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What is missing? An operational inundation mapping framework by SAR data

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I Abstract

Mapping Inundation area caused by severe weathers primarily relies on synthetic aperture radar (SAR) data because of its imaging capacity in all-weather, fine resolution and current abundance. A near real time(NRT) mapping system is crucial for loss assessment, disaster alleviation and insurance estimation and yet in vacant. We have develop an NRT radar produced inundation diary system (RAPID)(Shen et al., 2017) that attempts to address the automation and accuracy problems and to provide readily applicable inundation extent information. RAPID is fully automatic and the resultant quality is close to optical water mapping result in clear weather conditions by means of reducing over- and under-detections caused by noise-like speckle, water like radar response area and strong scatters, to an insignificant level. RAPID can serve as kernel algorithm for flood-inundation product of existing and to be launched satellites equipped with a high resolution SAR sensor such as ALOS, Sentinel-1, TerraSAR-X and SWOT.

II Introduction

- NRT inundation mapping is crucial to rescue, damage recovery decisions, facilitate rapid assessment of property loss and damages.
- SAR is the only reliable remote sensing resource for flood-inundation mapping due to its
  - all weather, diurnal working ability
  - high spatiotemporal resolution
- Existing algorithms did not address the operational demands of NRT SAR inundation mapping
  - No water body product exists for any SAR-equipped satellites
  - The automation and quality are compromised by shadowing areas, the noise-like speckle, strong-scatter.
  - Tedious manual editing that requires expertise may not always be available
- We have therefore built the RAPID system
  - is fully automated thus support NRT
  - integrates statistical, morphological and machine learning approaches
  - incorporates multi-source remote sensing data products
  - reduces over- and under-detection to an insignificant level.

II Method

The framework of RAPID is depicted in Figure 1. It consists of four automated steps

A. Self-optimized binary classification with multiple thresholds

B. Morphological removal of over-detection (water-like radar response areas);

C. Compensation of under-detection

D. Machine learning features based correction.

A. Binary Classification

- For incidence normalized dual-polarized intensities, I_1,I_2 (Mladenova et al., 2013), their joint probability density function (PDF) is given by (1) (Hagedorn et al., 2006)

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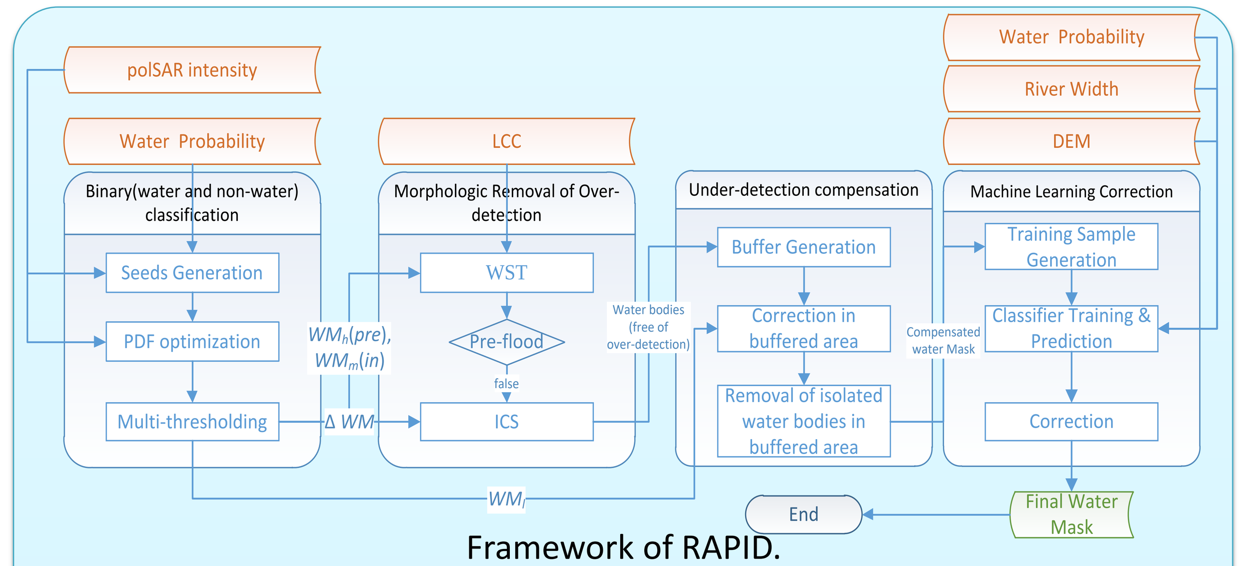


