'WetlandMapper: A Python package for automatic wetland mapping, dynamics classification, and cover-type characterisation from multispectral time-series data'

Manudeo Singh

Department of Geography and Earth Sciences, Aberystwyth University, Aberystwyth, Wales, UK

manudeo.singh@aber.ac.uk

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Quick install: pip install wetlandmapper

GitHub link: https://github.com/manudeo/wetlandmapper

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WetlandMapper: A Python package for automatic wetland mapping, dynamics classification, and cover-type characterisation from multispectral time-series data

Manudeo Singh [1¶]

1 Department of Geography and Earth Sciences, Aberystwyth University, Aberystwyth, Wales, UK ¶ Corresponding author

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Summary

`WetlandMapper` is an open-source Python package that operationalises two peer-reviewed remote-sensing frameworks for automated wetland analysis from multispectral satellite data. The package is available on PyPI (`pip install wetlandmapper`) and archived at Zenodo (Singh, 2026).

The first framework is a **wetland dynamics classification** method (Singh & Sinha, 2022a) that maps floodplain wetlands at basin scale from a multi-temporal MNDWI time series and classifies each wetland pixel into one of six temporal dynamics classes: *Persistent*, *New*, *Intensifying*, *Diminishing*, *Lost*, and *Intermittent*.

The second framework is a **Wetland Cover Type (WCT) classification** method (Singh et al., 2022) that combines the Modified Normalised Difference Water Index (MNDWI), Normalised Difference Vegetation Index (NDVI), and Normalised Difference Turbidity Index (NDTI) to characterise the biophysical surface composition of wetland pixels into stable, ecologically interpretable cover types including open clear water, turbid water, aquatic vegetation, and moist soil.

These two modules address complementary monitoring questions: the dynamics module characterises *when and how* wetland inundation is changing over time, while the WCT module characterises *what* is present at the wetland surface at any given time. Both operate on `xarray` `DataArray` objects (Hoyer & Hamman, 2017), enabling dask-backed parallel processing of large raster archives. Users may supply their own pre-processed imagery or retrieve analysis-ready surface-reflectance data directly from Google Earth Engine (GEE; Gorelick et al. (2017)) via an integrated optional acquisition submodule that supports all Landsat missions (4, 5, 7, 8, and 9), Sentinel-2, and shapefile-path or GeoJSON area-of-interest inputs.

Statement of Need

Wetlands cover roughly 5–8percent of Earth's land surface and deliver ecosystem services valued at tens of trillions of dollars annually, yet global wetland area has declined by approximately 35percent since 1970 (Davidson, 2014; Ramsar Convention Secretariat, 2018). Operational monitoring at basin to continental scales — tracking both inundation dynamics and biophysical surface conditions — is essential for conservation management, restoration prioritisation, and international reporting obligations under the Ramsar Convention.

Existing tools for remote sensing-based wetland analysis suffer from one or more of the following limitations: (1) they characterise only binary inundation extent and do not resolve temporal dynamics or surface cover composition (Pekel et al., 2016); (2) they are embedded in proprietary platforms (ArcGIS Model Builder, GEE JavaScript API) that resist integration into scripted, reproducible workflows; (3) they address either dynamics or cover characterisation but not both within a single interoperable framework; and (4) their methods are distributed as single-use scripts rather than tested, documented software libraries with version histories.

`WetlandMapper` addresses all four gaps. It provides a fully Pythonic, open-source library that unifies the dynamics-classification method of Singh & Sinha (2021) and Singh & Sinha (2022a) — previously dependent on ArcGIS — and the WCT method of Singh et al. (2022) — previously distributed only as GEE JavaScript code and an ArcGIS toolbox — while adding a flexible data-ingestion pathway that supports both user-supplied imagery and automated GEE retrieval. Both methods require no labelled training data and operate on any multispectral archive from which MNDWI, NDVI, and NDTI can be computed.

