GEE-PICX: Generating cloud-free Sentinel-2 and Landsat image composites and spectral indices for custom areas and time frames - a Google Earth Engine web application

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This manuscript is a non-peer-reviewed preprint submitted to EarthArXiv.

Abstract

Earth observation satellites are collecting vast amounts of free and openly accessible data with immense potential to support environmental, economic, and social fields. As the availability of remotely sensed data increases, so do the methods for accessing and processing it. Many solutions exist for creating cloud-free image composites from often cloudy satellite data, but these typically require coding skills or in-depth training in remote-sensing techniques. This technical barrier prevents many researchers and practitioners from utilising available satellite data. The few user-friendly solutions that exist often have limitations in terms of data export size and quality assessment capabilities. We developed *GEE-PICX*, a web application with an intuitive graphical user interface on the cloud computing platform Google Earth Engine. This tool addresses the aforementioned challenges by creating cloud-free, analysis-ready image composites for user-defined areas and time periods. It utilises Sentinel-2 and Landsat 5, 7, 8, and 9 images and offers global coverage. Users can aggregate image composites annually or seasonally, with data availability starting from 1984 (the launch of Landsat 5). The workflow automatically filters all available satellite data according to user input, removing clouds, cloud shadows, and snow. It provides spectral band information, calculates various thematic spectral indices (including vegetation, burn, built-up area, bare soil, snow, moisture, and water indices), and includes a quality assessment band indicating the number of valid scenes per pixel. *GEE-PICX* offers a customizable tool for creating custom data products from freely accessible satellite data, catering to researchers with limited remote sensing experience. It provides extensive temporal and global spatial coverage, with server-side processing eliminating hardware constraints. The tool facilitates easy export of time series as ready-to-use rasters with numerous spectral indices, supporting environmental programmes and biodiversity research across various disciplines.

Introduction

Understanding environmental changes such as deforestation, desertification, urbanisation, or the expansion of croplands over time is of utmost importance for quantifying and managing the anthropogenic impacts on earth and to support sustainable development and environmental protection (Chaves et al., 2020; Mallinis & Georgiadis, 2019; Weng et al., 2008). Satellite remote sensing is a widely used method for monitoring such environmental changes due to the multitude of available sensors and platforms providing continuous data of the earth's surface (Cord et al., 2017). Remote sensing data is often freely available (e.g. Landsat since the 1980s), enabling scientists to monitor and quantify short- and long term environmental changes.

Optical remote sensing imagery provides (multi-)spectral information, yet the presence of clouds, cloud shadows, and highly reflective surfaces such as snow can adversely affect sensor measurements, posing challenges in acquiring unbiased and gap-free information (Zhu et al., 2015). Opaque clouds cover approximately 31% of the Earth's surface on average at any time (Guzman et al., 2017), necessitating automatic detection and accurate removal from remote sensing data prior to analysis to prevent data errors at the respective positions. Cloud removal causes gaps in satellite images which can complicate analysis. This can be overcome by merging multiple images from different time points to create cloud-free and gap-free image products. These composite products can then be used for land cover classifications (Verhoeven & Dedoussi, 2022), land monitoring applications (Carrasco et al., 2019; Parmes et al., 2017), time series analyses (Lasaponara et al., 2022; Yin et al., 2020) or spatial modelling (Guharajan et al., 2021).

After cloud-correction, multi-spectral information can either be used directly (Zhu et al., 2018) or via derived spectral indices, which are combinations of the spectral reflectance from two or more wavelengths (Chaves et al., 2020; Rudd et al. 2021). Spectral indices are often more suitable for specific analyses than raw spectral information due to more clearly defined and interpretable properties (Rudd et al., 2021). The most popular spectral indices are vegetation indices, but other indices e.g. for burned areas, man-made (built-up) features, water or ice are available, too (Chaves et al., 2020; Montero et al., 2023; Petropulos & Kalaitzidis, 2011).

