing the output type to .img and the file type to Thematic, we eliminate the possibility of file errors in ERDAS and are ready to run the model. This process is repeated for each of our classified images from all five years, with the two classified image inputs replaced with our respective images to produce five maps (shown in yellow in Figure 2).

3. Results

3.1. Supervised Classification

A supervised classification was conducted initially to first separate the satellite images into three land covers, bare soil, vegetation, and water. From here, we were able to visually interpret the size of the water class within each year and begin to form our hypothesis.

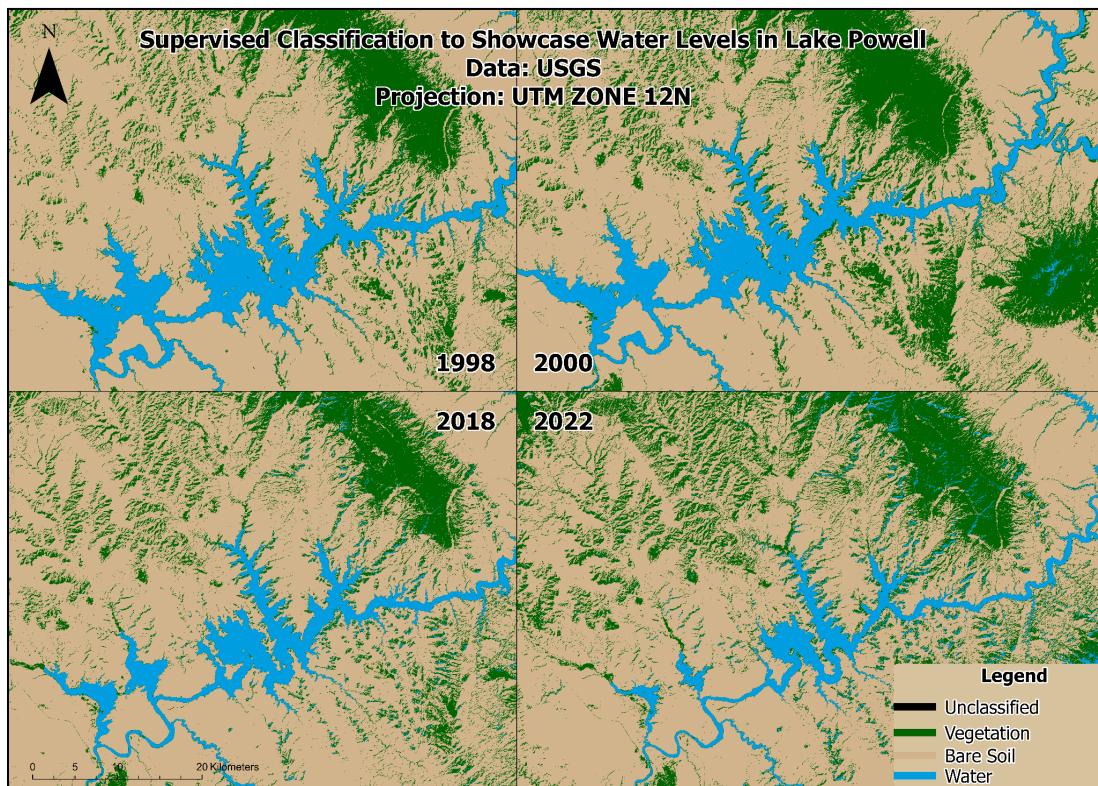


Figure 4. Thematic map showcasing supervised classification of three classes, vegetation, bare soil, and water; conducted through the years 1998, 2000, 2018, 2022 over Lake Powell. Satellite: Landsat 5, 7, 8.

Sensor: TM, ETM+, OLI/TIRS. Acquisition date: June 25 1998 (5), June 6 2000 (7), September 12 2015, August 19 2018, September 23 2022 (8). Bands shown: 1-7 (5), 1-7 (7), 2-7 (8).

Figure 4 was created to visually showcase the water classes between the years 1998, 2000, 2018, and 2022. Within Figure 4, it is evident that each year has the same projection/scale as well as three distinct classes. This was done to have similarity between the years and allow for a better comparison. It is evident that Lake Powell has seen a visible decrease in water levels between the years of 1998 and 2022.

