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Cloud-based geospatial services for building capacity and safeguarding heritage in climatically marginal landscapes

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Abstract

Our world is changing rapidly, and nowhere is this transition more pronounced than in the climatic extremes of our planet. For the people who call these places home, the myriad threats facing their rich cultural landscapes in the context of the current climate change crisis—rising sea levels, fluvial erosion, drought, sand dune encroachment—are becoming a source of great social anxiety. Furthermore, these environmental pressures are compounded by population growth and urban development.

Using two contrasting study regions, the Yukon-Kuskokwim Delta in Alaska, USA and Mauritania, we explore how free cloud-based geospatial services such as Google Earth Engine (GEE) might be used to build capacity for communities in the Arctic and the Sahel. We present five analytical remote sensing tools built in GEE, each one designed to address specific and urgent environmental concerns in the regions in question.

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1. Introduction

Our world is changing at a rapid pace, escalating and exacerbating many threats to our shared human heritage— natural disasters, climate change, armed conflict, and others. Many communities in rural areas are disproportionately affected by these issues, as they do not have the resources to mitigate threats to their built heritage. This disparity can be especially pronounced for people living in climatically marginal extremes of our planet, where temperatures and environmental conditions exceed or fall below the bounds of average human comfort. Almost half the landmass of our planet is located in very hot, arid deserts[1], or in very cold tundra and polar environments[2] (Beck et al., 2018) (Figure 1).

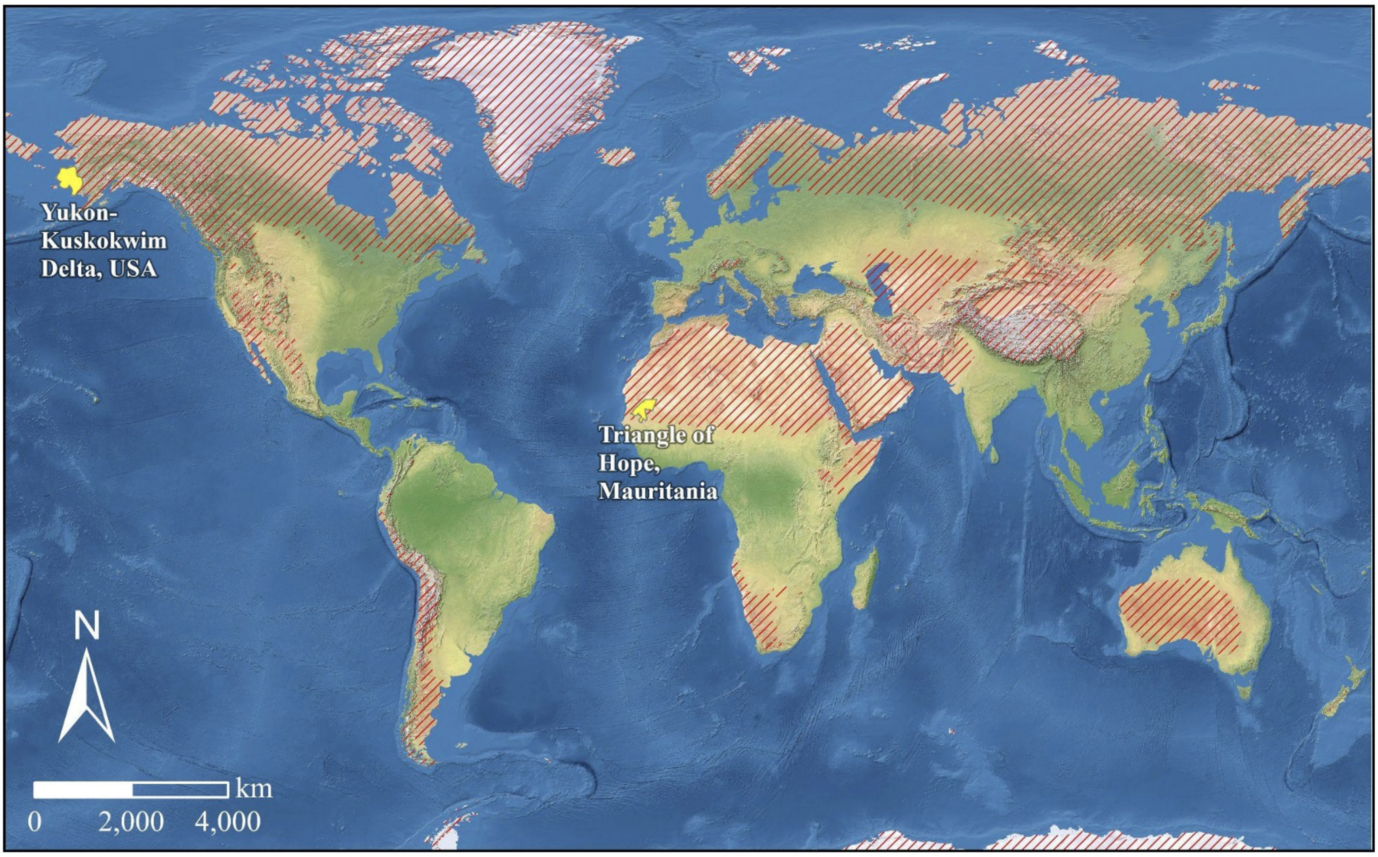


Figure 1. Climatically marginal regions of the world, approximately half of our planet's landmass, are shown in red shading. The two contrasting

study regions to be discussed in this article are also shown

In this article, we present five automated workflows designed for use in Google Earth Engine, showcasing how free cloud-based geospatial services like this one can be used to automate the entire spatial data visualization process for the purpose of analysis and communication of landscape change. These tools are designed for accessibility with minimal training based on local heritage preservation contexts— both for archival data stored on the external servers, and the user's own uploaded data.

Each of these regions faces a set of challenges as unique as the ebb and flow of their natural environments, and also of the people past and present who would call it home. Consider, for example, the Alaska Native Yup'ik (pl. Yupiit) people of the Yukon-Kuskokwim (Y-K) Delta. Much in the same way as their ancestors did in the past, the Yup'ik live in small traditional communities that subsist heavily on coastal and riverine resources throughout the year, such as salmon, sea mammals, and edible beach vegetation (Fienup-Riordan, 2007; Linares Matás & Lim, 2021b; Lim & Linares Matás, 2022) The soft fluvial sediments of the Y-K Delta are in a constant state of flux—accordingly, landscape change is very much an integral part of the cultural consciousness and cosmology of the Yup'ik people (Fienup-Riordan, 1995; Fienup-Riordan et al., 2015). Even so, the rate of climate-change-induced erosion is accelerating at an alarming and unsustainable rate, posing an existential threat to modern infrastructure and heritage alike (Gleason et al., 2023; Hillerdal et al., 2019; Lim et al., 2023). As mentioned above, the cosmology of the Yupik people is replete with accounts of landscape change. For example, within the community of Quinhagak in the Kuskokwim Bay (population c. 700), there is an oral history predicting that the village will move five times, and that it is currently situated in its third location (Rearden & Fienup-Riordan, 2013). A recent study by the Alaska Division of Geological & Geophysical Surveys (Buzzard et al., 2021) produced a comprehensive study with remotely-sensed data, predicting an astounding $15,262,200 of damage due to occur to Quinhagak's infrastructure over the next 20 years: However, the study was only done on the village itself, and does not take into account the damage and social/financial costs to the wider traditional land use area of Quinhagak— an almost 184,000 square acre area that the community travels to throughout the year gathering the resources they need to survive (Gleason et al., 2023).

