EGU26
GENERAL ASSEMBLY

A Multi-Source Remote Sensing and Machine Learning Framework for Detecting Ephemeral Sand Rivers across the West African Sahel

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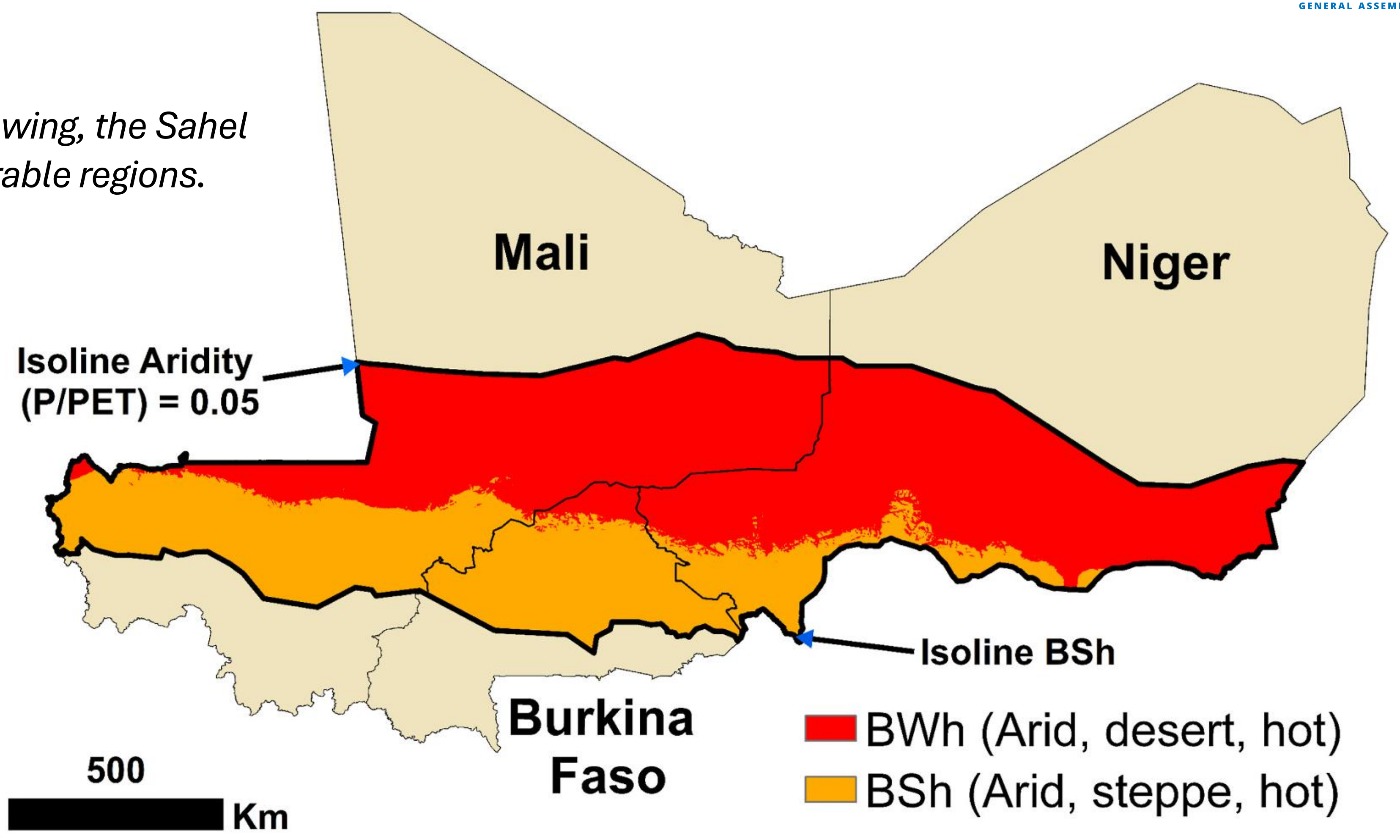
Background

Arid to semi-arid, rain-fed, and rapidly growing, the Sahel is one of the world's most water-vulnerable regions.

Climate

- Rainfall from < 100 mm/yr (northern Mali, Niger) to 1,200 mm/yr (southern Burkina Faso)
- Wet season : 2 to 5 months
- Warming projected up to +3°C by 2050, +4.3°C by 2080, with increasing drought frequency



Water and agriculture

- Agriculture is largely rain-fed, highly sensitive to rainfall variability
- Limited irrigation infrastructure
- Surface water bodies subject to high evaporation losses, which cannot sustain agriculture

People and pressure

- Population projected to increase by ~140 million by 2045
- Population is rural, depending on natural water sources

Background

Where rivers sleep: **Ephemeral Sand Rivers (ESRs)** as a strategic water resource