3.2. Vector based Manipulation

After the supervised classification, we were able to use each of the water classes to conduct a vector-based manipulation analysis whereby we calculated the areas in square kilometers for each of the water classes in our study period for the years 1998, 2000, 2015, 2018, and 2022. This was done to showcase quantitative data of Lake Powell and further answer our research question of whether or not Lake Powell is decreasing or increasing in water levels.

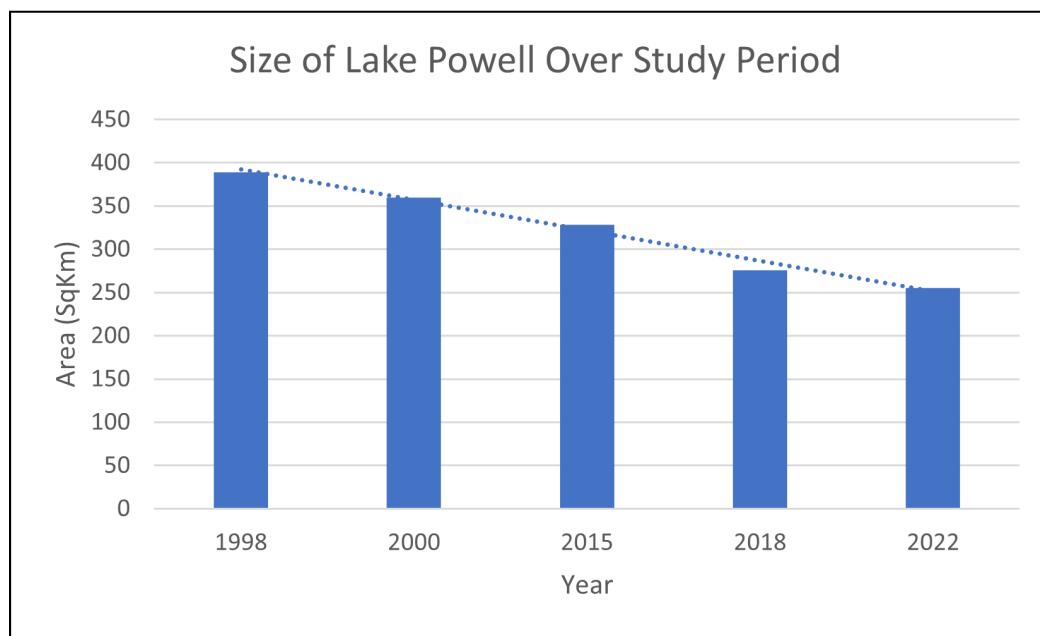


Figure 5. Bar graph displaying the change in area (in square kilometers) of Lake Powell from 1998 to 2022.

Through Figure 5, we are able to see that in the year 1998, the area of the water class was 375 square kilometers. Each year followed by this, the area calculated decreased in size up until the end of our study period, 2022. During this year, the area of the lake was 260 square kilometers. This indicates that from 1998 to 2022 (over a 24 year study period), Lake Powell experienced a 69.33% change in water levels.

3.3. Change Detection

Following our study, in order to spatially showcase the extent to which Lake Powell has decreased in size, we conducted a change detection analysis using the satellite images from 1998 and 2022. Through change detection, we are able to simply show how much the Lake has changed through two pixels, black and white.

