Rapid multispectral data sampling using Google Earth Engine [☆]

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Abstract

The advent of cloud-based GIS tools has enabled the rapid exploration and processing of geospatial datasets. The Google Earth Engine (GEE) platform provides a library of algorithms and a powerful application programming interface (API) to produce flexible cloud-based applications that leverage Google's computing infrastructure for geospatial analysis. The 40-year Landsat satellite image archive has provided an excellent means of assessing changing land use cover and has assisted geological mapping and aerial reconnaissance of field sites. We introduce Spectral Point, a new GUI tool developed in Google Earth Engine that allows users to explore Landsat 8 OLI/TIRS multispectral datasets, select a study area, pre-process imagery and gather

[☆]S.B. developed and tested all software, wrote the manuscript and led field campaigns to Death Valley. The concept for the project was developed by M.D. and P.M., who formalised the spectral point collection procedure in D'Arcy et al., 2018 (RSE). P.M. was primary consultant on remote sensing techniques such as BCET. A.W. was fieldwork supervisor and consultant on landscape evolution in Death Valley. M.D., P.M. and A.W. each contributed to the editing of the manuscript.

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spectral point data rapidly within a single browser window. Spectral values from composite imagery collected in GEE, valuable for the detection of changes in surface mineral composition, agree with corresponding point values using conventional desktop Landsat processing. The Spectral Point tool makes it fast and simple to extract quantitative, contrast-corrected brightness data from multispectral imagery compared conventional desktop-based approaches. At the same time, the user needs no experience developing code, proprietary third-party software or dedicated high-performance computing, only a modern web browser. The Spectral Point tool has many potential applications in the remote study of Earth's surface; for example, we explore a case study from the western United States that demonstrates how the tool can be used for mapping, geochronology, and estimating weathering rates for Quaternary landforms. With increasing numbers of satellites we are now faced with a growing deluge of geospatial data. Cloud-based solutions to mapping, field reconnaissance and image processing will be increasingly necessary to handle this valuable but untapped satellite image resource. Spectral Point is an example of a new generation of web-based remote sensing tools available for Earth scientists, leveraging the revolution in cloud-based processing power and access to satellite image archives.

Keywords: remote sensing, geomorphology, image processing, multispectral data, cloud computing, Google Earth Engine

1. Introduction

Desktop tools, such as Google Earth, have changed the way geoscientists approach field reconnaissance, providing a means to explore potential

study sites with ease and rendering geospatial information within an easily navigable cross-platform interface [e.g. 49, 43]. Whilst individual geospatial datasets have been available since before Google Earth’s inception, the power and popularity of the application resides in its intuitive interface and effective combination of elevation data and surface imagery. Virtual exploration of the Earth’s surface makes it possible to traverse vast distances, access any aerially-visible site, and collect a catalogue of satellite sensor data far beyond what can be collected in the field. The next step is to extend this ease of accessibility to a much larger and ever-improving archive of satellite image datasets. In particular, semi-automated tools that provide the ability to gather, process, and evaluate data rapidly (and without the need for data acquisition or pre-processing) have an important role to play in making geospatial data more accessible.

At the same time, the widespread availability of broader internet bandwidths, increased desktop processing power and cheaper memory has enabled individual workers with even modest computing power to handle geospatial datasets with a range of free and proprietary GIS tools. For low resolution or spatially-limited tasks, the problem of RAM or CPU bottlenecks rarely limits productivity or the spatial scope of projects. However, the inherent inability to scale projects on desktop hardware when it may be necessary to have very large datasets and/or more complex process algorithms increasingly necessitates access to higher performance machines. Recent developments in dedicated server infrastructure and web-based GIS tools for geospatial analysis are important as they may eventually negate the need for individuals or institutions to develop their own supercomputing resources [2]. One ex-

ample of an online geospatial platform is Google Earth Engine (available at <https://earthengine.google.com/>). In this paper, we outline the motivations, operational sensitivity and application of a spectral analysis tool developed in Google Earth Engine (GEE) for the general study of Earth surface spectral signatures using multispectral satellite imagery. The application we have built utilises a broad array of tools in GEE for data archive traversal, image processing and data export.