Shashane River, Zimbabwe

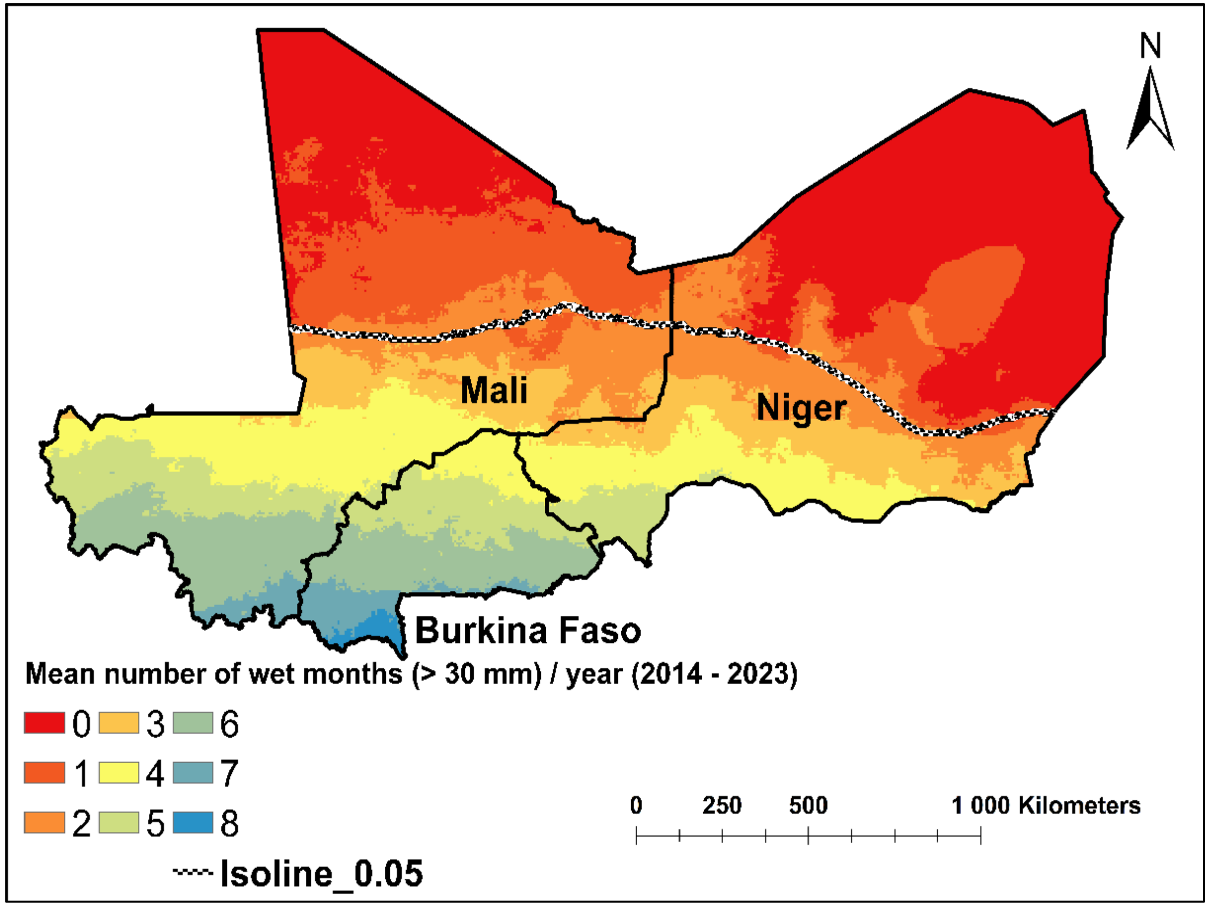
The knowledge gap

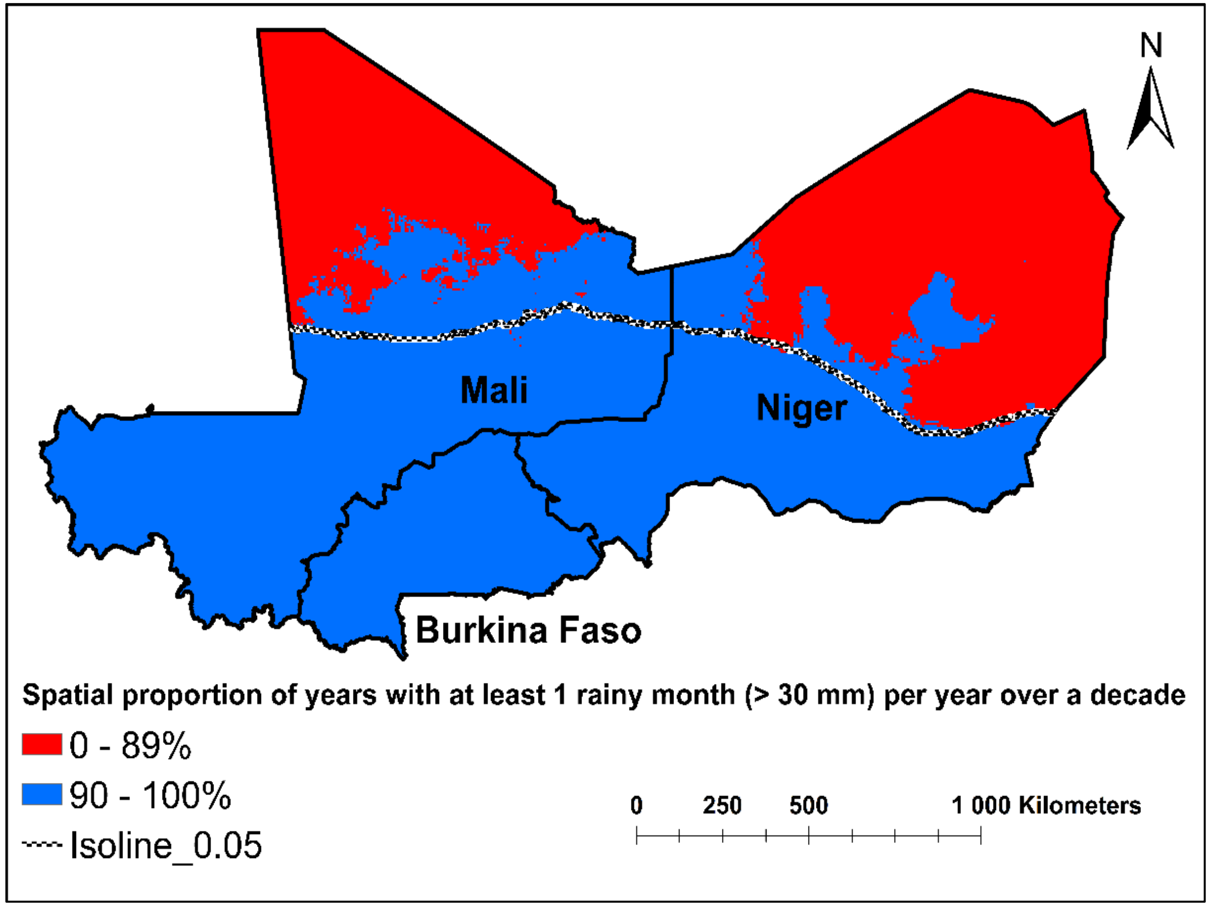
- ❑ Well studied in East and Southern Africa (Zimbabwe, Kenya, Mozambique...)
- ❑ In the West African Sahel: poorly documented, unmapped at regional scale - **No inventory exists!**
- ❑ Remote sensing and machine learning now offer a path forward

Image taken from : A4Store Project - https://sandrivers.org/

Methodology

Step 1-2: Identifying ephemeral rivers from hydrology





Mean number of wet months (> 30 mm) per year over the 2014-2024 decade / CHIRPS rainfall

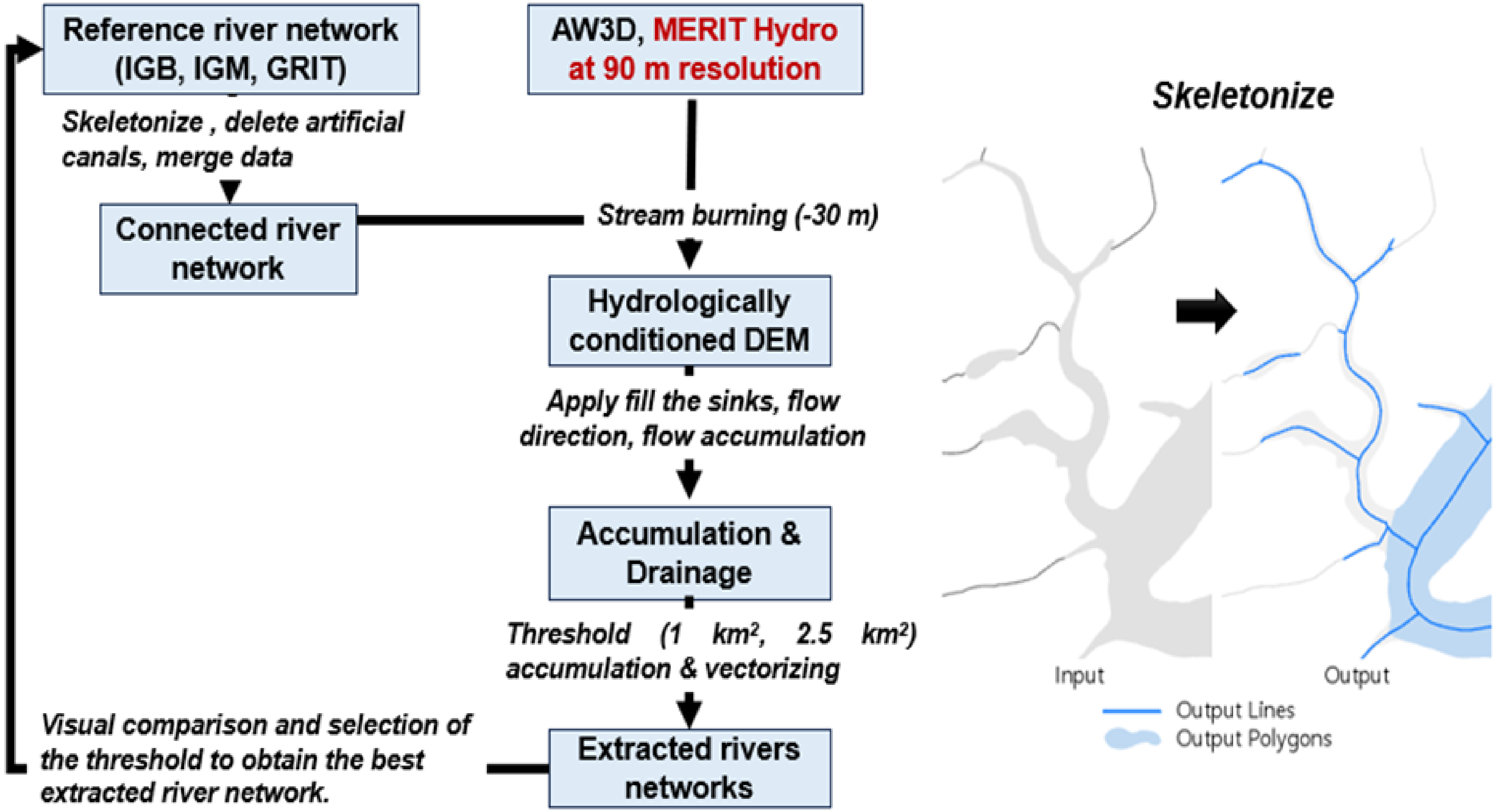
Proportion of years with at least 1 rainy month (> 30 mm) per year over the 2014-2024 decade / CHIRPS rainfall