The increasing availability of remote sensing data is accompanied by advancements in software for managing large data sets and processing chains. In the geospatial community, Google Earth Engine (GEE), a cloud computing platform powered by Google Cloud infrastructure, has gained popularity for generating analysis-ready image products for various applications across different spatial and temporal scales (Wu 2020; Lasaponara et al., 2022; Piao et al., 2019; Yang et al., 2021). In recent years, developers have created various tools and applications designed to streamline access and pre-processing of satellite imagery, for example *ClimateEngine* (Huntington et al., 2017), *Awesome Spectral Indices* (*ASI*, Montero et al., 2023), *geemap* (Wu, 2020), *rgee* (Aybar et al., 2020). Furthermore, platforms like *SentinelHub* (Sinergise, 2023a) or *EarthExplorer* (United States Geological Survey, 2023) provide user-friendly access to large databases of remote sensing data. While some of these tools require programming skills (*ASI*, *geemap, rgee*), others offer more user-friendly interfaces, but have limitations such as restricted downloads for larger areas (*ClimateEngine*, *SentinelHub*) or they do not provide options for image aggregation or further data processing like spectral index calculation (*EarthExplorer*). Thus, we developed *GEE-PICX*, a Google Earth Engine web application providing advanced satellite data products for non-expert, which addresses these limitations by offering cloud-masking, data aggregation, and spectral index calculation, similar to ClimateEngine or SentinelHub. It also provides a novel quality assessment band, specifying valid scenes per pixel in image aggregates. GEE-PICX allows for significantly larger data downloads compared to other platforms, though visualisation of large areas within the web application may be more limited than for smaller areas. Unlike specialised tools for specific applications such as land-cover classification (REMAP, Murray et al., 2018), or crop-climate-suitability mapping (Peter et al., 2020), GEE-PICX focuses on providing flexible access to satellite data with optional spectral index and data quality information. This approach ensures broad applicability across various research domains and analysis types. For an overview and comparison of available applications, see Supporting Information S1.

GEE-PICX generates, visualises and exports cloud-free, analysis-ready composites of satellite images for user-defined areas and time steps, with global data coverage. We followed five design principles in developing *GEE-PICX*:

1. **Flexibility of user input.** Users can select the satellite platform (Landsat or Sentinel-2), study area boundaries, time range, maximum cloud cover (for single images), aggregation mode, and image bands. Relevant scenes are automatically selected from the data catalogue according to user input. Moreover, the modular design allows users to easily add custom indices.
2. **Ease of use.** The application features a self-explanatory graphical user interface. It only requires a Google account, web browser, and internet connection, with no additional hardware or software requirements due to server-side processing.
3. **Export of large data sets.** Export size is limited only by Google drive storage capacity.
4. **Generation of analysis-ready data.** Produces cloud-free image composites with spectral bands, spectral indices, and a quality assessment band (valid scenes per pixel). Export image resolution and coordinate reference system are customizable.
5. **Data visualisation.** Data sets can be visualised in the browser prior to export.

This paper presents *GEE-PICX*, a web-based application designed to simplify access to satellite imagery analysis. Our objectives are to describe the technical workflow and features of *GEE-PICX*, highlighting how it addresses common challenges in satellite data processing, and demonstrate the tool's versatility through two diverse use cases in ecological research. We then present two examples that illustrate the application of *GEE-PICX* in different ecological contexts and discuss the potential impact of *GEE-PICX* on broadening the use of remote sensing data across various disciplines.

Workflow description

Overview

Users can access the web application via the provided application link (see Data availability). The script is written in JavaScript and commented to facilitate orientation. No manual code adjustments are necessary. With the application running, users can define parameters according to their requirements in the application interface next to the map. The application then internally processes user inputs, executing functions for satellite image (pre-)processing, visualisation, and export preparation. Data visualisations are available directly in the application. The products can be exported at user-defined spatial resolutions and coordinate systems and are ready to use for subsequent analyses.

User input

Below we provide a detailed overview of the choices users can make for creating customised data exports. For advanced information on data processing see Supporting Information S2.

Satellite data: The application can provide image composites based on either the Landsat or the Sentinel-2 mission. Both Landsat and Sentinel-2 data sets consist of atmospherically and topographically corrected Level-2A products that show surface reflectance values with atmospheric correction applied. The data set choice can be based on either the required spatial resolution or length of the time series. The earliest Level-2A products from Landsat date back to 1984 (at 30m resolution), whereas Sentinel-2 Level-2A products have been available since 2017 (at 10m resolution in the visible and NIR spectrum). The availability of Landsat data from the late 1980s and early 1990s is much lower than in recent years, when more Landsat missions are simultaneously acquiring imagery at a higher temporal frequency. When selecting Landsat missions for analysis it is important to consider the potential impact of the Landsat 7 scan line corrector (SLC) failure. The SLC, which normally ensures continuous image capture, failed in 2003. This failure resulted in data gaps affecting about 22% of each scene. While the overall image quality remains intact, these gaps can limit the usability of Landsat 7 images for applications requiring seamless coverage (United States Geological Survey, 2022). However, researchers developed gap-filling techniques to mitigate this issue (Storey et al., 2005). In GEE-PICX, when selecting Landsat as the platform, users have the option to include imagery from all Landsat missions (5, 7, 8, 9) to create image composites, or they can choose to include only Landsat-8 and 9 data, which avoids including erroneous Landsat-7 images. However, Landsat-8 data are only available from 2013 and Landsat-9 data from 2022. For more specific information on the satellite missions see Supporting Information S3.