State of the Field

The JRC Global Surface Water dataset (Pekel et al., 2016) characterises long-term open-water occurrence globally at 30 m resolution but does not distinguish wetland surface types. Machine-learning approaches achieve high classification accuracy but require labelled training data that are rarely available at regional scales (Mahdavi et al., 2018; Slagter et al., 2020). SAR-based methods handle cloud cover but require specialist pre-processing workflows (Tsyganskaya et al., 2018) and site-specific thresholding. The methods unified in `WetlandMapper` occupy a practical middle ground — no training labels, applicable to any cloud-free multispectral archive, and producing ecologically interpretable outputs — and `WetlandMapper` makes them accessible in a reusable, tested Python library for the first time.

Software Design and Methods

Wetland Dynamics Classification

This module implements the basin-scale inventory and hydrodynamics framework of Singh & Sinha (2022a). Given a multi-temporal MNDWI raster stack, each time step is first thresholded to a binary water-presence layer:

$$W_t = \begin{cases} 1 & \text{if } \mathrm{MNDWI}_t > \tau \\ 0 & \text{otherwise} \end{cases}$$

where $\tau = 0$ by default (positive MNDWI indicates a water-dominated pixel; Xu (2006)). Three summary statistics are then derived across the full time series of length T, split by a configurable temporal window n:

$$W_{\text{percent}} = \frac{\sum_{t=1}^{T} W_t}{T} \times 100, \quad W_{\text{historic}} = \sum_{t=1}^{n} W_t, \quad W_{\text{recent}} = \sum_{t=T-n+1}^{T} W_t$$

The temporal change signal $\Delta W = W_{\text{recent}} - W_{\text{historic}}$ is used together with W_{percent} and two user-adjustable wet-frequency thresholds (θ_{wet}, θ_{persis}) to assign each pixel to one of six dynamics classes:

Class	Primary condition
Persistent	$W_{\text{percent}} \geq \theta_{\text{persis}}$
New	$\Delta W = +n$

Class	Primary condition
Intensifying	$W_{\text{percent}} \geq \theta_{\text{wet}};\ \ 0 < \Delta W < n$
Diminishing	$W_{\text{percent}} \geq \theta_{\text{wet}};\ \ -n < \Delta W < 0$
Lost	$\Delta W = -n$
Intermittent	$W_{\text{percent}} \geq \theta_{\text{wet}}$; no directional trend
Non-wetland	$W_{\text{percent}} < \theta_{\text{wet}}$

The entire classification is implemented using vectorised `xr.where` operations, enabling chunked parallel execution via Dask with no Python-level pixel iteration.

Wetland Cover Type Classification

This module implements the multi-index WCT framework of Singh et al. (2022). Three spectral indices are computed from the same multispectral image:

$$\text{MNDWI} = \frac{G - \text{SWIR}}{G + \text{SWIR}}, \quad \text{NDVI} = \frac{\text{NIR} - R}{\text{NIR} + R}, \quad \text{NDTI} = \frac{R - G}{R + G}$$

MNDWI delineates the extent of surface water; NDVI quantifies vegetation presence and density; NDTI quantifies water turbidity. Their combined spectral signatures partition wetland pixels into five biophysically distinct cover types. Two classification implementations are provided: the original quartile-based combination code method (`classify_wct_ema`), and an improved continuous-threshold variant (`classify_wct`) that allows sub-quartile calibration for different sensors or seasons.

Data Acquisition and Temporal Aggregation

The optional `wetlandmapper.gee` submodule supports all five Landsat missions (4, 5, 7, 8, 9) and Sentinel-2. A `"LandsatAll"` option automatically merges available missions for any requested date range with harmonised band names, enabling long-record analyses from 1982 to the present day. An optional `use_slc_off` parameter controls whether Landsat 7 images acquired after the 2003 Scan Line Corrector failure (which cause ~22percent data gaps per scene) are included. Areas of interest may be provided as a GeoJSON dict, a shapefile path, or a GeoJSON file path; multi-feature shapefiles are dissolved to a single boundary automatically.