Methodology

Step 1-2: Identifying ephemeral rivers from hydrology

- ❑ We start by reconstructing a consistent river network using national datasets combined with the **MERIT DEM (90 m)** and **stream burning** techniques.

- ❑ Reference river datasets:
  - ❑ **BF** ~ digitized from RapidEye (5m) imagery
  - ❑ **Mali** ~ digitized from SPOT 6 (1.5m) imagery
  - ❑ **Niger** ~ merging Landsat River Mask (GWRL) FABDEM (30m)



Flowchart of the river network delineation

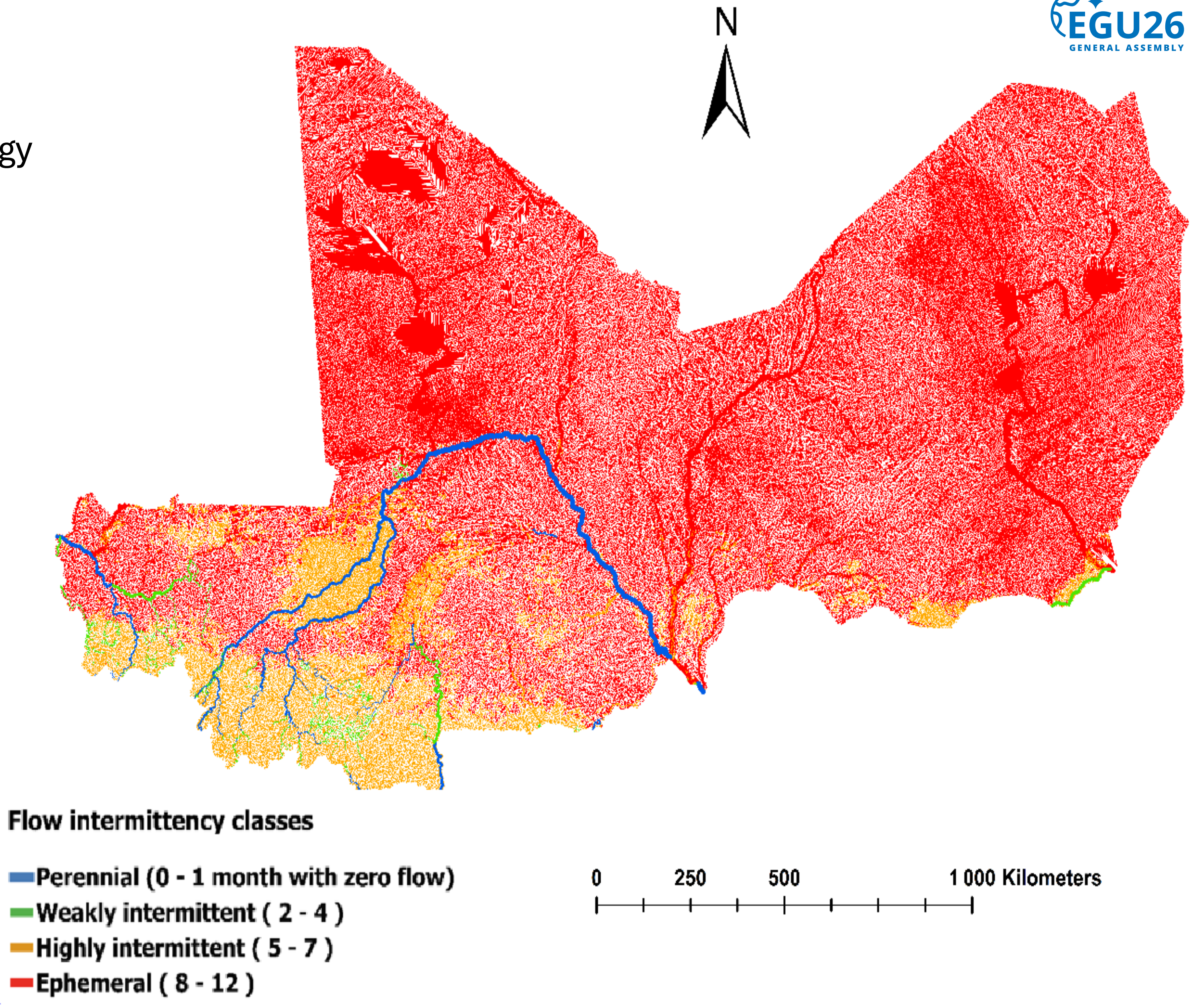
Methodology

Step 1-2: Identifying ephemeral rivers from hydrology

- We classify river flow regimes using a RF model trained on **~1,200 gauging stations** in Africa (Belemtougri et al. 2021, …)[1,2].

- The RF model uses **topography** (Area, slope, Elevation, TCI), **climate** (PET, Aridity, Temp.), **geology** (groundwater storage, permeability), **anthropogenic influence** (dam storage, human footprint) variables to predict river intermittency

- This allows us to map **four levels of intermittency** based on the number of zero-flow months ($\overline{N_{dry}}$): **perennial** (0-1, 70%), **weakly intermittent** (2-4, 13%), **highly intermittent** (5-7, 12%) and **ephemeral** (8-12, 5%)



Mapped flow intermittency classes

[1] *Belemtougri et al. 2021 (JoH:RS) - https://doi.org/10.1016/j.ejrh.2021.100908*
[2] *Belemtougri et al. Under Review (WRR)*

