Yale 耶鲁大学-南京信息工程大学大气环境中心

Yale-NUIST Center on Atmospheric Environment

NATURE | LETTER

High-resolution mapping of global surface water and its long-term changes

Jean-François Pekel, Andrew Cottam, Noel Gorelick & Alan S. Belward

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Reporter： Wang Yi

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Outline

- Introduction
- Meterial&Methods
- Thematic products
- Problems and prospects

➢ Introduction

- Surface water is only a part of the water resource. The location and persistence of surface water (inland and coastal) is both affected by climate and human activity, but the presence of water also influences the climate system. It is the most accessible to human populations, and provides wide-ranging ecosystem services.

- This analysis applies a consistent algorithm to all 32 years of the Landsat observations to produce a validated data set that documents global surface water dynamics with new levels of spatial detail and accuracy.

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➢ Meterial&Methods

1. Data

- Time period: from 16 March 1984 to 10 October 2015
- Data sources: the entire archive of the Landsat 5 Thematic Mapper (TM), the Landsat 7 Enhanced Thematic Mapper-plus (ETM+) and the Landsat 8 Operational Land Imager (OLI)
- produces orthorectified, top-of-atmosphere (L1T) reflectance and brightness temperature images
- At the time of this study 3,066,080 L1T images (1,823 terabytes of data) covered 99.95% of the landmass.

2. Water detection

a. Impact factor and challenge

- Water is a highly variable target
- Chlorophyll concentration; coloured dissolved organic matter; water-body bottom material for shallow waters; variations in observation conditions (sun-targetsensor geometry, and optical thickness)
- Separating water from other surfaces on the global scale, over multiple decades is a non-trivial challenge

✓ To address the challenge outlined above, techniques for big data exploration were exploited, namely expert systems, visual analytics and evidential reasoning

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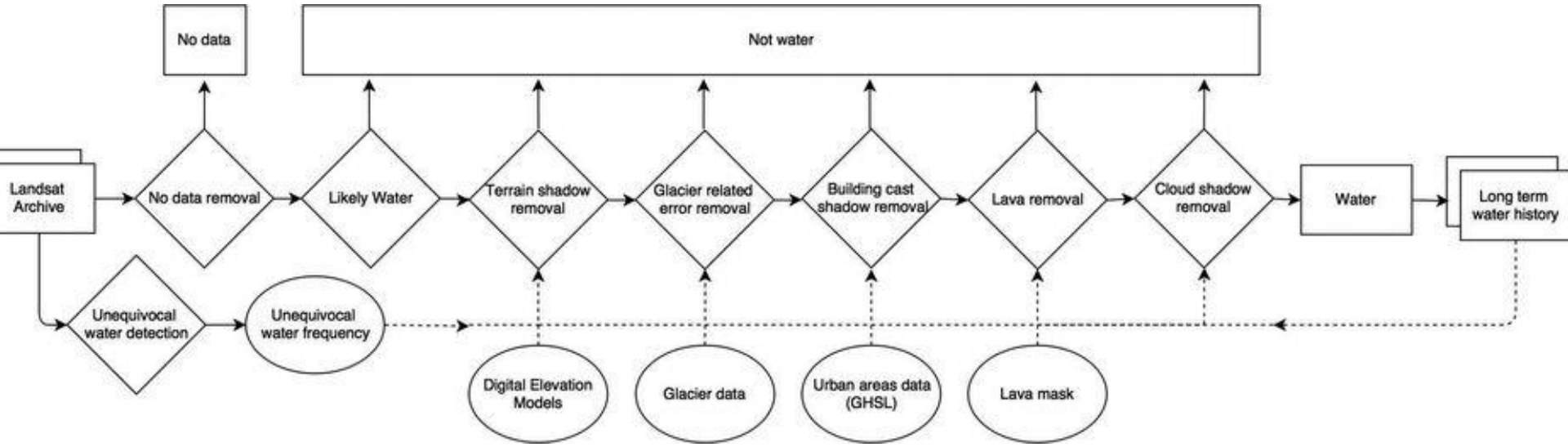
b. Expert systems: non-parametric classifiers; incorporate image interpretation expertise into the classification process

- ✓ three target classes: water, land or non-valid observations (snow, ice, cloud or sensor-related issues). Basis of a procedural sequential decision tree, using cluster analysis, in the form of rules having the form: IF condition THEN inference.



- The equations describing the cluster hulls used in the expert system were established through visual analytics.

The first step was to build a spectral library across as wide a range of conditions as possible.

- 64,254 samples obtained to record spectral variability of the target classes.
- The NDVI and HSV colour-space transformations for band combinations have enriched the records.
- The NDVI and HSV have been successfully used for surface water detection at continental scales.