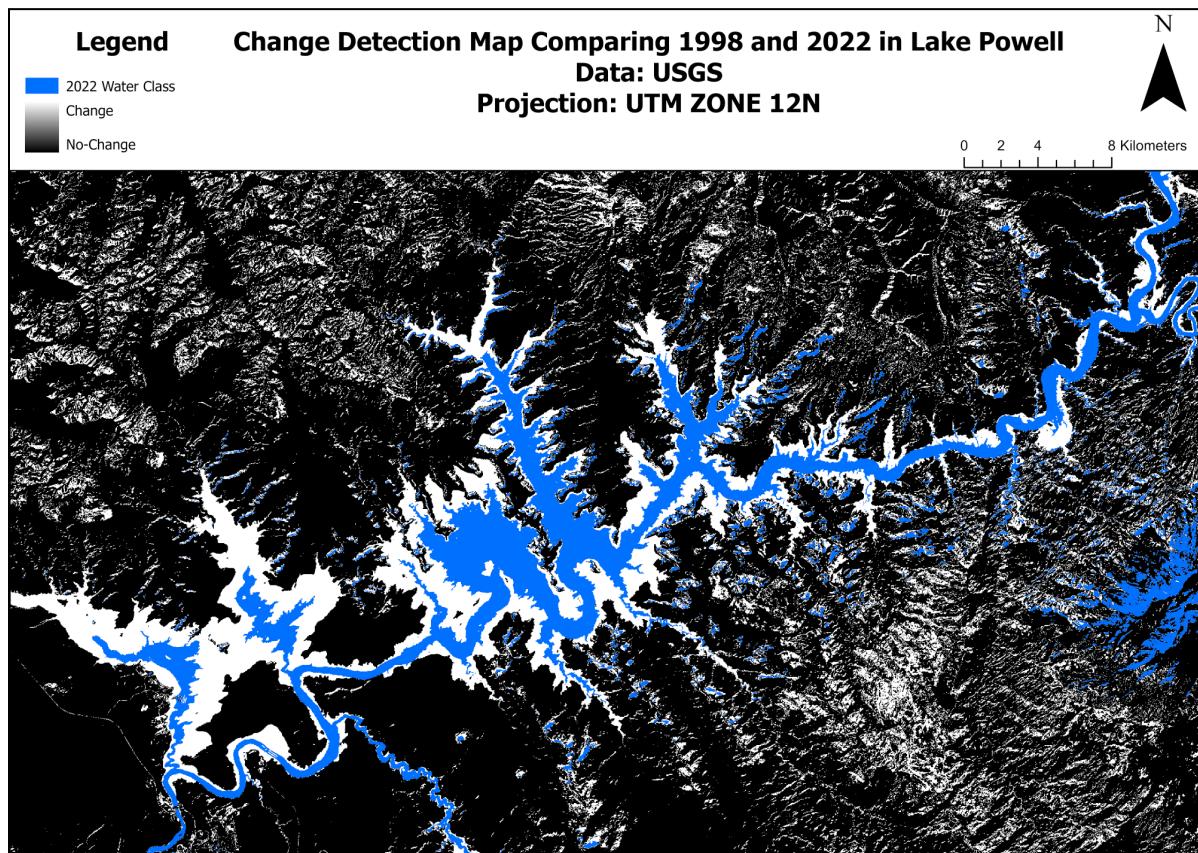


Figure 6. Thematic map showcasing change detection using imagery from 1998 and 2022. The 2022 water class was used to showcase present water levels in comparison to 1998 levels. Satellite: Landsat 5, 7, 8. Sensor: TM, ETM+, OLI/TIRS. Acquisition date: June 25 1998 (5), June 6 2000 (7), September 12 2015, August 19 2018, September 23 2022 (8). Bands shown: 1-7 (5), 1-7 (7), 2-7 (8)

In Figure 6, we are able to see that the white pixels represent change while the black pixels represent no change. We can see that the land around Lake Powell has not experienced much change due to there being more black pixels. However, the outer edges and banks of the lake showcase much more change due to there being more white pixels than black. We can also see that the 2022 water class was used to showcase current water levels in comparison to 1998 levels. This means that the white area around the lake was how the lake looked in 1998 and the blue areas showcase how the lake looks now. Although our study period included 5 years sequentially from 1998 to 2022, the change detection analysis done in the 1998 and 2022 years was the most crucial, to showcase absolute change during our study period. This way, Figure 5 spatially showcases how Lake Powell has decreased 69.33% (section 3.2) over the last 24 years.

4. Discussion

Our research question for this study was to analyze if Lake Powell is increasing or decreasing in size. Based on the supervised classification, vector-based manipulation, and change detection analysis, we can conclude that Lake Powell is experiencing drought. This is supported through the results which visually showcased that the lake areas were decreasing as well as calculating the water classes to quantitatively analyze the areas. In addition, the change detection showed that there are many more white pixels around the lake than black pixels.

This study provided answers to our questions by confirming the fact that Lake Powell is decreasing in water levels and agrees with other research done on Lake Powell. However, there are some limitations to our study such as not spatially analyzing the temperature and precipitation in Page, Arizona. Although, it is common knowledge that this state has a much drier climate, in order to prove this, a study on environmental factors could have also been useful. With this, another variable that could have been useful in determining the impact of Lake Powell's hydropower is the number of homes using it within the seven states. This would allow for better understanding of the use and impact of hydropower than just population data.

