

Detecting, Extracting and Monitoring Surface Water Using Space Technologies

The 4th International Conference on the Use of Space Technology for Water Management
Islamabad, Pakistan, 27 February 2018

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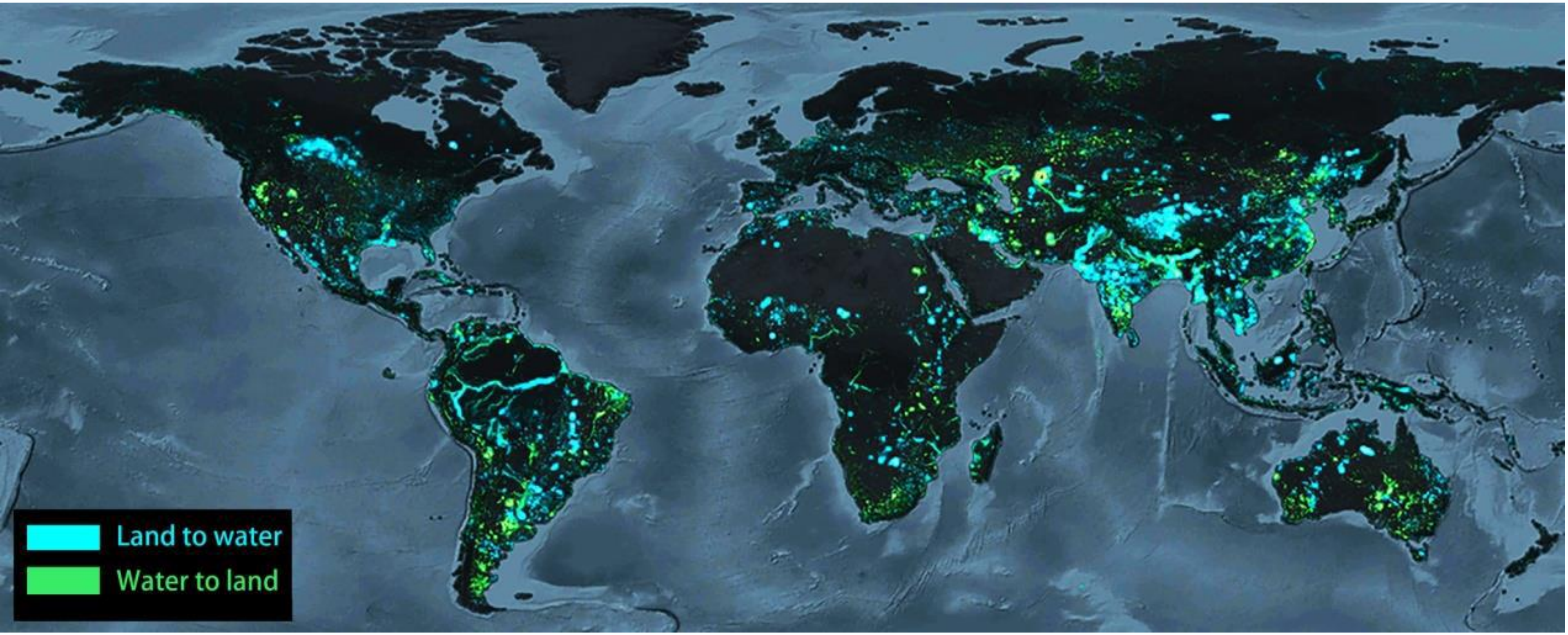
Outline

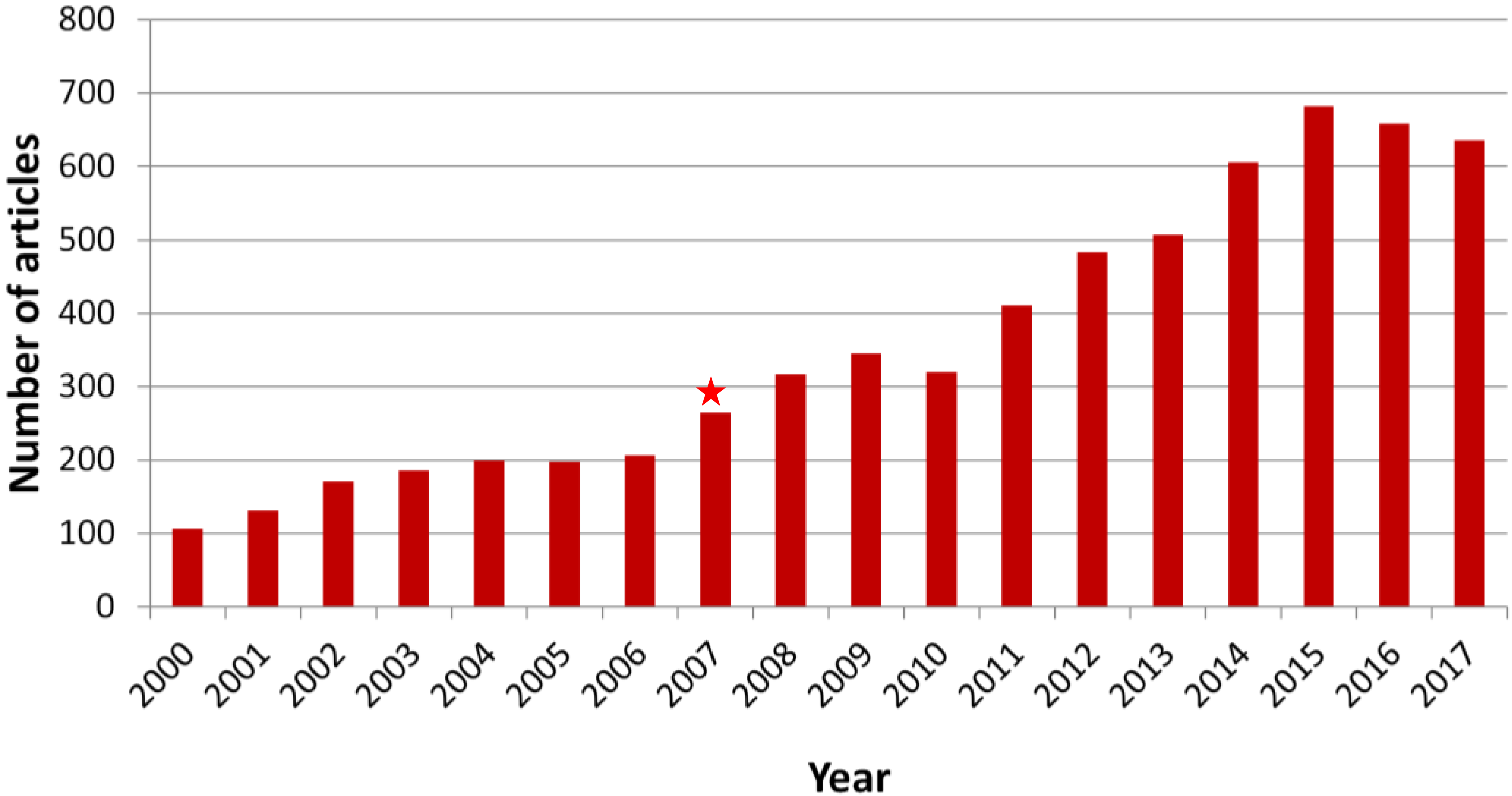
- Overview
- Detection with Different Sensors
- Extraction Using Different Methods
- Spatio-temporal Monitoring
- Progresses and Challenges

Global Surface Water and Land Changes (1985-2015)



Heat map of global surface water and land changes over the past 30 years, which was generated using time series of remotely sensed images (The Aqua Monitor - first global-scale tool at 30-m resolution). The intensity of the colors highlights the spatial magnitude of the change (from Donchyts et al., 2016).

Published Relevant Research (2000-2017)



Number of published articles (2000-2017) listed in Web of Science Core 106 Collection containing the terms “surface water” or “flood inundation”, and refined by 107 “remote sensing”

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- **Detection with Different Sensors**
- Extraction Using Different Methods
- Spatio-temporal Monitoring
- Progresses and Challenges
- Concluding Remarks

Commonly Used Space-borne Remote Sensors

Sensor group	Satellite /sensor	Number of bands	Spatial resolution (m)	Temporal resolution (day)	Swath at nadir (km)	Scale of application*	Data cost	Data availability
Coarse resolution sensor	NOAA/AVHRR	5	1100	0.5	2800	R-G	no	1978--
	MODIS	36	250-1000	0.5	2330	R-G	no	1999--
	Suomi NPP-VIIRS	22	375-750	0.5	3040	R-G	no	2012--
Medium resolution sensor	Landsat	4-9	15-80	16	185	L-G	no	1972--
	SPOT	4-5	2.5-20	26	120	L-R	yes	1986--
	Aster	14	15-90	16	60	L-G	no	1999--
	Sentinel-2	13	10-60	5	290	L-R	no	2015—
High resolution sensor	IKONOS	5	1-4	1.5-3	11.3	L-R	yes	1999--
	QuickBird	5	0.61-2.24	2.7	16.5	L	yes	2001--
	WorldView	4-17	0.31-2.40	1-4	17.6	L	yes	2007--
	RapidEye	5	5	1-5.5	77	L-R	yes	2008--
	ZY-3	4	2.1-5.8	5	50	L-R	yes	2012—

* L=Landscape, R=Regional, G=Global, L-R=Landscape to Regional, L-G=Landscape to Global, R-G=Regional to Global.

Comparisons of Landsat and Sentinel-2 sensors

	Thematic Mapper(TM) Landsat 4 and 5	Enhanced Thematic Mapper Plus(ETM+) Landsat 7	Enhanced Thematic Mapper Plus(ETM+) Landsat 8	Sentinel-2
Spectral Resolution (nm)	1. 450-520 (B) 2. 520-600 (G) 3. 630-690(R) 4. 760-900 (NIR) 5. 1550-1750 (MIR) 6. 2080-2350 (MIR) 7. 1040-1250 (TIR)	1. 450-520 2. 530-610 3. 630-690 4. 780-900 5. 1550-1750 6. 2090-2350 7. 10400-12500 8. 520-900 (Pan)	1. 430-450 (C/A) 2. 450-520 (B) 3. 530-600 (G) 4. 630-680 (R) 5. 850-890 (NIR) 6. 1560-1660 (SIR) 7. 2100-2300 (SIR) 8. 500-680 (Pan) 9. 1360-1390 (C) 10. 10300-11300 (LIR) 11. 11500-12500(LIR)	1. 430-450 (C/A) 2. 460-520 (B) 3. 540-580 (G) 4. 650-680 (R) 5. 700-710 (VRE) 6. 730-750 (VRE) 7. 770-790 (VRE) 8. 780-900 (NIR) 9. 860-880 (NNIR) 10. 940-960 (WV) 11. 1370-1390 (C) 12. 1570-1660 (SIR) 13. 2100-2280 (SIR)
Spatial Resolution (m)	30×30 120×120 (TIR)	15×15 (Pan) 30×30 60×60 (TIR)	15×15 (Pan) 30×30 100×100 (TIR)	10×10 (Pan) 20×20 60×60 (TIR)
Temporal Resolution (revisit days)	16	16	16	5
Spatial coverage (km)	185×185	183×170	185×185	290×290
Website	https://lta.cr.usgs.gov/TM	https://landsat.gsfc.nasa.gov/the-enhanced-thematic-mapper-plus/	https://en.wikipedia.org/wiki/Landsat_8	https://en.wikipedia.org/wiki/Sentinel-2