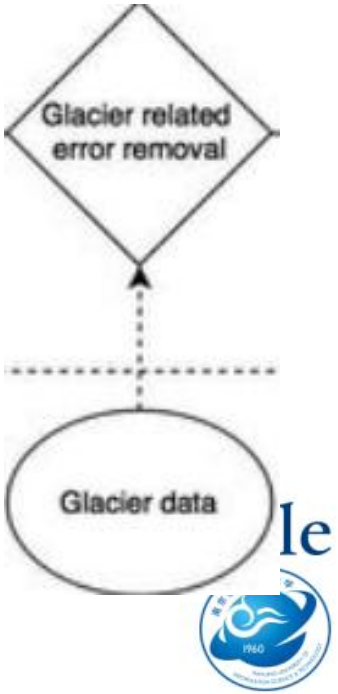
The second step is equations describing the cluster hulls used in the expert system were established through visual analytics.

However, not all pixels could be unambiguously assigned to one or other of the target classes. In these instances evidential reasoning was used to guide class assignment.

c. The spectral characteristic of water is similar to glacier, lava flow and shawdow from whatever source.

Glaciers

- Randolph Glacier Inventory 5.0
- Specific decision rules

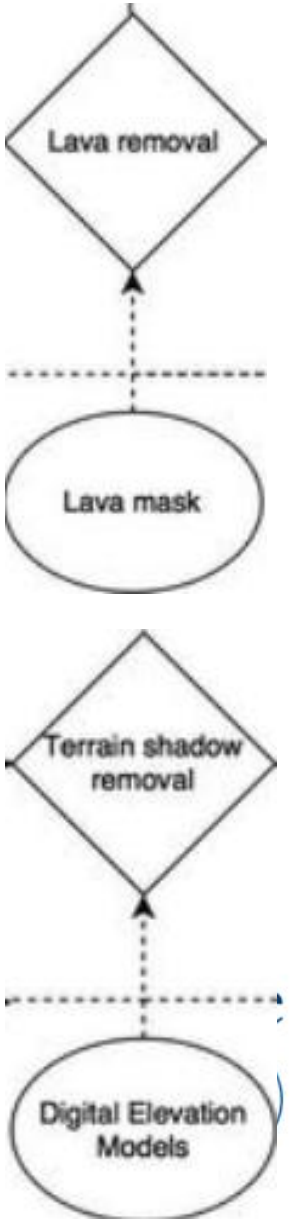


Lava flow

- A global-scale lava mask was established
- Within these boundaries the frequency with which pixels occupied ‘lava overlap-free’ portions of the water cluster were computed.

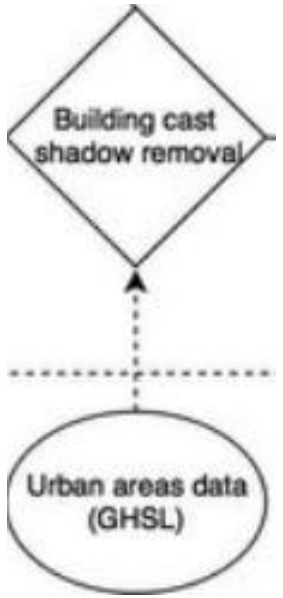
Terrain shadows:

- Using a threshold applied on slopes derived from a DEM



Buildng shadows

- The Global Human Settlement Data Layer
- It are seasonally dependent
- The frequency with which a pixel occupies the unequivocal water hull



Cloud shadows

- It can occur anywhere and anytime
- A temporal sliding window was used across the water history record

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3. Validation

- Using a total of 40,124 control points distributed both geographically (globally), temporally (across the 32 years), and across sensors (TM, ETM+ and OLI).
- Two reference data sets were produced:

  a.27,268 pixels →the estimation of the error of omission

  b.12,856 pixels →the estimation of the error of commission

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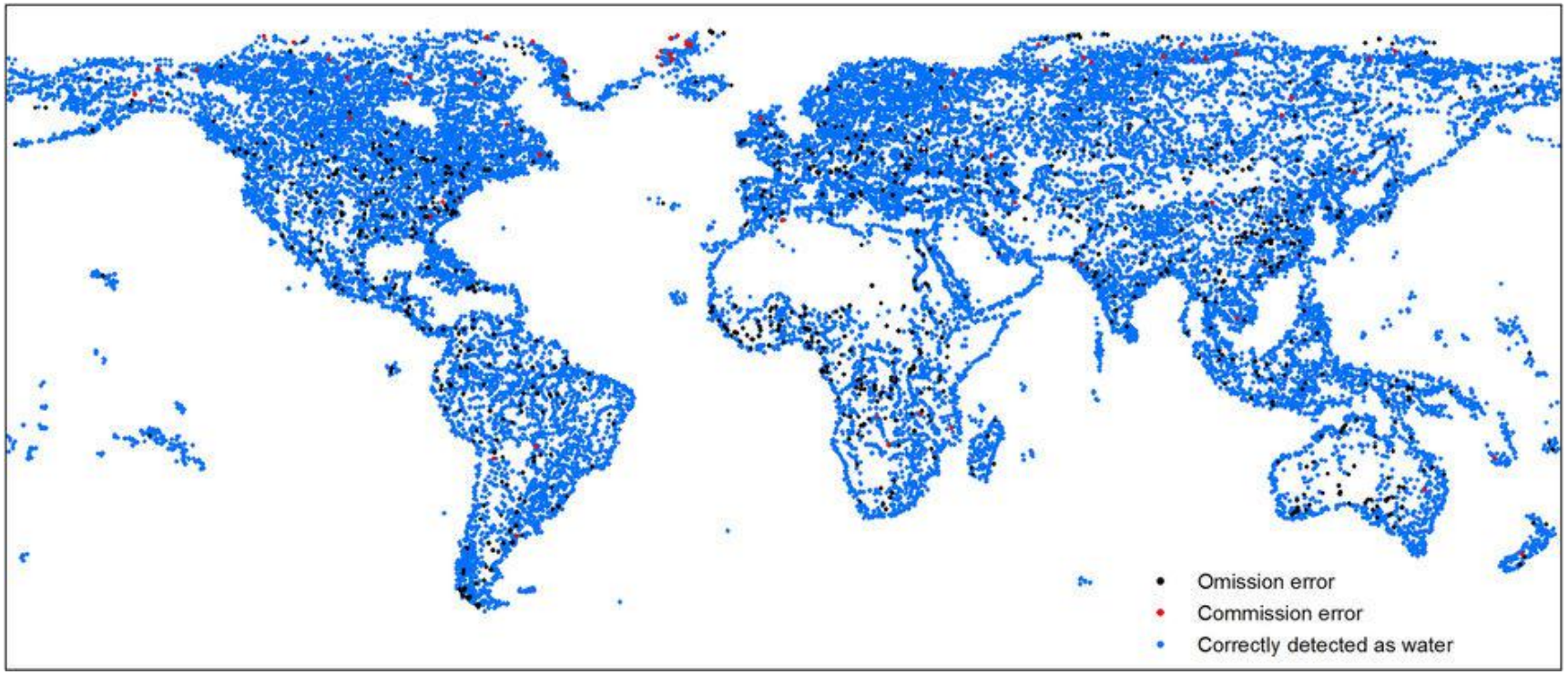
Diagram of the validation protocol



Finally, errors of omission were less than 5% and commission less than 1%.