Mauritania, located in the Sahel region of Africa, comprises mostly rangelands, with viable agricultural areas being restricted to oases or areas along the Senegal River (Jahel et al., 2020). The socio-economic landscape of the country heavily relies on agriculture and pastoralism—primarily centered on sheep and goats—as well as iron and fish exports. Smallholder farmers and marginalized seasonal workers, particularly women, face challenges such as declining crop yields, an early lean season, and limited market access (Meemken & Bellemare, 2020). The most socially and ecologically vulnerable areas in the country are named the "Triangle of Hope", which encompasses the provinces of Guidimagha, Tagant, Assaba and Brakna. This region is characterized by extreme poverty and cyclical extreme climatic pressures, such as droughts and floods, leading to food insecurity and malnutrition (d'Errico et al., 2018; Nyong et al., 2007; Tiepolo et al., 2019). In departments such as Moudjeria, Tichitt, Kaedi or Tamchekett, there are no institutional actors positioned for immediate crisis response (IFRC, 2022). The southernmost provinces, especially Brakna and Gorgol, experience threatening hydro-climatic risks, such as heavy rains and subsequent flooding of the River Senegal and its tributaries, which recurrently leave hundreds of families homeless and severely impact local agricultural production; concerns about epidemics emerge each time due to poor sanitation in temporary resettlement centers (Tiepolo et al., 2019). In most regions of this arid country, however, problems related to desertification and sand dune encroachment are even more threatening for human and livestock survival, as well as cultural heritage protection, particularly in places such as Nouakchott, Tichitt, or Chinguetti (Gómez et al., 2018).

Fortunately, analytical remote sensing is rapidly emerging as a highly effective tool for assisting with the protection of heritage at risk (Fisher et al., 2021; Khan et al., 2022; Klehm, 2023; Lim & Linares Matás, 2023; Linares Matás & Lim, 2021a; Lintott & Rees, 2023). Powerful sensors mounted on satellites orbiting our planet passively observe light reflected from the earth's surface. This is done at regular intervals for most parts of the world, creating a robust longitudinal record of our planet's surface spanning years or decades. Furthermore, advances in unpiloted aerial vehicle (UAV, known colloquially as "drones") technology is rapidly democratising the field of remote sensing— with relatively little training, operators can obtain landscape imagery at a higher quality and lower cost than with satellite-based sensors (Campana, 2017; Casana et al., 2017). Also, unlike satellite imagery, UAV operators own the data they collect(Lim et al., 2022). However, satellite data has the advantage of not requiring an operator to be present in the study area (although any remotely sensed data should, ideally, be ground-truthed after the fact) (Parcak, 2009). Both these approaches offer unique advantages when monitoring and protecting heritage sites. By harnessing the strengths of satellite-based longitudinal records and the high-resolution, cost-effective imagery from UAVs, a more robust and accessible approach to heritage preservation can be achieved.

Nevertheless, processing and interpreting remotely sensed data has traditionally entailed a significant barrier to entry. Specialist training and knowledge are often required, not to mention access to expensive software and hardware designed for this purpose. As such, rural communities like those in the Y-K Delta and in Mauritania often do not have access to the resources and expertise required to employ remote sensing to protect their heritage. In order to qualify for federal grants, remote Alaska Native villages must pay a premium to engage the services of outside geospatial companies to conduct environmental studies. Likewise, Vousdoukas et al. (2022) call for urgent site-specific local studies to address the urgent fluvial threats to Mauritanian world heritage sites.

In response, we call for the development of software workflows that can be utilized by non-specialists in remote rural communities to process and interpret spatial data. This is broadly in line with the United Nation's 17 Sustainable Development Goals— in particular, developmental targets 11.4 to "Strengthen efforts to protect and safeguard the world's cultural and natural heritage" and 11.a to "Support positive economic, social and environmental links between urban, peri-urban and rural areas by strengthening national and regional development planning". Accordingly, both Arctic and Sahel communities would benefit from user-friendly spatial software packages to conduct community-based remote sensing on satellite and UAS-acquired imagery

An ideal solution may be found in the form of cloud-based geospatial services, of which Google Earth Engine (GEE) is the current dominant presence. This service was made freely available to the public in December 2010; it is a cloud-based platform that allows users to analyze and visualize archival datasets of satellite imagery and geospatial data hosted on

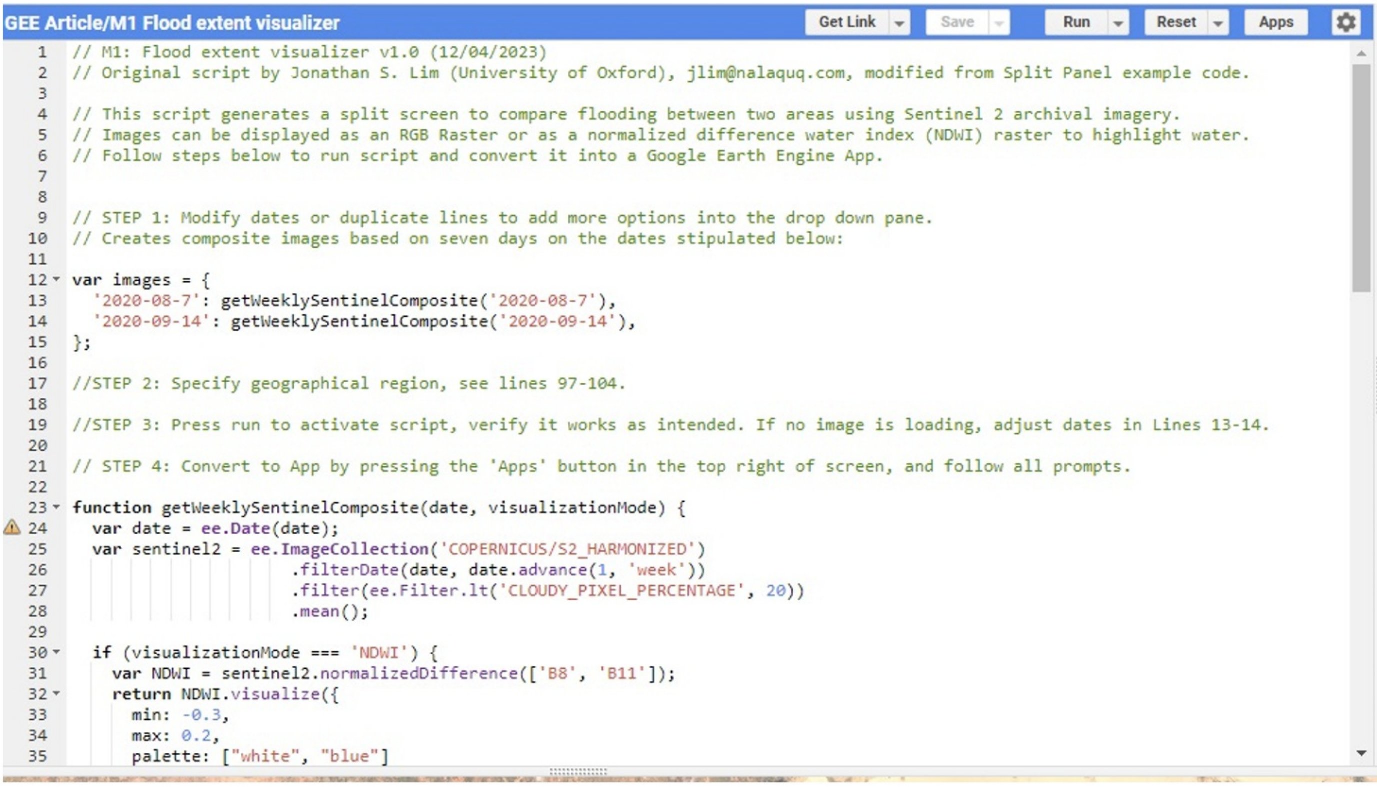
Google's servers. Since its release, it has become an essential tool for researchers across many disciplines, including those involved in landscape heritage work (Kennedy et al., 2018; Adhikari, 2021; Danese et al., 2021; Moreno et al., 2022; Conesa et al., 2023; Zhang et al., 2023). The primary benefit of GEE is the ability to stream, process, and analyse vast repositories of archival data on Google's servers, which allows users to compare and predict landscape change across decades-long longitudinal datasets. However, what has yet to receive attention in the literature is the fact that user-owned data—such as High-resolution imagery not hosted on the server or UAV imagery— can also be processed with GEE. The implication of this is significant: Land managers working in a rural setting with few resources can easily process spatial data on a cloud-based service with the need for a powerful computer or specialised software, as long as they have access to the Internet. The advent and rapid growth of affordable satellite-based broadband Internet, most notably Starlink and OneWeb (Dvorsky, 2023), makes this an increasingly viable option with every passing month.