The development of ground/airborne hyperspectral and satellite multispectral sensors has particularly benefitted the geosciences. For example, spectral data has enabled the detection of diagnostic spectral profiles based on a target material’s physical properties and chemistry [24, 7, 19] and has been applied to detect and classify lithology using a range of methods including ground-based observation at outcrop [e.g. 5], aircraft spectral imagery [e.g. 39] and satellite spectral imagery [e.g. 28]. Other examples of spectral analysis include the isolating of specific clay mineral in soils [4], mapping of alluvial fan surfaces [18, 8, 15, 9], the detection of changes in global surface water [36], and many other geological applications [c.f. 44]. Here, we focus entirely on multispectral data from the NASA/USGS Landsat archive given its free availability, global scope, and proven utility in a wide range of commercial and research applications [c.f. 45, 38]. These multispectral datasets have been used to tackle a wide variety of problems, from measuring changes in land use and vegetation cover [48, 46], geological mapping [28], and the study of landforms and surface processes [13, 32]. Our application takes advantage of (i) the combination of major computational capability available from cloud-based GIS platforms and (ii) the ever-increasing application of

spectral analysis in the geosciences to build a new tool for both field reconnaissance and data acquisition.

2. Methodology

2.1. Google Earth Engine

Google Earth Engine (GEE) is a cloud-based browser platform that leverages Google’s high-performance cloud computing infrastructure to process large geospatial datasets [20]. The GEE platform is equipped with publicly available multi-resolution optical imagery, global digital elevation models and the entire Landsat, Sentinel-1 and Sentinel-2 archives, among others. The GEE code-editor with its Python or JavaScript API allows for the development of simple scripts to fully-fledged graphical applications within a browser environment [20]. Google Earth Engine has been demonstrated as an effective and versatile tool for a number of geospatial applications assessing human settlement growth [1, 35], soil development [34] changing land use [11] and vegetation change [25, 40]. For the geosciences, the major advantage of GEE lies in its ability to access the complete Landsat archive and run algorithms quickly over large spatial extents, with the potential to develop bespoke tools for mapping, spectral analysis, topographic modelling, and other tasks.

2.2. Spectral Point

Spectral Point is run in a single browser window within the Google Earth Engine development environment [c.f. 20]. As such, use of the application requires a registered account with Google and a modern web browser. Any data collected in Spectral Point is also be exported to the user’s personal Google Drive cloud storage.

The GEE application Spectral Point accomplishes the following workflow:

- Exploration of field locations
- Selection of Landsat 8 imagery by date range or as a cloud-free composite
- Selection of a region of interest (ROI) for contrast enhancement
- Balance Contrast Enhancement Technique (BCET - [29]) image processing
- Generation of RGB composites with the option to export scenes to the user's Google Drive
- Point selection and sampling for gathering multiple spectral profiles
- Export of location and spectral point information to the user's Google Drive

The full workflow capabilities of the Spectral Point application are illustrated in Figure 1 in the form of a flowchart diagram.

2.3. Landsat Scene Selection

The Spectral Point application utilises the 2013-onwards Landsat 8 datasets available in Google Earth Engine, with spectral bands 1-9 collected by the Operational Land Imager (OLI) and bands 10-11 collected by the Thermal Infrared Sensor (TIRS). Using the GEE development environment, all satellite imagery is accessible via an interactive viewport, similar to other Google mapping platforms. This viewport contains a standard series of tools to pan,

Figure 1: Application workflow for Spectral Point

zoom and alter layer visualisation by default. The Spectral Point interface also allows selection of Landsat 8 (16- or 32-day composites) between user-defined two dates, enabling the user to find the most suitable scene without cloud obstruction or in the desired time of year. A cloud-free composite can also be produced using a cloud scoring algorithm that selects the least-cloudy pixel for a range of Landsat images to develop a new composite raster. All imagery in Spectral Point is projected in the WGS 84 (EPSG:4326) coordinate system.

2.4. Pre-processing and Visualisation

Table 1: Copy of the 1-9 Landsat Band descriptions provided by the USGS [3]

Band	Wavelength (m)	Uses
Band 1 Coastal Aerosol	0.435 - 0.451	Coastal and aerosol studies
Band 2 Blue	0.452 - 0.512	Bathymetric mapping, distinguishing soil from vegetation, and deciduous from coniferous vegetation
Band 3 - Green	0.533 - 0.590	Emphasizes peak vegetation
Band 4 - Red	0.636 - 0.673	Discriminates vegetation slopes
Band 5 - Near Infrared (NIR)	0.851 - 0.879	Emphasizes biomass content and shorelines
Band 6 - Short-wave Infrared (SWIR) 1	1.566 - 1.651	Discriminates moisture content of soil and vegetation; penetrates thin clouds
Band 7 - Short-wave Infrared (SWIR) 2	2.107 - 2.294	Improved moisture content of soil and vegetation and thin cloud penetration
Band 8 - Panchromatic	0.503 - 0.676	15 metre resolution, sharper image definition
Band 9 - Cirrus	1.363 - 1.384	Improved detection of cirrus cloud contamination
Band 10 - TIRS 1	10.60 11.19	100 metre resolution, thermal mapping and estimated soil moisture
Band 11 - TIRS 2	11.50 - 12.51	100 metre resolution, improved thermal mapping and estimated soil moisture

