GOES-R AWG FSW Team: Flood/Standing Water Detection

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LST Product Team

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- Others
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  - » Wei Guo (Proxy data)
  - » Tong Zhu (Proxy data)

Outline

- Executive Summary
- Algorithm Description
- Examples of Product Output
- Validation Approach
- Validation Results
- Summary

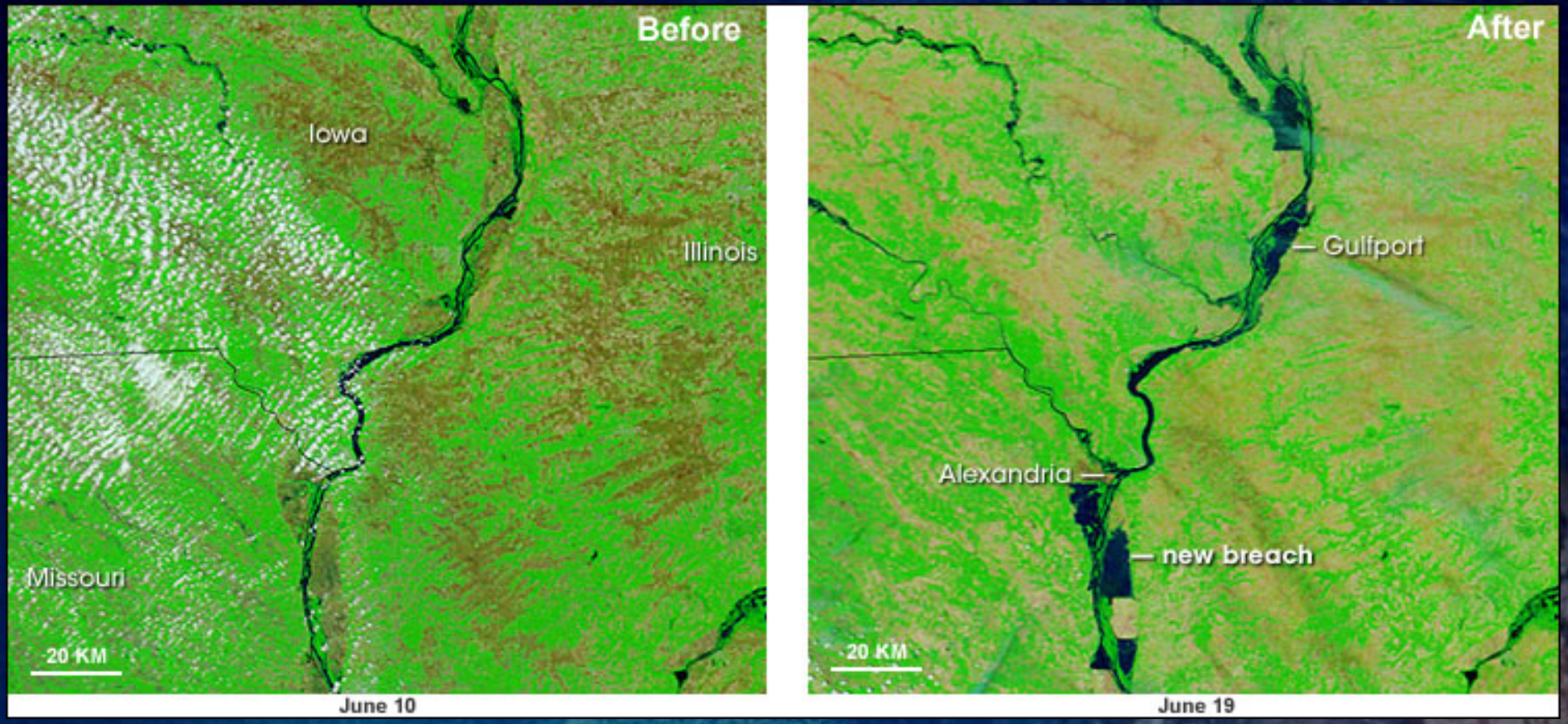
Executive Summary

- This ABI Flood/Standing Water (FSW) detection algorithm generates binary (yes/no) water/land identification products
- Software Version 3 was delivered in March. ATBD (80%) and test datasets are scheduled to be delivered in June 2010
- Algorithms perform spatial sampling of **binary "yes/no" detection of water accumulation over 5 cm vertical depth.**
- **Provide state-of-the-art water identification and flood detection over the GOES-R observation domain, in all ABI scanning modes**
- **Satisfy the GOES-R mission requirement for the FSW product**
- Evaluation Datasets: ***Map of river flooding from the USGS,*** River Flood Outlook and River Forecasting from the National weather Services of NOAA and analysis of flood/water spatial distribution and temporal change

