Remote Sensing Methods for Identifying Ephemeral Water Bodies Across Arizona

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Abstract

A variety of remote sensing methods are investigated for their ability to detect ephemeral water bodies across the state of Arizona. The strengths and weaknesses of each are discussed.

Plain Language Summary

Results and methods for detecting transient water bodies using satellite data.

1 Introduction

As part of the Arizona Tri-University Recharge (ATUR) project, multiple methods for identifying and quantifying ephemeral water bodies across the state of Arizona (AZ) have been investigated. For reasons that will be discussed, accurate identification of ephemeral, or temporary, water bodies is a challenge, and efforts to-date have shown limited success. Methods, results, and challenges are discussed, and potential paths forward shall be explored.

Ephemeral water bodies are common features in the arid American southwest. Typically very shallow, these water bodies range in size from a few cm rock pools to sheet flow associated with flash floods, and playas up to several km in diameter (Crawford, 1981; Whitford & Duval, 2020). While playas and intermittent streams are well mapped across AZ, there is no consensus on the volume of water which flows through these systems. More to the point, there is no widely accepted estimate of the volume of water which either evaporates or recharges from these internally draining basins.

It is not clear what fraction of water which flows onto a playa is evaporated vs. recharged. On the one hand, the nature of playas results in the slow accumulation of surface salts and fine sediments (clays and silts), which are generally impervious and detrimental to infiltration and subsequent recharge (Whitford & Duval, 2020). Additionally, playas may be an oasis for drought resistant flora, increasing local evapotranspiration, even after shallow surface soil layers have dried out (Crawford, 1981). Alternately, these mineral rich surface crusts may be prone to expansion when wetted, and are frequently characterized by deep cracks which provide avenues for water infiltration below the impervious layers (Whitford & Duval, 2020). While the majority of water flowing onto most playas will be lost to evaporation, there may be specific playas where water loss by infiltration may exceed evaporation (Whitford & Duval, 2020). At least initially, we will assume that all water flowing onto playas shall be evaporated, subject to later reevaluation and refinement.

The primary target of this study is to estimate and quantify the volume of water flowing into small to medium sized playas, on the order of ~50 m to ~1 km in diameter, although identification of sheet flow may also be incidental. The general method outlined is to use remote sensing technology to identify standing water broadly across the study area, across a time series. By identifying standing water, and assuming a constant water depth, water volume can be estimated. Additionally, an approximation of "continuously wetted" days can provide an initial estimate of evaporation rates, and through comparison with alternate evapotranspiration estimates, may be useful for estimating infiltration rate (e.g. if water loss rate is 2 cm/day and the evapotranspiration rate is 1.5 cm/day then the implied infiltration rate would be 0.5 cm/day).

The study area used for method development is primarily Hualapai Playa (a.k.a. Red Lake), located in northwest AZ, approx. 60 km south-southwest of Lake Mead (Figure 1). This ephemeral playa is roughly 8 km in diameter, and is one of the largest playas in AZ. Furthermore, local landowners surrounding Hualapai Playa have expressed sincere interest in our project, creating additional public-relations incentives related to this particular playa. Lastly, it's proximity to Lake Mead and Lake Mohave provide a convenient region for testing these methods against known areas of permanent surface water. Additional playas are investigated as needed.

