



### **Water Detection Algorithms and Prior Data**

Roger Fjørtoft, <u>Damien Desroches</u>, Victor Poughon, Brent Williams, Lucie Labat-Allée, Emmanuelle Sarrazin, Nadine Pourthié, Denis Carbonne, Hervé Yesou







1

SWOT Science Team Meeting, Montreal, Canada 23 June 2018





SWOT Science Team Meeting, 23-26 June 2018

2 © cnes

## OUTLINE

- Water detection in SWOT HR images
  - Phenomenology
  - > Algorithms
  - Performance assessment
- Use of prior data
  - > Objectives, applications
  - > Dark water flagging: performance gain assessment
  - PIXC inclusion zones: assessment of prior water masks
- Status and way forward

#### **SWOT** water detection phenomenology

Water signal is assumed to be distinct from land signal

- Primarily by the power/brightness/ $\sigma_0$
- May be some information in coherence or in height/phase flatness

#### Nominal $\sigma_0$ : bright water, dark land

- Water is expected to be bright ( $\sigma_0 \sim 10$  to 15 dB)
- Most land types are dark ( $\sigma_0 \sim -5$  to 0 dB)

#### $\sigma_0$ exceptions:

- Dark water: Weak water backscattering off-nadir for very low wind speeds (smooth surface)
- \* Rain and vegetation attenuate the surface signal
- Some bright land types (e.g., roads, urban areas, hills/mountains (layover), snow?)

#### SWOT has high thermal noise floor

- ~ 0 dB noise-equivalent-  $\sigma_0$  in best part of swath for single channel (CBE)
- Most land signals dominated by noise
- Up to 3 dB SNR gain by combining two channels coherently, using a DEM to rotate phases

Coherence time of water limits azimuth focusing (widens azimuth PTR)





## **SWOT** water detection baseline method

Iterative parameter estimation and classification



#### Water detection performance assessment

Assessment w.r.t science requirement: relative error in area [m<sup>2</sup>]

		Relative Error	Lake size	River size
	Req.	15% (1σ)	>(250m²)	>100m (x10km)
	TSM Req.	15% (1σ)	>1km <sup>2</sup>	>170m (x10km)
	Goal	25% (1σ)	(100m) <sup>2</sup> - (250m) <sup>2</sup>	[50-100]m (x10km)

Principle: assessment at water body level (river reach or lake)



#### Example: attribution of pixels to reaches



5 ) © cnes

- Attribute detected and ground truth water pixels to known water bodies
- For each water body, compute relative error in surface area between detected water body and ground truth.
- Compute histogram of relative errors, 1σ value
- Compare with requirement: < 15% (1 $\sigma$ )

#### Remarks

- Science requirement is on area: perfect overlap not explicitly required
- Assessment on rivers only for Measurement Review 2 (using river DB, RiverObs)

#### Water detection performance assessment

Performance assessment presented at Measurement Review 2 (5-6 Dec 2017)

- Po river (1 year) + US lidar scenes (altogether > 270 images x 2 configurations)
- Current Best Estimate (CBE) and Worst Case (WC) simulation configurations
- Example: US lidar scene (extract)



**Coherent power** 



#### Water detection performance assessment

Preliminary water detection results without dark water flagging

Po river (1 year) + US lidar scenes (altogether > 270 images x 2 configurations)



7) © cnes

- \* Within science requirements: <15% (1 $\sigma$ ) for rivers >100m (CBE and WC)
- Errors mainly due to dark water (area underestimated)
- Slight overestimation of extent mainly due to azimuth smearing

Données spatiales, in-situ et hydrologie, 31/05/2018

## Use of prior water masks in SWOT HR processing

#### Dark water flagging

- Extend detected water mask (compensate dark water, misclassification)
- GSWO (Pekel et al.): identify occurrence level (%) that fits detected water

Zones to always include in the HR L2 Pixel Cloud product (floodplain, wetlands...)

Prior water probability > 0 for at least one water probability map (GSWO + ~ 2-3 others), or covered by the prior river and lake databases prepared for SWOT

Zones to always exclude from the HR L2 Pixel Cloud product (water unlikely)

Could be based on prior water masks, map information, DEM... (TBC)

#### Other potential applications (TBC)

- Water detection(as training set or additional data layer)
- Land/water layover prediction?
- Phase unwrapping?



Study: Identify a limited number of global water masks, ranked by accuracy and complementarity w.r.t. GWSO.