2. Automatic Workflows for Remote Communities

2.1. Introduction to Google Earth Engine (GEE)

In Google Earth Engine (GEE), users input code via an online code editor interface using the Javascript language after signing up for a Google account. By default, this also comes with intuitive drawing tools to allow a user to interact with the imagery— script authors may easily insert panels with buttons using intuitive code functions, which is key to improving the accessibility of this software to new users who may not have experience with remote sensing.

Another advantage to GEE as a resource is its very thorough documentation, which includes detailed explanations of code syntax, functions, and examples. In keeping with the GEE developers' commitment to accessibility, the scripts we have written below have easily navigable user interfaces and ample documentation (including step-by-step instructions) within the code themselves (Figure 2):



GEE Article/M1 Flood extent visualizer Get Link Save Run Reset Apps

```
1  // M1: Flood extent visualizer v1.0 (12/04/2023)
2  // Original script by Jonathan S. Lim (University of Oxford), jlim@nalaquq.com, modified from Split Panel example code.
3
4  // This script generates a split screen to compare flooding between two areas using Sentinel 2 archival imagery.
5  // Images can be displayed as an RGB Raster or as a normalized difference water index (NDWI) raster to highlight water.
6  // Follow steps below to run script and convert it into a Google Earth Engine App.
7
8
9  // STEP 1: Modify dates or duplicate lines to add more options into the drop down pane.
10 // Creates composite images based on seven days on the dates stipulated below:
11
12 var images = {
13   '2020-08-7': getWeeklySentinelComposite('2020-08-7'),
14   '2020-09-14': getWeeklySentinelComposite('2020-09-14'),
15 };
16
17 //STEP 2: Specify geographical region, see lines 97-104.
18
19 //STEP 3: Press run to activate script, verify it works as intended. If no image is loading, adjust dates in Lines 13-14.
20
21 // STEP 4: Convert to App by pressing the 'Apps' button in the top right of screen, and follow all prompts.
22
23 function getWeeklySentinelComposite(date, visualizationMode) {
24   var date = ee.Date(date);
25   var sentinel2 = ee.ImageCollection('COPERNICUS/S2_HARMONIZED')
26                       .filterDate(date, date.advance(1, 'week'))
27                       .filter(ee.Filter.lt('CLOUDY_PIXEL_PERCENTAGE', 20))
28                       .mean();
29
30   if (visualizationMode === 'NDWI') {
31     var NDWI = sentinel2.normalizedDifference(['B8', 'B11']);
32     return NDWI.visualize({
33       min: -0.3,
34       max: 0.2,
35       palette: ["white", "blue"]
```

Figure 2. We provide detailed, step-by-step instructions for use in the scripts themselves for ease of training new operators in these methodologies.

We present five tools to address environmental issues in a rural heritage management setting, available for download here (Table 1): https://github.com/Nalaquq/gee

Table 1. List of automatic workflows developed by the authors for use in this study, and associated costs. A wide range of different remote sensing analyses and applications for use in marginal landscapes are represented (highlighted in **bold**.)

	GEE Tools Case Study Location and ID		Notes	
	Alaska	**Mauritania**	**Costs**	**Remarks**
Streaming dataset scripts	A1: Archaeology and Coastal Change (ACC) [**Coastal erosion visualisation**]	M1: Flood extent visualizer of Sentinel-2 imagery [**NDWI visual comparison, for use in a GEE App**]	None for non-commercial use, computer with browser and internet access required. Optionally, GIS software needed for further analysis and cartographic outputs, free options available (e.g. QGIS)	Data resolution depends on the hosted dataset. Sentinel-2 has a G.S.D. of 10m.
Uploaded dataset scripts	A2: Automatic waterway change detection of very high resolution (VHR) satellite Planetscope imagery [**Relative Pixel Change Detection**] A3: Spectral analysis of multispectral UAV imagery [**Spectral profile graphs**]	M2: Pattern Recognition for quantifying urban grown and sand dune shifts in VHR Planetscope imagery [**Supervised classification, Absolute Pixel Change Detection**]	Cost associated with data storage in Google Drive, $12 a month for 2TB*. Computer with internet access required. For UAV imagery, additional software needed to process orthomosaic, free options available (e.g. OpenDroneMap) Optionally, GIS software needed for further analysis and cartographic outputs, free options available (e.g. QGIS)	Up to the highest possible resolution. Costs may be associated with storage and processing, but precludes the need for purchasing expensive remote sensing software. Planetscope imagery is free for educational and NGO use, on application.

[*] *At time of writing*

2.2. Scripts for streaming archival data: M1 and A1

We will now demonstrate how GEE can enable powerful landscape-scale visualizations and analyses by querying archival imagery stored on Google's servers.

Tool M1: Flood extent visualizer of Sentinel-2 imagery

Mauritania, like other hyperarid regions of the world, is characterized by great temporal variability for rainfall (Schick, 1988). As such, it periodically suffers from devastating floods that pose a risk to life, infrastructure, and heritage. We present here a tool for visualizing the scale of a flooding event, which can often be very alarming in scale. In this example, we use a known flooding event dated September 14th 2020 that affected settlements on the northern bank of the Senegal River, and in other parts of Mauritania (Floodlist, 2020). This region potentially contains culturally sensitive archaeological remains: At distances of *c.*30km east and northeast of Tiguere, we also find some ring tumuli clusters on low elevation hills: the Haïré Pofoy site.

By specifying two dates in lines 12-14, a weekly composite is generated for the area and dates in question. After running the script, a split screen panel is provided, allowing the user to interactively move and compare the extent of flooding in the older and newer imagery. There is also an option to display the rasters on either side as a Normalized Difference Water Index, which uses the Green and Near Infrared (NIR) bands in the following equation to highlight the presence of water:

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

The histogram of the NDWI raster has been visually optimized to show the presence of water as a bright blue hue in the context of an arid environment (Lines 31-32).