Framework of RAPID.

$$p(I_1,I_2)=\frac{n^{n+1}(I_1I_2)^{\frac{n-1}{2}}exp\left[-\frac{n(I_1/C_{11}+I_2/C_{22})}{1-|\rho_c|^2}\right]}{(C_{11}C_{22})^{\frac{n+1}{2}}\Gamma(n)(1-|\rho_c|^2)|\rho_c|^{n-1}}\mathrm{I}_{n-1}\left(2n\sqrt{\frac{I_1I_2}{C_{11}C_{22}}}\frac{|\rho_c|}{1-|\rho_c|^2}\right)$$

  - $\Gamma(\cdot)$ and In $(\cdot)$-Gamma function and modified Bessel function
  - n - the equivalent number of looks (ENL).
- Iterative optimization for each swath of SAR image
  - $(C_{11},C_{22},|\rho_c|)$-expectation and covariance of (I_1,I_2)
  - probability density-based segment threshold, th_{PD}
  - bring the theoretical PDF closest to the histogram of water pixels
  - Multiple water masks , WM_h, WM_m, WM_l, are generated using multi-level threshold, th_{PD}, $th_{PD}/30$, $th_{PD}/300$.
  - WM_h - best separability,
  - WM_m - balanced over- and under detection
  - WM_l - low level under-detection & high level over-detection.

B. Morphologic Processing

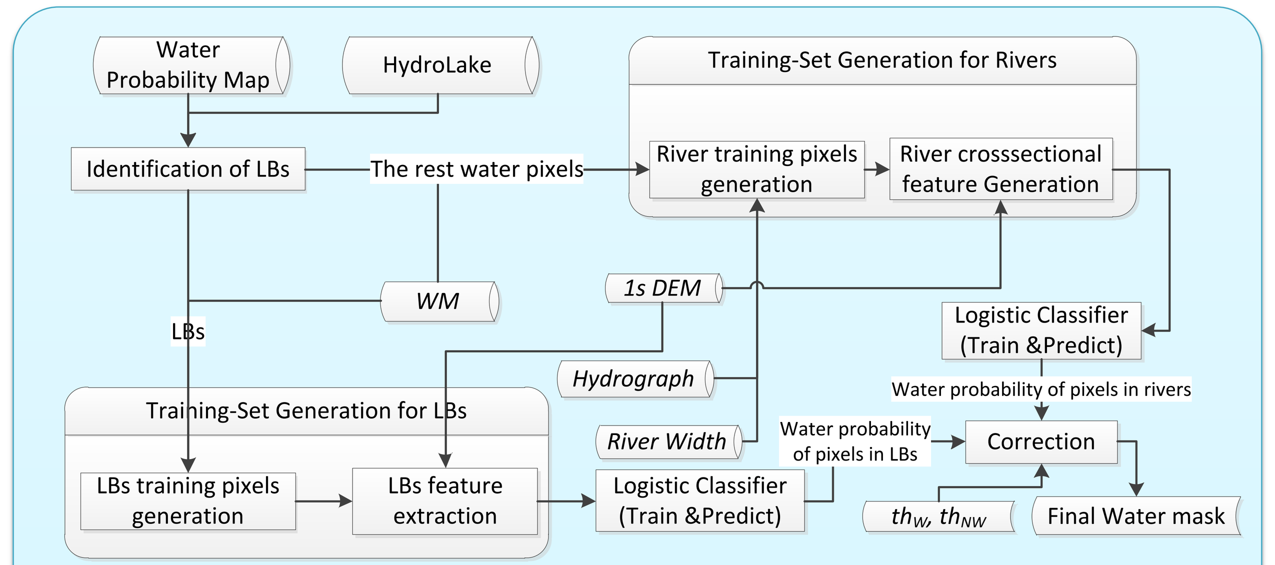
- Water source tracing (WST)
  - Region grow algorithm (RGA) on $WM_h(pre)$ and $WM_m(in)$
  - Seeds-High resolution land cover classification (LCC) (Gong et al. 2013)
  - Improved change detection (ICD)
  - RGA on $WM_m(in)$
  - $seeds\text{-}\Delta WM= WM_h(in)- WM_m(pre)$
- Over-detection prevention criterion
  - th_{size}>50 pixels-size threshold - WST+ICD
  - r_{dev}<80% - developing ratio -WST+ICD
  - r_{inund}>30% - inundation ratio - WST+ICD
  - r_p>50% - probability ratio – ICD

C. Compensation

- Create a buffer region (extending 15 pixels) WM from Step B
- Label a buffered pixel as water if it is identified as water in the WM_l
- Use RGA to remove disconnected patches this step.