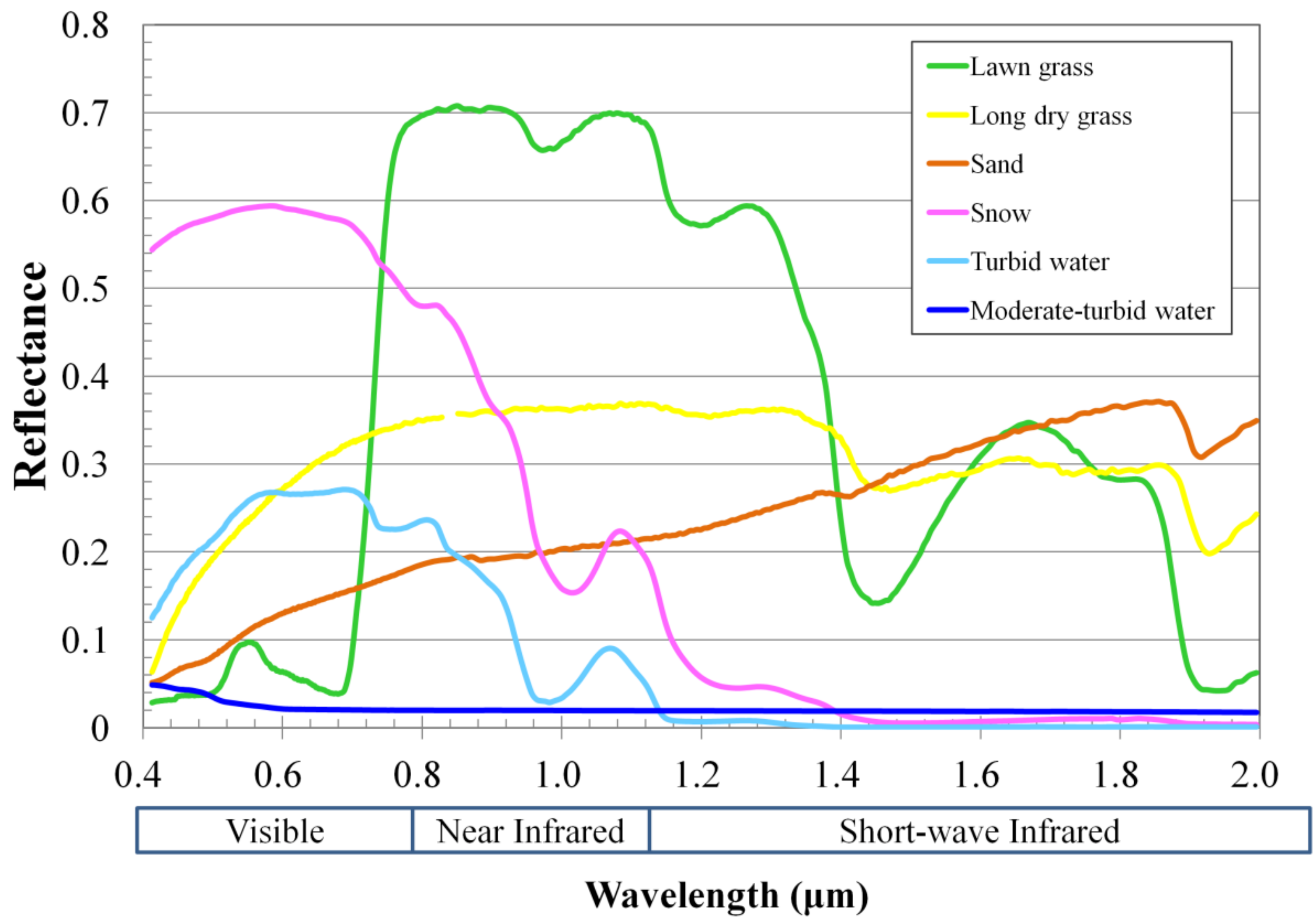
Note: B=blue, G=green, R=red, C/A=Coastal/Aerosol, NIR=near-infrared, SIR=short-wavelength infrared, MIR =mid-wavelength infrared, LIR=long-wavelength infrared, TIR=total infrared, Pan=Panchromatic, C=Cirrus, VRE =Vegetation Red Edge, WV=Water vapour.

Comparisons of Worldview Series Sensors

	Ikonos	Quickbird	GeoEye-1	Worldview-1	Worldview-2	Worldview-3	Worldview-4
Spectral Resolution (nm)	445-900 (PAN) 445-516 (B) 506-595 (G) 632-698 (R) 757-853 (NIR)	450-900 (PAN) 450-520 (B) 520-600 (G) 630-690 (R) 760-900 (NIR)	450-800 (PAN) 450-510 (B) 510-580 (G) 655-690 (R) 780-920 (NIR)	400-900 (PAN and NIR)	400-450 (C1) 585-625 (Y) 705-745 (RE) 860-1040 (NIR)	450-800 (PAN) 400-1040 (R, RE, C1, B, G, Y, NIR) 405-2245 (DC, A, G, water, SWIR, C2, S) 1195-2365 (SWIR)	450-800 (PAN) 450-510 (B) 510-580 (G) 655-690 (R) 780-920 (NIR)
Spatial Resolution (m)	1.83×1.57	2.9×2.62	1.84×0.46	3.6×2.5	4.3×2.5	5.7×2.5	5.3×2.5
Pan resolution (m)	0.82	0.65	0.46	0.50	0.46	0.31	0.31
Multispectral resolution (m)	4	2.44/1.63	1.64	N/A	1.85	1.24	1.24
Accuracy specification (m; CE90)	9 (measured) /15 (specification)	23	3	6.5	6.5	3.5	4
Temporal Resolution (revisit in days)	3	1-3	2.1 (0.59 m GSD) 2.8 (0.50 m GSD) 8.3 (0.42 m GSD)	1.7 (1 m GSD) <5.9 (20° off-nadir or 0.55 meter GSD)	1.1 (1 m GSD) <3.7(20° off-nadir or 0.52 meter GSD)	<1.0 (1 m GSD) <4.5 (20° off-nadir or 0.31 meter GSD)	< 1.0 (1m GSD) >4.5 (Total constellation)
Swath width (km)	11.3	16.8/18	15.3	17.7	16.4	13.2	13.1
Spatial coverage (km)	50x112 (Mono) 11x120 (Stereo)	16.8x16.8 / 11.2 x11.2 (Mono) 16.8/11.2x360(Stereo)	50x300 (Mono) 28x224 (Stereo)	60x110 (Mono) 30x110 (Stereo)	96x110 (Mono) 48x110 (Stereo)	66.5x112 (Mono) 26.6x12 (Stereo)	66.5x112 (Mono) 26.6x112 (Stereo)
Operational Altitude (km)	681	450 / 482 (Early 2013)	681	496	770	617	617
Data availability	Sep 1999-Jan 2015	Oct 2001-Jan 2015	Sep 2008-	Oct 2007-Jan 2015	Oct 2009-	Sep 2014-	Dec 2016-
Mission life (years)	16	14	7-15	10.36	7.25	10-12	10-12
Data distribution policy (costs)	no	yes	yes	yes	yes	yes	yes
Website	https://www.satimagingcorp.com/satellite-sensors/ikonos/	https://www.satimagingcorp.com/satellite-sensors/quickbird/	https://www.satimagingcorp.com/satellite-sensors/geoeye-1/	https://www.satimagingcorp.com/satellite-sensors/worldview-1/	https://www.satimagingcorp.com/satellite-ensors/worldview-2/	https://www.satimagingcorp.com/satellite-sensors/worldview-3/	https://directory.eoportal.org/web/eoportal/satellite-missions/v-w-x-y-z/worldview-4

Note: PAN=panchromatic, C1=Coastal, A=Aerosol, Y=yellow, B=blue, R=red, G=green, RE=red edge, NIR=near-infrared, SWIR=short-wavelength infrared, C2=Cirrus, DC=desert clouds, W=Water, S= snow. GSD=Ground sample distance, Mono= Monaural, CE90=90% of the time, when compared to the true position on the Earth.

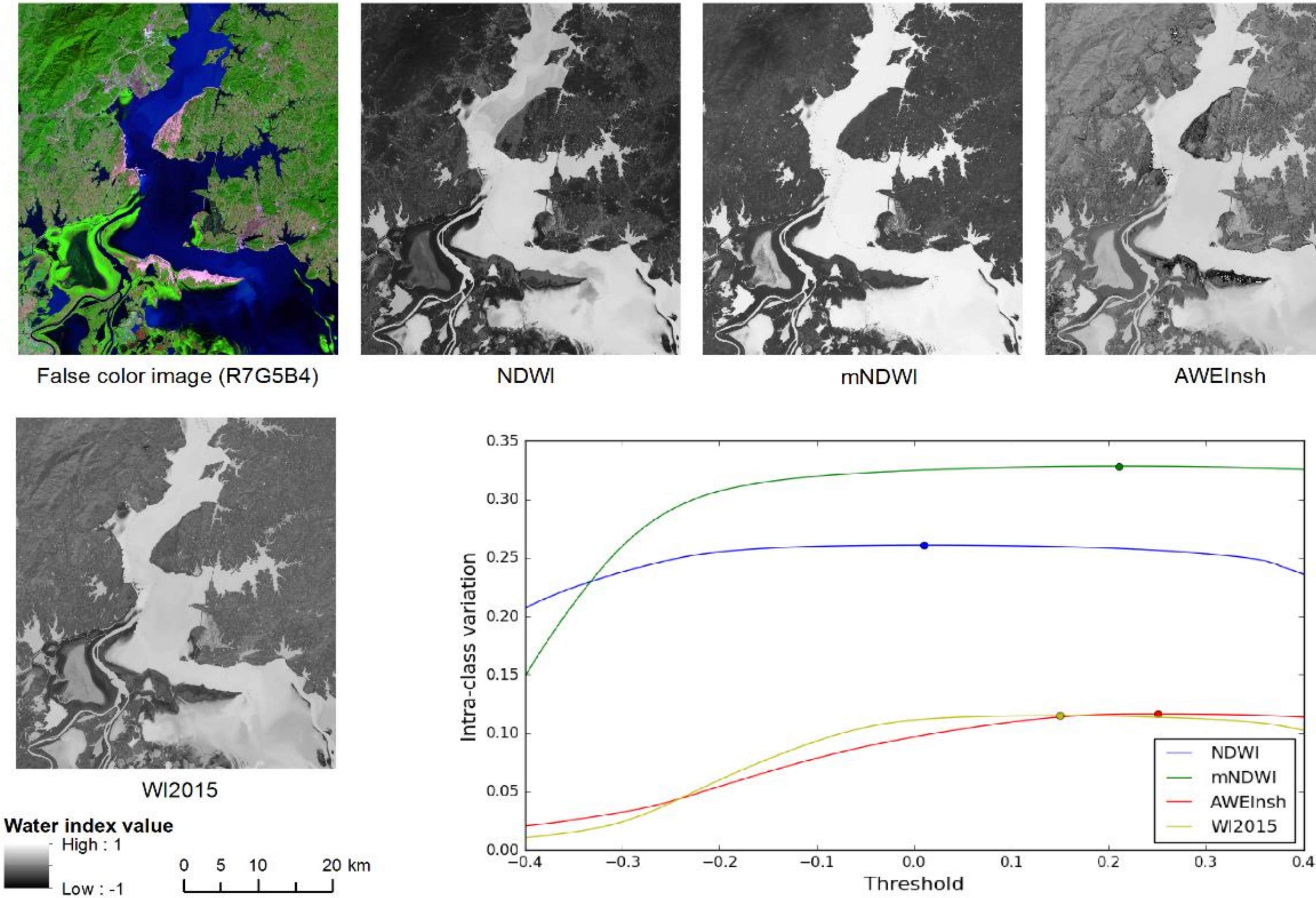
Reflectance of Several Typical Land Cover Objects



Popular Water Indices

Indices	Equation	Sources
NDWI	NDWI=(GREEN - NIR)/ (GREEN + NIR)	McFeeters 1996
mNDWI	mNDWI=(GREEN - SWIR)/ (GREEN + SWIR)	Xu (2006
AWEI	$AWEI_{nsh}$: 4×(GREEN - SWIR1) - (0.25×NIR + 2.75×SWIR2) $AWEI_{sh}$: BLUE + 2.5×GREEN - 1.5× (NIR + SWIR1) - 0.25×SWIR2	Feyisa et al. (2014)
WI_{2015}	1.7204 + 171×GREEN + 3×RED - 70×NIR - 45×SWIR1 - 71×SWIR2	Fisher et al. (2016)