This tool, unlike others here, is intended to be converted into a persistent Google Earth Engine App with a simplified interface (Figure 4). Such an application is not just useful for quantifying flood extents and threats to heritage (Figure 5), but is designed to effectively communicate the scale of a flooding event to non-specialist audiences in a very public-facing way, and so lacks the ability to download the data for further analysis (A limitation of converting the code from a GEE code editor format to a GEE App). GEE apps can also be customized with graphics, like the logo of the organisation using it.

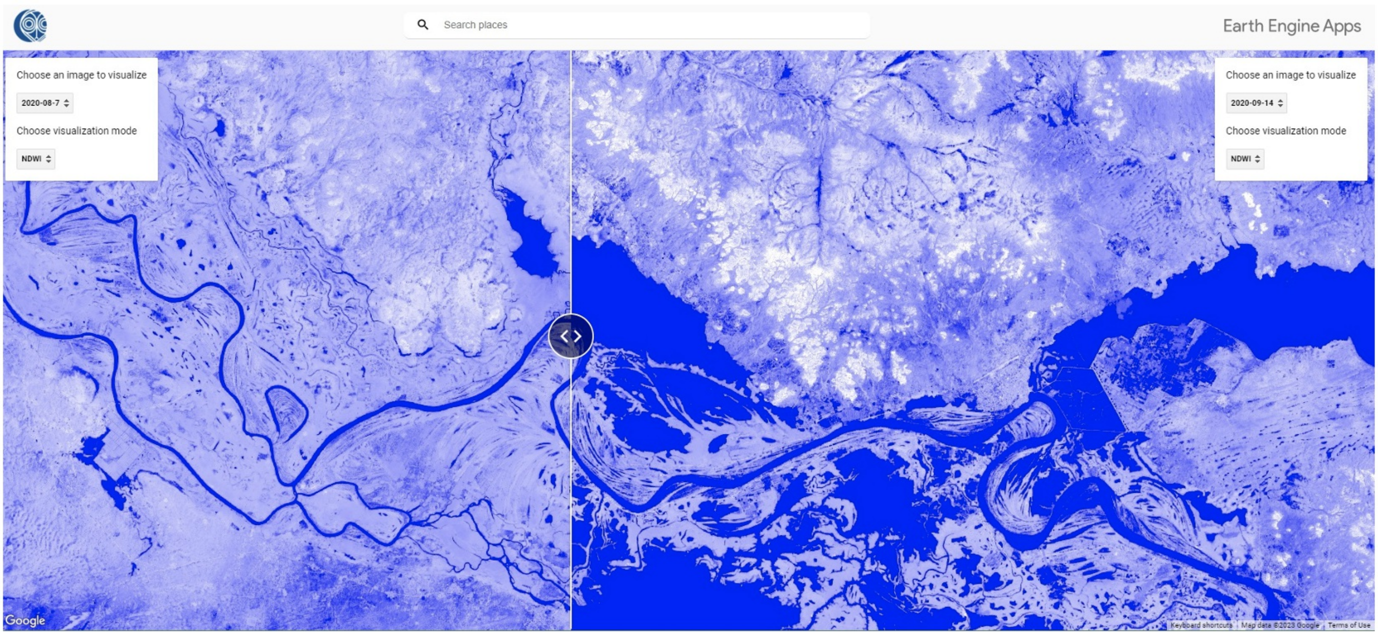


Figure 3: Tool M1 consists of a slider that can be used to compare and communicate flooding extents across two different user-specified years.

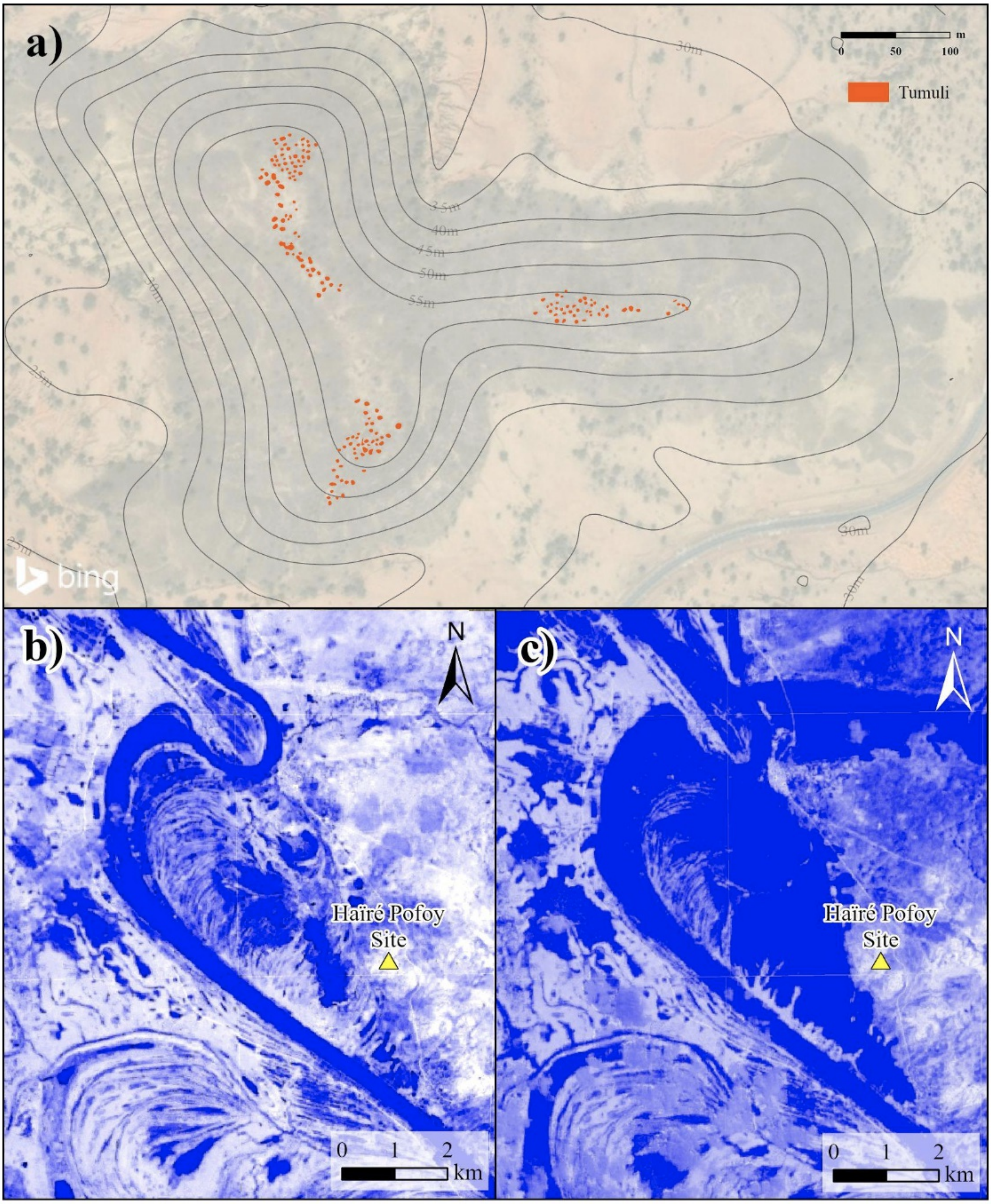


Figure 4: Tool M1 in action. a) the Haïré Pofoy site consists of three clusters of tumuli on a prominent hill (c. 35m) near the Haïré Pofoy mountains. b) NDWI raster October 10th 2020, just before the flooding event, showing the normal location of the river in relation to the site. c) NDWI raster after the September 14th 2020 flooding event reveals that the site is safe

in its elevated position.