To eliminate colour bias in the image and to enhance the spectral contrast between the Landsat 8 spectral bands, Spectral Point uses the Balance Contrast Enhancement Technique, or BCET [29, 30], to normalise the image histograms from bands 1-7 (Table 1). The BCET algorithm is a commonly used colour normalising tool that can pre-process highly correlated visual to shortwave infrared bands, isolating purely spectral information and allowing for effective comparison between bands [30, 9]. Once implemented, the BCET algorithm is applied to all the bands (converted to 8 bit), within the entire viewable portion of the image, and based on the image statistics of a user-defined region of interest (ROI).

$$i_{BCET} = a(i_{input} - b)^2 + c \quad (1)$$

Where i_{input} is the input image band, i_{BCET} is the transformed image band, and a , b and c are coefficients derived using the equations provided in Liu [29]:

$$a = \frac{H - L}{(h - l)(h + l - 2b)} \quad (2)$$

$$b = \frac{h^2(E - L) - s(H - L) + l^2(H - E)}{2[h(E - L) - e(H - L) + l(H - E)]} \quad (3)$$

$$c = L - a(l - b)^2 \quad (4)$$

With s being the mean square sum of the given input image band:

$$s = \frac{1}{N} \sum_{i=1}^N i_{input}^2 \quad (5)$$

The parameters l , h and e are the minimum, maximum and mean of the 8-bit input image band (i_{input}). L , H and E are the target minimum (0), maximum (255) and mean (110) of the transformed image band (i_{BCET}).

The ROI is defined as a rectangular polygon with a top-left and bottom-right set of user-defined coordinates. Within the ROI, all spectral band image histograms will be transformed, without distorting the basic histogram shape, using equations 1-5, to stretch the image DN values to a range of 0 to 255, and a mean of 110, using each band's original minimum, maximum and mean values (Figure 2). This transformation has the added advantage of cancelling out the strong inter band correlation inherent in all multispectral image data. It is important that the ROI encompasses an area that contains a representative range of values across all bands. For further detail on BCET algorithm we refer the reader to Liu [29] and Liu and Mason [30].

The BCET-transformed image bands can be exported as GeoTIFF RGB composites with any combination of Landsat 8 bands (1-7) at a user-specified resolution. The RGB viewer in Spectral Point updates the current image layer to the selected RGB composite, enabling the user to explore a range of combinations and determine which visualisation of bands best suits their needs. For example, we can use the natural colour combination of bands (RGB - 432) or the false colour 543 combination to help detect vegetation. To detect subtler but valuable information pertaining to rock or soil composition we can adopt the 642 band combination; where the inclusion of a SWIR (Short-wave infrared) band can assist in discrimination of different geochemical elements on the surfaces of landforms in arid and semi-arid areas. The Spectral Point application also allows for the use of unmodified

Figure 2: Image DN value histograms for each Landsat 8 band in the Visible, Near and Short-Wave InfraRed (VIS, NIR & SWIR). **a.** Image DN histograms for unmodified Landsat 8 TOA spectral bands; **b.** Image histograms for Landsat 8 spectral bands normalised using the Balance Contrast Enhancement Technique, BCET [29], each with a minimum DN_{BCET} value of 0, a maximum of 255 and mean of 110.

Landsat image composites before proceeding to the point selection menu.

2.5. Point Selection and Data Export

With the chosen RGB colour composite for visualisation of the Landsat imagery, Spectral Point lets the user to select a range of query points by either interactive selection, single coordinate input, or the loading of a pre-defined list of coordinates from Google's Fusion Table data visualisation service (or a another Google service once Fusion Tables are superseded). Each option will load a series of points into the menu that can subsequently be removed or selected to reorient the viewport to the query point's location. Depending on which bands the user chooses to collect data from, a BCET band relative brightness profile is displayed and automatically updated with each additional point selection. As demonstrated in the user manual (see supplementary materials), a user can immediately view the relative spectral profile of any point within the map viewport and compare any selection of points across a range of spectral bands. As a visual aid, the user can also produce a semi-transparent Kirsch-filtered edge detection layer to highlight areas that may be subject to edge or boundary effects, making pixel selection problematic (See section [2.6](#)).