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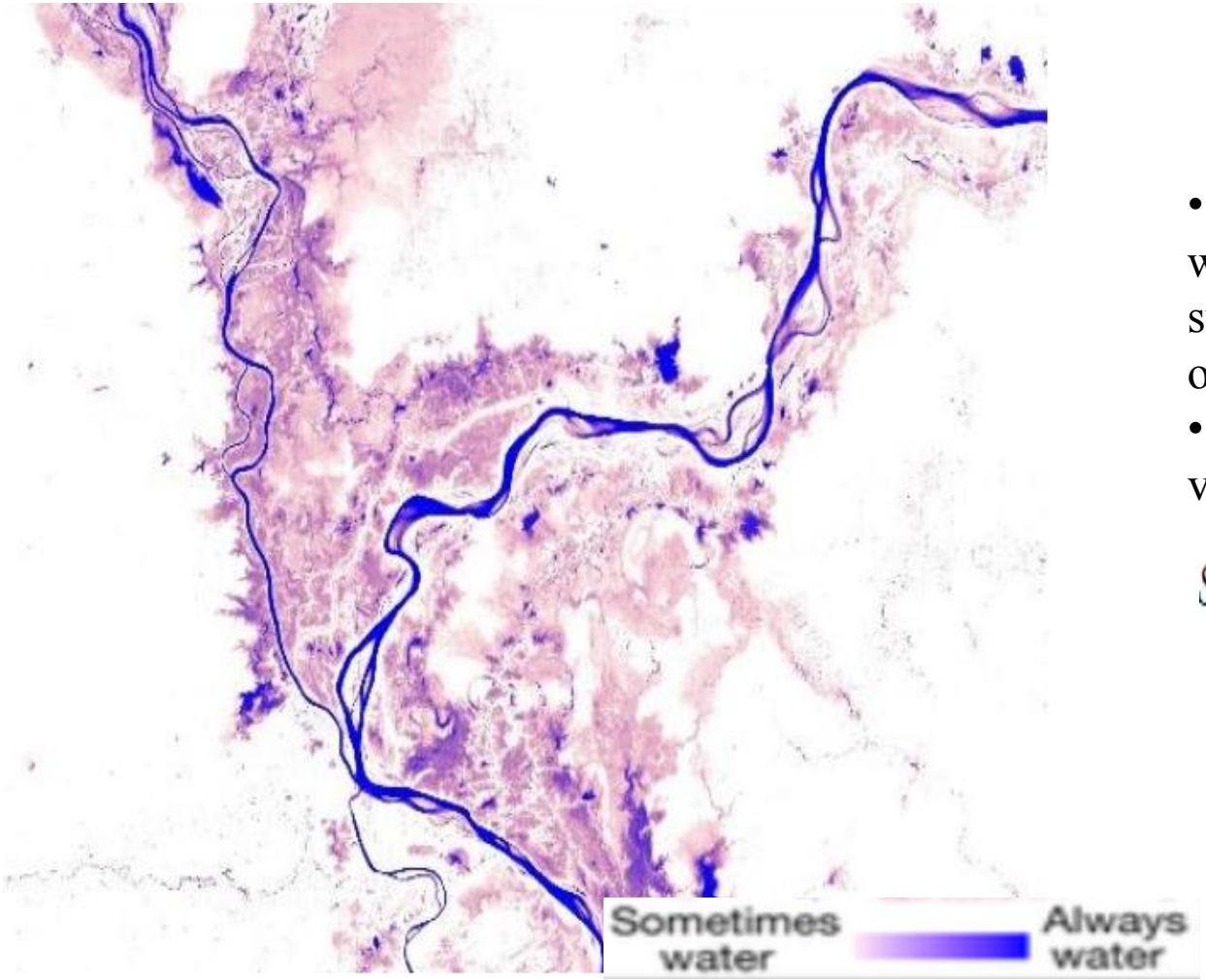
➢ Thematic products

1.surface water occurrence



Northern Bangladesh

- The frequency with which water was present on the surface called surface water occurrence (SWO).
- The water detections (WD); valid observations (VO)

$$SWO^{month} = \Sigma WD^{month} / \Sigma VO^{month}$$

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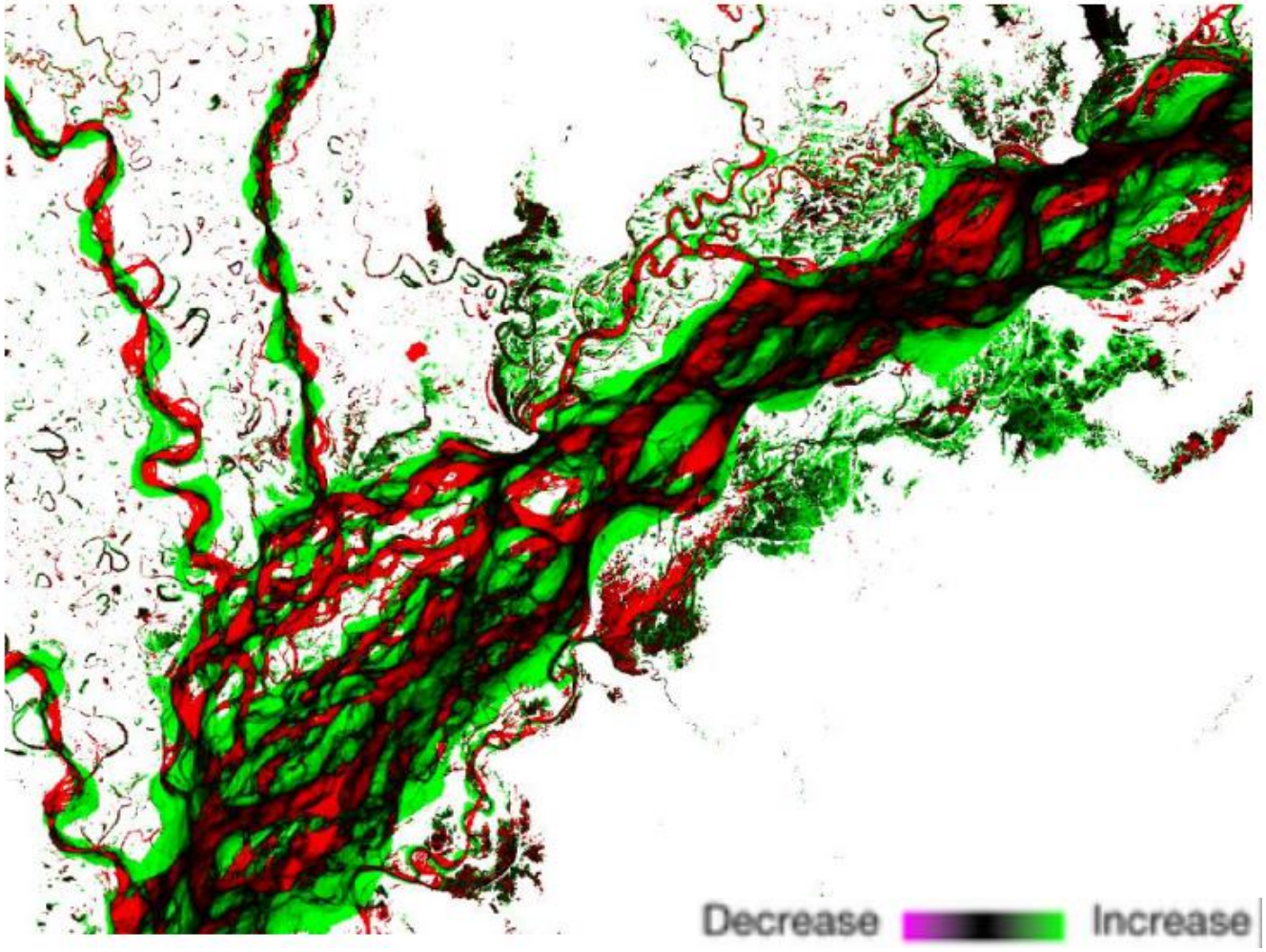
2.surface water occurrence change intensity