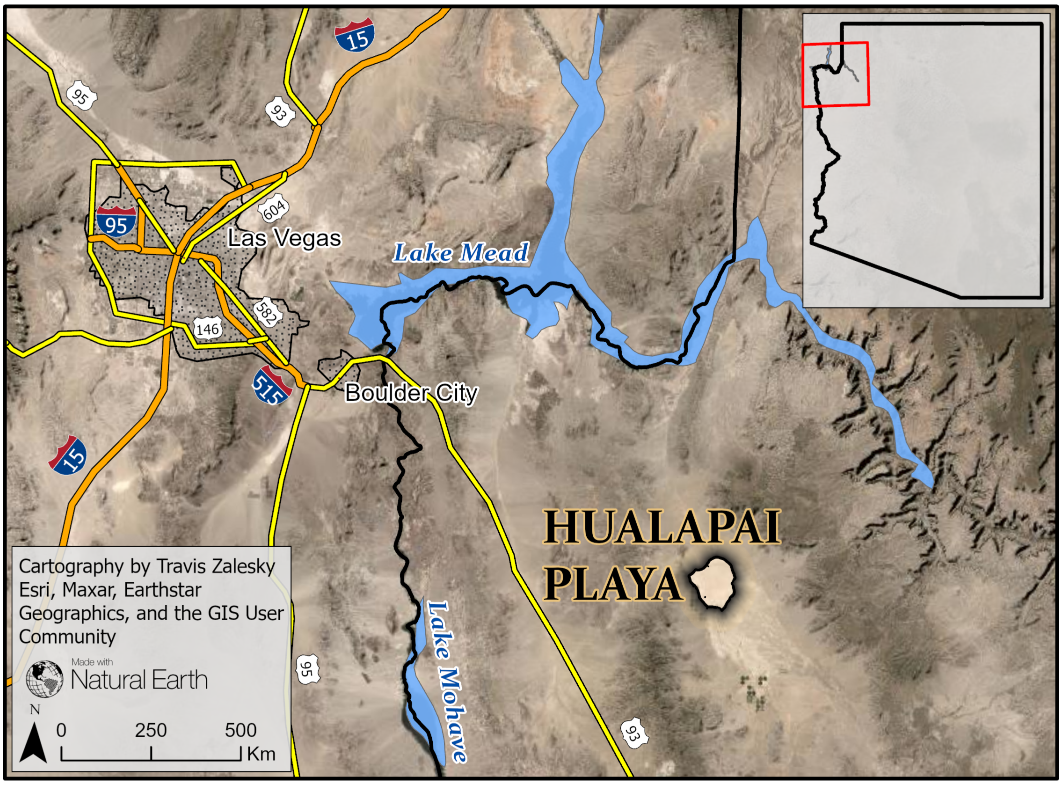

Figure 1: Hualapai Playa locator map.

One of the most challenging aspects of developing these methods is the lack of quality ground-truth data. Without existing data regarding date and duration of standing water within these ephemeral features, it is extremely difficult to validate our methods. While reasonable assumptions can be made about method accuracy (or inaccuracy as the case may be), any method, either those presented herein, or future methods not yet considered, will have to be validated using a known and well characterized ephemeral water body, ideally within AZ, or elsewhere in a similar arid environment.

2 Methods & Results

2.1 Method 1: Otsu Thresholding with Synthetic Aperture Radar

Otsu thresholding is an unsupervised machine vision technique which seeks an optimal threshold for segmenting an image into a binary classification based on a simple histogram classification (Otsu et al., 1975). The method was initially developed in the late '70s, and is widely applicable to a range of computer vision classification problems. It assumes a bi-modal histogram distribution and determines an optimal thresholding value through the integration of the histogram, rather than simply relying on local properties "such as valley[s]" (Otsu et al., 1975). In recent years, Otsu thresholding has been combined with Synthetic Aperture Radar (SAR) satellite imagery to map surface water, such as flood monitoring in the Mekong Delta (Tran et al., 2022). The properties of surface water and SAR make an ideal pairing for use in Otsu thresholding. The smooth surface characteristics of surface water create low

SAR back-scatter, appearing as very dark pixels (Figures 2-3). Compared to the surrounding land surface, water typically has a very high contrast in SAR imagery, which can be leveraged for Otsu thresholding. Additionally, the cloud penetrating characteristics of SAR offer unparalleled all-weather monitoring capabilities.

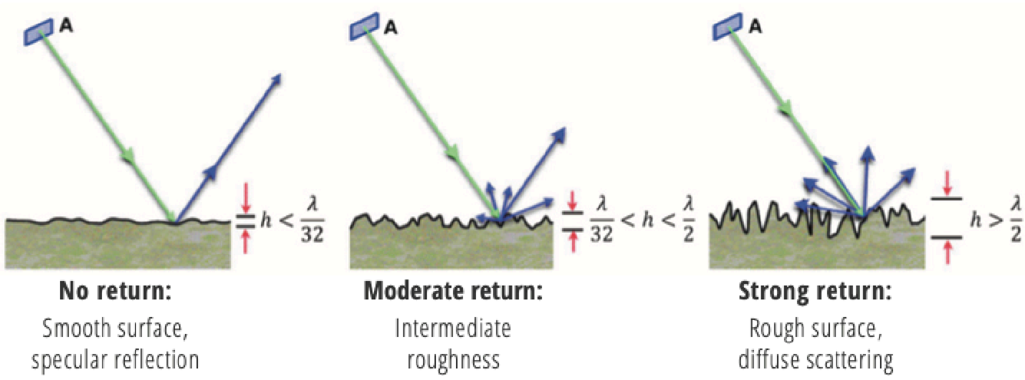

Figure 2: Synthetic Aperture Radar signal return strength (i.e. back-scatter) is a function the roughness of the ground surface. Credit: Meyer (2019), Figure 2.8. For educational purposes only.