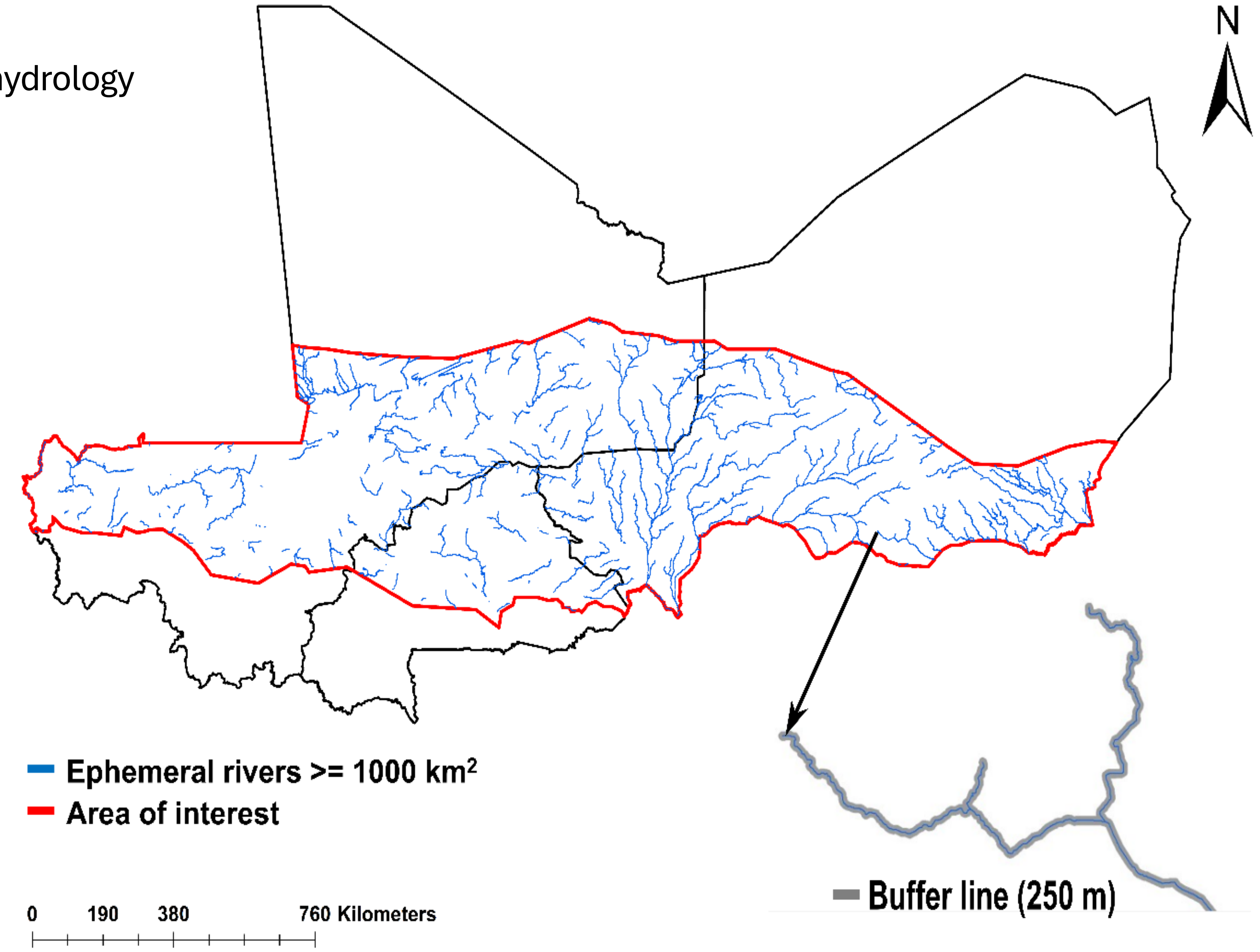
Methodology

Step 1-2: Identifying ephemeral rivers from hydrology

- We restrict the analysis to **rivers draining at least 1000 km^2** to focus on hydrologically significant systems with sufficient water storage potential for sustainable use.

- This also ensures that we are avoiding small streams where water use conflicts may arise.

- We also define a **buffer width of 500 m** width (centered around the extracted rivers centerline) to capture the rivers channel width.



Selected ephemeral rivers

Methodology

Step 3-4: Satellite data and spectral detection of sandy riverbeds

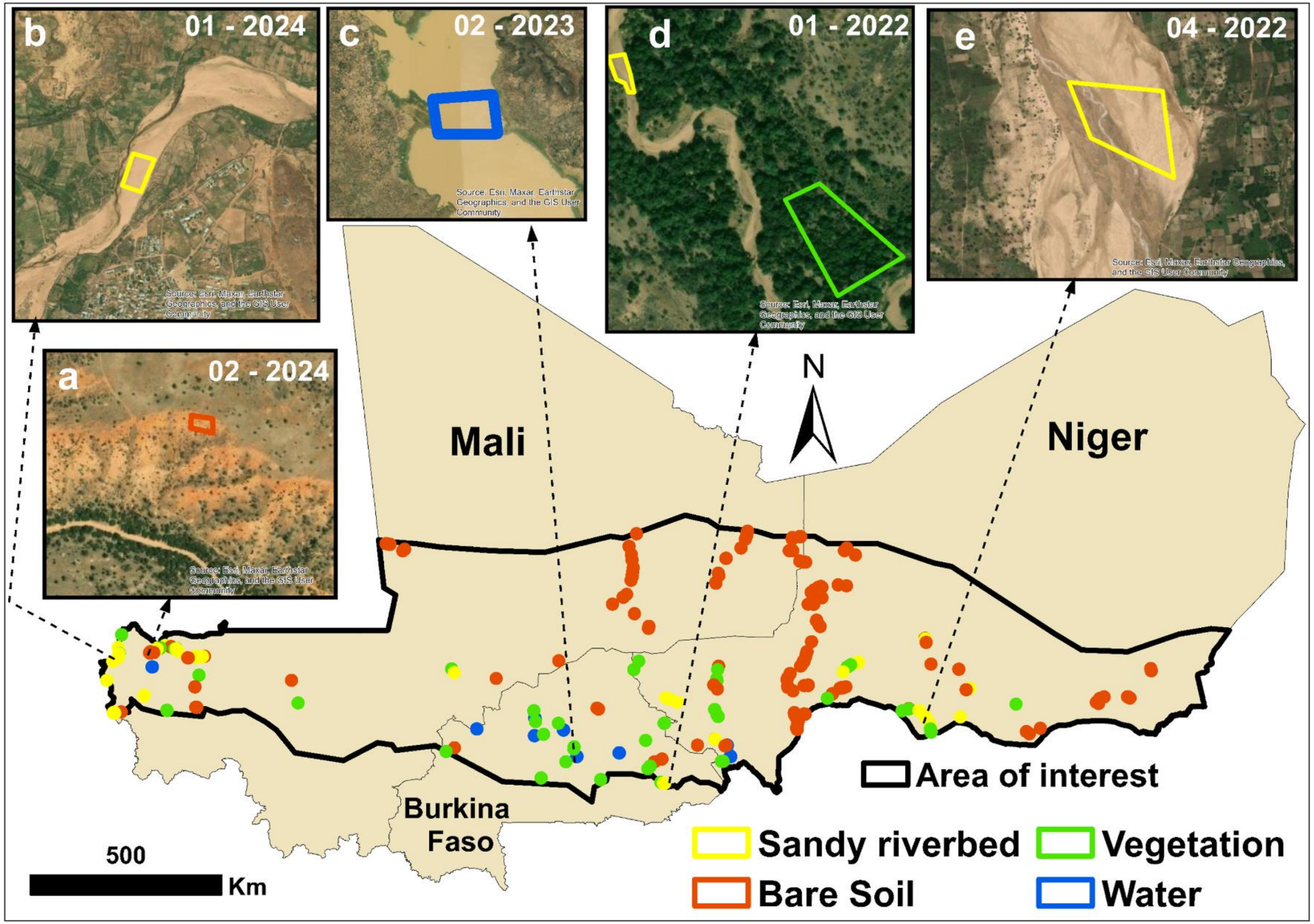
- We build a multi-temporal median cloud composites of Sentinel-2 (10 m resolution) satellite images over the period 2020-2024:
  - **Dry period** (Feb-May)
  - **Wet period** (Jun-Sep)
  - **Transition period** (Oct-Jan)
- We tested a **spectral detection approach** based on various spectral indices (NDESI, NSI, NDSI)
- We coupled the best result overall to **NDVI** to separate vegetation and reduce confusion with water