A1: Coastal erosion susceptibility of Sentinel-2 imagery

Several coastal villages already have evacuation plans in place and one, Newtok, has already had to uproot their entire community. The community of Newtok, population 354, is already in the process of evacuating at a projected total cost of $120 million dollars (Schwing, 2023), relinquishing generations of specialized local subsistence knowledge in the process, and making them one of the first climate change refugees of the 21st century.

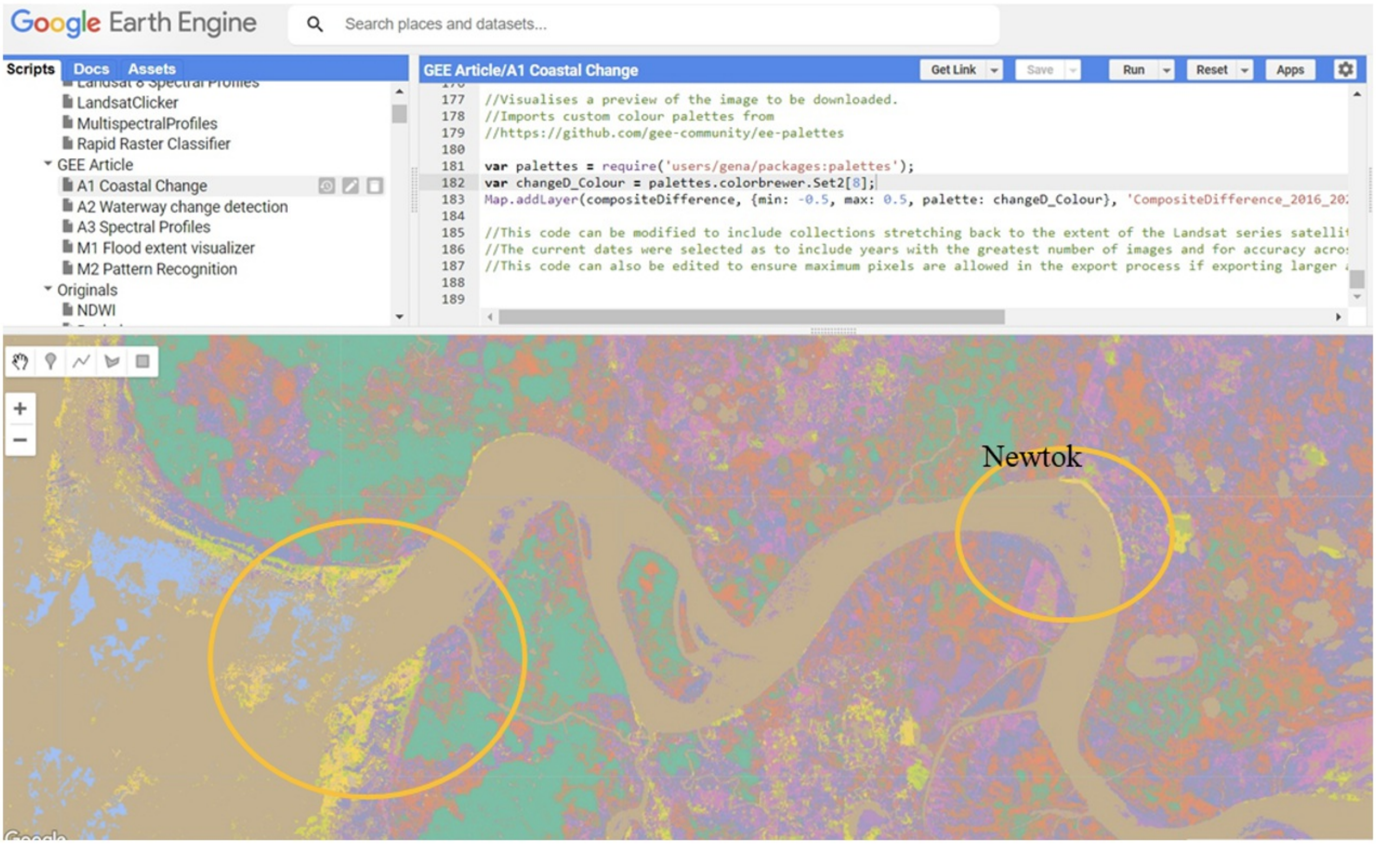


Figure 5: Tool A1: ACC is a powerful tool that streams Landsat 8 data stored on Google's servers to communicate the severity of waterway erosion.

The A1: Archaeology and Coastal Change (ACC) tool utilises the Landsat 8 Tier 1 (T1) Surface Reflectance (SR) Collection stored on Google's servers to visualise land loss. This code applies a cloud mask to all collected images, extracting all images per year and creating a composite image for the specified year. The two spectral indices are generated to accentuate the presence of water, and therefore the shape of the waterways: Normalised Difference Water Index (NDWI) and Modified Normalized Difference Water Index (MNDWI) which use the green, medium infrared, and near-infrared bands are applied to the collections, with a resultant composite image of the combined for each year specified:

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

$$MNDWI = \frac{Green - MIR}{Green + MIR}$$

Where Green (0.533-0.590 μm), MIR (1.566-1.651 μm), and NIR (0.851-0.879 μm) represent the Green, Middle Infrared, and Near Infrared bands, respectively.

Finally, the difference between these images is calculated to visualise the change over time as evidenced by the indices:

$$Change = Year_{FINAL} - Year_{INITIAL}$$

The change is visualised within GEE's platform; however, the result can also be exported as a GeoTiff for utilisation in a GIS. The present example visualises land loss from 2015 to 2020, with specific input areas of interest of the waterways near the village of Newtok.

2.3. Tools for processing own data: A2, A3, and M2

In this subsection, we showcase how GEE can be used to analyse and visualize remotely-sensed data that is not hosted on Google's servers, demonstrating its viability as an alternative to expensive remote sensing software. In the examples below, we use imagery from two sources: The Planetscope constellation of satellites (~3m G.S.D. four-band multispectral), and 3cm G.S.D. four-band UAV multispectral imagery from a Parrot Sequoia+ sensor collected by Lim and Gleason in Quinhagak, Alaska, 2022 (Lim et al., 2022).

Tool A2: Automatic waterway change detection of very high resolution (VHR) satellite imagery (Planetscope)

Unmitigated loss of traditional lands is becoming a reality for many coastal communities in the Y-K Delta, not just at Newtok. For instance, the community of Napakiak is enduring a high amount of erosion at the center of its village, raising the possibility that they may have to evacuate imminently if they do not receive assistance (Taylor et al., 2022; Buzard et al., 2023). There is, therefore, an immediate need for user-friendly algorithms to quantitatively assess erosion rates for Yup'ik coastal villages. The following tool (A2) is an alternative option to Tool A1, as it may be used on UAV or VHR satellite imagery to automatically define areas lost to erosion between user-specified date ranges (Figure 6), if the user has access to these higher-resolution datasets that are not stored on GEE servers. The resulting high-resolution change raster may be used for communicating the extent of land loss and also for municipal planning purposes, for example by calculating the rate of change of waterways. This script works by calculating a normalized difference vegetation index (NDVI), as a way of distinguishing land from water, using the Red (Band 2) and NIR (Band 4) bands of Planetscope imagery:

$$NDVI = \frac{Red - NIR}{Red + NIR}$$

For this reason, it is best deployed on images where vegetation is known to grow on the banks of waterways. In the context of Alaska, this type of analysis is best carried out on images taken in the summer: in the example below from Napakiak, the two images in question date from July 2017 and August 2022

The user uploads the two images to be compared, and runs the script. A change raster (*Change*) is calculated and displayed using the following formula

$$\text{Change} = \frac{(\text{Newer} - \text{Older})}{\text{MaxValue}\,(\text{Newer}\,,\ \text{Older})}$$

Where:

Newer and *Older* refer to the most recent and oldest imagery uploaded, respectively.