D. Machine Learning-Based Correction

- Correct over- and under-detections caused by strong scatterers and speckles
- Identify lake bodies (lakes, ponds, reservoirs) LBs from all water bodies
- Train LBs and rivers separately
- Water Unit: River Cross-section (RC) and LB
- Generate training set as pixels in a buffered area from water bodies (Allen and Pavelsky 2015; Yamazaki et al. 2014)
- Logistic Classifier
  - Probability as water for each pixel of training
  - Double probability thresholds (water>0.8, non-water <0.1, no change in between)

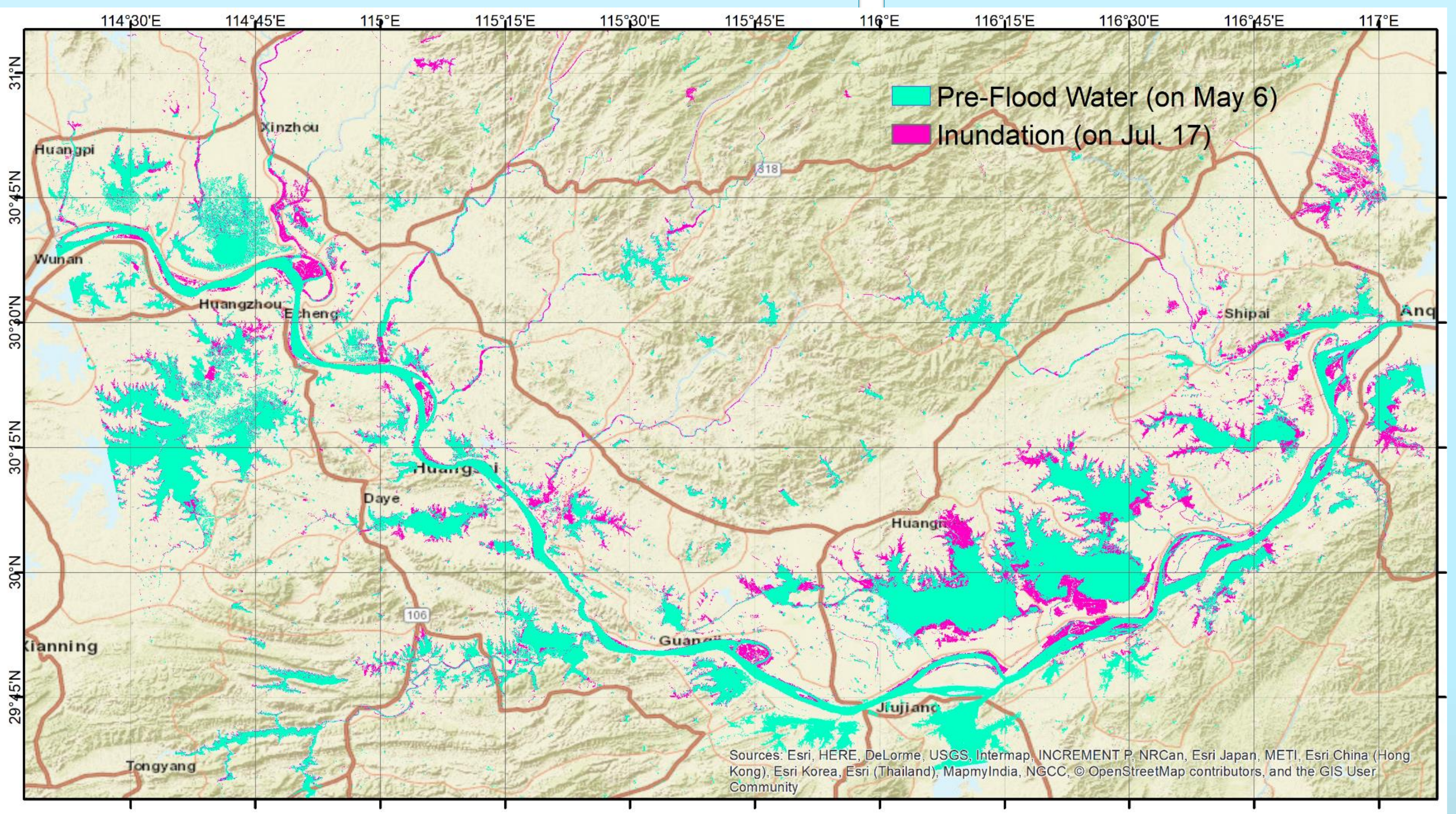


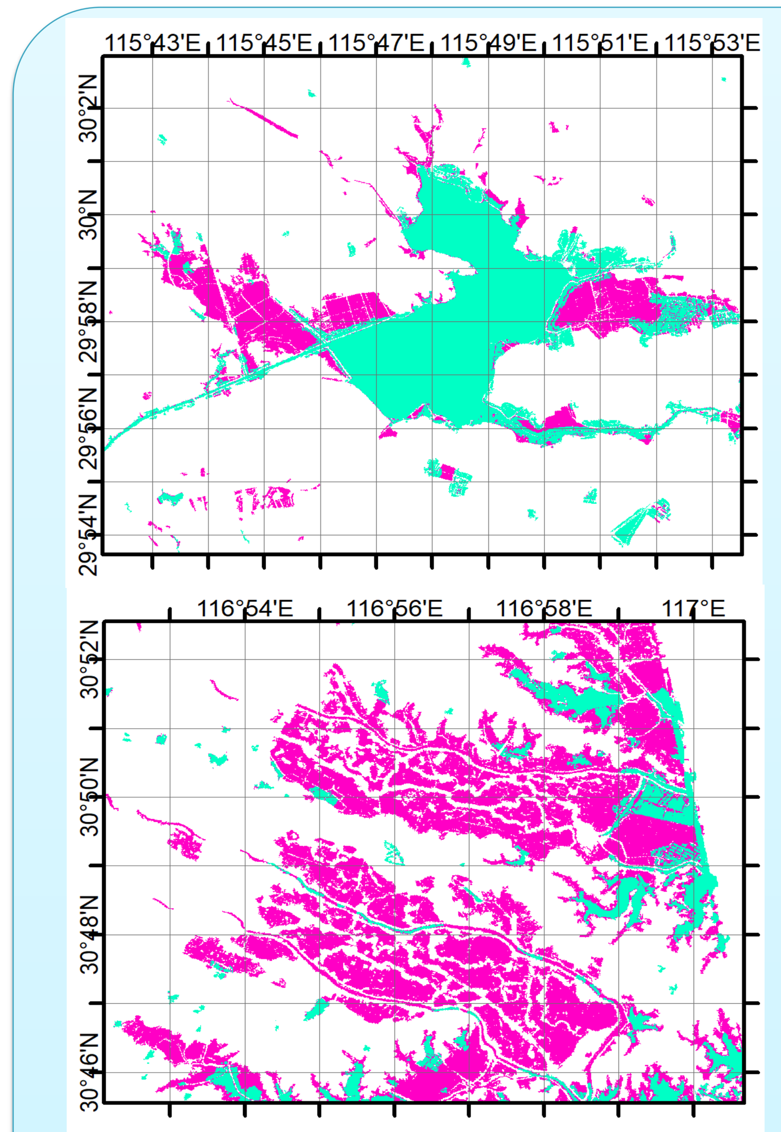
Machine learning correction.

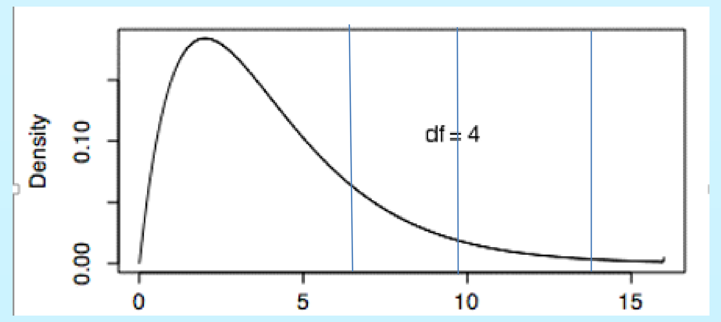
Feature space of water bodies for the training