Spectral indices definition	Formulas	Range/Sand threshold values	References
Normalized Difference Enhanced Sand Index (NDESI)	$NDESI = \frac{Red - Blue}{Red + Blue} - \frac{SWIR2 - SWIR1}{SWIR2 - SWIR1}$ (1)	[-2; 2]/> 0.24	(Marzouki and Dridri, 2022)
Normalized Sand Index (NSI)	$NSI = \frac{Green + Red}{\log(SWIR1)}$ (2)	]-∞; 1]	Secu et al. (2022)
Normalized Difference Sand Index (NDSI)	$NDSI = \frac{Red - Coastal\ aerosol}{Red + Coastal\ aerosol}$ (3)	[-1; 1]	Pan et al. (2018)

Methodology

Step 5: ML classification of ESRs

- We set up a **RF classifier**, trained on 90,000 training samples on the multi-temporal image datacube, across four classes: **sandy riverbed**, **bare soil**, **vegetation**, **water**
- We first map the **water** class (using MNDWI thresholding), then mask it and further map the remaining classes using the RF classifier (57,157 samples)
- The **performance** of the classification was assessed using **overall accuracy** and per-class **F1-score**



Selection of training sites for LULC classification

Methodology

Step 6: Identifying shallow groundwater potential

Identify Shallow Groundwater Potential

Recognize sandy riverbeds as potential groundwater sources

Use Riparian Vegetation as Proxy

Employ vegetation as an indicator of groundwater presence

Extract Vegetation from LULC

Obtain vegetation data from land cover classification

Retain Dense Vegetation Patches

Filter vegetation data to keep only consistent patches

Apply Canopy Height Threshold

Ensure vegetation canopy height is at least 5 meters

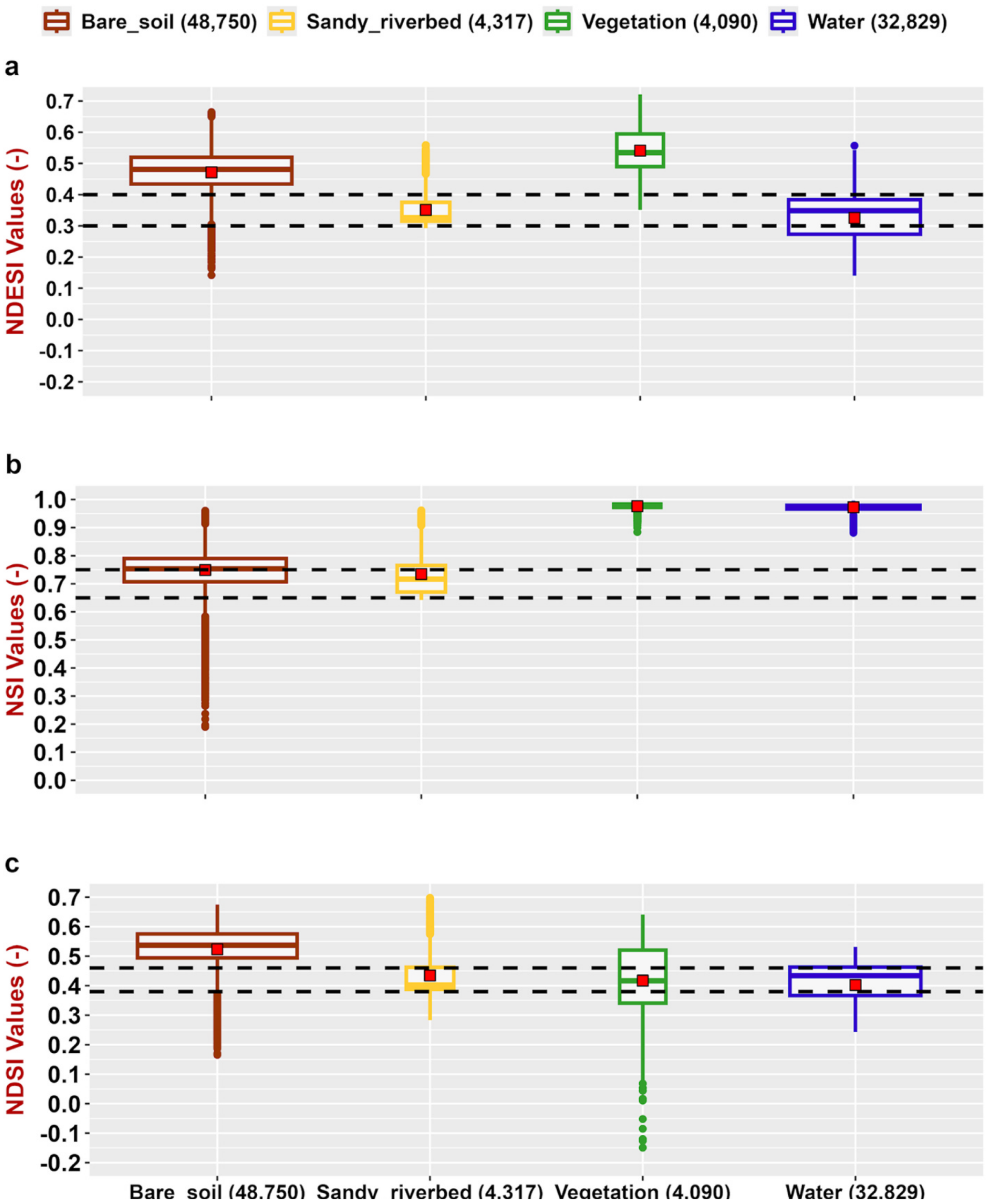
Assess Accessibility for Populations

Evaluate population access within a 5 km radius

Results

Mapping ESRs using spectral indices

- ❑ This figure compares the distribution of three spectral indices across training samples.
- ❑ **NDESI** shows the clearest separation of sandy riverbeds, with most values concentrated in a distinct range, while limiting overlap with vegetation and, to a lesser extent, bare soil.
- ❑ In contrast, **NSI** exhibits strong overlap with bare soil, and **NDSI** shows considerable confusion with both vegetation and water.
- ❑ We conclude that **NDESI** provides the **best discrimination of sandy riverbeds** in this context.