- Determine the two periods:

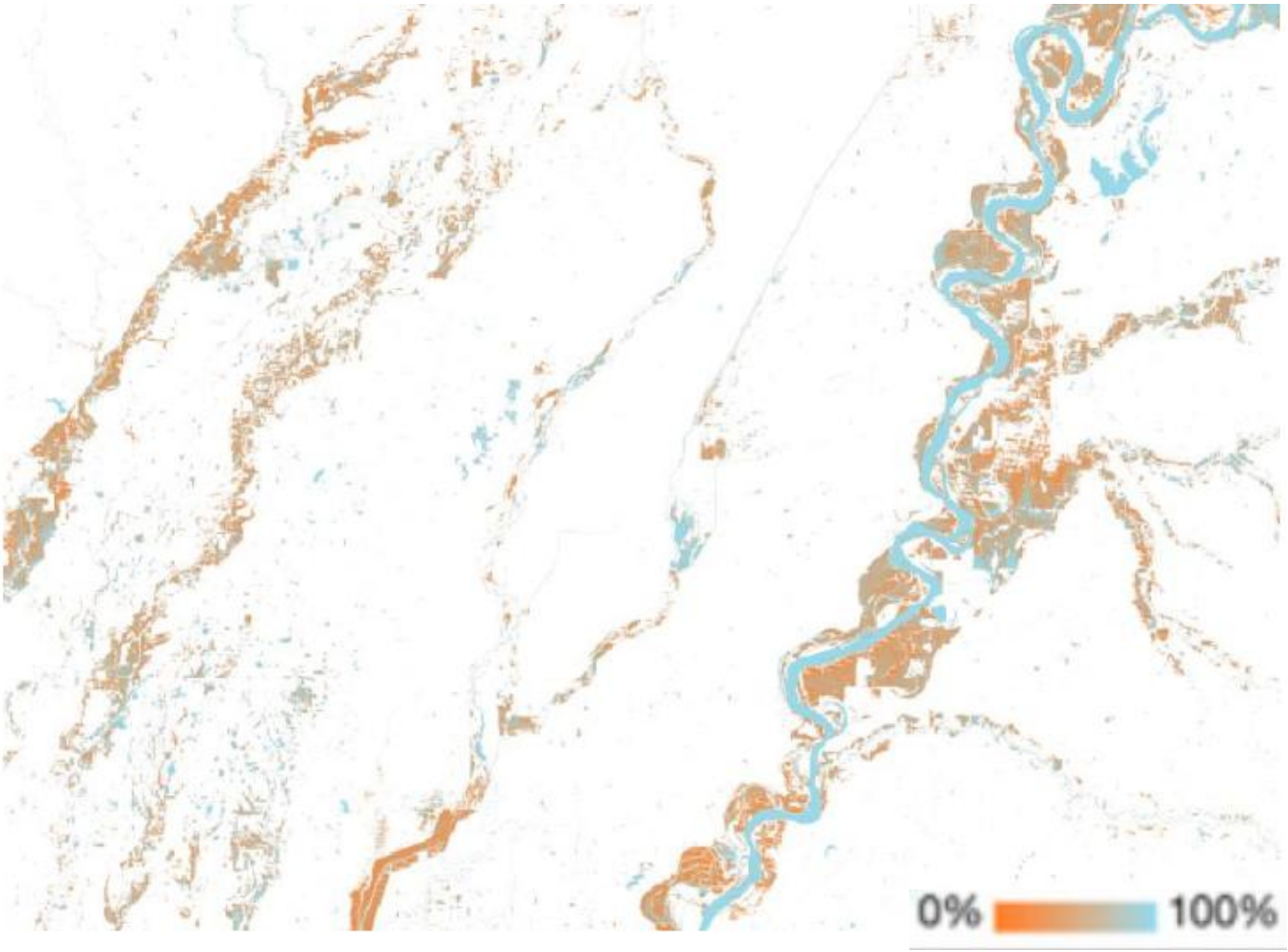
16 March 1984 to 31 December 1999;