MaxValue refers to the highest value of the items in brackets, in this case, whatever is the highest value in either the Newer or Older rasters.

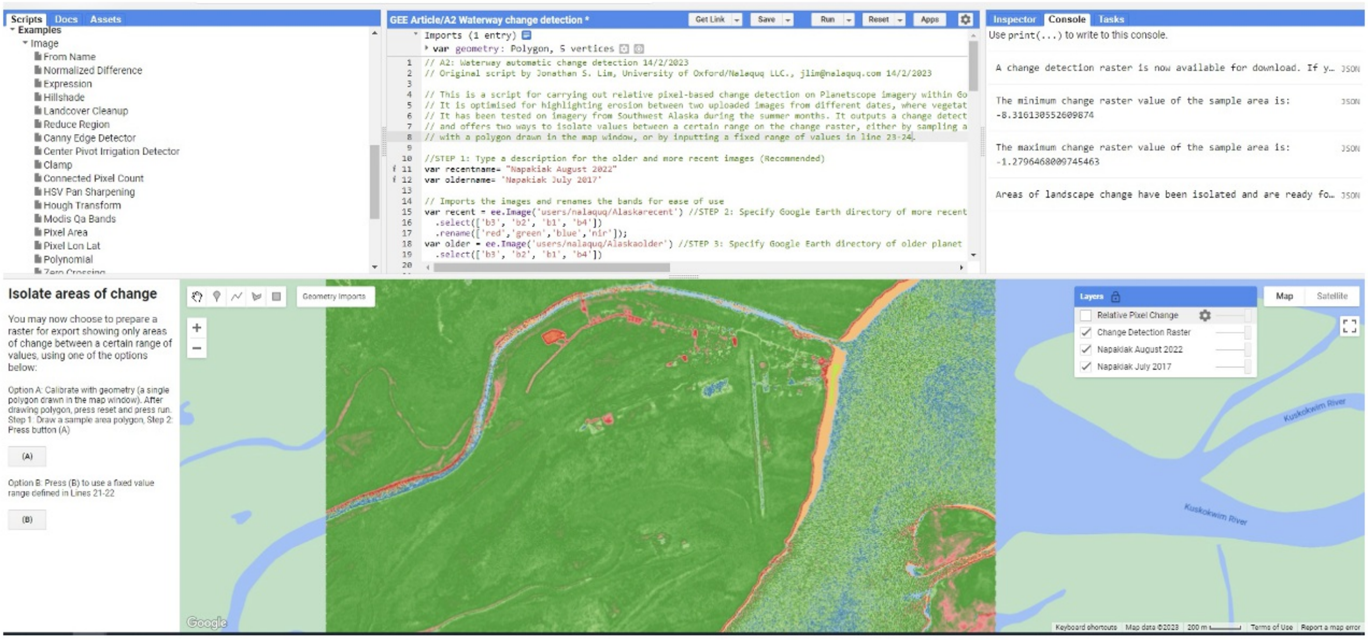


Figure 6. A screenshot illustrating the use of NDVI to quantify land lost due to erosion near Napakiak, AK. Note the presence of a user interface to the left of the change raster, which provides an intuitive way for new users to interact with the tool.

The user may then export the eroded region for further analysis and visualization in a GIS. This may be done in one of two ways: 1) Drawing a polygon on the change raster representing an area of erosion, then pressing button A). This will sample the value ranges, and isolate only a region with those values for download 2) Manually specifying the values in lines 23-24, then pressing button B

This output can be further processed with the Waterway Erosion Tool by Lim et al. (2023) in ArcGIS Pro to describe the extent of the damage. We are urgently working towards integrating this tool with Google Earth Engine in a later update, potentially using the GEEmap integration framework (Wu, 2020). It must be noted that Alaska Native communities are eligible for free copies and training in ArcGIS Pro via the Bureau of Indian Affairs.

Tool A3: Spectral analysis of multispectral UAV imagery

The authors have extensively studied the use of multispectral image datasets for locating and characterising cultural heritage in the context of ancestral sites in the Yukon-Kuskokwim Delta (Lim et al., 2021, 2022). Archaeological features, particularly the remains of culturally important sod-built houses, cause the growth of vegetation that is markedly different from surrounding plant communities— likely caused by anthropogenic activity like soil compaction and enrichment in the construction process and food preparation, respectively (Knudson et al., 2004; Fenger-Nielsen et al., 2019) This script is intended to empower researchers or local land managers with the ability to inspect a multispectral UAV or VHR satellite image, and then determine if an area suspected to contain cultural surface remains has a spectral signature that is appreciably different from the surroundings. This would help inform decisions about whether a site is indeed archaeological in nature, if it is in an area that is threatened by erosion, and if researchers should be deployed to ground-truth the area. This tool may also be used to examine the health and distribution change over multiple years of important subsistence vegetation, like salmon berries (*Rubeus Chamaemorus*), a process that is accelerating due to climate change (Herman-Mercer et al., 2020; Jorgenson et al., 2018)

To generate areas of interest, users simply place polygons in the regions to be compared, taking care to modify the requisite code after line 36 to reflect the desired name of the sample area. This outputs a spectral profile graph and a bar chart showing average NDVI values for each sample area. Optionally, the user can download the values from each sample area as a.CSV file for further analysis in a statistical package of their choice, like R, an open-source software. This table is derived from generating a point feature within the sample area at an interval specified in line 116, which samples the values of the pixel.