Results

Mapping ESRs using spectral indices

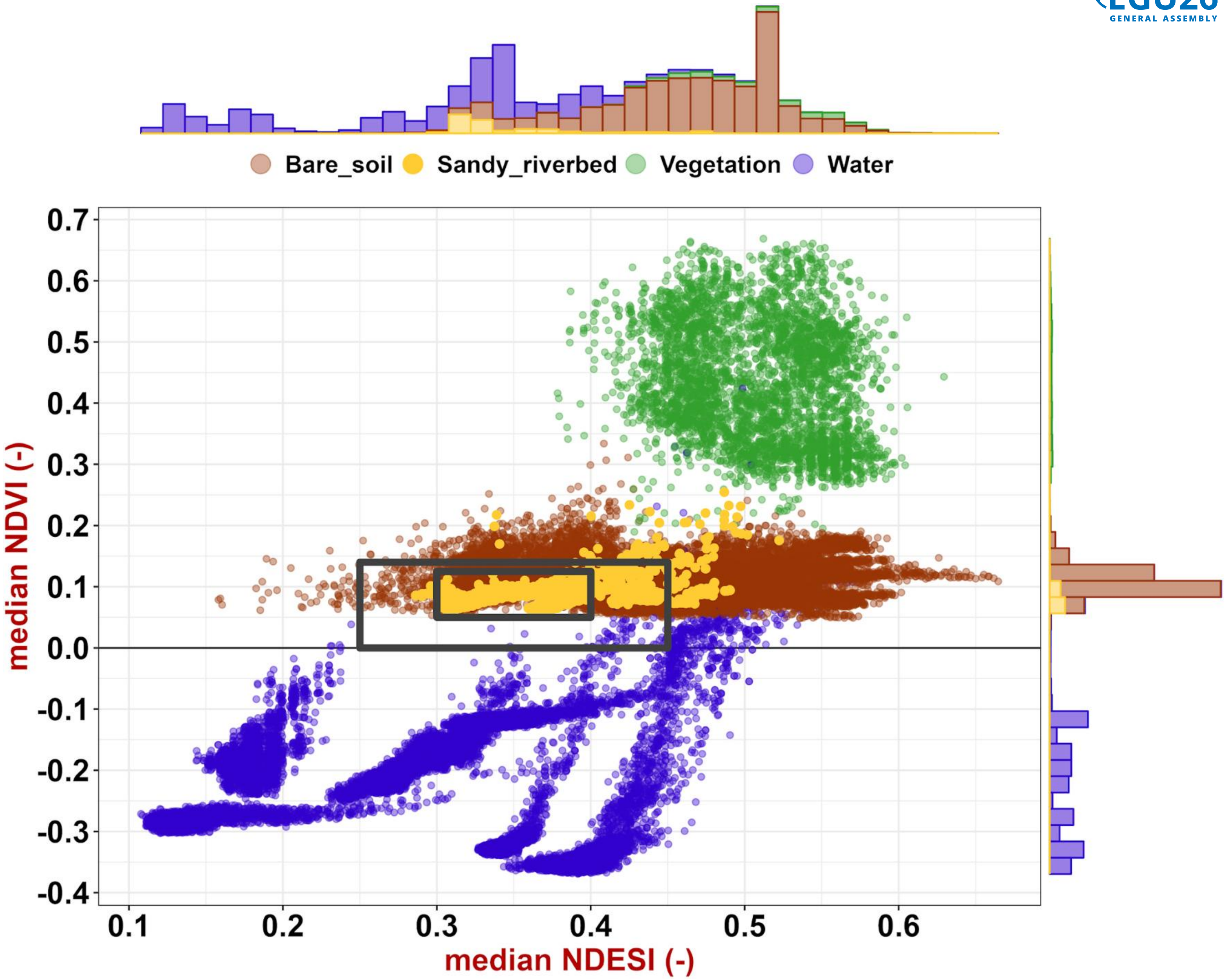
- ❑ **NDESI + NDVI** improves class separation. However, confusion between **sandy riverbed** and **bare soil** remains.

- ❑ Two thresholds were defined:
  - ❑ **CT1**: restrictive, high precision

$$\begin{cases} 0.30 \leq NDESI \leq 0.40 \\ 0.05 \leq NDVI \leq 0.125 \end{cases}$$

  - ❑ **CT2**: extended, higher detection of sandy riverbeds but more false positives)

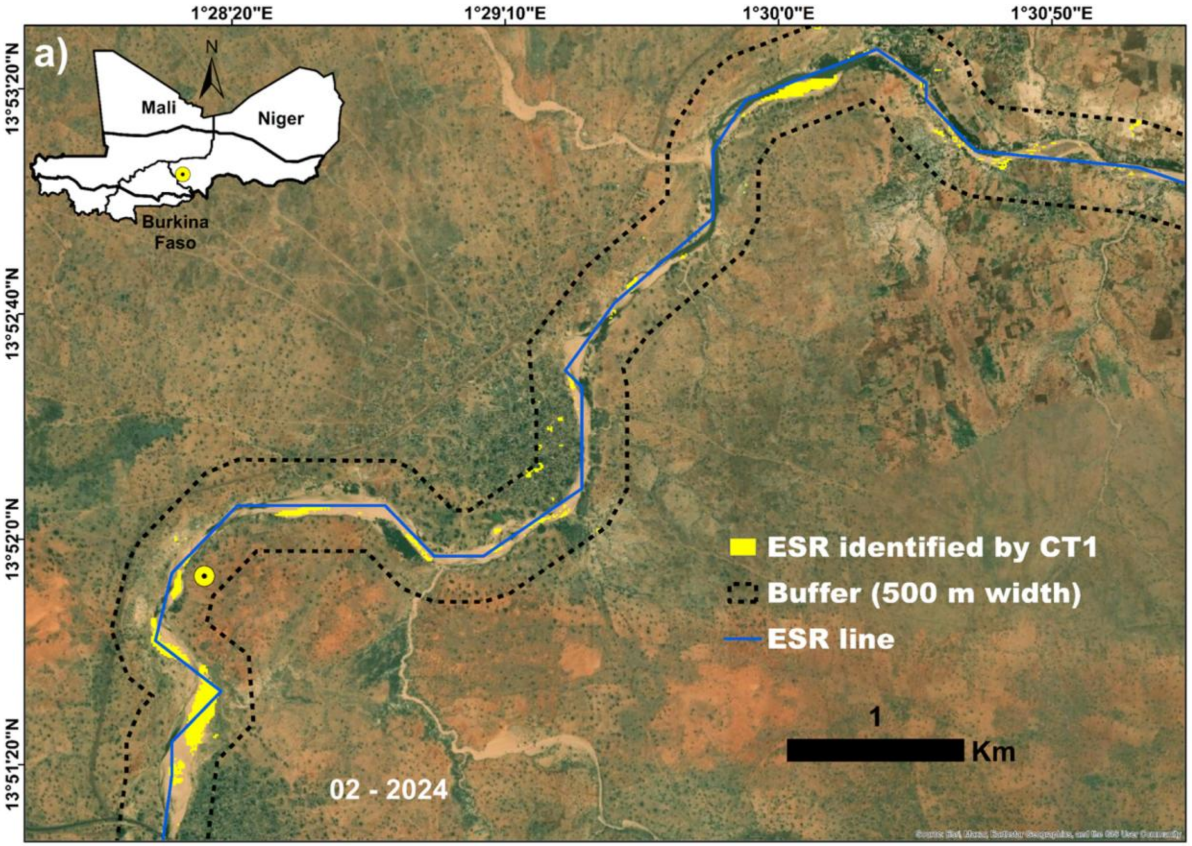
$$\begin{cases} 0.25 \leq NDESI \leq 0.45 \\ 0.00 \leq NDVI \leq 0.14 \end{cases}$$