Requirements and Product Qualifiers FSW Detection

Name	User & Priority	Geographic Coverage (G, H, C, M)	Vertical Resolution	Horizontal Resolution	Mapping Accuracy	Measurement Range	Measurement Accuracy	Product Refresh Rate/Coverage Time Option (Mode 3)	Vendor Allocated Ground Latency (O2) Mode 3	Product Measurement Precision	Temporal Coverage Qualifiers	Product Extent Qualifier	Cloud Cover Conditions Qualifier	Product Statistics Qualifier
Flood/Standing Water	GOES-R	M	N/A	1 km	5 km	Binary yes/no detection of water accumulation over 5 cm vertical depth	60% correct detection	60 min	19,435 sec	N/A	Day with sun at less then 67 degree solar zenith angle	Quantitative out to at least 67 degrees LZA and qualitative at larger LZA	Clear conditions associated with threshold accuracy	Over specified geographic area
Flood/Standing Water	GOES-R	F	N/A	1 km	5 km	Binary yes/no detection of water accumulation over 5 cm vertical depth	60% correct detection	60 min	19,435 sec	N/A	Day with sun at less then 67 degree solar zenith angle	Quantitative out to at least 67 degrees LZA and qualitative at larger LZA	Clear conditions associated with threshold accuracy	Over specified geographic area