With a selection of query points, the data that can be exported includes a tabulated series of BCET transformed relative brightness values across each selected band and a KMZ file containing the position of each query point. Each exported file is saved as a task in a GEE submenu that the user must activate to begin processing and stored in the user's Google Drive.

2.6. GEE Data Continuity and Sensitivity

We generated a series of random sample points to test whether a separate workflow using a desktop Python-based method (Python-BCET) achieves similar results to GEE. The comparison was conducted between the pixel averaged composite of 10 separate cloud-free Landsat 8 scenes and a cloud-free composite image in Spectral Point. The advantage of using averaged Landsat images and multi-scene composites is an improved signal to noise ratio, reducing the influence of variable lighting conditions and seasonal surface changes between images.

The test area for sensitivity analysis encompasses a region of eastern California (including the White Mountains) extending into Nye County in southwestern Nevada (Figure 3a). This region was chosen given its low annual and seasonal atmospheric and climatic variability; such variations may significantly increase the signal to noise ratio by altering the spectral reflectance from the ground surface. For example, the sudden growth of natural vegetation or change in surface water extent, or slight fluctuations of the snowline on the White Mountains can significantly affect or skew the shape of the relative brightness profile.

In order to sample from as wide an area as possible, the ROI is also the largest orthogonal area possible within a single Landsat tile. The ROI has a total area of 18,368 km² and extends latitudinally from 38.011311 to 37.037639 and longitudinally from -118.457336 to -116.542969 (Figure 3b).

To appropriately test individual point measurements over a range of Landsat images it was necessary to focus on areas that retain a stable spectral character through time, i.e. do not seasonally vary due to snow melt,

Figure 3: Contextual images of sensitivity test "White Mountains" ROI. **a.** Landsat 432 RGB true colour composite image with several geographical locations for reference; A - Leidy Creek Alluvial Fan. B Bishop. C Mt. Barcroft. D Last Chance Mountain. E Alkali Ghost Town. F Stonewall Mountain. G Boulder Cuesta. **b.** Location of ROI on the border between California and Nevada, within the context of the selected Landsat scene footprint (Path 041/Row 34, green polygon). **c.** Monochromatic image of ROI with sample points from randomised low pixel variability sampling strategy (yellow crosses).

Figure 4: **a.** Landsat 432 RGB true colour composite image of Leidy Creek alluvial fan and adjacent area (contextual location in Figure 3a, box A). **b.** Pseudocolour overlay of Kirsch edge detection values >100 , the remaining area comprising of areas under the threshold. **c.** Pseudocolour raster of pixel value differences through time, areas with differences ≤ 20 are heuristically considered low in variation. **d.** Single colour overlay with regions with pixel value differences through time > 20 or with edge detection values over 100 coloured red. This combination of high edge detection values and large pixel difference through time leaves the remaining uncoloured pixel area available for random sampling, with white crosses marking the location of actual random sample sites in sensitivity study.

vegetation change or crop rotation. If an area has a stable spectral signature through time, or spectral ‘persistence’, we expect linear correlation between the GEE and offline Python-BCET methods. The pixel sampling strategy we employ seeks to preclude locations that vary significantly between image acquisitions on a sub-annual timescale. For Nye County we focused on masking out areas seasonal changes in vegetation, fluctuations in lake or salt-playa levels, the changing position of shadows in valleys, snow-cover, and man-made landscape change due to agriculture. This method constitutes a per-pixel change detection process, measuring how a single pixel value changes through time.

The operation to mask out regions of high spectral variability through time was conducted across corresponding pixels from each of the 10 Landsat images (See appendix [Appendix B](#)) using the following:

$$d_{i,j} = \max(p_{i,j,t=1..n}) - \min(p_{i,j}, t = 1..n) \quad (6)$$

where d is the difference between pixel values at a coordinate (i, j) calculated from the difference between minimum and maximum pixel values, p , across a set of n Landsat images, t . The resulting composite raster image records the difference between the minimum and maximum of a range of possible pixel values for a given sample coordinate (Figure 4c), the sample area is set by a heuristic threshold value, where the difference value can be no greater than 20. This value was chosen based on its ability to adequately capture both snow cover changes and vegetation in the ROI.