Feature Description	Reason to Select	Water Unit	Feature Type
Central channel pixel (CCP) FAC	River width is related to drainage area	RC	Uniform
Maximum distances from both sides to CCP	Further distance indicates smaller chance of being inundated	RC	Uniform
Distance from CCP		RC	Distributed
Maximal elevation difference to the lowest pixel	Elevation difference should below the upper limit	Both	Uniform
Elevation difference ranked at 99%, 97%, 95% and 90%		LB	Uniform
Elevation difference the lowest pixel		Both	Distributed
Elevation Ratio to the highest pixel		RC	Distributed
Minimal probability	Central river has a high probability (works better for drier situation)	Both	Uniform
Probability ranked at 1%, 2%, 5%, 10% and 20%		LB	Uniform
probability		Both	Distributed

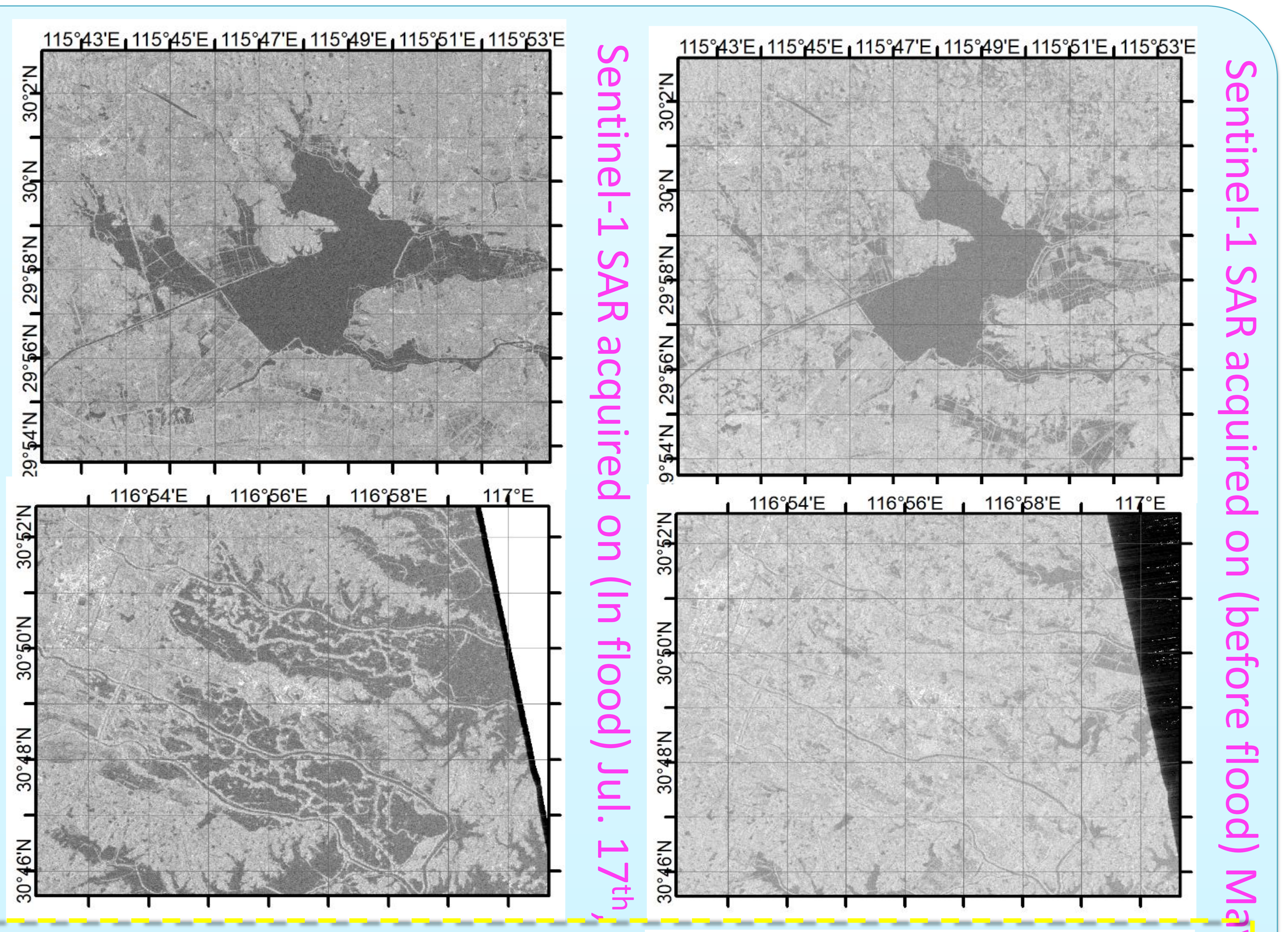
Flood Triggered by Typhoon Nepartak in Yangtze River, Jul. 17, 2016