Thresholding in Using Water Indices



Landsat OLI image for Poyang Lake on 2013-10-05, its corresponding images of water indices, and line graph showing the intra-class variation between water and land with different thresholds on these index images

Combined Water Indices

- **Combination of TCW and NDWI**
  - TCW: Tasseled Cap Wetness
  - NDWI: Normalized Difference Water Index
- **Deference between LSWI and vegetation indices (NDVI and EVI)**
  - LSWI: Land Surface Water Index
  - NDVI: Normalized Difference Vegetation Index
  - EVI: Enhanced Vegetation Index
- **Integration of NDWI, mNDWI and AWEI: AMERL**
  - AMERL: Automated Method for Extracting Rivers and Lakes
  - mNDWI: modified NDWI
  - AWEI: Automated Water Extraction Index
- **OWL (Open Water Likelihood) index**

OWL – Open Water Likelihood

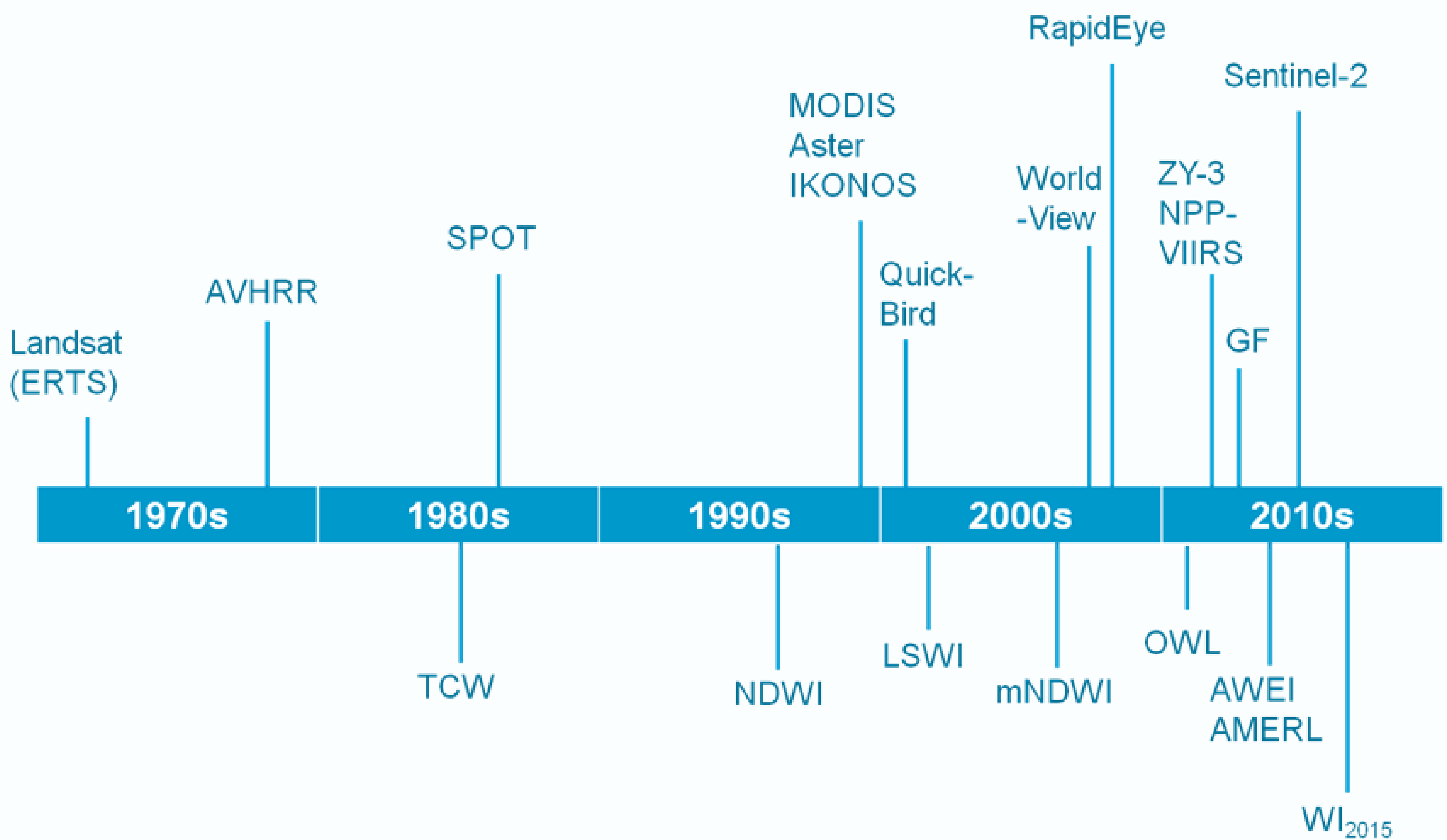
$$OWL = 1/[1 + \exp(-f)]$$

$$f = a_0 + \sum_{i=1}^{5} a_i * x_i$$

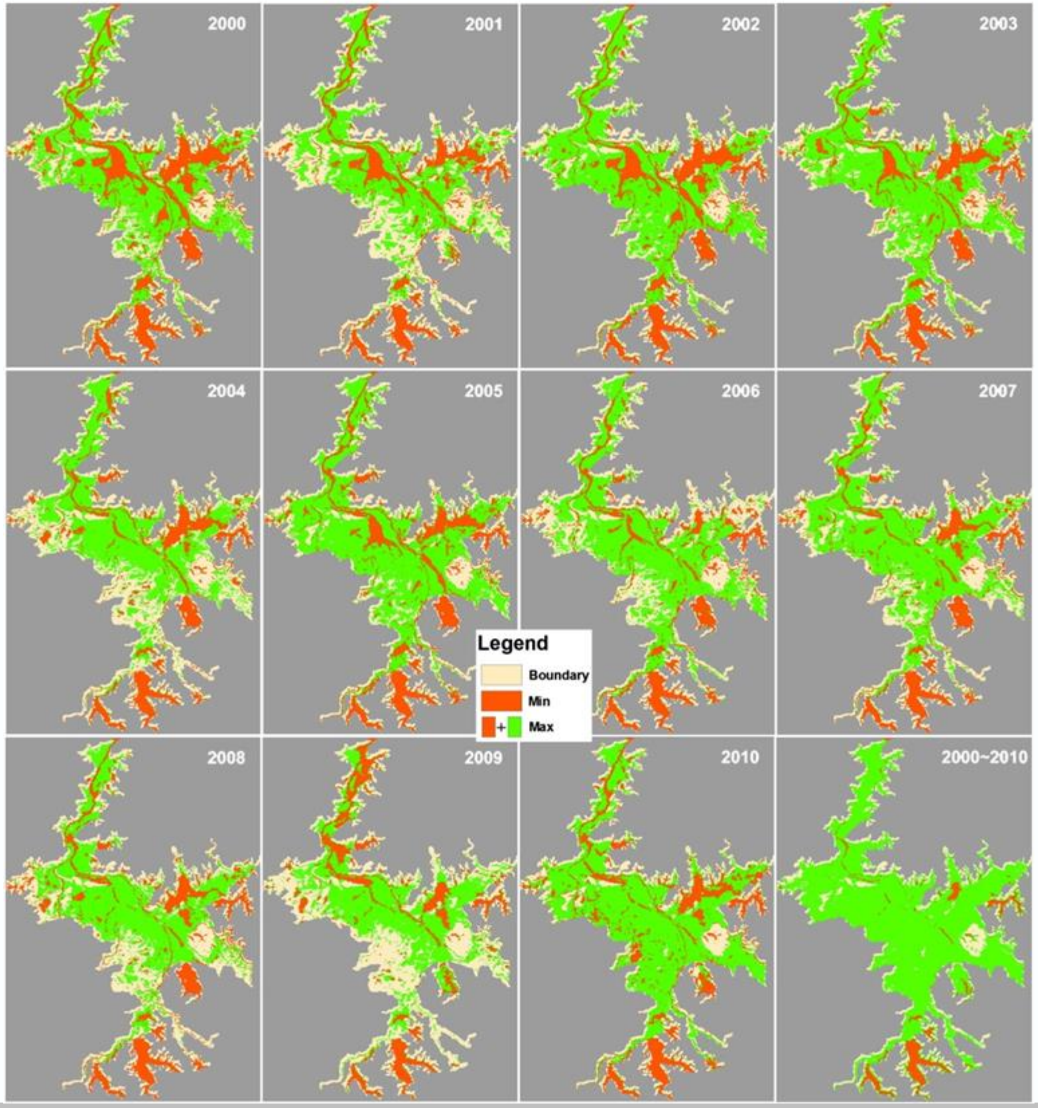
a0 = -3.41375620,
a1 = -0.959735270,
a2 = 0.00417955330,
a3 = 14.1927990,
a4 = -0.430407140,
a5 = -0.0961932990,

x1 = SWIR band 6,
x2 = SWIR band 7,
x3 = NDVI (NDVI = (band2-band1)/(band2+band1)),
x4 = NDWI (NDWI = (band2-band6)/(band2+band6)),
x5 = MrVBF (an index derived from DEM indicating the degree of valley bottom flatness

Timeline Diagram of Major Water Indices and Satellites



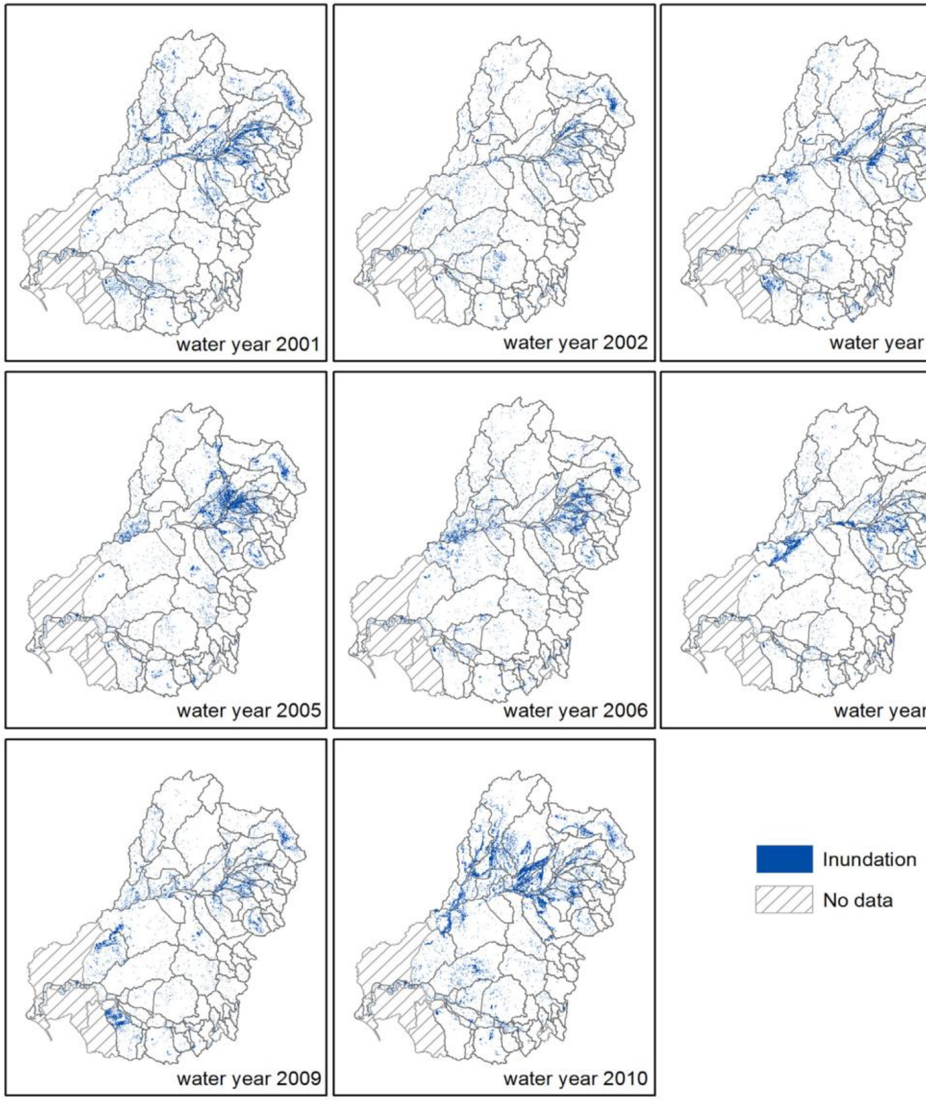
Spatio-temporal Monitoring



A study used time series of MODIS data to assess the surface water area of Poyang Lake from 2000 to 2010, and found that the Lake had been extremely variable over the 11-year period.