A second consideration for point selection involves the discrepancies produced by edge or boundary effects, where a single pixel value may vary

greatly depending on its location. Such pixels can be detected using a multi-directional edge detection algorithm and a threshold value. For our sample image, we employ a 3x3 Kirsch kernel across 8 compass directions every 45° [26] in order to detect edges that may be irregular such as meandering or braided river banks,

$$h_{n,m} = 1, \dots, 8 \sum_{i=-1}^1 \sum_{j=-1}^1 g_{ij}^{(g)} \cdot f_{n+1,m+j} \quad (7)$$

Where the initial kernel $g^{(1)}$ is;

$$g^{(1)} = \begin{bmatrix} +5 & +5 & +5 \\ -3 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix} \quad (8)$$

Given that any temporal variation in pixel values is captured by pixel-change thresholding, the Kirsch filter needs only to be performed on a single Landsat band to capture persistent boundaries or edges within the Landsat scene, such as roads or lithological boundaries. The threshold to detect edges using the Kirsch filter is adjusted to capture centre-pivot irrigation fields, irregular boundaries produced by salt-lakes, exposed lithological boundaries, shadow edges and man-made features (Figure 4b). Within these areas of low spectral variation, 1000 random samples are chosen using a Monte Carlo methodology, where query coordinates are chosen via the Python pseudorandom number generator (Figure 3c).

2.7. Example Hanaupah Canyon Fan

From previous field observation and spectral analysis of preserved and well-exposed landforms, alluvial fans are believed to retain an age-dependent

Figure 5: **a.** Location of the Hanaupah Canyon alluvial fan within the context of Death Valley, California, as a prominent alluvial fan along the eastern flank of the Panamint Range; **b.** Alluvial fan surfaces mapped from ground field observation, with 3 fan surfaces shown: the active channel deposits (Q4), a series of low elevation undated terraces of presumed late-glacial/early-interglacial age (Q3) and a well-preserved Late Pleistocene surface approximately 80 ka in age (Q2c surface - Machette et al. 31) with clear desert varnish development; and **c.** The location of prospective query points on the fan, along apex-to-toe transects, for assessing the spectral contrast between the active (Q4) and ancient (Q2c) alluvial fan surfaces.

spectral signature, either as a result of developing rock varnish and desert pavement [14, 8, 9], or as a consequence of soil development [15]. The mapping and demarcation of alluvial fans surfaces of different ages has been demonstrated effectively by D’Arcy et al. [9] in Owens Valley, California, using spectral information derived from BCET-processed 642 band composites, specifically the ratio between the SWIR 1 and blue bands (Band 6 / Band2). The D’Arcy et al. [9] study provides theoretical rigour and valuable use case analysis for the style of spectral data collection and interpretation we can conduct easily using the Spectral Point workflow. D’Arcy et al. [9] show that a spectral profiling method is highly applicable to the alluvial fans in neighbouring Death Valley as well as Owens Valley, demonstrating that for two alluvial fans in northern Death Valley (each with an independently dated 70 ka fan surface) an age model can be developed based on the changing spectral signatures of Late Pleistocene to Holocene aged fan surfaces. Inspired by this work, we apply a similar approach to an alluvial fan in the southern portion of Death Valley (Figure 5)

Figure 6: Field photographs of Hanaupah Canyon fan alluvial fan surfaces: **a.** downstream photo of active channel fan surface (Q4); **b.** active channel fan surface morphology and colouration; **c.** ancient alluvial fan surface (Q2c); and **d.** ancient fan surface morphology and colouration. Photograph locations on Figure 5c.

Field observation of the prominent 7 km length Hanaupah Canyon alluvial fan in Death Valley shows a clear presence of darker coating on the exposed gravel surfaces of preserved fan terraces (Figure 6). These observations are typical of ancient sediments in arid basins, with the darker coating a product of desert varnish development over time [23, 10]. The presence of desert varnish, desert pavement and relative differences in fan surface elevation has provided field-based sedimentological criteria for Quaternary stratigraphic correlation of surfaces across Death Valley [23, 6, 21, 22, 27]. Since the original work by Hunt and Mabey [23], the majority of Death Valley fan surfaces can be separated into three units: Q4 comprising the most recent deposits, Q3 Late Pleistocene to mid-Holocene surfaces and Q2 Mid to Late Pleistocene fan surfaces. Many alluvial fans in Death Valley have extensive and well-preserved surfaces from the Holocene to the Late Pleistocene, the ages of which have been constrained using cosmogenic nuclide dating of surface clasts and depth profiles [16, 31, 33], luminescence techniques [42, 41], and relative age indicators such as the change in surface roughness over time [17, 37, 12].