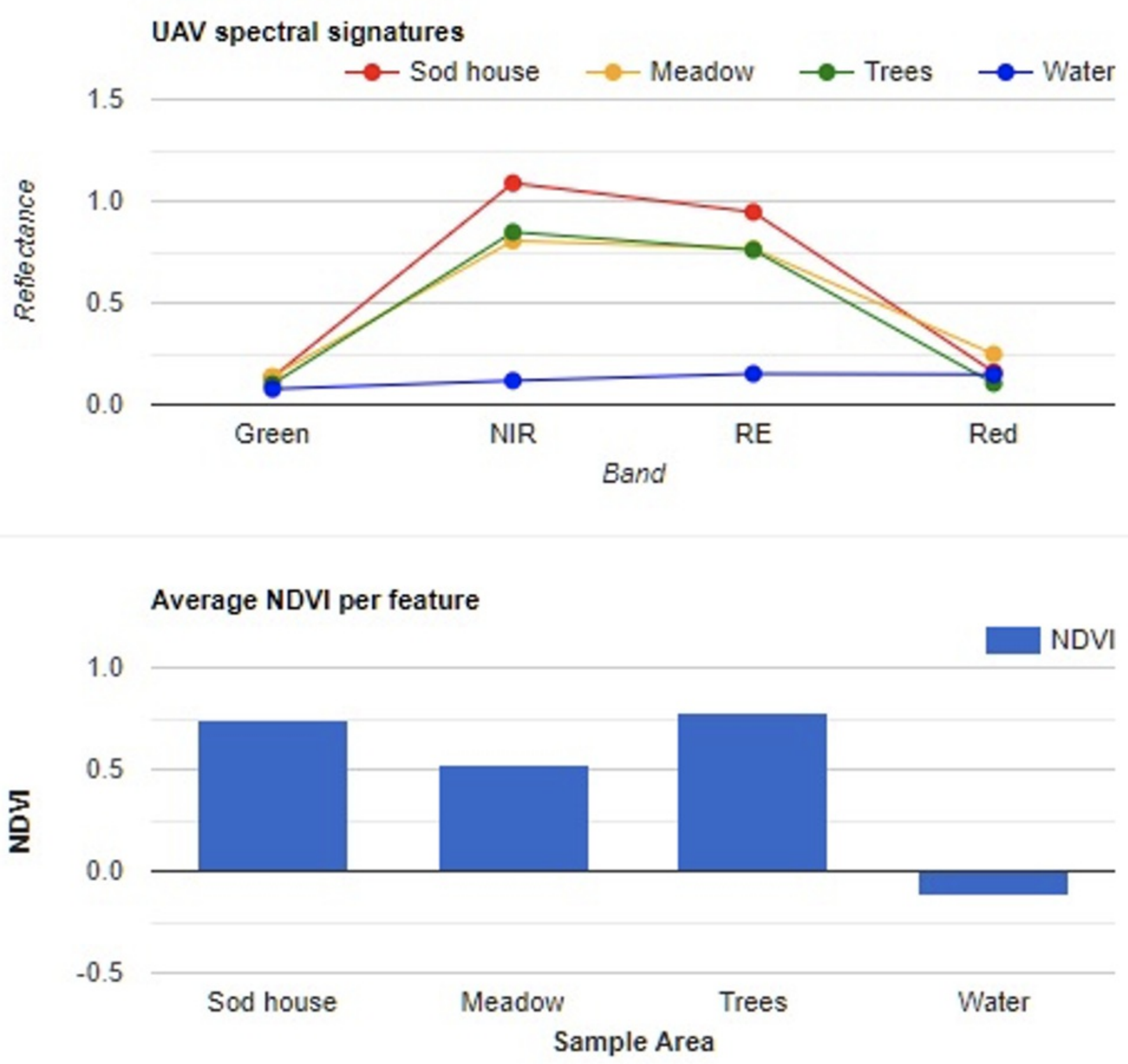


Figure 7. Sample output of script A3. In this example from archaeological site GDN267 near Quihagak (see Lim et al., 2022), the spectral signature of the vegetation around the sod house remains is noticeably different from the surrounding tundra vegetation (meadow and short birch trees) and nearby river, even if its NDVI values are not appreciably different. The raw values may be exported as a.csv table for further analysis in a statistics package.

Tool M2: Pattern Recognition for quantifying and visualizing urban grown and sand dune shifts in VHR Planetscope imagery

Another regional threat to Saharan heritage is the effects of sand dune shifts and rapid urbanisation. In the wake of the colonial era, Mauritania has been undergoing a period of rapid urban growth since the mid-20th century, particularly around the capital of Nouakchott, but other fledgling urban centres as well (Taine-Cheikh, 2007). To a lesser degree, this includes Chinguetti, a former Medieval entrepôt and UNESCO World Heritage site.

The ksar of Chinguetti, situated on the Adrar Plateau in central Mauritania, rose to prominence in the 13th century as a key node of trans-Saharan trade. The city is famous for its dry stone architectural splendor and ancient manuscript libraries (Moreno Adán et al., 2020). However, the encroaching desert poses a significant threat to the city(Marvin, 2007), which has already led to the abandonment of several structures due to towering sand dunes. Conservation efforts and sustainable tourism practices are imperative to safeguard cultural heritage in the region from desertification.

Tool M2 uses a form of machine learning to detect land cover change, like urban growth and sand dune shifts, in which a user 'trains' the algorithm on their own high-resolution imagery to detect features of interest— also known as 'supervised classification'. This tool is configured to use the RandomForest algorithm, but can be adapted to one of four supervised classification algorithms prebuilt into GEE: CART, NaiveBayes and SVM. Users follow a guided workflow to classify rasters across two different years, and a change raster is automatically calculated and displayed. Clicking on a particular land cover class isolates it for download, if needed, for further analysis in an external GIS (Figure 8).