Area of interest: The boundary of the study area can be defined either by uploading a shapefile as an Earth Engine asset (Google Earth Engine, 2021), or by manually drawing a polygon on the Google Earth Engine map. Data coverage is global.

Time period: The time frame can be specified by year- and month range. By default, scenes are aggregated for one year (months 1 - 12). Users can create seasonal image aggregates by narrowing the selection to specific consecutive months (also crossing the year boundary). Users can request export of imagery from multiple years at once.

Cloud cover filter: Optical satellite images may exhibit partial or complete cloud coverage. The pixel-level cloud masks included in scenes cannot perfectly detect and filter out all clouds and cloud shadows (Sanchez et al., 2020). Therefore, the cloud cover percentage per scene is utilised to enhance the quality of image composites by removing scenes exceeding a cloud cover threshold. By default, images with cloud cover exceeding 65% are excluded prior to aggregation. Opting for a 100% threshold includes all images captured within the specified study area and time frame. Cloud masking leads to data gaps in all images affected by cloud cover. If all scenes have data gaps at the same pixels, the image composite will also have data gaps at this location.

Image bands: Users can select single or multiple spectral bands, as well as spectral indices and a valid pixel band, by activating the corresponding checkboxes. Spectral bands convey surface reflectance data and are correlated with chlorophyll and other pigments, vegetation structure and water content (Petropulos & Kalaitzidis, 2012). Key correlations include Green, Red, and Red-edge bands with chlorophyll and pigments, NIR bands with leaf structure, and SWIR with vegetation structure and water content (Chaves et al., 2020; Fernández-Manso et al., 2016). Spectral indices result from mathematical combinations of the spectral bands (see Supporting Information S4 for details on all available indices). The valid pixel band is a quality assessment layer specifying the number of valid scene values that are aggregated at each pixel.

Aggregation mode: The aggregation mode determines which summary statistic is applied to the pixel values of all selected images. Available choices are mean, median and standard deviation.

Coordinate system: The application offers the choice to export rasters in UTM and WGS 84 (EPSG 4326) formats. If UTM is selected, the application automatically identifies the appropriate zone. If the study area spans multiple UTM zones, images can only be exported in WGS 84.

Spatial pixel resolution: The application provides the options to export images at four different spatial resolutions ranging from 10 to 100 metres. Opting for high resolutions in extensive study areas could yield products exceeding several gigabytes, potentially posing challenges for subsequent analyses. Users should choose a resolution that matches their research or monitoring objectives.

Image export

After initiating the export in the application user interface, users can inspect and execute the actual image export(s) within the upper-right window via the *Console* and *Tasks* tabs (see Data availability). Two image collections will be automatically added to the *Console*. The first contains all individual satellite images after filtering, the second contains the image aggregates available for export. Each annual / seasonal image that appears in the *Tasks* manager needs to be exported individually. When clicking "Run", a pop-up window will appear in which the user can optionally modify export names, coordinate reference system, scale, export destination and file format.

The easiest way to save the files on a local computer is to export them to a Google drive folder which is connected to the users' Google account, and then download the data from there. Multiple image exports run in parallel and depending on study area size each export can take from minutes to hours (or even days for study regions measuring hundreds of thousands of square kilometres). When exporting large data sets, Google Earth Engine splits each image into smaller tiles. After downloading them from Google Drive, they can either be merged to a large contiguous mosaic, or be used as a virtual raster.

Except for the "valid-pixel" band, all band values of the export images are multiplied by 10,000. This allows the raster values to be stored as integer values (signed 16-bit) instead of floating point values, thus reducing the file size of exports.

Google Earth Engine assigns a value of zero to data gaps in image composites during export to Google Drive, potentially biassing subsequent analyses. We provide an R script for converting zero values back to NA with the help of the valid pixel layer prior to further analyses (see Data availability).