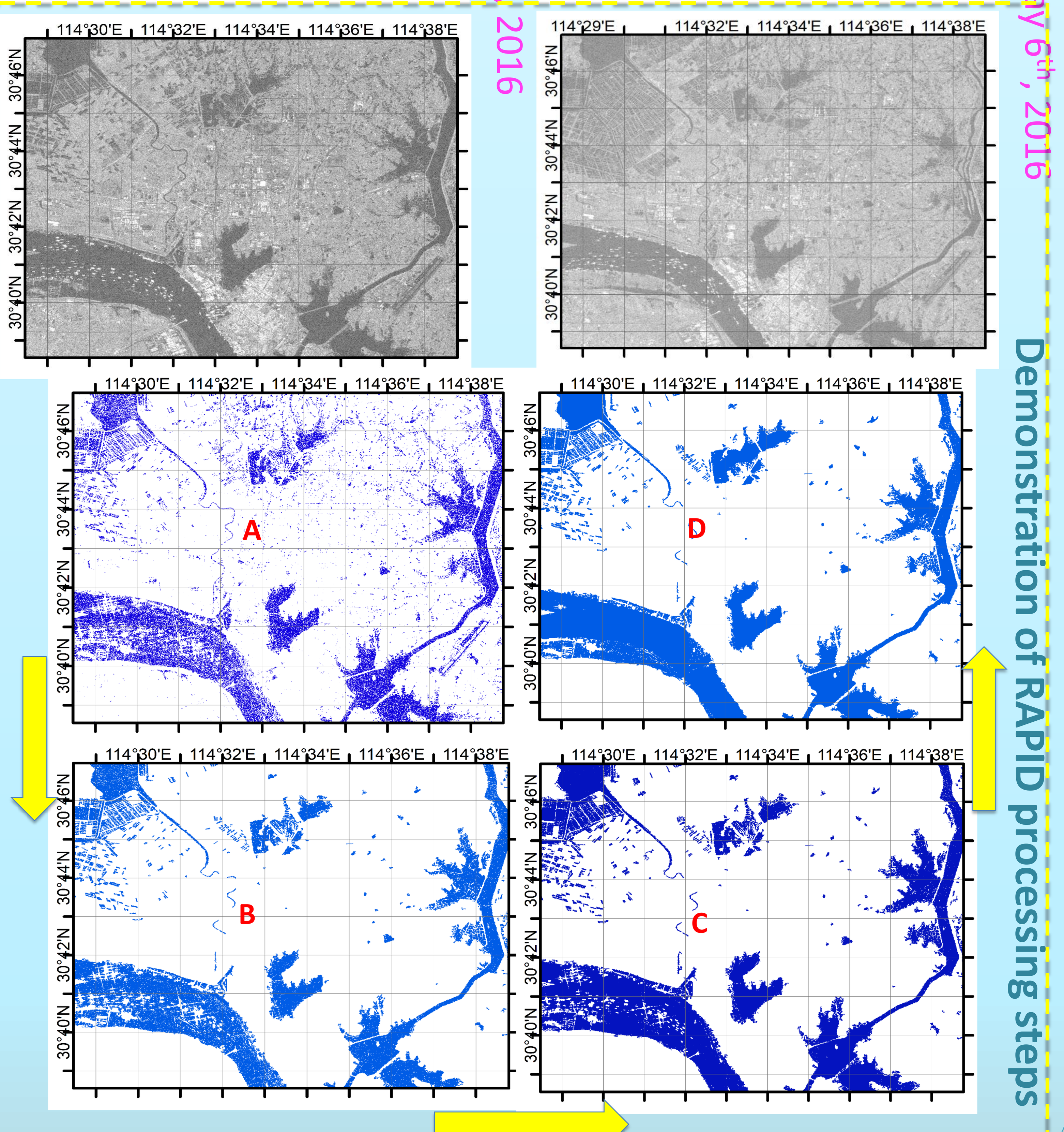






Concept of Multi-threshold for binary classification





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