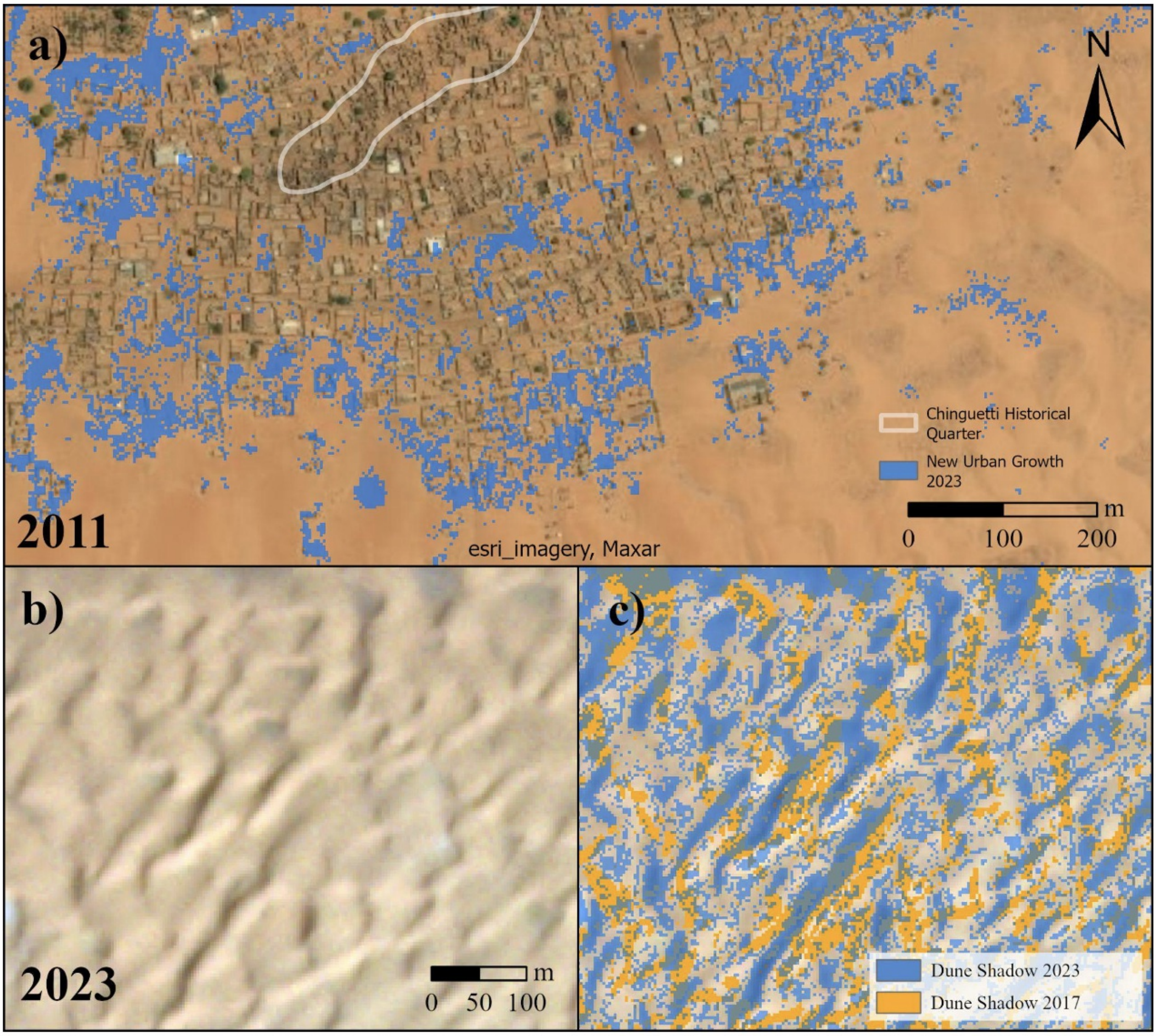


Figure 8. a) Result of change detection between two rasters that have undergone supervised classification to detect buildings. Urban growth as new buildings are displayed at the periphery of the city, we very little change around the historical quarter. b) Noting the location of sand dune shadows is a good way of measuring how they have shifted across time. c) In this example, the dunes have shifted from east to west around 20m over 6 years.

In the future, we hope to implement elements of Gómez et al's (2018) Sand Dune Encroachment Vulnerability Index in GEE.

3. Discussion

The field of environmental remote sensing is highly advanced, and will only become more sophisticated as technology improves (Alahacoon & Edirisinghe, 2022; Cavender-Bares et al., 2022; Klehm, 2023). However, the skills needed to execute and interpret remote sensing data are not widely taught (Chasmer et al., 2022; Schulman et al., 2021) especially in remote, impoverished societies.

In this article we have presented five tools written in a cloud-based geospatial platform, Google Earth Engine (GEE). Each tool represents a remote sensing workflow that can be used to address a diverse range of urgent environmental concerns in some of the most remote communities on Earth, at the climactic extremes of our planet. Sharing these tools is a simple matter of providing a block of Javascript code that a user can copy into the interface of the GEE code editor, allowing them to carry out robust analyses facilitated by cloud computing— improving access by reducing the need for expensive hardware. However, this approach is not without its limitations. Although we provided comprehensive documentation for the use of these tools, most people require a period of adjustment before becoming comfortable with using coding to interact with a virtual environment (Bers, 2019). In essence, sharing these codes is not simply a matter of sending them to a remote community and hoping this will instantaneously build capacity. Rather, it requires an element of in-person contact— Workshops to understand community environmental concerns, working with local land managers to produce the tools, and then further workshops to teach community members how to use them.

However, as a proprietary technology GEE is limited compared to other Free and Open Remote Sensing Source Software (FOSS) such as QGIS or Python's Rasterio, and GDAL libraries: First, the code editor contained within GEE does not allow users to install external javascript libraries. Compared to other web-based Integrated Development Environments (IDEs), such as Jupyter Notebooks, this severally limits code extensibility and flexibility. For instance, although developers can select from a limited number of User Interface features (e.g., buttons, date sliders, text boxes, etc), GEE's UI API does not harness the power of javascript as a robust front-end development language in conjunction with HTML and CSS. Accordingly, users must manually edit code themselves, which requires beginner fluency in javascript. Likewise, the GEE IDE offers limited machine learning and deep learning frameworks when compared to standard data science libraries including Scikit.js and Tensorflow.js. For these reasons, developers interested in crafting fully customizable, user-friendly Web User Interfaces (WUIs) should install the client library and its dependencies in either Javascript (via npm) or Python (via Conda/Pip). Here, developers working with the Python API benefit from the robust data science offerings (e.g., Pytorch, OpenCV, Pandas, etc) and existing web frameworks, such as Flask or Django. However, Python's API requires the use of external libraries (e.g., Folium) for visualizations that are limited to static maps rendered in HTML. Alternatively, developers working with the javascript API benefit from a web-friendly language capable of producing fast, dynamic maps, albeit with less out-of-the-box support for existing remote sensing modules.

There is also a degree of precarity inherent in Google's dominance of this sector. Simply put, at time of writing, there is no comparable service that can provide the same functionality as Google Earth Engine. Furthermore, there is no guarantee that Google will maintain the current price point of GEE (Free for non-commercial use) or the low subscription price point of data storage in Google Drive. We call for governments and educational institutions to recognise the value of cloud computing for building remote sensing capacity, and consider the profound and diverse ways in which such tools can empower people in the rural margins of our planet (Table 2). They should also invest more heavily in the rural broadband solutions required to deploy cloud computing in these communities, given its well-documented benefits of improving economic growth and quality of life (LaRose et al., 2007; Whitacre et al., 2014)

Table 2. Common threats to heritage in developing countries after Bowonder & Kasperson (2005), with examples of how they are studied and mitigated with remote sensing workflows, all of which can be implemented in GEE or supplemented by data from this platform. Hazards italicised in bold were addressed directly in this article.

Hazard to Heritage	Examples of remote sensing solutions
Floods	Historical flood extent mapping, hydrological models (Klemas, 2015)
Droughts	Historical NDVI levels, data fusion products (eg ESA CCI Soil Measure dataset) (West et al., 2019)
Earthquakes	Building damage detection (Dong & Shan, 2013), surface deformation detection (Geiß & Taubenböck, 2013)
Volcanoes	Infrared radiance observations (Blackett, 2017)
Erosion	Comparison with georeferenced historical imagery and archival datasets (Gleason et al., 2022; Lim et al., 2023), erosion projections (Buzzard et al., 2021)
Deterioration of monuments	Inspection of aerial imagery (Fisher et al., 2021), automatic change detection (Cerra et al., 2016)
Rapid urbanisation	Land cover change detection (Abass et al., 2018)
Destruction of natural habitats	Analysis of elevation and NDVI readings (Rodway-Dyer & Ellis, 2018)
Inadequate infrastructure and low levels of technical skill	Capacity building with remote sensing workshops, embedding methodologies with local organisations (Fisher et al., 2021; Laugier et al., 2022; Lim et al., 2021)— perhaps using tools created in GEE.

4. Conclusion

Analytical remote sensing is a powerful tool for visualising and mitigating threats to heritage in some of the most remote parts of the world, at the climatic extremes of our planet. However, local communities in these places often lack the specialist skills and infrastructure to implement such methodologies. However, cloud-based spatial analysis platforms like Google Earth Engine (GEE) facilitate the training of local operators, allowing the automation of complex analytical remote sensing methods. it also reduces the need for powerful computers, as long as there is an internet connection— a technological innovation that has only become viable in recent years with the advent of high-speed satellite broadband internet usable in a rural setting. In this article we have presented five tools written in GEE that demonstrate this principle in both hyper-arid and subarctic cultural contexts, showing the versatility of spatial cloud computing and remote sensing in general— they provide ways of communicating threats to heritage posed by flooding, erosion, sand dune movements, and rapid urbanisation, allowing for more informed mitigation strategies. We call for governments to invest more heavily in the provision of satellite-based internet and technological infrastructure in rural communities, as well as further development of open cloud-based geospatial services like GEE.

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Footnotes

[1] Köppen climate classifications: BWh, BWk (Kottek et al., 2006)

[2] Köppen climate classifications: Dsc, Dwc, Dwd, Dfc, Dfd, ET, EF(Kottek et al., 2006)

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