Data visualisation

Users can visualise their export data on the map by selecting either a spectral index or various band combinations. Band combinations can highlight certain features (e.g., vegetation types, water bodies, and urban areas) due to correlations between measurable biophysical properties on the Earth's surface and remotely sensed surface reflectance (Price et al., 2002). After choosing the visualisation parameter, all aggregated images will be added to the map with default visualisation settings. Adjustments to visualisation parameters can be made individually within the map's layer panel box (follow instructions on Github link, see Data availability). All indices have a valid value range from -1 to 1 in the web application. Google Earth Engine may encounter computational problems for visualisation if the data is too large due to the size of the study area and/or the length of the time period. This may lead to scaling error messages and some objects would not be displayed on the map (or also *Console*). Visualisation problems, however, do not affect image exports, which are always possible and only limited by the storage capacity of the user’s Google drive.

In addition to the visualisation options in Google Earth Engine, we provide an interactive R Shiny application for visualising image time series (see Data availability).

Case examples

Example A shows deforestation in Brazil using historical Landsat images, while Example B focusses on seasonal land cover changes in the city of Würzburg (Germany), emphasising the enhanced level of detail provided by Sentinel-2 imagery. In both examples a combination of three spectral bands (SWIR1-NIR-R; NIR-R-G) and a spectral index (NDVI) are shown together with the number of valid pixels (see Fig. 1). The data contain more spectral bands and indices not shown here.

In the Amazon rainforest, deforestation has become a pressing environmental concern over the past several decades. Soy farms, along with other agricultural expansion, have played a significant role in driving deforestation in the Amazon (Nepstad et al., 2006). We used *GEE-PICX*, to generate and export annual image aggregates for an area in Ariquemes, Rondônia, Brazil for 1991 and 2021, illustrating the magnitude of change over three decades. Such annual aggregates (or composites) are suitable for inferences on broad trends, but average seasonal dynamics or land cover changes within a year, making them unsuitable e.g. for mapping floods.

The second example shows the seasonal changes in land cover/land use in the city centre of Würzburg, Germany, and highlights the surrounding ring-shaped park. The region's transition between summer and winter was captured in seasonal satellite image composites and showcases the distinct phenological variations. The higher spatial resolution of Sentinel-2 imagery allows better discrimination of small-scale features and proves particularly valuable in the context of land cover and land use monitoring. Seasonal variation in cloud cover can lead to seasonal bias in the available data. Snow cover can also affect the quality of seasonal image compositions because the applied cloud mask algorithm (see Supporting Information S2) does not perfectly mask highly reflective surfaces such as clouds or snow in individual scenes.

Conclusion

Satellite imagery is essential for many environmental and conservation studies. However, utilising freely available satellite products often requires expertise in data selection, pre-processing, and substantial computational resources. Many environmental and conservation studies therefore primarily rely on pre-packaged thematic products (Wong et al., 2022), which may lack the detail necessary to address specific research questions. *GEE-PICX* addresses these challenges by simplifying access to cloud-free satellite image composites. It effectively addresses cloud cover issues, which are particularly problematic in tropical or mountainous regions (Sanchez et al., 2020; Hribljan et al., 2017). Through its intuitive interface, users can easily generate and export (multi-)temporal cloud-free satellite images for any region, with data availability starting from 1984 (varying by region).

GEE-PICX offers access to both Landsat and Sentinel-2 archives and provides multispectral information complemented by various spectral indices and a data quality metric. These are typically not or only partly present in the output of other platforms. *GEE-PICX* is further set apart by its capability to process extensive areas with very large download sizes. By making these rich satellite data archives accessible to non-remote-sensing scientists and practitioners, *GEE-PICX* supports the integration of satellite data into a wide range of environmental and conservation projects.

By lowering the barriers to satellite data analysis, GEE-PICX aims to bridge the gap between satellite data availability and its practical use in environmental research and conservation efforts.

Acknowledgements

We would like to express our gratitude to several individuals and organisations who have played an important role in the successful completion of this project. First of all, we would like to thank Marius Philipp, who gave us great technical support as a tutor during workflow and app development in Google Earth Engine. Moreover, we thank Matthias Baumann and Julian Oeser for insightful discussions about processing and utilisation of satellite data time series. The work was financially supported by the Leibniz Institute for Zoo and Wildlife Research and parts of the work were done during the implementation of the USAID funded Biodiversity Conservation project in Viet Nam (7204402CA00001).

Conflict of Interest statement

The authors declare no conflicts of interest.

Author contributions

Jürgen Niedballa and Andreas Wilting conceived the idea, Luisa Pflumm led the development of the GEE script and Hyeonmin Kang led the development of the GEE App user interface. Luisa Pflumm developed the case examples. Luisa Pflumm, Jürgen Niedballa and Andreas Wilting led the writing of the manuscript, and Hyeonmin Kang contributed to the drafts. All authors gave final approval for publication.