The largest preserved fan terrace on the Hanaupah Canyon fan (Figure 5b) has been dated to ~ 80 to 30 ka using cosmogenic ^{36}Cl depth profiles by Machette et al. [31]. This period of time constrains the now-abandoned fan surface to the Late Pleistocene, which we classify as the Q2c unit (Figure 5b, c). From field observation (Figure 6) the pronounced increase in desert varnish between the active (Q4) and ancient (Q2c) fan surfaces on the Hanaupah Canyon fan suggests that a strong contrast in spectral signatures should exist between active depositional surfaces and ancient abandoned sur-

faces. Depending on the addition of desert varnish or minerals generated by weathering, the older spectral profile will be modified in specific bands between Q4 and Q2c [c.f. 9].

To assess the comparative spectral profiles of the two alluvial fan surfaces, each surface will have multiple point measurements taken using Spectral Point along a transect from the fan apex, closest to the river output from the mountain front, to the fan toe downstream (Figure 5c). If the spectral signal is robustly stable across the surface, a per-band average spectral profile from all measurements should represent an accurate spatially-averaged spectral signature for each fan surface.

3. Results and Discussion

3.1. Sensitivity Analysis

Our pixel sampling strategy (Section 2.6) successfully excludes areas affected by either the spectral similarity (higher temporal variation between images) or edge detection filters (higher spatial variation). Areas with lower spectral variation are predominantly, in the case of desert regions, exposed flat terrain in wide valley floors with potential desert pavement formation or stable geomorphic landforms such as abandoned alluvial fan surfaces (Figure 4d).

Figure 7: Band 7 (SWIR 2) DN_{BCET} relative brightness values from pixel averages of 10 Landsat 8 images (Composite) correlated with corresponding values from a cloud-free composite in GEE. **a.** Correlation of random samples with no pixel exclusion; and **b.** Correlation of random samples from only low pixel variation sampling areas. Dashed lines show the fitted regressions.

Figure 8: BCET (DN_{BCET}) relative brightness values from low variation sampled pixel averages of 10 Landsat 8 images (DN_{BCET} Composite) correlated with corresponding values from a cloud-free composite in GEE (DN_{BCET} GEE) for, left to right, bands 1, 2 and 3 (top row) and 4, 5 and 6 (bottom row). Dashed lines show fitted regressions.

The comparison of GEE-derived (DN_{BCET} GEE) and average relative brightness values from 10 Landsat images (DN_{BCET} Composite) shows that for band 7 (SWIR 2), without any pixel sampling strategy, a correlation plot has a high degree of variability that could be caused by systematic differences between the two data collection methods or an additive noise signal produced by spatial and temporal variability (Figure 7, left). Using the low variation pixel sampling there is a significant reduction in noise in the correlation plot that subsequently shows a strong 1:1 linear correlation with no systematic difference between DN_{BCET} Composite or DN_{BCET} GEE (Figure 7, right).

For bands 1 to 6, the same linear correlation is observed between DN_{BCET} values collected by GEE cloud-free composite (using low variation pixel sampling) and from the 10 image Landsat composite (Figure 8). These plots suggest that strong correlation exists for all spectral bands in each of the composite images and no systematic error is introduced as a function of band wavelength. The outcome of the sensitivity tests shows that Spectral Point generates surface relative brightness data that are not systemically biased or error-prone and can be considered an equally viable tool for collecting such measurements from Landsat imagery.

The sensitivity analysis, by its design, also highlights the long-term stability of spectral values for certain landform surfaces, such as alluvial fan surfaces, that can be relied upon for generating reproducible spectral signatures over different Landsat scenes [c.f. 9]. The sensitivity analysis further emphasises the importance of target area appraisal before gathering Landsat or other multispectral data to ensure that point value targets have a sufficient buffer separation from edges or boundaries, as well as the overriding

need to mask out areas of cloud, shadow or snow [e.g. 47].

3.2. Use Case: Spectral profiles of Alluvial Fan Surfaces

Using the predetermined location of multiple query points on the active (Q4) and ancient (Q2c) Hanaupah Canyon fan surfaces (Figure 5c), the spectral profile of each location is collated and plotted using Spectral Point workflow (Figure 1). Spectral Point makes this data gathering straightforward and fast, with a simple input of each query point coordinate, placement of a corresponding map marker and automatic generation of a spectral profile on the adjacent menu (See supplementary materials).