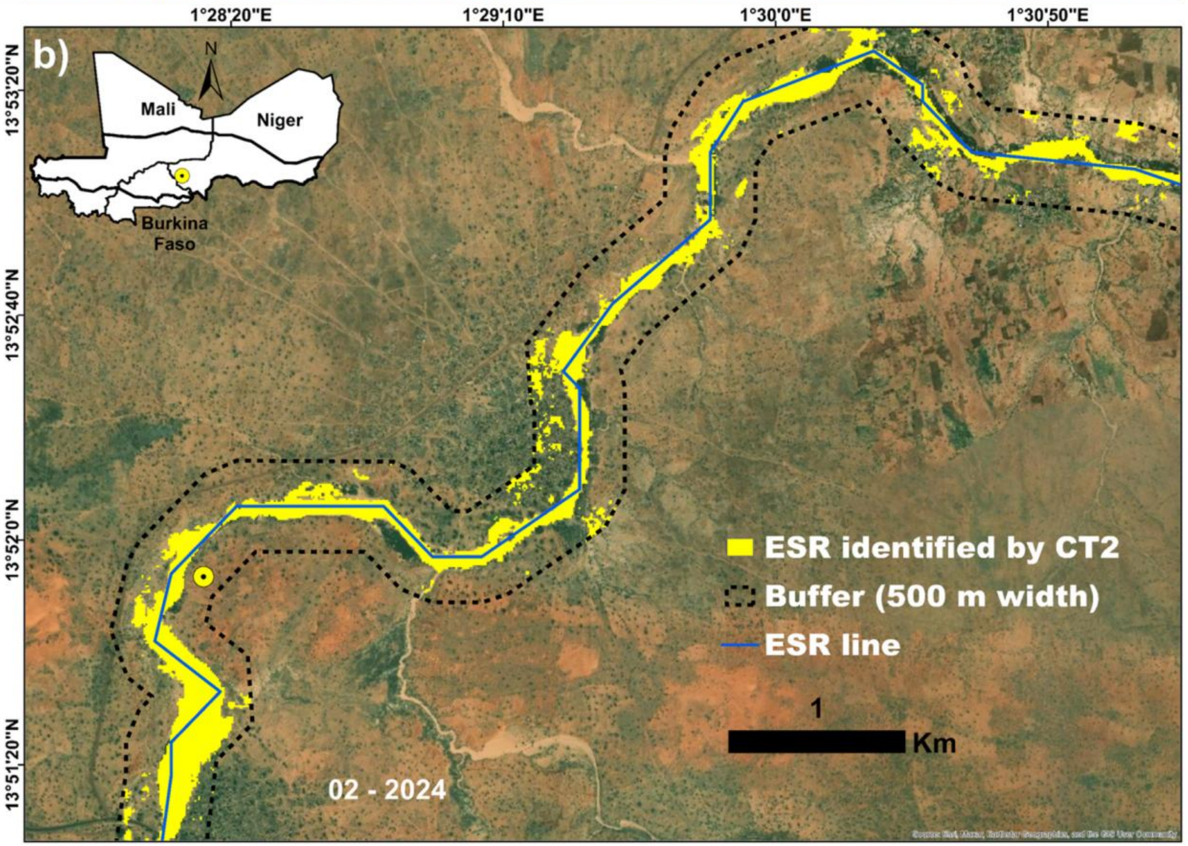


Results

Mapping ESRs using spectral indices

Selected study site in Niger





CT1: **Under-detection,** large portions of the sandy riverbed are missed (**high false negatives**).

CT2: **Over-detection**, many non-river areas are incorrectly classified as sand (**high false positives**).

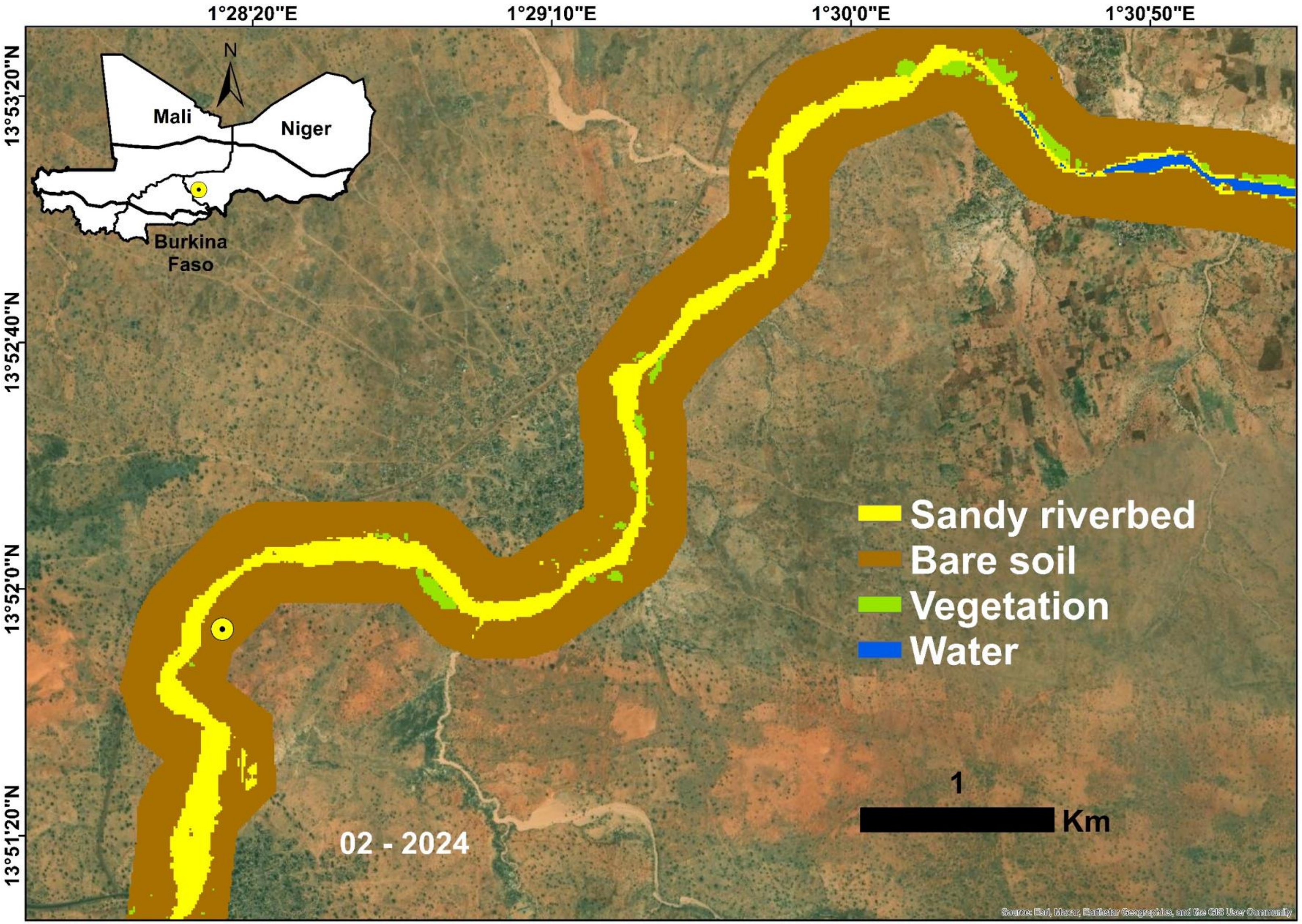
Results

Mapping ESRs using RF LULC classification

- ❑ The **multi-temporal RF LULC classification** provides a much more accurate and spatially consistent delineation of sandy riverbeds, significantly reducing both omissions and false detections.

- ❑ **Overall accuracy: 92%**
- ❑ **F1-scores : sandy riverbed** (**0.90**), **bare soil** (**0.86**), **vegetation** (**0.96**), **water** (**0.93**)