Data availability

All necessary information for *GEE-PICX is available in our GitHub repository*: https://github.com/EcoDynIZW/GEE-PICX. To use *GEE-PICX,* users need to log in to Google Earth Engine with a Google account. The application opens in JavaScript code editor mode (required for data export). Clicking the “Run” button opens the graphical user interface. In the user interface, user inputs are specified and products can be exported to users' Google drive. The repository includes a comprehensive step-by-step user guide.

Important note on no data values: When exporting rasters from GEE, all pixels with no data are assigned a value of 0. This can affect subsequent analysis by misrepresenting true no data values as 0. We provide an R script in the GitHub repository to convert these misassigned 0 values back to no data. Users should apply this script to all GEE-exported rasters before further analysis.

Additionally, we offer an R Shiny app on GitHub for visualising and querying time series of annual images downloaded via GEE-PICX.

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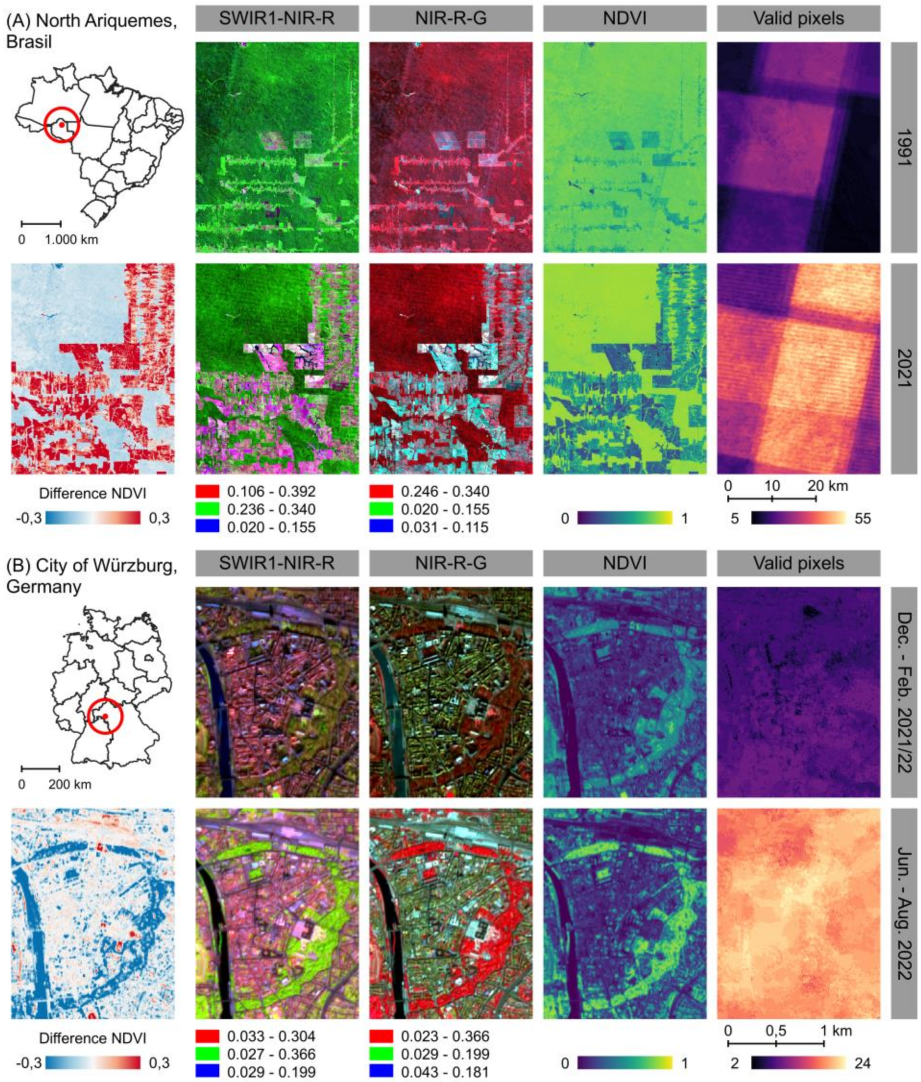
Figures