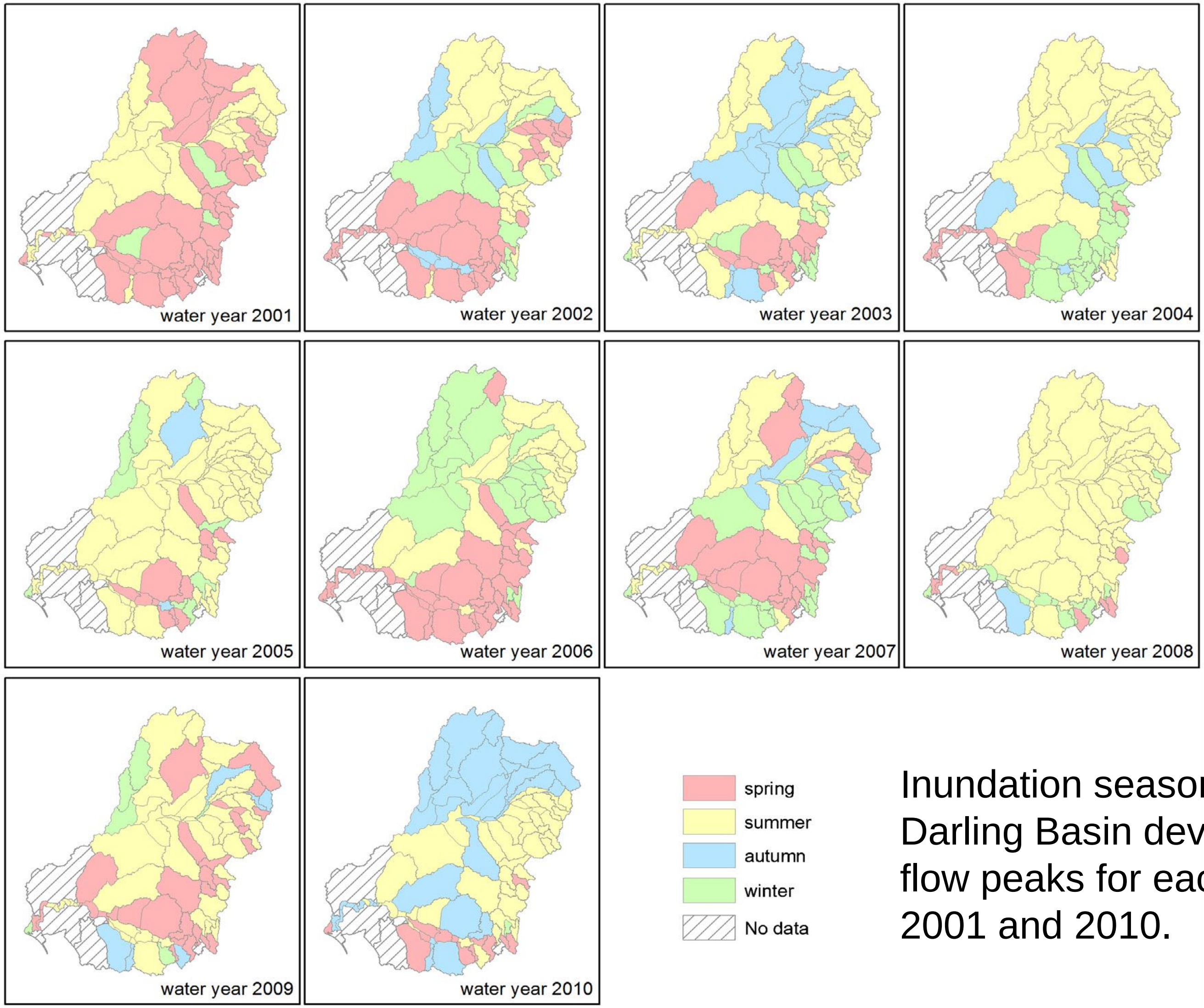
Inundation extent for each calendar year between 2000 and 2010. The two extreme inundation states are presented in the last panel (annotated as "2000–2010")
(*from Feng et al. , 2012*)

Spatio-temporal Monitoring



Annual maximum inundation maps of Murray-Darling Basin, Australia, showing the max. inundated area of each water year defined as from July 1 of the preceding year to June 30 of the current year (2001-2010).

Spatio-temporal Monitoring

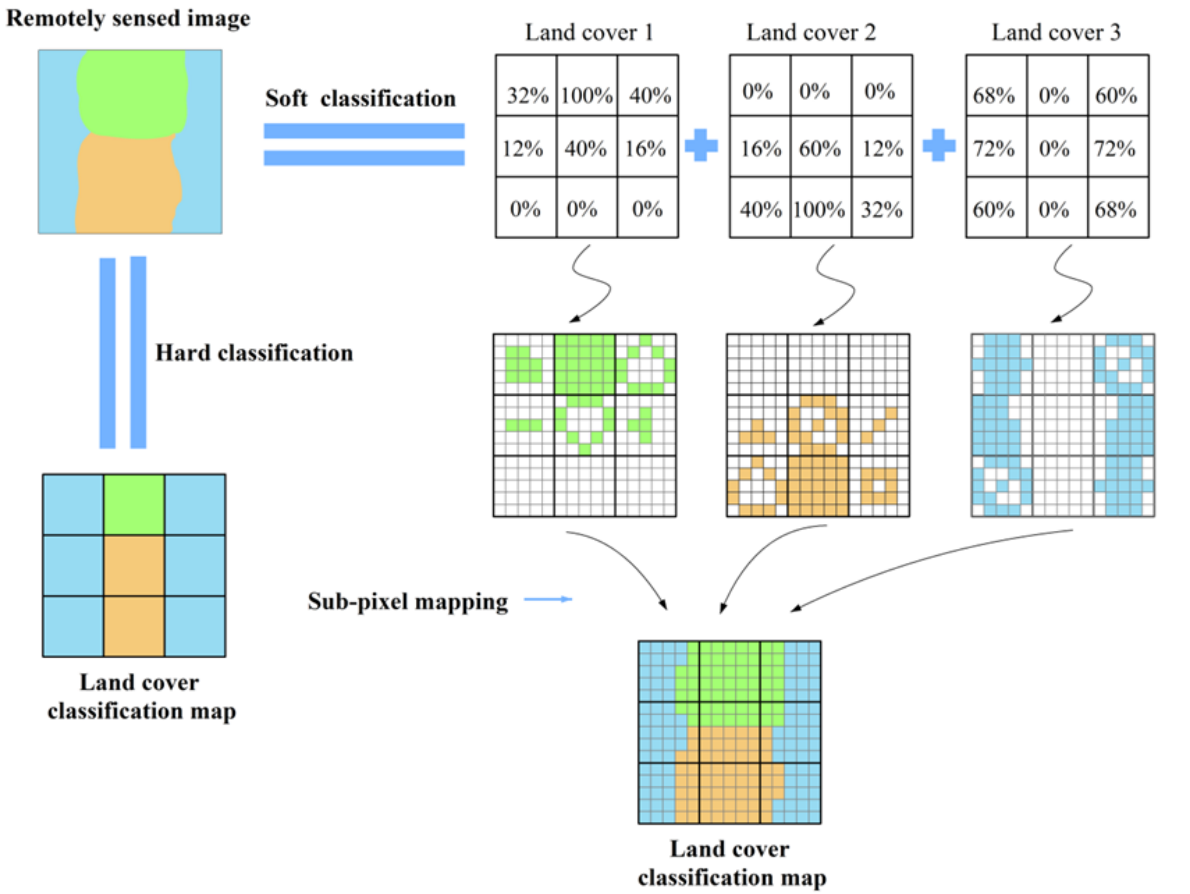


Inundation seasonality maps of Murray-Darling Basin developed from the date of flow peaks for each water year between 2001 and 2010.

Progresses and Challenges

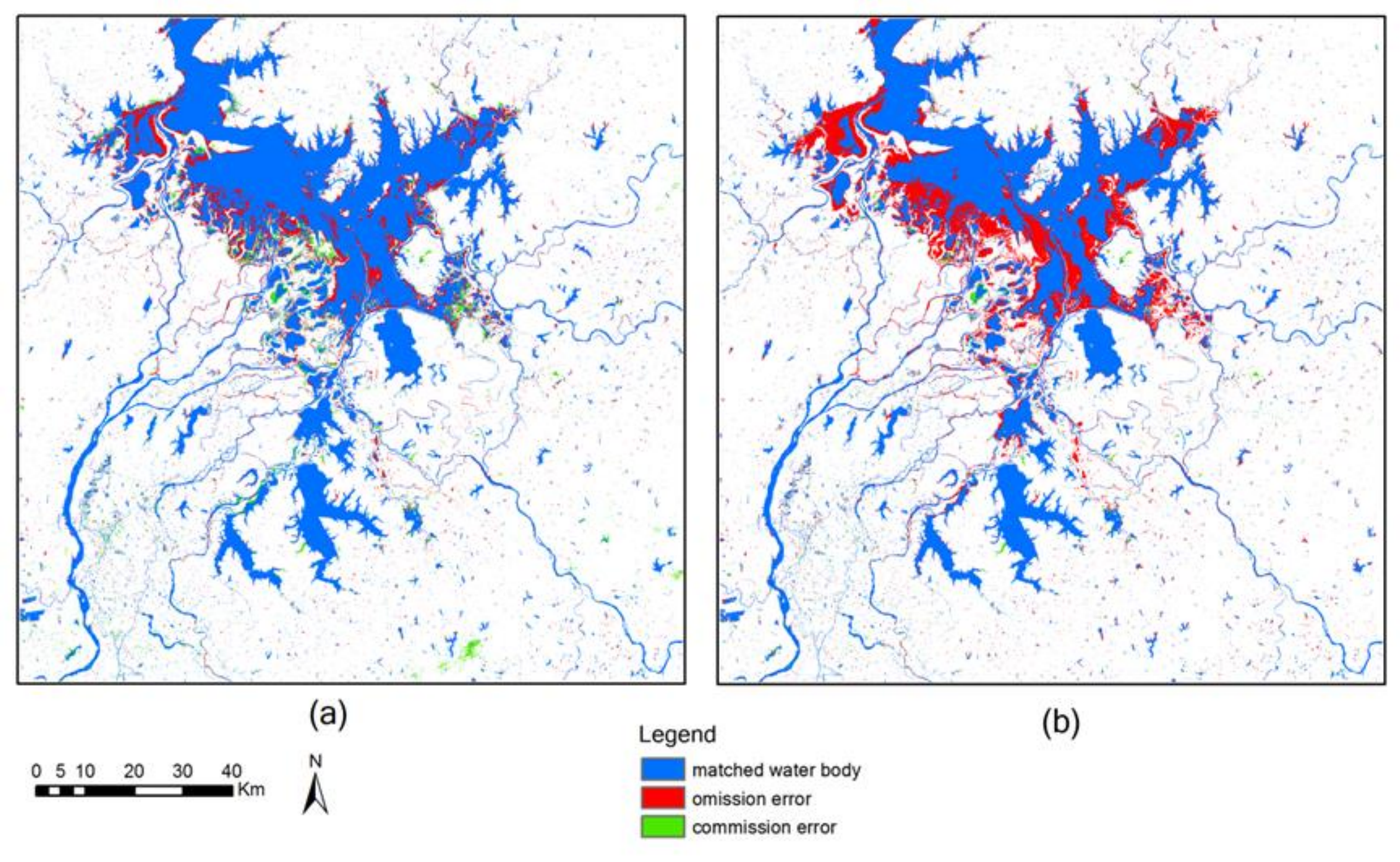
- **Spatial and temporal scale issue**
  - Pixcel unmixing and reconstruction
  - Spatial and temporal fusion
- **Integration with in situ gauge data**
  - Combination of in situ gauge data
  - Estimating gauge flow using remote sensing
- **Dependency of terrain**
  - Digital Elevation Model: sub-pixel mapping
  - Lidar DEM: water depth
- **Global water monitoring**
  - New satellite sensors
  - BIG data & Cloud platform
  - Google Earth Engine (GEE) and Data Cube