1 January 2000 to 10 October 2015

epoch1-epoch2/epoch1+epoch2

Brahmaputra River

3.Surface Water Recurrence

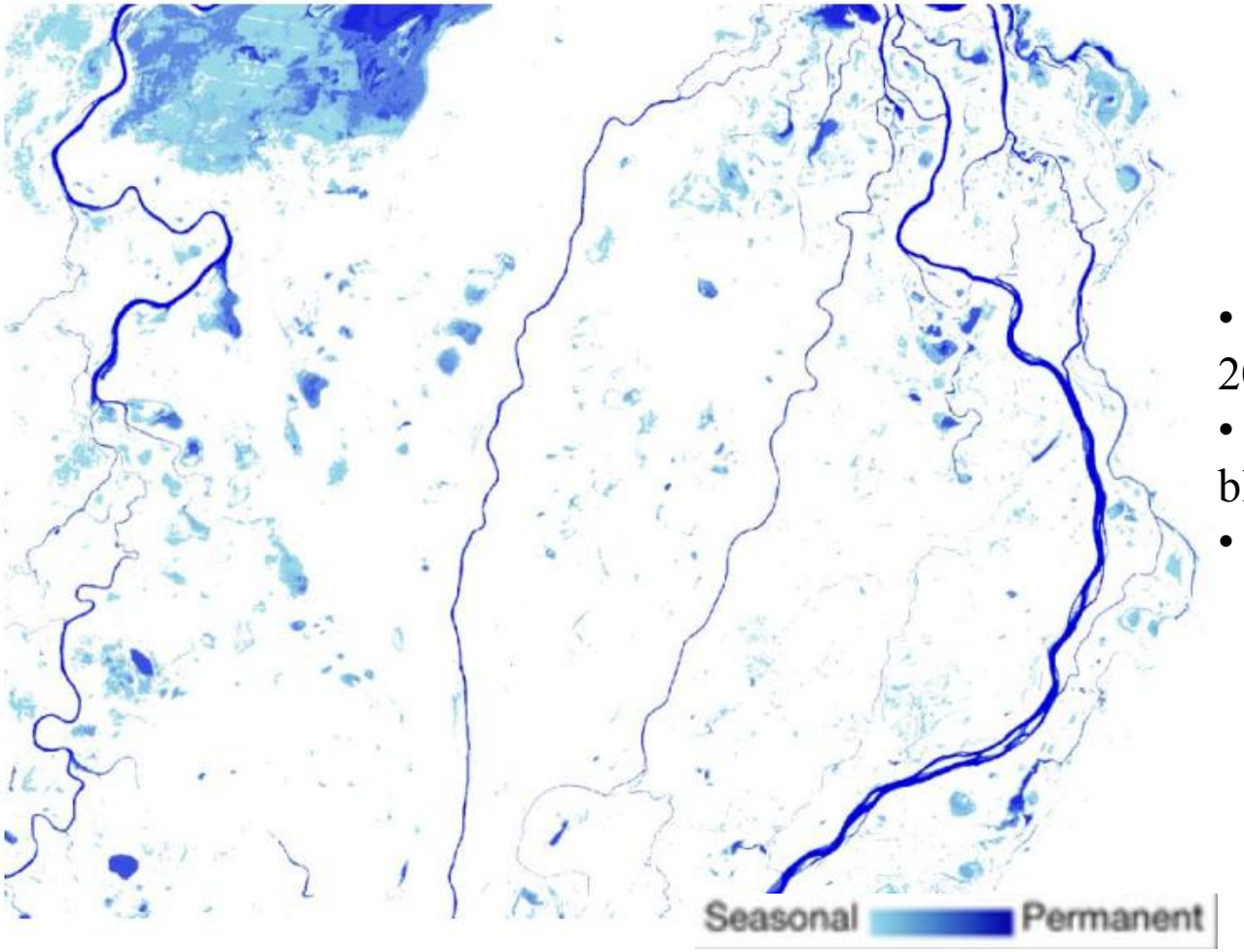


- A ‘water year’
- A‘observation year’