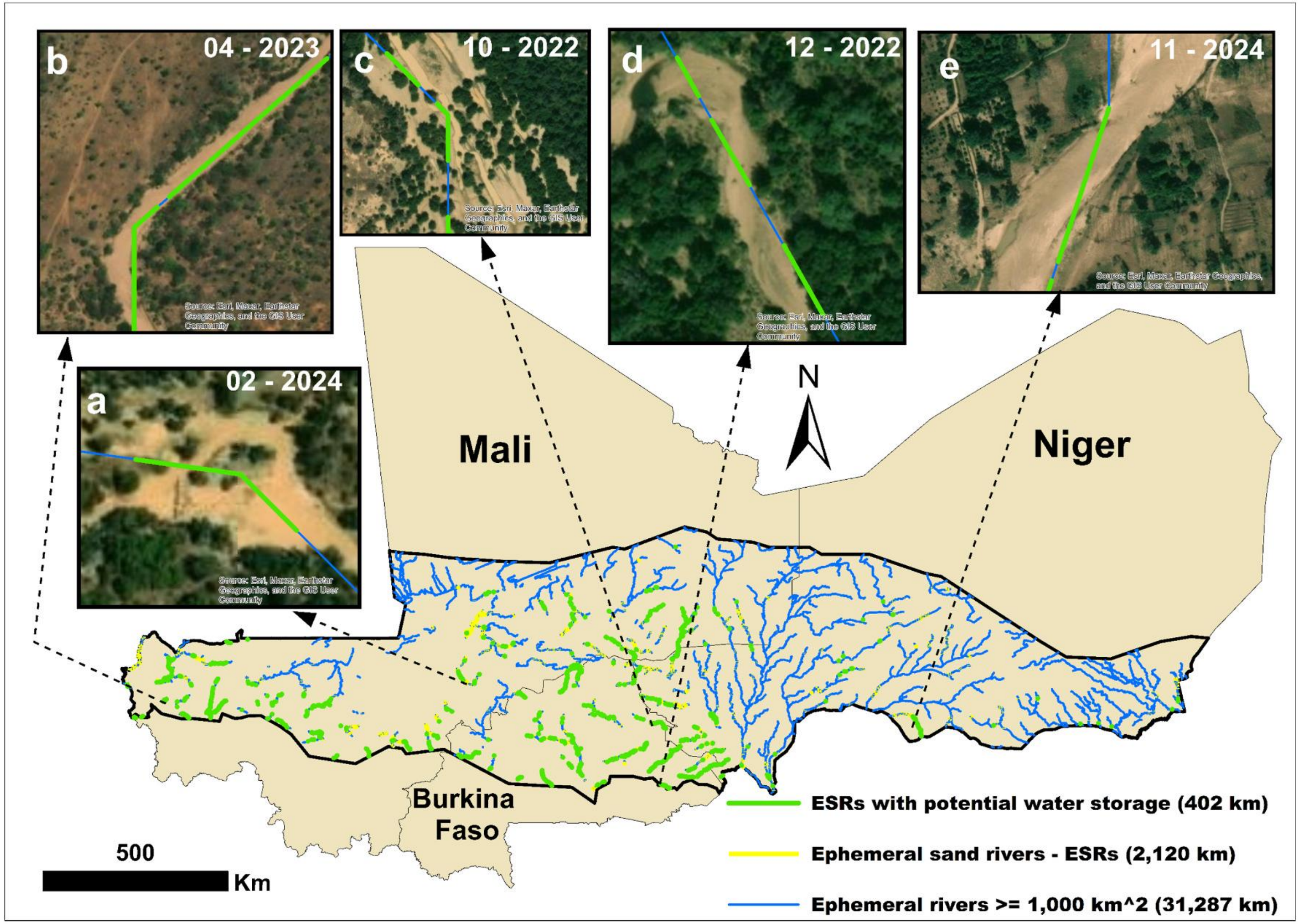
Selected study site in Niger



Results

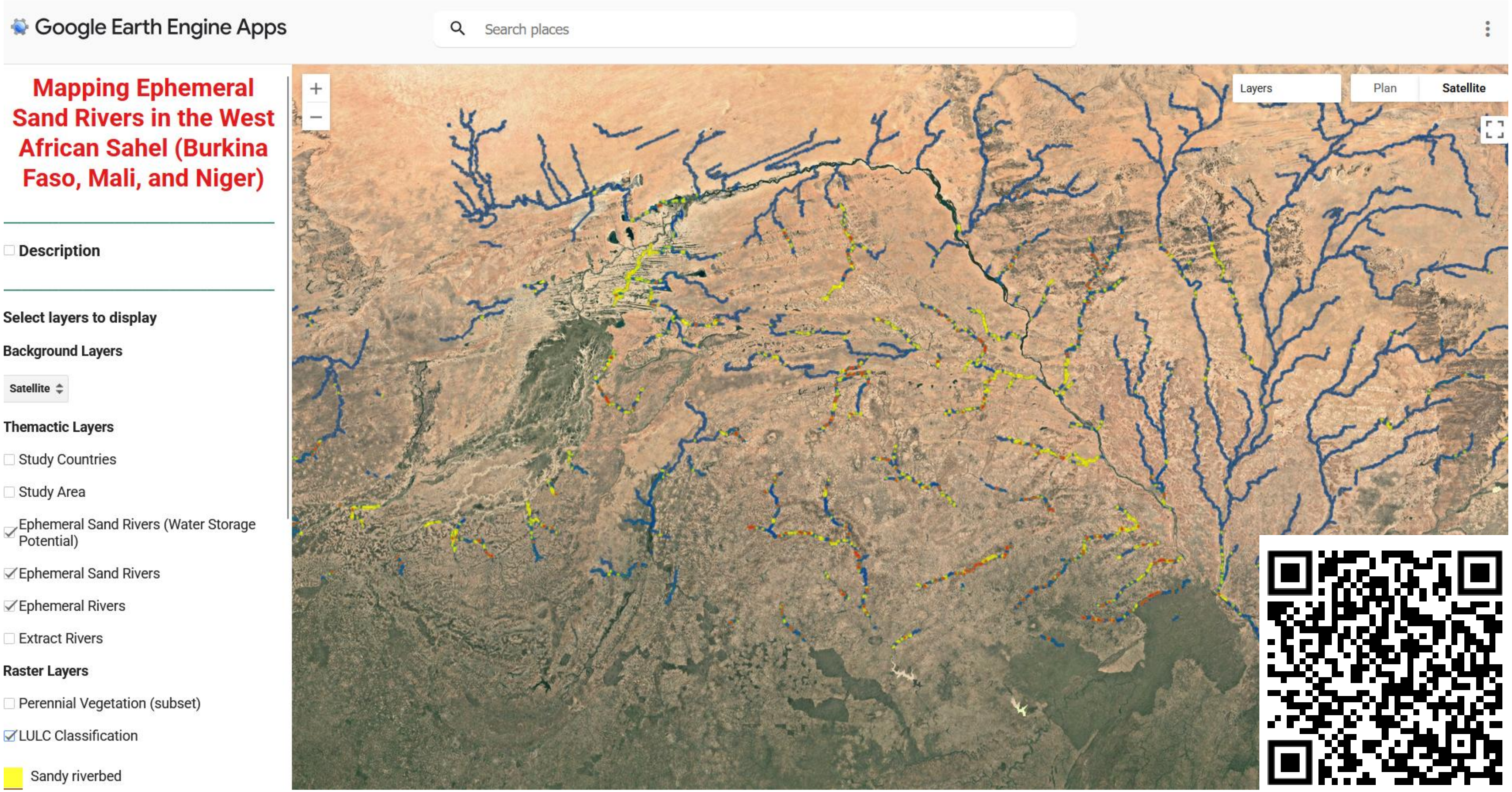
Mapping ESRs with water storage potential

- ❑ Ephemeral rivers are widespread across the Sahel, forming an extensive network over Burkina Faso, Mali, and Niger.
- ❑ **2,120 km are identified as ESRs**, with **402 km showing potential shallow groundwater storage**.
- ❑ These segments are spatially clustered and often located near populated areas, highlighting their relevance for water resource development.



Results

A GEE App to browse our findings



https://axelbelemtougri.users.earthengine.app/view/a4store-sand-rivers-project

Conclusions and Future Work

Conclusions

- ❑ Combining hydrology, remote sensing, and machine learning can help mapping reliably ESRs at regional scale.
- ❑ Multi-temporal RF classification significantly improves detection over spectral methods.
- ❑ 402 km of rivers show potential shallow groundwater storage.

Future work

- ❑ Field validation of groundwater presence and storage capacity.
- ❑ Quantification of extractable water volumes.
- ❑ Integration with socio-economic and irrigation planning.
- ❑ Development of decision-support tools for local stakeholders.

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Where rivers sleep: mapping ephemeral sand rivers in the West African Sahel

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Thank You!