Our analysis is crucial since non-renewable energy sources are taught in schools and throughout society as being unsustainable and terrible for the environment. This is why we create renewable energy sources like hydropower plants. The problem with Lake Powell is not that it is decreasing in size, rather the problem is that the places which depend on the hydropower of this lake will have to look somewhere else for their energy. This means all seven states, 6 million people, businesses, homes, and manufacturing plants will have to start using nonrenewable energy sources like coal, gas, and oil.

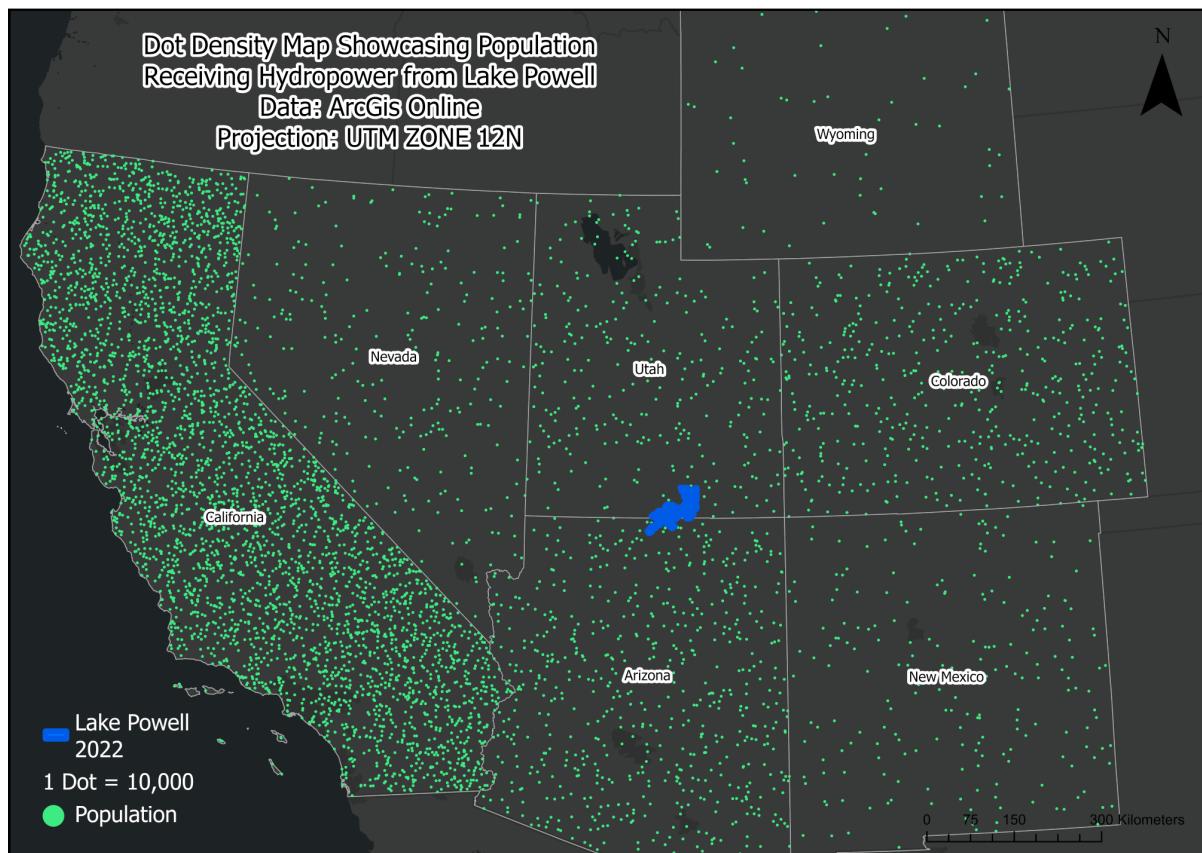


Figure 7. Thematic map showcasing states/population at risk of losing hydropower supplied from Lake Powell. Satellite: Landsat 5, 7, 8. Sensor: TM, ETM+, OLI/TIRS. Acquisition date: June 25 1998 (5), June 6 2000 (7), September 12 2015, August 19 2018, September 23 2022 (8). Bands shown: 1-7 (5), 1-7 (7), 2-7 (8).