Options	(A) North Ariquemes (Brasil)	(B) City of Würzburg (Germany)
Satellite platform	Landsat-5,7,8,9	Sentinel-2
Study area	Polygon coordinates (in degree): -63.1 to -62.6 °W, -9.7 to -9.3 °S	Polygon coordinates (in degree): 49.78 to 49.8 °E, 9.92 to 9.94 °N
Month, year, max. cloud cover (per scene)	(1) 1-12, 1991, 65% (2) 1-12, 2021, 65%	(1) 12-2, 2022-23, 65% (winter) (2) 6-8, 2022, 65% (summer)
Number of selected scenes	(1) 44 scenes (2) 97 scenes	(1) 9 scenes (2) 26 scenes
Band selection	B, G, R, NIR, SWIR1, SWIR2, NDVI, valid pixels	
Aggregation mode	median	
Spatial resolution	30 meter	10 meter
CRS	UTM (EPSG: 32620)	UTM (EPSG: 32632)

Figure 1: Example GEE-PICX products. A: Annual aggregates based on Landsat scenes for 1991 and 2021. B: Seasonal aggregates based on Sentinel-2 scenes for summer (June 2022 - August 2022) and winter (December 2021 - February 2022). The maps show a subset of the available band information. The striking pattern in the valid-pixel scenes results from the orbital path overlap of the Landsat satellites and does not affect image composites.

Supporting Information

Supporting Information S1

Table S1: Comparison of available tools and applications which allow for satellite image processing similar to GEE-PICX.

	Geospatial platforms				Packages			Analysis tools	
Tool name	**GEE-PICX**	**Climate Engine**	**Sentinel Hub**	**Earth Explorer**	**Awesome Spectral Indices**	**geemap**	**rgee**	**REMAP**	**CropSuit GEE**
Website	https://github.com/EcoDynIZW/GEE-PICX	https://app.climateengine.org/climateEngine	https://apps.sentinel-hub.com/eo-browser/	https://earthexplorer.usgs.gov/	https://github.com/awesome-spectral-indices/awesome-spectral-indices	https://github.com/gee-community/geemap	https://github.com/r-spatial/rgee	https://remap-app.org/remap	https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/UFC6B5
Purpose	Data acquisition, visualisation, export	Data acquisition, visualisation, export	Data acquisition, visualisation, export	Data acquisition, visualisation, export	Spectral Indices Catalog	GEE access for python users	GEE access for R users	Land-cover/ Land-use classification	Crop-Climate-Suitability Mapping
Graphical user interface	Yes	Yes	Yes	Yes	No	No	No	Yes	No
Coding required	Optional [1]	No	Optional	No	Yes	Yes	Yes	No	Optional
Language	GEE Javascript API	-	Sentinel Hub API	-	GEE Javascript API, Python, Julia, R	Python	R	-	GEE Javascript API

Data sources	Sentinel-2, Landsat	> 10 different datasets [2]	> 10 different datasets [2]	> 10 different datasets [2]	Entire GEE catalogue	Entire GEE catalogue	Entire GEE catalogue	Landsat & climate data	MODIS & climate data
Time Range	1984 - present; custom month range	1984 - present; custom date range	1972 - present; custom date range	1972 - present; custom date range	Custom	Custom	Custom	No	2000 - 2017; custom date range
Cloudfree mosaics	Yes	Yes	Yes	No	User-specific	User-specific	User-specific	No	No
Custom cloud cover value	Yes	No	No	Yes	User-specific	User-specific	User-specific	No	No
Spectral indices calculation	Yes	Yes	Yes	No	Yes	User-specific	User-specific	Yes	No
Data quality assessment	Yes [3]	Yes [4]	No	No	User-specific	User-specific	User-specific	No	No
Data visualisation	Yes	Yes	Yes	Yes	User-specific	User-specific	User-specific	Yes	Yes
Export product	Aggregated multi-band mosaic(s)	Aggregated single-band mosaic(s)	Aggregated multi-band mosaic(s)	Single product(s)	User-specific	User-specific	User-specific	Classification map	
Export limitation	Unlimited [5]	10,000 x 10,000 pixel	2,500 x 2,500 pixel	10,000 products	Unlimited	Unlimited	Unlimited	100,000 km^2	Unlimited [5]
Reference	Pflumm et al., 2024	Huntington et al., 2017	Sinergise, 2023a	United States Geological Survey, 2023	Montero et al., 2023	Wu, 2020	Aybar et al., 2020	Murray et al., 2018	Peter et al., 2020

[1] Only for adding custom spectral indices to app
[2] Several datasets from satellite, climate, hazard, forecast (see websites for list of data)
[3] Add valid-pixel band
[4] Calculate statistics
[5] maxPixels of 10,000 can be exceeded, only limited by Earth Engine Quota (https://developers.google.com/earth-engine/guides/usage) and Google Drive storage capacity

Supporting Information S2

Data processing in GEE-PICX

Table S2: Functional setup of GEE-PICX application script.