This method initially seemed like an ideal solution. High resolution SAR imagery is freely available from the European Space Agency (ESA) Sentinel-1 satellite, with a global coverage from late 2014 to present, and a 6-day revisit time. Google Earth Engine (GEE) code for Otsu thresholding was easily adapted from Markert et al. (2023), and preliminary results appeared to be promising. Initial analysis appeared to show surface water ponding on Huyalapai Playa in mid-Jan 2020. These preliminary results were circulated internally, and purported to be both evidence of surface water, and proof-of-concept for method validation. However, further research and wider application of this method revealed two critical flaws.

Firstly, the method, as applied in GEE, was highly sensitive to the size and characteristics of any given playa. For larger playas, the method was generally suitable, but required a substantial amount of manual parameter optimization to function properly. For small to medium sized playas, the method was largely unstable, resulting in persistent errors. As a result this method is not particularly scalable, and at best could be used for a selection of the states largest playas, such as Huyalapai and Willcox Dry Lake (southeast AZ).

More critically, this method is sub-optimal for arid regions, as flat sandy surfaces also result in low SAR back-scatter, appearing similar or indistinguishable from surface water. The hard-pan surface of a dry playa is particularly apt to be misidentified by this method, resulting in a high likelihood of false positives. It is currently unclear if the preliminary results purporting to have identified surface water on Huyalapai Playa in Jan. 2020 are true or false positives, as there is no associated ground-truthing data against which to compare. Regardless of the truthiness of these results it is evident that this method can not be used reliably within the study area without widespread and comprehensive testing and validation of results. Given the scheduling and budgetary constraints of this project widespread survey data collection is not feasible, and while further development of this method may be

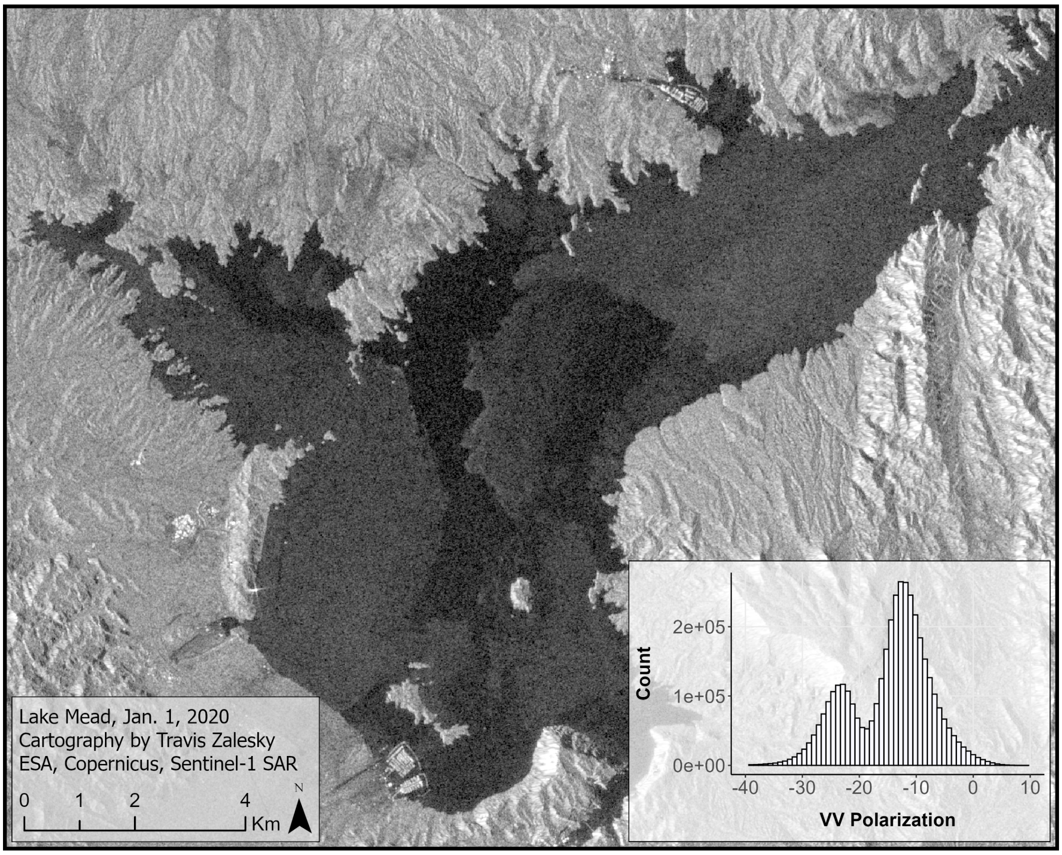

Figure 3: High resolution Synthetic Aperture Radar (SAR) imagery of Lake Mead, obtained from the European Space Agency (ESA) Sentinel-1 satellite (1-1-2020). Surface water appears dark, and contrasts strongly with the surrounding land surface, resulting in a bimodal histogram distribution, ideal for use in Otsu thresholding.

warranted (generally), it is not appropriate for our purposes. Therefore alternate methods must be explored.