8 Cnes

#### Water detection performance assessment

Preliminary water detection results with dark water flagging

Po river (1 year) + US lidar scenes (altogether > 270 images)



• Well within science requirements: <15% (1 $\sigma$ ) for rivers >100m (CBE and WC)

\* On boarderline for meeting goal: <25% (1 $\sigma$ ) for 50-100m rivers (CBE OK, WC NOK)



**80%** 

9) © cnes

## **Approach for prior water mask assessment**

Comparison of available and relevant global water masks on 5 different test sites

- List of water masks and test sites in backup slides
- Focus on maximum water extent (for PIXC inclusion zones)

Quantitative analysis

- Computation of statistical metrics relative to Pekel et al.'s GSWO
  - Knowing that GSWO is not perfect (water under vegetation, persistent cloud cover...)
  - False positives (FP) in ha and %, Recall = TP / (TP + FN), Precision = TP / (TP + FP)

Qualitative assessment

- Further analysis of false positives by visual interpretation
- Sentinel-2 and/or Sentinel-1 data (two dates in the hydrologic cycle)
- Other available ground truth

Ranking by site and overall







## **Prior water mask assessment**

Example: Quantitative assessment on Inner Niger Delta (IND)

#### Comparison with GSW maximum water extent

	FP	FPR	Recall	Precision
	(ha)	(%)	(%)	(%)
GlobeLand30 Water	39194	3.49	19.49	84.37
GlobeLand30 Wetland	43281	3.83	2.33	36.85
GlobeLand30 Water & Wetland	82475	7.06	21.82	74.17
OSM	230461	17.51	31.97	60.1
From GLC Hierarchy	30406	2.72	19.96	87.69
GIEMS-D3 75-100%	381281	25.99	22.96	39.53
GIEMS-D3 50-100%	1896613	63.6	42.7	19.64
GIEMS-D3 25-100%	4136583	79.21	52.86	12.18
GIEMS-D3 0-100%	6047652	84,78	55,69	9,09
Global Water Pack				
GLWD	3677563	77.21	85.53	20.16
ESA CCI 300m	26799	2.41	16.8	87.19
ESA CCI 20m	58427	5.11	27.46	83.61

On the Inner Niger Delta test site we expect (want) a high FPR in order to cover the large delta not covered by GSW.









#### **Prior water mask assessment**

## **Prior water mask assessment**

Ranking based on quantitative results and qualitative analysis: highly dependent on test site!

Ranking	Inner Niger Delta	Ganges Brahmaputra Delta	Poyang Lake	Canadian Lakes	Alsace-Lorraine
1	GLWD	GIEMS-D3 75-100%	Global Water Pack	ESA CCI 300m	GIEMS-D3 0-100%
2	GIEMS-D3 50- 100%	GlobeLand30 Water & Wetland	GlobeLand30 Water & Wetland	GlobeLand30 Water	HRL
3	OSM	GLWD	OSM	GLWD	OSM

Preliminary overall top 3 ranking (i.e. for all sites, as a complement to GSWO)

- > GIEMS-D3 (provides considerable additional surface; the choice of occurrence range is delicate)
- GLWD (excellent on Inner Niger Delta, very rough elsewhere (Poyang, Ganges-Brahmaputra...))
- GlobeLand30 (provides limited additional surface, good overall precision)





14 © cnes

SWOT Science Team Meeting, 23-26 June 2018, Montreal, Canada

## **Status and way forward**

#### Water detection algorithms

- Baseline water detection method prototyped and integrated in PIXC SAS prototype
  - > Iterative MRF classification and estimation (PhD of Sylvain Lobry, Télécom ParisTECH/CNES, Nov. 2017)
- Large-scale testing on simulated data in conjunction with Measurement Review 2 (Dec. 2017)
  - Science requirements w.r.t. water surface area met for rivers
  - Further improved by dark water flagging (based on GSWO)
- Ongoing and upcoming work
  - > Further algorithm tuning, extension of performance assessment to lakes, larger data set
  - > Writing of journal paper and ATBD section on baseline water detection method
  - Prototype evolving towards operational code (handling of degraded cases, computational efficiency...)
  - PhD of Nicolas Gasnier (Télécom ParisTECH/CNES/C-S), 2018-21
    - ✓ Further work on narrow river detection (supported by river database)
    - ✓ Multi-temporal and multi-sensor water detection (risk mitigation)





15 © cnes

#### **Status and way forward**

#### Use of prior data related to water detection

- Dark water flagging
  - > Based on GSWO (Pekel et al.): identify occurrence level (%) that best fits detected water, expand
    - Shown to provide a gain in accuracy on simulated data
- Zones to always include in the HR L2 Pixel Cloud product (floodplain, wetlands...)
  - Prior water probability > 0 for at least one water probability map, or covered by the prior river and lake databases prepared for SWOT
    - ✓ Quantitative and qualitative assessment of water masks w.r.t. GSWO: accuracy highly dependent on test site
    - ✓ Preliminary overall top-3 ranking establish, but continue to follow new masks and meta-mask initiatives
- Ongoing and upcoming work
  - > Assessment of DEM quality and coherence between DEMs and water masks
  - Study masks, DEMs and other data to define exclusion zones for SWOT HR L2 products
  - Prototyping of inclusion and exclusion zone processing steps



16 © cnes

# BACKUP

#### **SWOT** water detection phenomenology



Courtesy of Sylvain Lobry, Télécom ParisTECH



## **SWOT** water detection phenomenology



Simulated coherent power

Detected water mask





## Water probability maps of Pekel et al.

#### **Global Water Surface (GWS) dataset**

- Based on 32 years (1984-2015) of LandSat images at ~30 m resolution
- Available globally
  - GeoTiff files, WGS84, 10° x 10° tiles
- Several data layers (backup slides)
- Of particular interest for SWOT HR processing:
  - Global Surface Water Occurrence (GSWO) = water occurrence frequency between 1984 and 2015 (0-100%)
- Known weaknesses
  - > Areas where water is covered by vegetation
  - > Areas with persistent cloud cover

≻ ...