Figure 9: Spectral profiles of active (Q4, blue) and ancient (Q2c, red) alluvial fan surfaces, showing the complete spread (semi-transparent blue and red polygons) and average values (solid lines) of each band DN_{BCET} value.

The resulting series of spectral profiles shows a clear contrasting signal between the modern active and ancient alluvial fan surfaces (Figure 9). The

darker and more varnished ancient surface has systemically lower DN_{BCET} values compared to the active surface for bands 1-6, with a convergence of values for SWIR 2 band 7. The largest difference in DN_{BCET} values is for the shorter wavelength bands, with a 30% drop in relative brightness values in band 1 and a 12% drop in band 6 from the active to the ancient surface. As such, the contrast in DN_{BCET} spectral profiles suggest that development of desert varnish on the fan surfaces has resulted in stronger absorption in shorter wavelength bands over time. The limited spread in points for each band, visualised as individual points with a semi-transparent polygon (Figure 9), also suggests that the spectral values collected on each fan surface are robustly indicative of the spatially-averaged spectral profile, and that the measurements are reproducible.

The Hanaupah Canyon fan study exemplifies the usage of Spectral Point for a simple appraisal of the change in landform spectral profiles through time. Using the Spectral Point interface, a large selection of query points can be collected rapidly, similarly, a change in study area for gathering new data is also relatively simple, affording the user a high degree of flexibility. The potential wider uses of this software include the identification of surface processes that alter spectral signatures, such as weathering or subsurface moisture changes. This software is also a valuable tool for field site mapping or appraisal, where the ability to investigate the multiple combinations Landsat 8 composites quickly and easily will greatly improve efficiency and may help facilitate the discovery new relationships between landscape dynamics and satellite data.

3.3. Advantages of GEE Platform

In general, the collated archive of easily-navigable Landsat 8 OLI/TIRS and Sentinel 2 datasets in GEE in combination with its persistent layer assets and algorithms enables a user to explore multispectral detail in landscapes both spatially and through available time series.

GEE has clear exploratory benefits for researchers interested in processing large areas of the Earth’s surface where it can be used to rapidly move around multispectral imagery whilst preserving prebuilt or user-defined processing algorithms. Conventionally, this would require the downloading of multiple Landsat scenes, local storage of data and pre-processing, particularly if the region of interest spans across two or more tiles. The GEE Spectral Point GUI presented here is an example of the types of application that will be of most benefit to both field and remote sensing workers in the multi-disciplinary geosciences, aided by the ability to gather and export datasets simply using an intuitive user-interface that can command a wide catalogue of geospatial datasets provided in GEE.

4. Conclusions

The cloud-based geospatial analysis tool Google Earth Engine (GEE) is a versatile and powerful platform for developing flexible remote-sensing tools with applications in the geosciences. We have developed one such tool, Spectral Point, that aims to provide a comprehensive means to traverse the catalogue of multispectral datasets made available by GEE. Spectral Point can pre-process imagery rapidly using Google’s computing infrastructure, gather data, and export reliable spectral data from the Earth’s surface.

Spectral Point is entirely written in JavaScript within the GEE interactive development environment with no limitations on code access. The software requires no pre-installation of geospatial software libraries and is run from a single browser window subject to a registered Google account. Spectral Point leverages the available Landsat 8 OLI/TIRS data catalogue from GEE to collect raw or normalised spectral profiles from interactive point selection or a predefined set of coordinates rapidly across any available multispectral image.

We have shown that composite imagery from GEE as displayed in Spectral Point is suitable for point spectral data collection with no systematic error in any of Landsat 8 bands 1-7, with consideration of variability within the target area or within a temporal observation window. We demonstrate the ability of Spectral Point to detect distinctive spectral profiles across alluvial fan surfaces in Death Valley of modern and ~ 80 ka age; a product of field-verified increasing accumulations of desert varnish over time.

GEE scripting capabilities and API show considerable promise in developing tools for a multitude of geoscientific studies. The integrative power of Google's computing infrastructure in combination with a plethora of geospatial datasets removes any prerequisite for greater desktop processing power or data access to tackle problems in GIS and remote sensing. Spectral Point is an example of a fully-graphical application developed in GEE that does not ostensibly require the user to manipulate code to run. Spectral Point is free to access when registered to GEE and can deliver spectral profile information from any point on a multispectral image of the Earth's surface.