Functionality	**Description**
Image selection and filtering	Select Landsat / Sentinel-2 surface reflectance (SR) products (Level-2). Filter single scenes by study area, time frame and maximum cloud cover.
Cloud masking *	Landsat SR data: mask clouds, cloud shadows and snow from the Cloud Quality Assessment band (QA_PIXEL bitmask). Sentinel-2 SR data: mask clouds, cloud shadows and highly reflective surfaces with auxiliary S2 cloud probability data set (s2cloudless).
Band selection	Select and rename S2 bands according to spectral wavelength range Select and rename LS 8 & 9 bands according to spectral wavelength range Select and rename LS 5 & 7 bands according to spectral wavelength range
Scale factor application	Apply scale factor for Landsat SR data (0.0000275) and add offset value (- 0.2) before usage Apply scale factor for Sentinel-2 SR data (0.0001)
Spectral indices calculation	Calculate indices with respective formulas and add as band information to each individual scene
Image aggregation & data quality assessment	Aggregate filtered scenes from year or season by median, mean or standard deviation Count valid pixels at each pixel location for data quality assessment
Visualisation	Aggregated scenes can be added to the map. Users can choose spectral indices as single bands or choose from various 3-band combinations. Further changes can be applied manually in the layer panel box. May fail if data size or area of interest are too large (limitations in Google Earth Engine).
Export preparation	Create a batch task to export images as raster to Google Drive. All image band values are multiplied by 10,000 in advance and converted to signed 16-bit integer to reduce output file size (except for valid-pixel band)

* Additional information on s2cloudless:

The development of the s2cloudless algorithm (Zupanc, 2019), however, has allowed researchers to refine cloud masking, resulting in greater confidence in the final analysis. There is currently no equivalent method for images from the Landsat collection. While the QA60 band is limited to a binary classification of thick and cirrus clouds (European Space Agency, 2020), s2cloudless generates an image with cloud presence probabilities ranging from 0 to 100 percent, at 10 metre scale (Braaten et al., 2020). This provides the opportunity to customise the cloud masking process to better suit the specific requirements of a project. Higher values of the s2cloudless layer are more likely related to clouds or highly reflective surfaces such as snow or roof tops (Google Earth Engine, 2023).

The s2cloudless layer is a separate data set from which matching scenes are automatically selected and filtered. The default cloud probability threshold in the application is 50 % to define cloud / non-cloud masks, which generally allows a very good cloud masking performance (Braaten et al., 2020). The optimal value for the best performance can depend on factors such as cloud type, cover type, location, etc. Users who wish to further customise the cloud mask need to adjust the variable "isNotCloud" in the application script where cloud masking is applied to the selected Sentinel-2 images. In this case, we suggest experimenting with a few different values to better understand the distribution of cloud probability values. For example, thin clouds may not be detected at 90 % cloud probability threshold, but are detected at 10 % (Braaten et al., 2020). The single scenes from the cloud-masked image collection in the *Console* tab could be used to investigate changes due to cloud mask tuning. Nevertheless, for proper inspection and evaluation, basic knowledge of using the Google Earth Engine API is beneficial. For most use cases it is not necessary to modify the cloud probability threshold.

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Supporting Information S3

Satellite data available in GEE-PICX

Table S3: Information on satellite data accessible from GEE-PICX web application.

Platform	**Sentinel-2**		**Landsat**			
Mission	**Sentinel-2A**	**Sentinel-2B**	**Landsat-5**	**Landsat-7**	**Landsat-8**	**Landsat 9**
Mission Launch	2015-06-23	2017-03-07	1984-03-01	1999-04-15	2013-02-11	2021-09-27
Data availability in GEE-PICX app	2017-03-28 - present		1984-03-16 - 2012-05-05	1999-05-28 - present	2013-03-18 - present	2021-10-31 - present
Sensor*	MSI		MSS + TM	ETM+	OLI + TIRS	OLI + TIRS
Temporal resolution	10-days each, 5-days combined constellation		16-days each, 8-days combined constellation Landsat-8 and 9			
Spatial resolution	10-metre		30-metre			
Spectral resolution**	*Bands 2-5, 8, 8A, 11-12:* visible, NIR, red-edge, SWIR		*Bands 1-5, 7* visible, NIR, SWIR		*Bands 2-7*	
Spectral & spatial resolution (bands, in meter)	*Bands 2-5, 8, 8A, 11-12:* 10 m: R, G, B, NIR; 20 m: Red-edge, SWIR		*Bands 1-5, 7:* 30 m: B, G, R, NIR, SWIR	*Bands 1-5, 7:* 30 m: B, G, R, NIR, SWIR	*Bands 2-7:* 30 m: B, G, R, NIR, SWIR	*Bands 2-7:* 30 m: B, G, R, NIR, SWIR
Additional information	-	-	-	Scan Line Corrector (SLC) failure since 2003-05-31 (22 percent of each image affected by data gaps)	-	-
Operator***	ESA		NASA & USGS			