Example: Occurrence map over the Mississippi River (courtesy of J.-F. Pekel) 0.000000 0.1 0.250000 0.50000 0.750000 1.000000



## **Objective: Cover highly different hydrological environments**

- Poyang Lake, Yangtze, China
- Alsatian flood plain and Lorraine lakes, France
- Ganges Brahmaputra Delta, Bangladesh/India
- Northern Lakes, Nunavut Province, Canada
- Inner Niger Delta and Niger Loop, Mali









#### Inner Niger Delta & Niger Loop

- Sahel
- Semi-arid to semi-desert environment
- Yearly flood period start in September, peak in November, and end in April/May.
- Moderate slopes, braided river channels, wetlands, marshes and lakes
- A series of lakes, such as Debo Lake, Oro Lake, Korientze Lake, Faguibine Lake (590 km<sup>2</sup>)



900x460 km<sup>2</sup>



#### **Ganges Brahmaputra Delta**

- Third and tenth biggest rivers in the world by discharge
- Mangrove wetland ecosystems and agricultural and aquaculture activities
- Strong influence of vegetation
- Monsoon climate: heavy rainfall June to September and dry period October to March



380\*280 km<sup>2</sup>



#### **Canadian lakes**

- Nunavut Province
- ♦ 63°30-65°N
- Aberdeen, Wharton, Princess Mary, Mallery, Tebesjuak lakes (Upstream Baker Lake)
- Rivers: Dubawnt, Thelon...
- Ice/snow cover in winter
- Permafrost
- AirSWOT Mission July 2017
- Access to ground truth through Canadian Environmental Ministry
- 200 x160 km<sup>2</sup>







24 © cnes

#### SWOT Science Team Meeting, 23-26 June 2018, Montreal, Canada

#### Water masks

#### **Global masks**

- GWSO (Pekel et al.): Landsat optical data, 30 m
- GIEMS-D3 (Aires et al.): optical and passive/active microwave data, downscaled to 90 m
- Copernicus Global Land Service Water bodies (Vito): PROBA-V, 333 m
- GLOBELAND30 Water & Wetlands (National Geomatics Center of China): Landsat 30 m
- Global Water Pack (DLR): Terra/Aqua, 250 m
- FROM-GLC-Hierarchy (Tsinghua University): MODIS, Landsat, 30 m
- ESA CCI 300/20m (ESA/Univ. Louvain): MERIS 250 m, S2 10 m (Africa)
- GLWD = Global Lakes and Wetlands Database (Lehner et al.): various maps and data
- OSM = Open Street Map (collaborative project)

Also some masks with continental or regional coverage (backup slide)



25 © cnes

#### SWOT Science Team Meeting, 23-26 June 2018, Montreal, Canada

#### Water masks

WORLDWIDE COVERAGE								
	n°	Alsace-Lorraine (France)	Poyang-Yangtze (Chine)	Inner Niger Delta	Canadian lakes	Gange-Brahmaputra (Bangladesh-Inde)		
GSW (Pekel-JRC)	1	✓	√	✓	✓	1		
GIEMS-D3 (Aires)	2	✓	✓	✓	<ul> <li>Image: A second s</li></ul>	✓		
Water bodies (Copernicus/Vito)	3	✓	✓	✓	✓	1		
GLC-30 (Chen)	4	✓	✓	✓	<ul> <li>Image: A second s</li></ul>	✓		
Global Water Pack (DLR)	5	*	✓	<ul> <li>✓</li> </ul>	<ul> <li>Image: A set of the set of the</li></ul>	✓		
From GLC Hierarchy	6	✓	✓	<ul> <li>Image: A set of the set of the</li></ul>	<ul> <li>Image: A set of the set of the</li></ul>	✓		
OSM	7	✓	✓	✓	<ul> <li>Image: A second s</li></ul>	✓		
GLWD (Lehner)	8	✓	✓	✓	✓	1		
ESA LCCS 2010	9	✓	✓	<b>√</b>	<b>V</b>	1		

		1				1
CONTINENTAL COVERAGE						
	n°	Alsace-Lorraine (France)	Poyang-Yangtze (Chine)	Inner Niger Delta	Canadian lakes	Gange-Brahmaputra (Bangladesh-Inde)
ESA CCI LC 2016 (Africa)	10	*	*	1	×	*
HR layers (Europe)	11	✓	*	×	×	*

	1	1		1				
LOCAL COVERAGE								
	n°	Alsace-Lorraine (France)	Poyang-Yangtze (Chine)	Inner Niger Delta	Canadian lakes	Gange-Brahmaputra (Bangladesh-Inde)		
CES OSO (Cesbio France)	12	✓	a de la companya de l	×	3E			
Database dowloaded totally	-	]						
Database dowloaded partially (subset)	-	]						
Not available or not distributed	x	]						
		-						