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Appendix A. Software

The version of “Spectral Point” described and operated in this paper can be access at the following link:

<https://code.earthengine.google.com/6facddb97649f02cafd0974ce2a8969>.

The “Spectral Point” codebase can be accessed in full at:

<http://doi.org/10.5281/zenodo.2548787>.

The Python-BCET calibration code can be accessed in full at:

<http://doi.org/10.5281/zenodo.2548791>.

A full manual for “Spectral Point” is supplied in the supplementary materials.

Appendix B. Landsat Data

Table B.2: Landsat composite imagery used for sensitivity analysis

DATE	RASTER IDENTIFIER
25/02/2014	L8_OLI_TIRS_C1_Level_1/LC08_L1TP_041034_20140225_20170307_01_T1
05/09/2014	L8_OLI_TIRS_C1_Level_1/LC08_L1TP_041034_20140905_20170303_01_T1
08/11/2014	L8_OLI_TIRS_C1_Level_1/LC08_L1TP_041034_20141108_20170303_01_T1
20/06/2015	L8_OLI_TIRS_C1_Level_1/LC08_L1TP_041034_20150620_20170226_01_T1
26/10/2015	L8_OLI_TIRS_C1_Level_1/LC08_L1TP_041034_20151026_20170225_01_T1
02/03/2016	L8_OLI_TIRS_C1_Level_1/LC08_L1TP_041034_20160302_20170224_01_T1
06/06/2016	L8_OLI_TIRS_C1_Level_1/LC08_L1TP_041034_20160606_20170223_01_T1
26/09/2016	L8_OLI_TIRS_C1_Level_1/LC08_L1TP_041034_20160926_20170220_01_T1
27/07/2017	L8_OLI_TIRS_C1_Level_1/LC08_L1TP_041034_20170727_20170810_01_T1
13/09/2017	L8_OLI_TIRS_C1_Level_1/LC08_L1TP_041034_20170913_20170914_01_RT

Table B.3: GEE output ($DN_{BCE\tau}$)

SURFACE	LON (W)	LAT (N)	B1	B2	B3	B4	B5	B6	B7
Q4	116.9624	36.2090	138.91	140.21	135.98	127.21	117.58	112.03	102.71
Q4	116.9570	36.2101	135.47	136.64	133.55	125.41	116.61	112.08	101.75
Q4	116.9509	36.2090	143.40	143.72	136.89	126.26	115.41	109.69	101.52
Q4	116.9462	36.2097	142.46	142.80	136.75	127.40	116.96	109.77	105.39
Q4	116.9401	36.2112	142.01	142.10	135.86	126.02	115.96	109.86	102.08
Q4	116.9269	36.2095	145.80	145.39	137.46	126.68	115.40	110.15	107.14
Q4	116.9160	36.2092	143.99	142.58	135.14	125.16	113.75	108.26	102.91
Q4	116.9077	36.2107	142.69	140.72	133.18	122.45	110.50	106.17	104.60
Q4	116.8933	36.2162	147.90	146.41	136.68	124.36	112.55	106.32	101.86
Q4	116.8821	36.2217	143.81	142.78	135.14	125.08	116.11	113.35	110.26
Q4	116.9343	36.2108	143.59	144.02	137.08	126.15	114.18	108.22	104.44
Q2C	116.9457	36.2137	103.60	102.90	101.89	101.75	98.43	105.47	116.23
Q2C	116.9409	36.2146	101.25	100.31	98.92	99.83	97.74	101.45	113.08
Q2C	116.9356	36.2148	101.35	99.01	94.22	93.75	92.04	98.05	109.36
Q2C	116.9303	36.2144	106.36	106.44	103.70	101.40	98.91	102.67	111.44
Q2C	116.9257	36.2136	104.95	103.22	99.65	100.15	99.77	100.19	109.69
Q2C	116.9211	36.2155	94.53	90.51	83.08	85.14	86.20	92.62	104.35
Q2C	116.9151	36.2162	95.87	91.05	85.46	87.14	87.07	93.74	106.34
Q2C	116.9092	36.2170	104.03	100.40	93.83	92.45	89.67	93.64	104.93
Q2C	116.9053	36.2177	101.23	97.50	91.42	90.40	87.98	91.75	103.33
Q2C	116.8998	36.2183	102.44	98.17	91.51	89.79	86.16	90.49	101.78

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