* OLI, Operational Land Imager; TIRS, Thermal Infrared Sensor; ETM+, Enhanced Thematic Mapper Plus; TM, Thematic Mapper; MSS, Multispectral Scanner; MSI, Multispectral Instrument
** Visible: blue, green, red; NIR: near-infrared; SWIR: shortwave-infrared
*** ESA, European Space Agency; NASA, National Aeronautics and Space Administration; USGS, United States Geological Survey

Supporting Information S4

Spectral Indices available in GEE-PICX

Table S4: Available spectral indices derived from Landsat or Sentinel-2 imagery.

Band name	Full name	Formula	Group	Interpretation
NDVI	Normalised Difference Vegetation Index	$\frac{(NIR - Red)}{(NIR + Red)}$	Vegetation Index	Highlights density and health of photosynthetically active vegetation. Tends to saturate in densely vegetated areas. Sensitive to the contribution of soil brightness and atmospheric effects.
EVI	Enhanced Vegetation Index	$2.5 * \frac{(NIR - Red)}{(NIR + 6 * Red - 7.5 * Blue + 1)}$	Vegetation Index	Highlights photosynthetically active vegetation, but does not saturate in densely vegetated areas. Accounts for soil brightness variation. Less affected by atmospheric effects than NDVI.
SAVI	Soil-Adjusted Vegetation Index	$\frac{(NIR - Red)}{(NIR + Red + L)} * (1 + L)$	Vegetation Index	Highlights photosynthetically active vegetation and accounts for soil brightness variation.
MSAVI	Modified Soil-Adjusted Vegetation Index	$\frac{(NIR - Red)}{(NIR + Red + L_0)} * (1 + L_0)$	Vegetation Index	Modified version of SAVI to further minimise the soil background influences on the vegetation signal.
GNDVI	Green Normalised Difference Vegetation Index)	$\frac{(NIR - Green)}{(NIR + Green)}$	Vegetation Index	Highlights the density and health of photosynthetically active vegetation. It is sensitive to chlorophyll content, making it effective for assessing green crop biomass. May saturate in dense vegetation but is generally less influenced by soil brightness and atmospheric effects compared to NDVI.
NDMI	Normalised Difference Moisture Index	$\frac{(NIR - SWIR1)}{(NIR + SWIR1)}$	Water & Moisture Index	Sensitive to moisture levels in vegetation and soil. Useful for vegetation analyses, for identifying areas prone to drought stress or excess moisture.
NDWI	Normalised Difference Water Index	$\frac{(Green - NIR)}{(Green + NIR)}$	Water & Moisture Index	Sensitive to water bodies. Useful for water resource management, wetland monitoring, and flood assessment.

NBR	Normalised Burn Ratio	$\frac{(NIR - SWIR2)}{(NIR + SWIR2)}$	Burn & Fire Index	Detects and quantifies burnt areas. In general, low NBR values indicate recently burnt areas and bare ground.
BSI	Bare Soil Index	$\frac{(SWIR1 + Red) - (NIR + Blue)}{(SWIR1 + Red) + (NIR + Blue)}$	Built-up & Urban Index	Highlights bare ground and rock surfaces. Useful in identification of soil erosion, land degradation, and urbanisation processes.
NDBI	Normalised Difference Built-up Index	$\frac{(SWIR1 - NIR)}{(SWIR1 + NIR)}$	Built-up & Urban Index	Highlights built-up and urban areas by contrasting impervious surfaces with vegetation. Higher NDBI values indicate the presence of buildings and other man-made structures.
NDSI	Normalised Difference Snow Index	$\frac{(Green - SWIR1)}{(Green + SWIR1)}$	Snow & Ice Index	Detects snow cover by differentiating snow from clouds and other land surfaces. High NDSI values indicate snow-covered areas, making it useful for monitoring snow extent and water resource management.

For more information on spectral indices see: Petropoulos & Kalaitzidisz (2012), Zeng et al. (2022), United States Geological Survey (2022), Qi et al. (1994), Keeley (2009).

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