Spatial and temporal scale issue – pixel unmixing & reconstruction



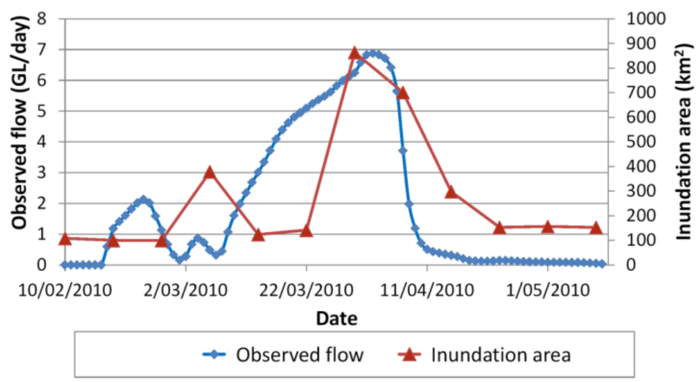
Demonstration of pixel unmixing and reconstruction process (comparied with hard classification)

Spatial and temporal scale issue – spatial & temporal fusion

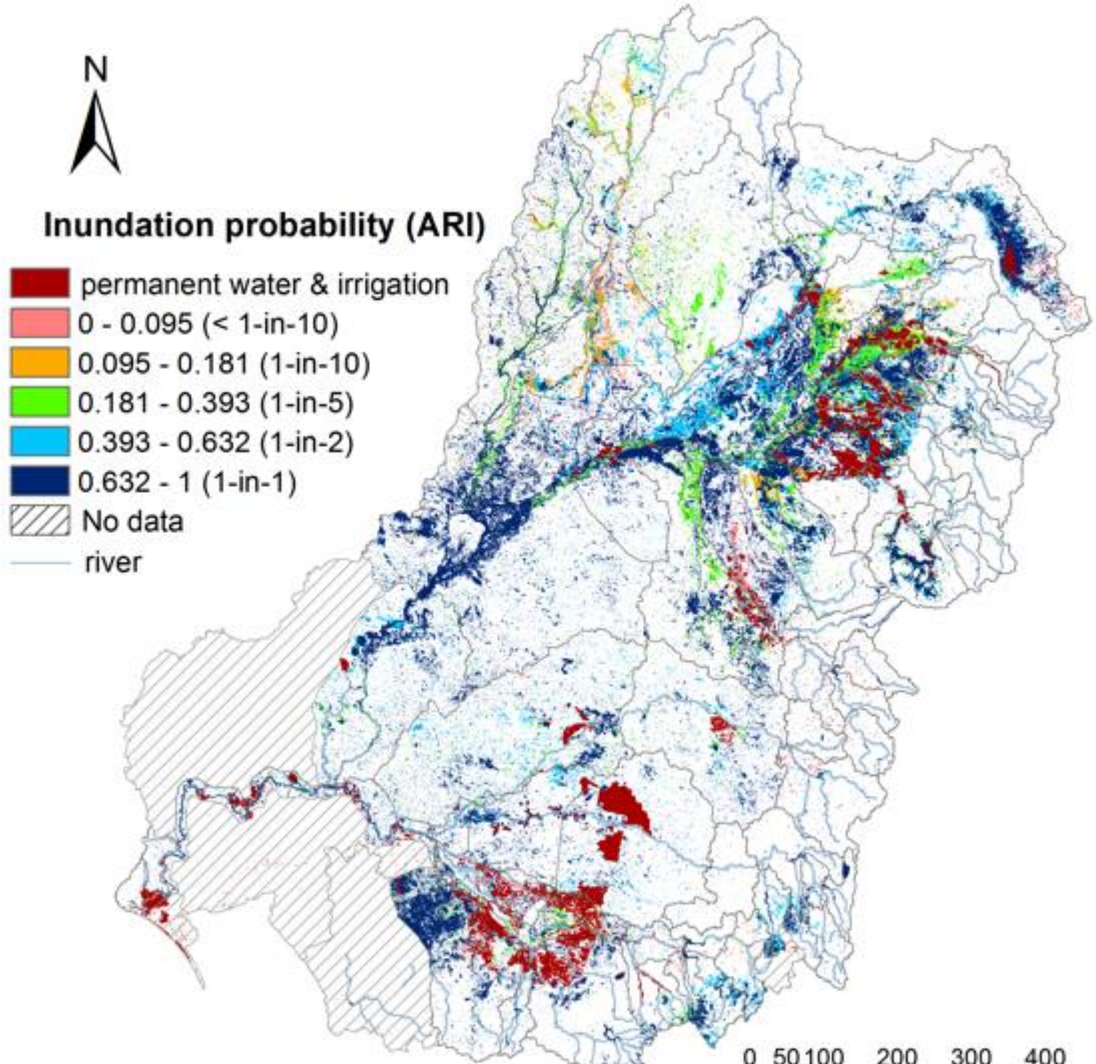


(a) Evaluation map of index-then-blend (IB) result. (b) Evaluation map of blend-then-index (BI) result (reprinted from Huang et al. 2016).

Integration with *in situ* gauge data – Combination of gauge data



(a)

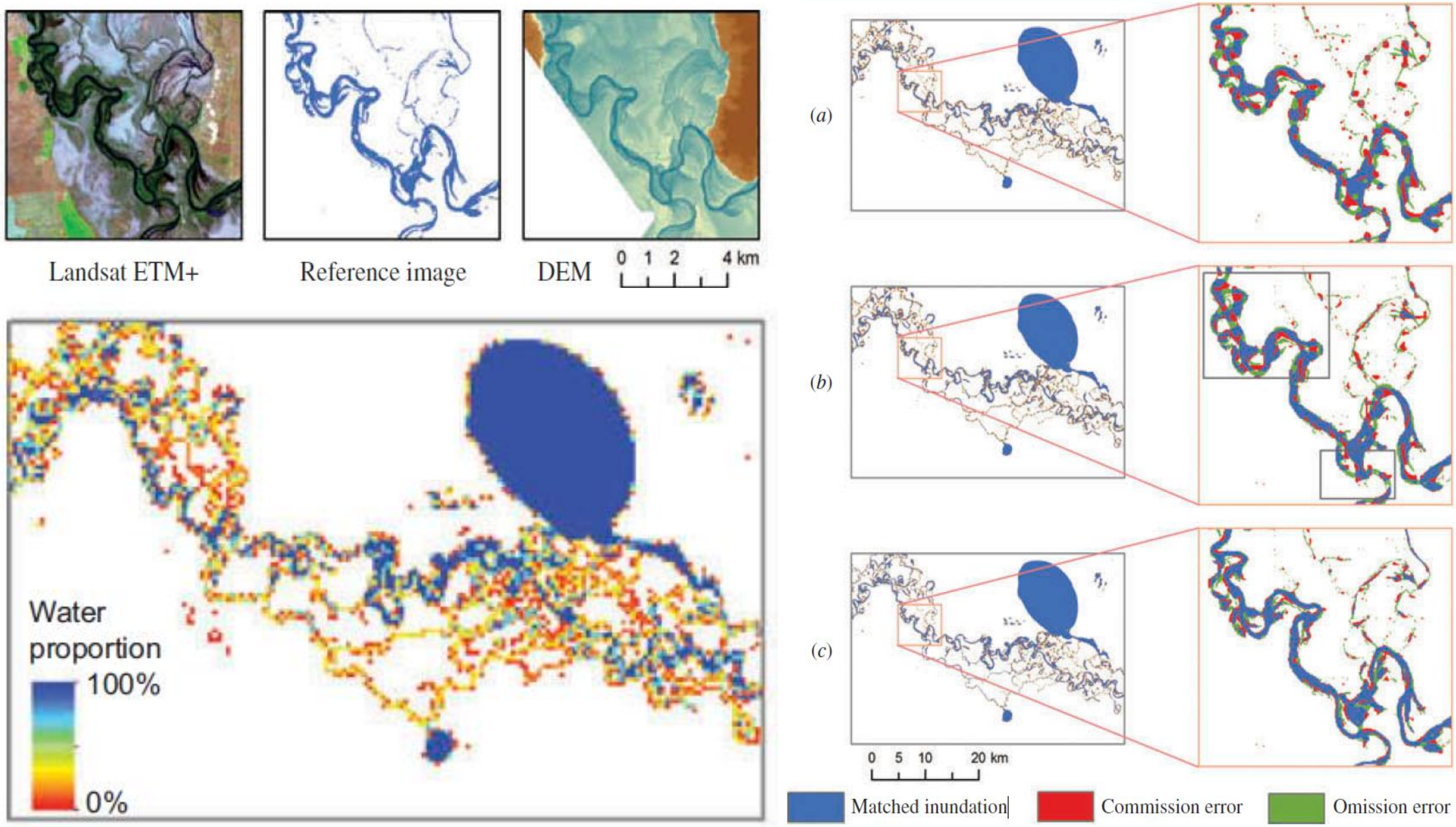


(b)

(a) Observed flow at the upstream gauge and inundation area derived from time-series MODIS images during a flood event in Narran floodplain in Murray-Darling Basin (MDB), Australia.

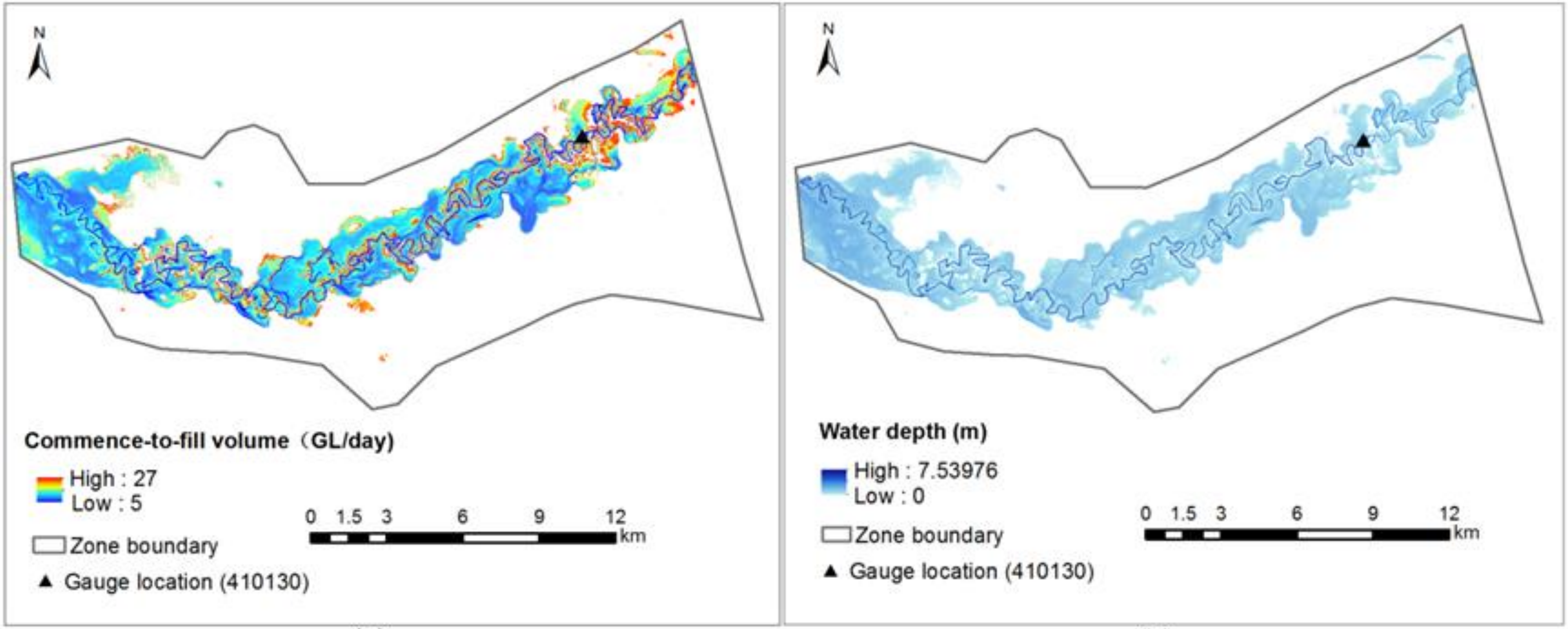
(b) Modeled flood inundation probability for MDB based on time series MODIS data and time series observed flow data.