2.2 Method 2: Normalized Difference Water Index with Landsat Multispectral Imagery

Collectively, the 9 Landsat satellites provide the longest continuous record of space-based earth observations, from 1973 to present. Therefore, it may seem like an obvious candidate for monitoring infrequent phenomena, such as surface water ponding on playas, which may only happen once every several years (depending on the playa). However, Landsat imagery has several disadvantages compared to SAR. Firstly, the 30 m resolution of Landsat imagery is nine times coarser than the 10 m resolution of Sentinel-1 SAR. Second, the revisit time for Landsat satellites is 16-days, more than double that of Sentinel-1. By combining data from multiple Landsat satellites this effective revisit time may be cut to 8-days, but this may not be possible throughout the full time series of interest. Additionally, the visible and infrared spectral bands used by Landsat sensors is not capable of penetrating clouds, and while cloud-masking can be achieved through post-processing, the presence of clouds has the potential to obfuscate the phenomena of interest. Combined, these three disadvantages compound, resulting in much sparser data availability for Landsat imagery in comparison to Sentinel-1.

Furthermore, while indices for surface water monitoring utilizing Landsat spectral bands, such as the Normalized Difference Water Index (NDWI), are widely used, they are imprecise classifiers on their own. NDWI in particular, is suspectable to misclassifying shadows as water. NDWI is defined as the difference between the green and near-infrared (NIR) bands divided by the sum of the green and NIR bands (for Landsat 8/9, bands 3 and 5 respectively; Equation 1).

$$NDWI = \frac{Green - NIR}{Green + NIR} \tag{1}$$

Despite these disadvantages, it may still be possible to characterize and quantify ephemeral water bodies using this dataset.

Fortunately, Landsat data is freely available, easily accessible through GEE, and Landsat Collection 2 datasets have added post-processing data which is directly applicable to this method, including cloud and cloud shadow masks, as well as a pre-calculated water mask (which appears to be largely coincident with NDWI > 0). However, this water mask is over inclusive, and not suitable for use as is.

A large number of features identified as water in the provided Landsat layer appeared to correspond to the northward aspect of terrain features. Therefore, the first and most important step in refining the provided water mask layer was to reduce the false positives as a result of natural terrain shadows. This was accomplished by creating a hillshade (or hill shadow) layer in GEE from a high resolution (10 m) USGS digital elevation model (DEM).

3 Further Recommendations

4 Conclusion

References

Crawford, C. S. (1981). Chapter 17 - the invertebrate community of ephemeral waters. In *Biology of desert invertebrates* (pp. 234–247). Springer-Verlag.

Markert, K., Donchyts, G., & Haag, A. (2023). Chapter A2.3 surface water mapping. In J. A. Cardille, N. Clinton, M. A. Crowley, & D. Saah (Eds.), *Cloud-based remote sensing with google earth engine: Fundamentals and applications* (1st ed.). Springer Cham. https://docs.google.com/document/d/

12cwzbNXtBQnm5switfL1vlv1stnp5D5gXcQeZMP_iJI/edit?tab=t.0#heading=h.2gd4k88k0hkr

Meyer, F. (2019). Chapter 2 - spaceborne synthetic aperture radar: Principles, data access, and basic processing techniques. In A. Flores-Anderson, K. Herndon, R. Thapa, & E. Cherrington (Eds.), *The SAR handbook: Comprehensive methodologies for forest monitoring and biomass estimation.* https://doi.org/10.25966/nr2c-s697

Otsu, N. et al. (1975). A threshold selection method from gray-level histograms. *Automatica*, *11*(285-296), 23–27.

Tran, K. H., Menenti, M., & Jia, L. (2022). Surface water mapping and flood monitoring in the mekong delta using sentinel-1 SAR time series and otsu threshold. *Remote Sensing*, *14*(22). https://doi.org/10.3390/rs14225721

Whitford, W. G., & Duval, B. D. (2020). *Chapter 8 - consumers and their effects* (W. G. Whitford & B. D. Duval, Eds.; pp. 203–263). Academic Press. https://doi.org/10.1016/B978-0-12-815055-9.00008-4