water year/observation year

North-East Arkansas in the USA

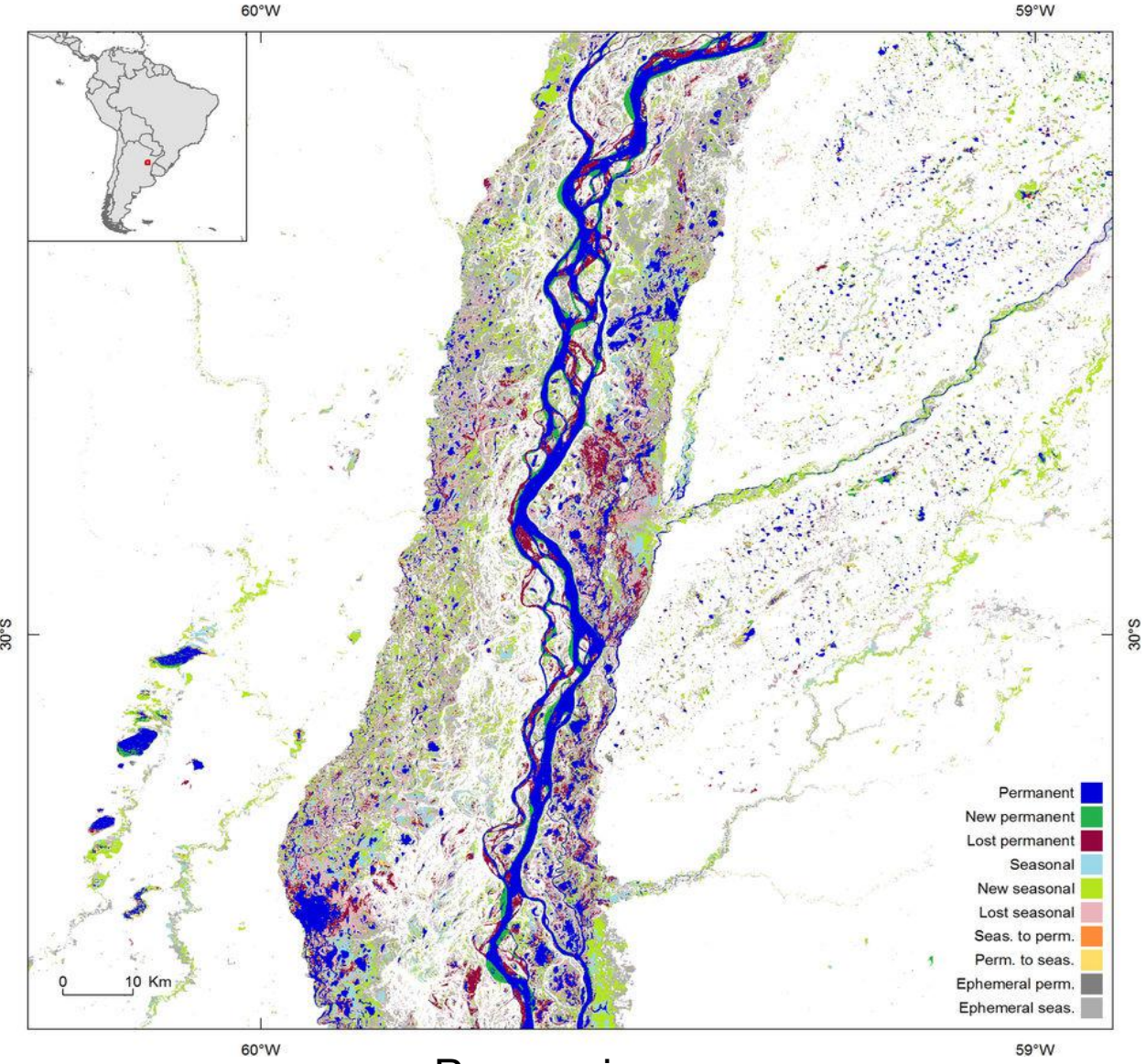
4.surface water seasonality



- October 2014 to October 2015
- ‘permanent’ water→ Navy blue
- 'seasonal’ water→ Light blue