Dependency of terrain – DEM-based subpixel mapping



Chowilla Floodplain of the Murray–Darling Basin of Australia (a section of the main channel of the Murray River and its tributaries, including Lake Victoria): (a) Evaluation map of the original PS (Pixel-swapping) algorithm; (b) evaluation map of the LPS (Linearised PS) algorithm; (c) evaluation map of the DMPS (DEM-based Modified PS) algorithm.

Dependency of terrain – water depth derivation from Lidar DEM



(a) (b)

In a section of floodplain in Lower Murrumbidgee in Murray-Darling Basin, Australia, (a) Modeled commence-to-fill volumes, (b) modeled water depth under the scenario that the observed gauge flow is 26 GL/day. (figure produced from the published dataset of Sims et al. 2014)

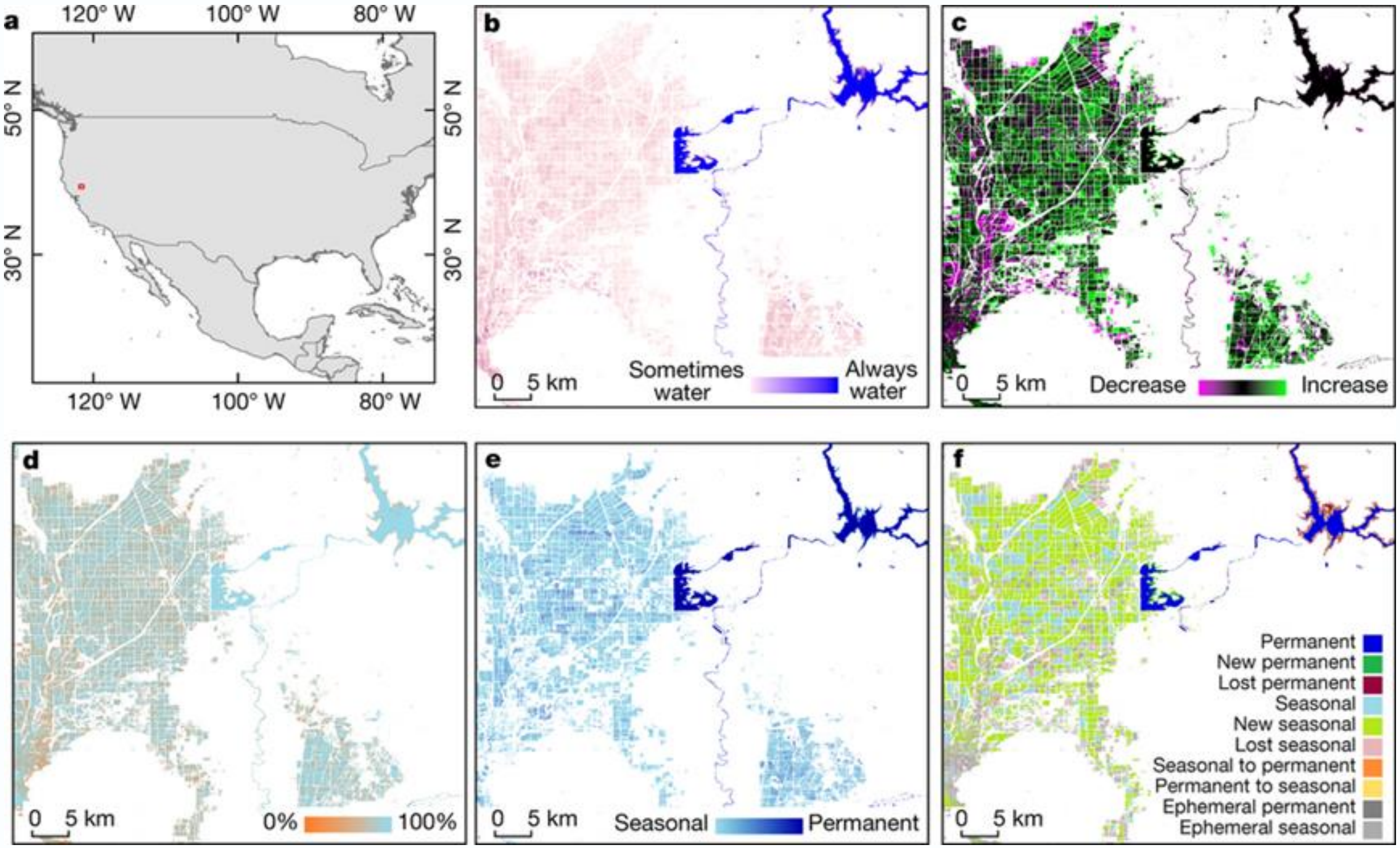
Remarks

- The last decade has been a golden period for optical remote sensing applications, largely due to the stable performance of MODIS and Landsat sensors, as well as the free distribution policy of their data.
- Many studies have been conducted using these data to detect, extract and monitor surface water bodies. The results have greatly supported research work in many related fields, such as water resource management eco-hydrological studies.
- A most serious limitation is that optical remote sensing data are easily affected by cloud cover. Therefore, solely relying on optical images is not wise. It is better to introduce other data sources, such as SAR. An integrated use of optical and radar satellite data will certainly improve the ability to detect and monitor surface water.

Global water monitoring – new satellite sensors

Satellite Name:	Surface Water and Ocean Topography (SWOT)
Launch Year:	2021
Purpose:	Survey of global surface water (extent and storage),
Spectral Resolution (nm):	395-740 (Pan); 750-1040 (NIR)
Spatial Resolution (m):	3×2.8×2.8 (Land water); 5×10.6×1.5 (Ocean)
Temporal Resolution (day):	22
Spatial Coverage (km^2):	120 x120
Altitude (km):	727
Website:	https://swot.jpl.nasa.gov/home.htm

Global water monitoring – Google Earth Engine



A more detailed and comprehensive global surface water map and its long-term change derived by Pekel et al. (2016) through analyzing on three million Landsat images collected over the past 32 years using the Google Earth Engine platform. The figure shows the Sacramento Valley, one of the major rice-growing regions in the USA, extracted from the global data set (figure reprinted from *Pekel et al.* 2016):

a) Map of the USA showing Sacramento Valley location (red square). b) Surface water occurrence 1984–2015.
c) Surface water occurrence change intensity 1984–2015. d) Surface water recurrence 1984–2015.
e) Surface water seasonality 2014–2015. f) Transitions in surface water class 1984–2015.

The Australian and International Datacube

- CSIRO- Geoscience Australia- National Computational Infrastructure initiative for enabling the use of big data Earth Observation

Slides courtesy Stuart Minchin, Geoscience Australia

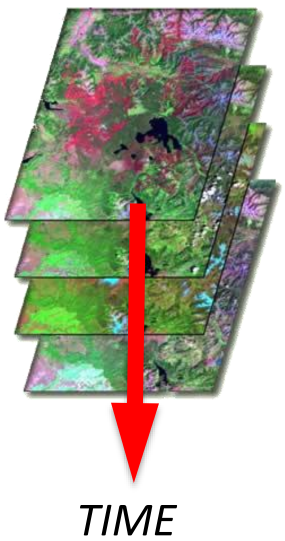
Satellite Data Trends

- More and more free and open data
- Growing data volumes
- Improved computing technologies
- Open source software
- Pre-processed products