Figure 7 illustrates the spatial benefits Lake Powell brings to the seven states. Lake Powell is shown as the blue lake in the center, and around it are the boundaries surrounding it. With this, each green dot represents 10,000 people. This proves that losing a renewable energy source can be detrimental to society as it pushes us back from a greener future rather than towards. Although climate change plays a huge role in this, we know that Arizona is a drier climate with minimal precipitation and warmer weather, it does not allow policy makers to not make a conscious effort in ways to preserve or refill this lake.

Our study does not stop here, rather continues as we urge future researchers and policy makers to come up with ways to preserve these areas rather than deter away from them. This means finding alternatives, backup solutions, and lake preservation techniques to continue supplying renewable energy to these 7 states and over 6 million people.

5. Conclusion

In conclusion, based on the outcomes of the supervised classification, vector-based manipulation, and change detection, our analysis of Lake Powell has determined that it is experiencing a drought. The thematic map for supervised classification clearly shows that Lake Powell's water levels significantly declined between 1998 and 2022, which is the study period. Using vector-based manipulation to calculate the areas in square kilometers for the various water classes during the 24-year study period, we found that Lake Powell's water levels changed by 69.33%. Another important finding was the area of the water class also had a significant decrease as it was 375 km^2 in 1998, however, in 2022, it was reduced to 260 km^2 . In addition, the change detection of the study period showcased that the outer areas of the lake experienced significant change whereas the lake itself hasn't experienced much change yet as it was covered by black pixels representing no change. Lastly, due to the drought it is experiencing, Lake Powell is in danger of losing its capacity to generate hydropower, which has a definite impact on the nearby states and millions of Americans, compromising the livelihood and ecosystem of these geographic locations.

References

- [1] Rutledge K., McDaniel M., Teng S., Hall H., Ramroop T., Sprout E., Hunt J., Boudreau D., Costa H., 2022. Lake. A lake is a body of water that is surrounded by land. There are millions of lakes in the world. Available online at: <https://education.nationalgeographic.org/resource/lake> (accessed December 4, 2022).
- [2] Stokstad E., 2021. A voice for the river. Available online at:
<https://www.science.org/content/article/colorado-river-shrinking-hard-choices-lie-ahead-scientist-warns>
(accessed December 4, 2022).
- [3] Stokstad E., 2013. Warning sign on the Colorado River. Available online at:
<https://www.science.org/content/article/warning-sign-colorado-river> (accessed December 4, 2022).
- [4] The National Renewable Energy Laboratory, 2014. Hydropower Basics. Available online at:
<https://www.nrel.gov/research/hydropower.html> (accessed December 3, 2022).
- [5] Vliet, M. T. H. van, Sheffield, J., Wiberg, D., Wood, E. F., 2016. Impacts of recent drought and warm years on water resources and electricity supply worldwide. Environmental Research Letters. Available online at: <https://iopscience.iop.org/article/10.1088/1748-9326/11/12/124021/meta> (accessed October 30, 2022).
- [6] Wang, Y., Li, H., Sun, B., Chen, H., Li, H., Luo, Y., 2020. Drought impacts on hydropower capacity over the Yangtze River basin and their future projections under 1.5/2°C warming scenarios. Frontiers in Earth Science. Available online at: <https://www.frontiersin.org/articles/10.3389/feart.2020.578132/full>
(accessed October 30, 2022).
- [7] Wheeler K., Udall B., Wang J., Kuhn E., Salehabadi H., Schmidt J., 2022. What will it take to stabilize the Colorado River? Available online at:
https://www.science.org/doi/full/10.1126/science.abo4452?casa_token=480GboUYAxoAAAAA%3Alg3sUTPTGR31dHh2aXGdeGaLWtj4y_J_oaUaftvQ1Avfqv06mWW8SM815qd9FkF5Vn4cCGP4IEYcA
(accessed December 4, 2022).
- [8] Yeung, P., 2022. As drought shrivels Lake Powell, millions face power crisis. Available online at:
<https://www.theguardian.com/us-news/2022/jul/13/lake-powell-drought-electricity#:~:text=Lake%20Powell's%20considerable%20power%2Dgenerating,a%20 large%20 fossil%20fuel%20plant> (accessed December 3, 2022).