Server-side temporal compositing reduces data transfer volume for long time series: users may request one median composite per year, month, or meteorological season (DJF / MAM / JJA / SON) rather than every individual scene. The same temporal aggregation functionality is also available client-side via `aggregate_time()`, which operates on any `xarray` `DataArray` or `Dataset` regardless of data source.

Dependencies and Installation

`WetlandMapper` requires Python $\geq$ 3.9. Core dependencies are `numpy` (Harris et al., 2020), `xarray` (Hoyer & Hamman, 2017), and `rioxarray` (Snow & others, 2022). The GEE submodule additionally requires `earthengine-api`, `rasterio`, `xee`, `dask`, and `geopandas`. Installation:

```
pip install wetlandmapper                  # core
pip install "wetlandmapper[gee]"           # with GEE + shapefile support
pip install "wetlandmapper[plot]"          # with visualisation utilities
```

Detailed platform-specific installation instructions, including GEE authentication setup, are provided in `INSTALL.md` in the repository.

Usage

A minimal end-to-end example for each workflow:

```python
import xarray as xr
from wetlandmapper import compute_mndwi, classify_dynamics
from wetlandmapper import compute_indices, classify_wct_ema
from wetlandmapper.gee import fetch

# --- Dynamics: fetch annual composites from all Landsat missions ---
mndwi = fetch("study_area.shp", "1984-01-01", "2023-12-31",
              sensor="LandsatAll", temporal_aggregation="annual")
dynamics = classify_dynamics(mndwi, nYear=3,
                             thresholdWet=25, thresholdPersis=75)
dynamics.rio.to_raster("wetland_dynamics.tif")

# --- WCT: single composite → 5 biophysical cover types
# --- ds_composite is an xarray multispectral dataset (a Landsat .tiff)
ds_composite = xr.load_dataset('Landsat.tiff')
indices = compute_indices(ds_composite, green_band="B3", red_band="B4",
                          nir_band="B5", swir_band="B6")
wct = classify_wct_ema(indices)
wct.rio.to_raster("wetland_cover_types.tif")
```

A Jupyter notebook demonstrating both workflows on synthetic data, with full GEE acquisition and interactive visualisation sections, is included at `notebooks/demo_wetlandmapper.ipynb`. Full API documentation is available at https://wetlandmapper.readthedocs.io.

Research Impact and Context

The dynamics module is derived from the methodology of Singh & Sinha (2022a), where it was applied to over 3,000 floodplain wetlands in the Ramganga Basin, north India, using a Landsat time series spanning 1994–2019.

That study demonstrated that frequency-based temporal aggregation can effectively distinguish permanently inundated, seasonally active, and recently changed wetlands at basin scale, providing a validated inventory framework applicable to wetland restoration prioritisation (Singh & Sinha, 2022b).

The WCT module is derived from Singh et al. (2022), where the MNDWI–NDVI–NDTI combination was validated across three Ramsar-listed wetlands in contrasting geomorphic and climatic settings — Kaabar Tal (Ganga floodplain), Chilika Lagoon (coastal), and Nal Sarovar (semi-arid) — demonstrating that the WCTs are stable in space and time, meaning comparable biophysical conditions correspond to the same WCT irrespective of geographic location.

By unifying both workflows in a single, tested Python package with flexible data ingestion, `WetlandMapper` enables application of these frameworks globally in fully scripted, reproducible workflows, without dependence on proprietary GEE or ArcGIS environments.

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AI Assistance

Development of this software package was assisted by Claude (Anthropic), an AI language model, for tasks including code scaffolding, packaging configuration, continuous integration setup, docstring writing, and debugging. The scientific methodology, classification algorithms, spectral index thresholds, and validation are based entirely on the author's prior peer-reviewed work (Singh et al., 2022; Singh & Sinha, 2021, 2022a), and all scientific content, design decisions, and results presented here are the author's own.

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