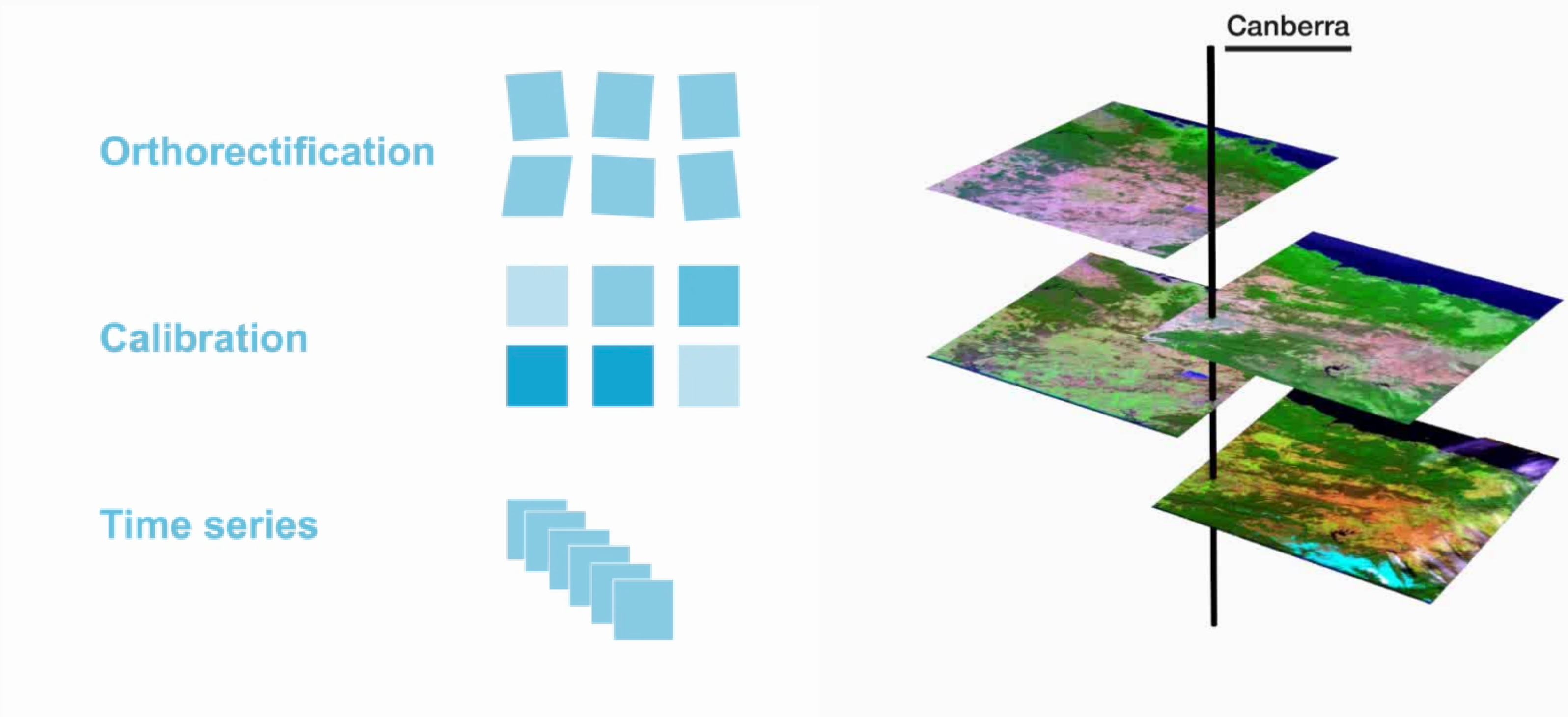
OPEN DATA CUBE

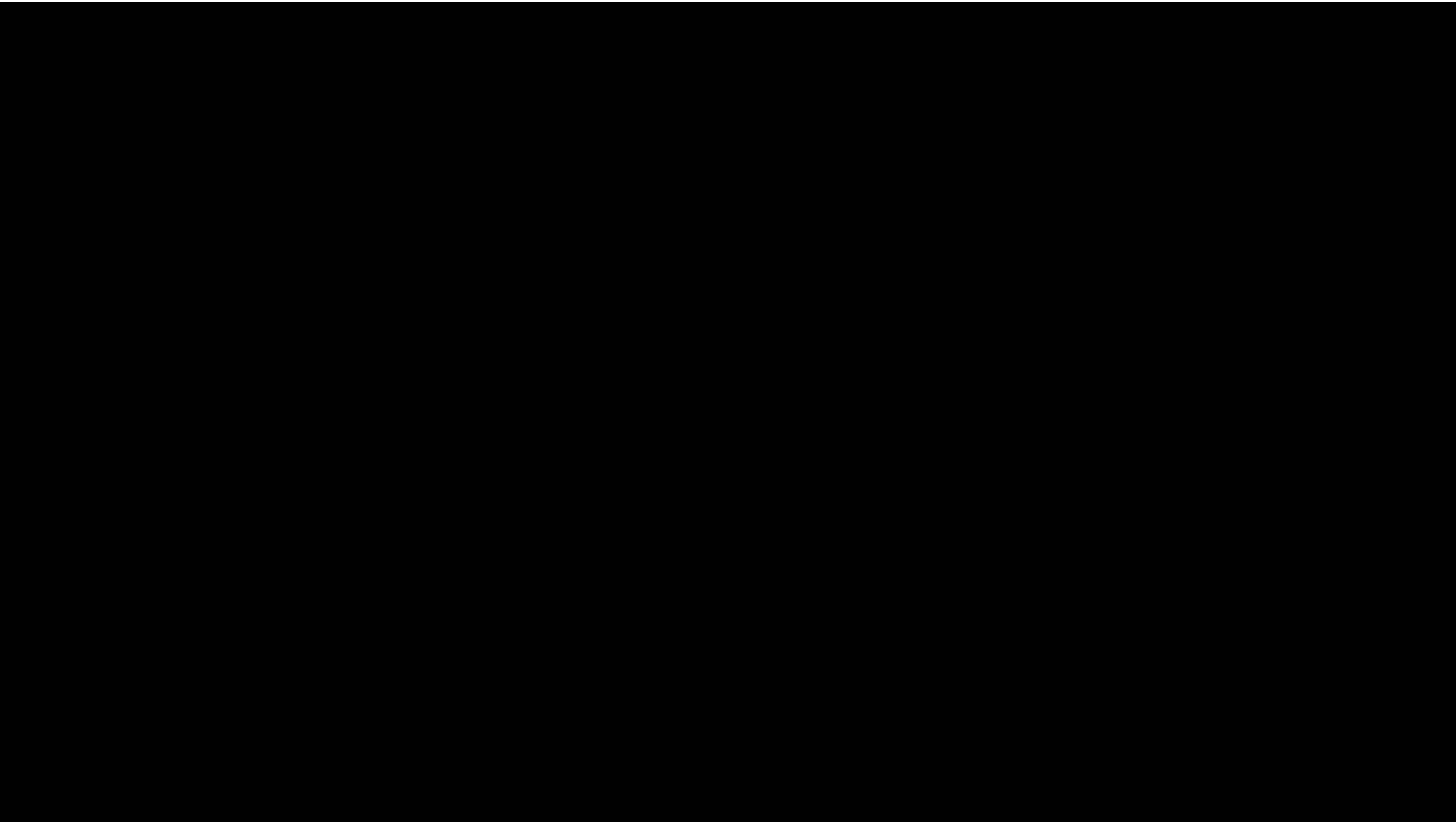
What are Data Cubes?

- **Data Cube** = Time-series multi-dimensional (space, time, data type) stack of spatially aligned pixels ready for analysis
- **Proven concept** by Geoscience Australia (GA) and the CSIRO and planned for the future USGS Landsat archive.
- **Analysis Ready Data (ARD) ...** Dependent on processed products to reduce processing burden on users
- **Open source** software approach allows free access, promotes expanded capabilities, and increases data usage.
- **Unique features:** exploits time series, increases data interoperability, and supports many new applications.



Developing the Australian Geoscience Data Cube





Continental Scale

Water Observations from Space

27 YEARS
1987–2014 DATA

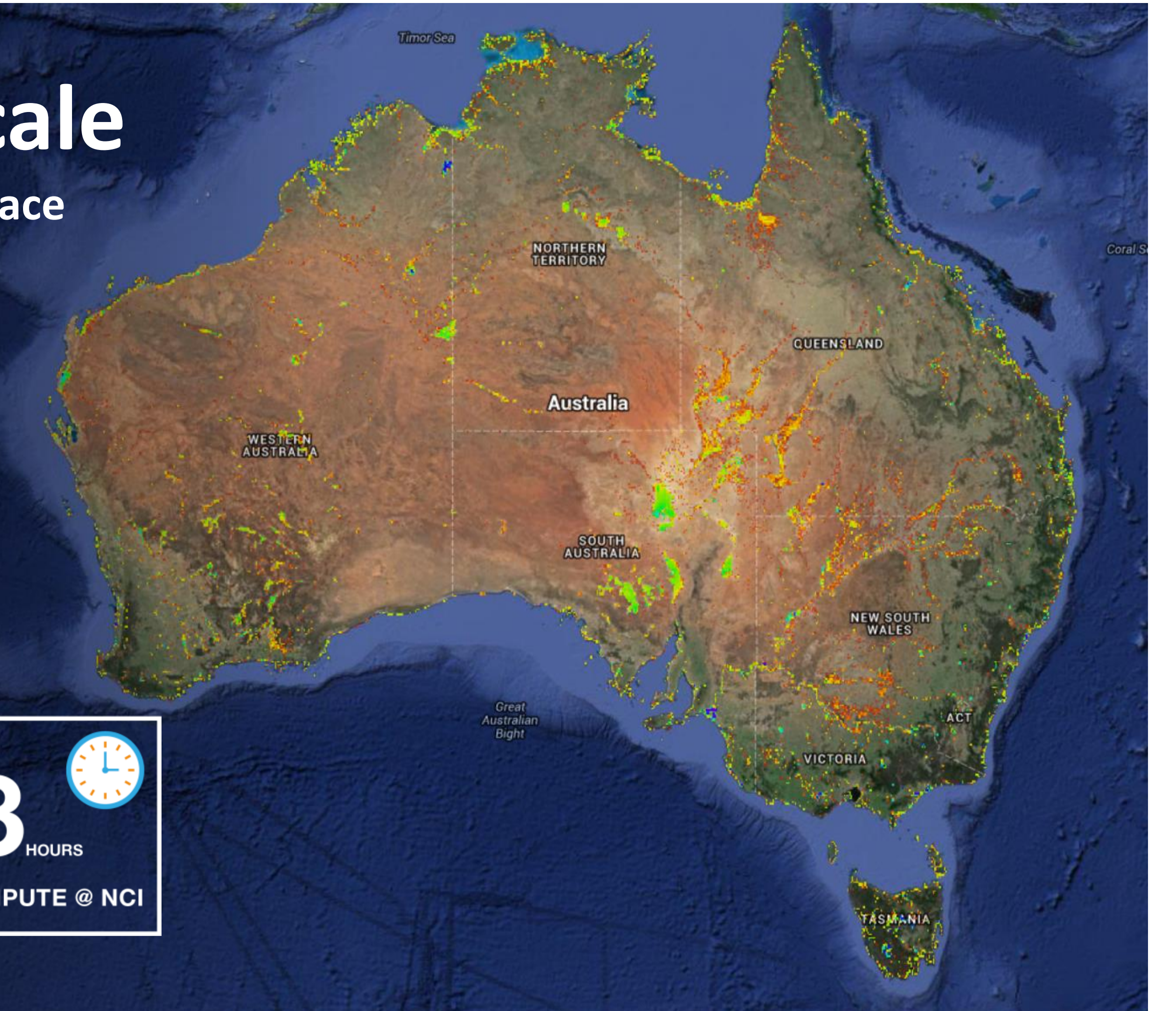
25 METRE PIXEL
RESOLUTION

300 000 SCENES
20 000 PASSES

93×10^{12}
PIXELS

0.75
PETABYTES

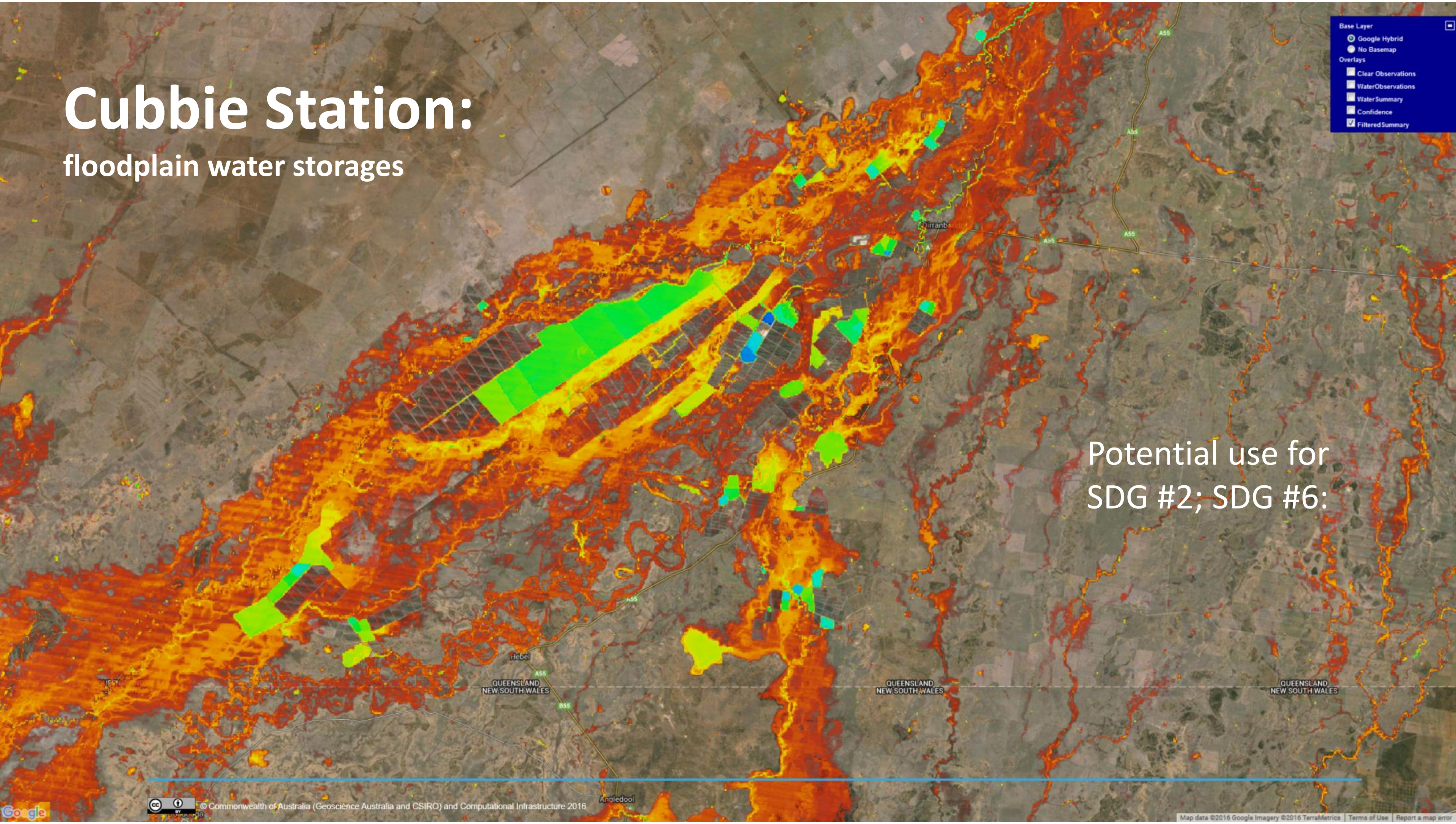
3 HOURS
COMPUTE @ NCI



CSIRO

Cubbie Station:

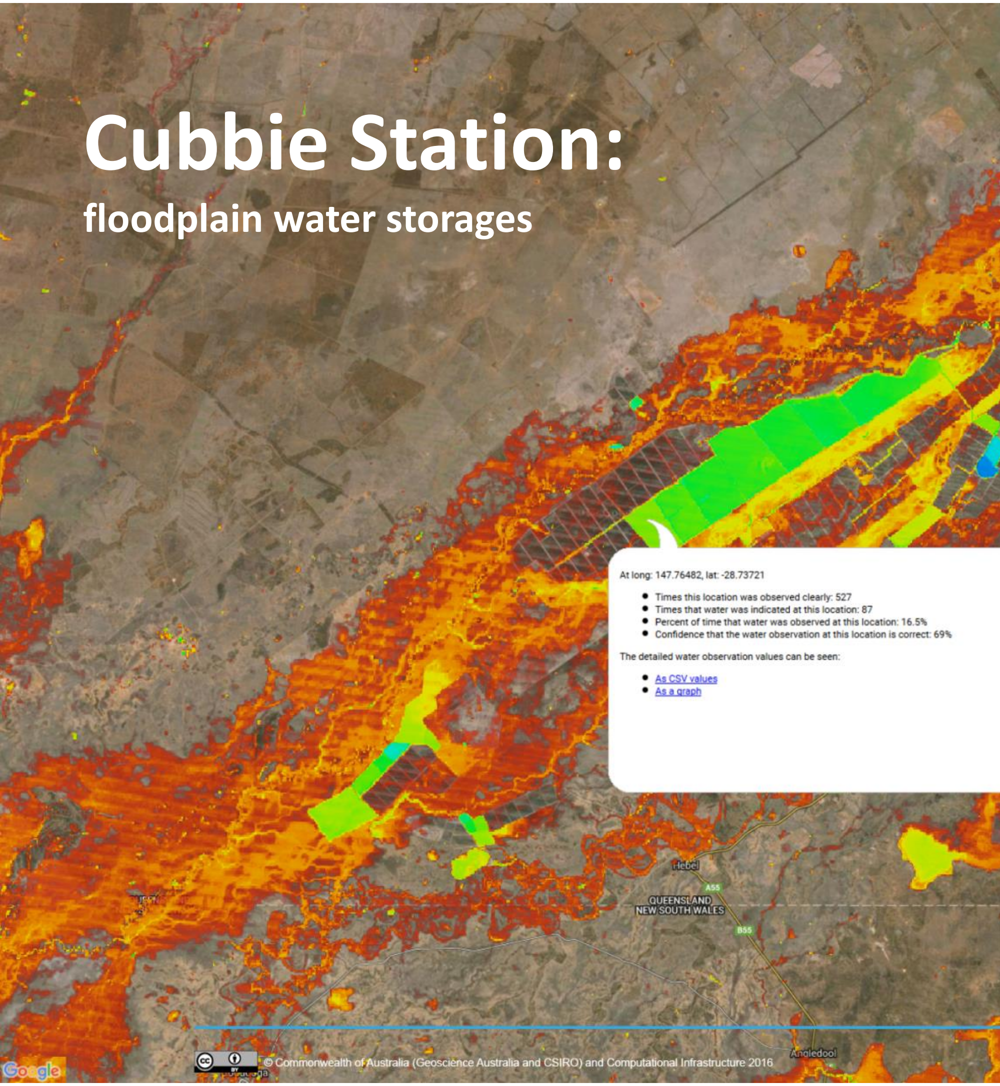
floodplain water storages



Potential use for SDG #2; SDG #6:

Cubbie Station:

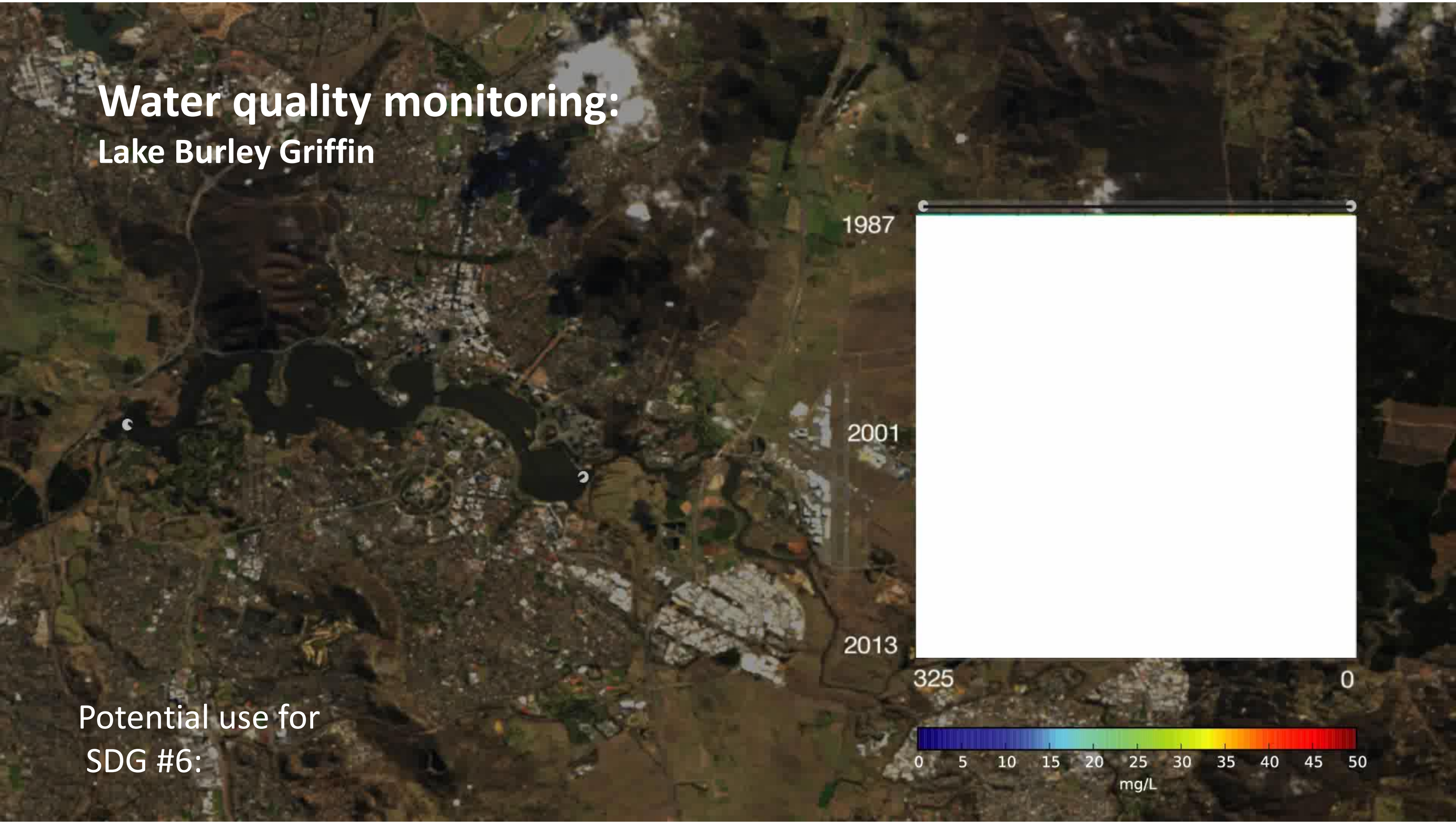
floodplain water storages



CSIRO


1987

Water quality monitoring:
Lake Burley Griffin

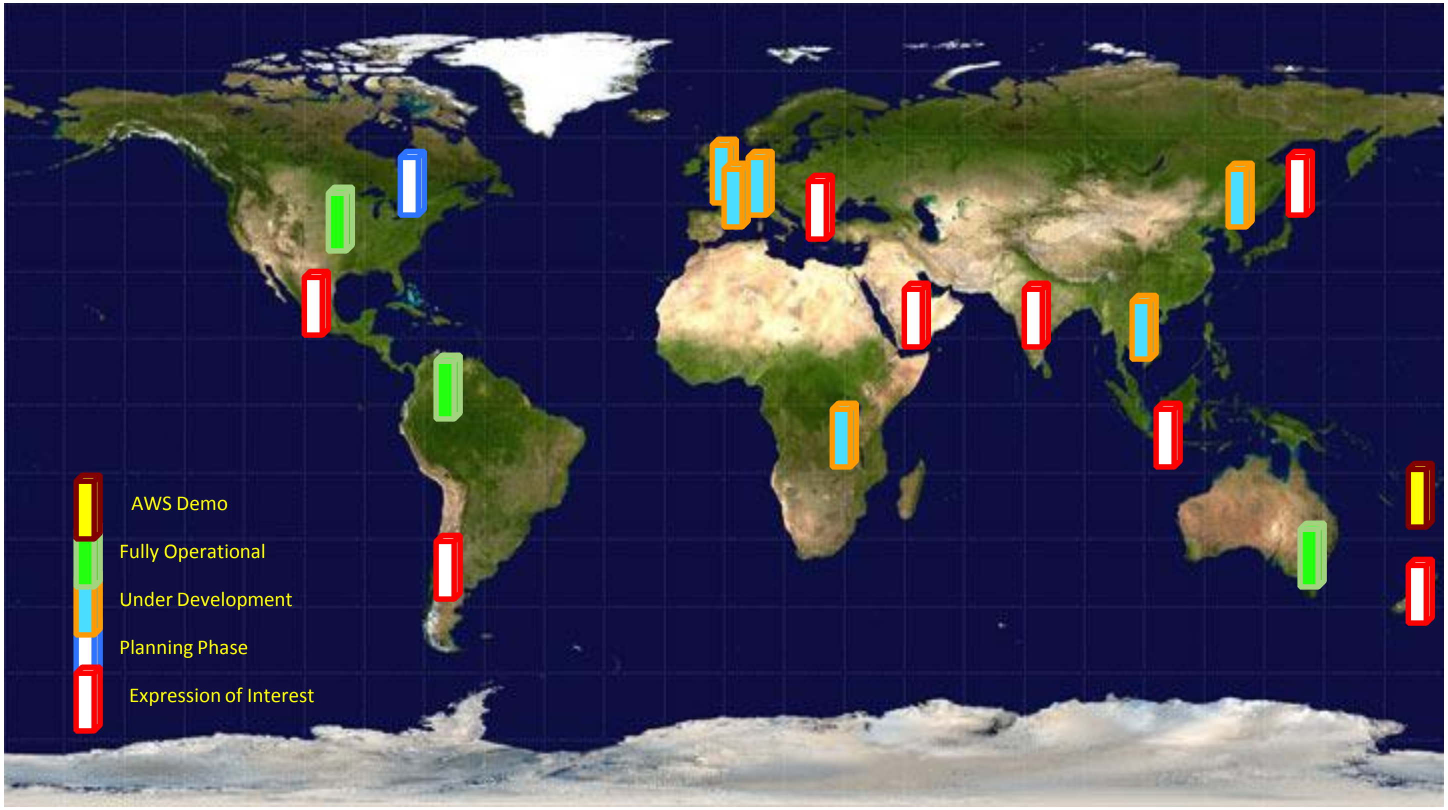


Potential use for
SDG #6:

Potential use for
SDG #2; SDG #6:

Tracking agricultural change

OpenDataCube.org: Growing a Network of Compatible Open DataCubes



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Thank you