Mopti area of Mali

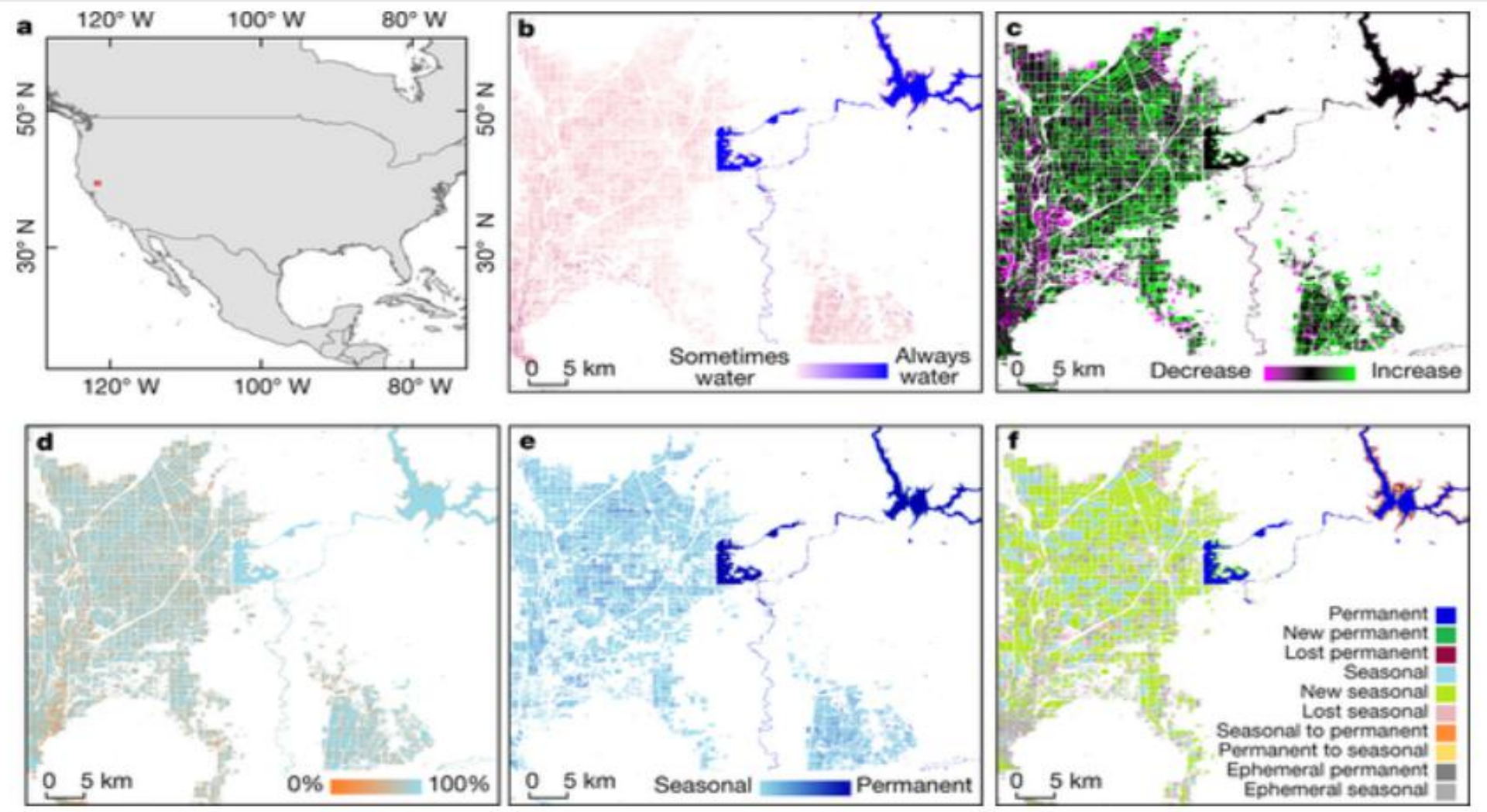
5.transitions in surface water class



Parana river

- Using the longterm water history described by the temporal profiles plus the recurrence and occurrence maps.

the USA Sacramento Valley



Problems and Prospects

Problems:

- The seasonality of the ocean is occasionally wrongly reported as seasonal at high latitudes.
- Roofs, coal and waste heaps an runways are the most common sources of confusion in urban areas.

Prospects:

- Future reanalysis will include the Landsat 4 data and could possibly be extended back to 1972 through the inclusion of data from the Landsat Multi Spectral Scanner (MSS).

https://globalsurfacewater.appspot.com

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