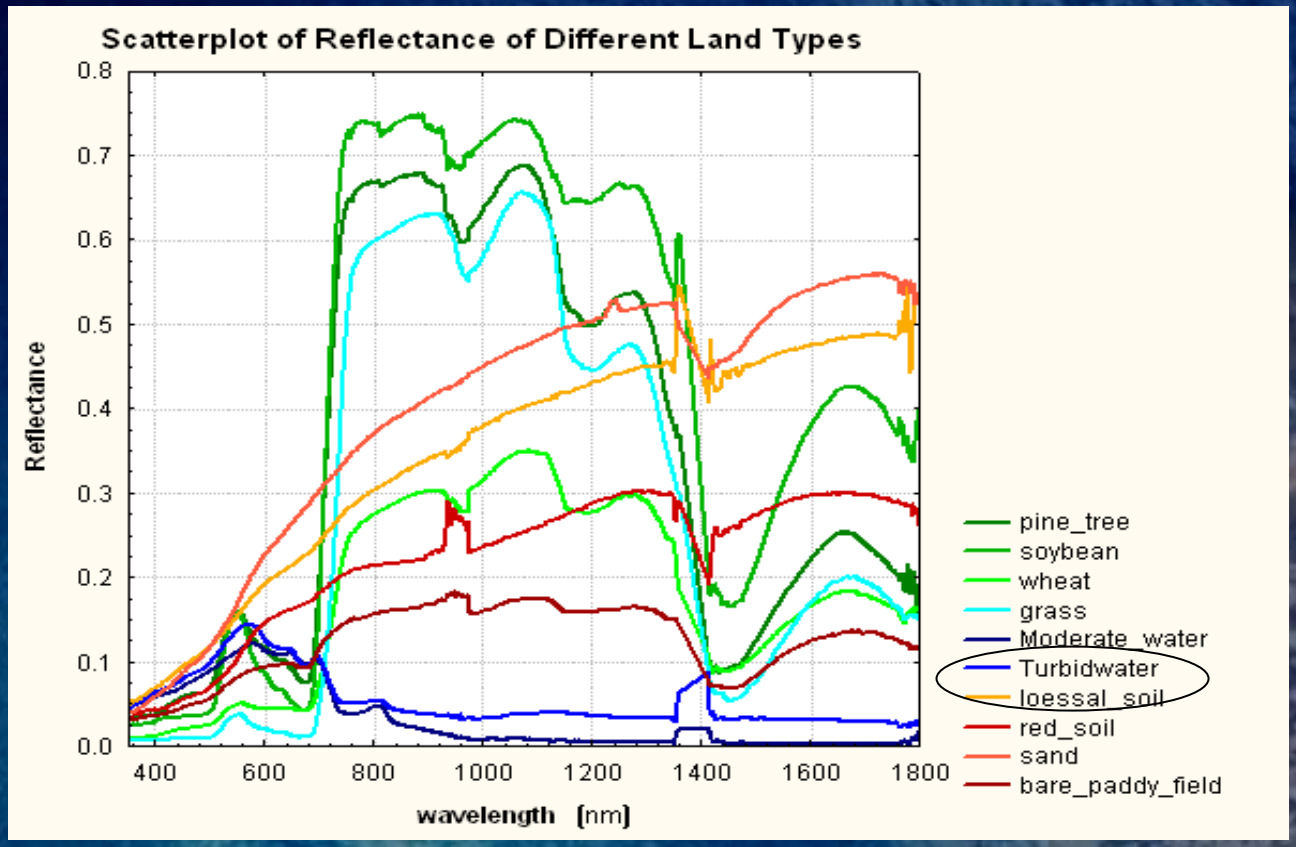
What Is Food/Standing Water



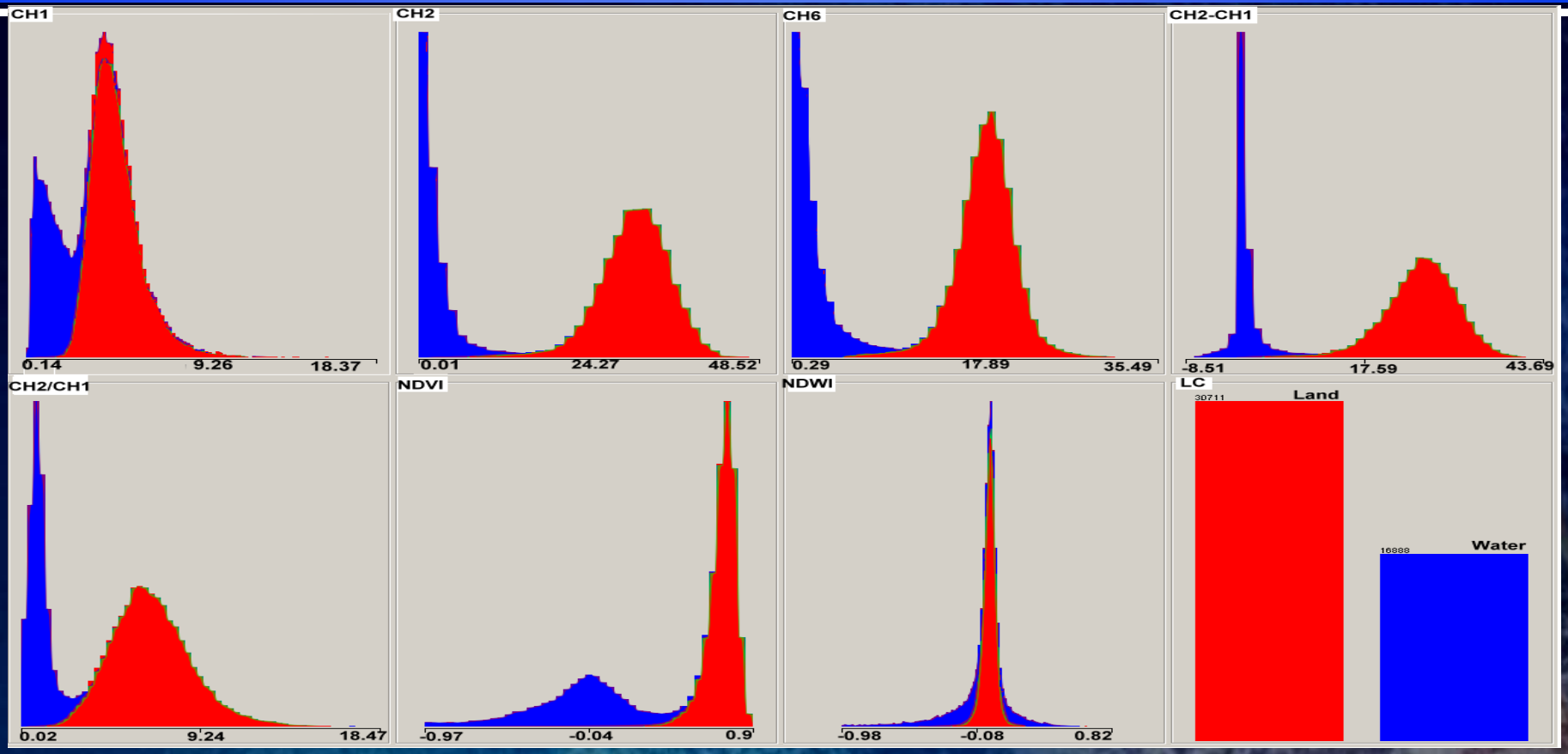
Due to the strong absorption or the low reflectance of water in the near-infrared range, flooded areas were delineated based on the sharp contrast between water spread and adjacent areas. The standing water areas appeared as dark blue to light blue depending upon the depth of water, while the receded water and wet areas appeared as dark to light gray. NASA image from Earth Observatory.

Algorithm Description
Theoretical Basis(1)

Comparing with the reflectance of vegetation and bare land, as shown in the following figure, the reflectance of water at the near infrared (NIR) (ABI ch3 or MODIS Ch2 at around 85 nm) and shortwave-infrared (SWIR) (ABI ch5 or MODIS 6 at around 160 nm), is significantly low.



Algorithm Description
Theoretical Basis(2)



The histograms show that the Water is clearly separated from the Land by using these attributes, especially the CH2 reflectance, the reflectance difference (CH2-CH1), and the reflectance ratio (CH2/CH1). Therefore binary Yes/No or Water/Land classification is a reasonable product.

Algorithm Description
DT Algorithm

Decision tree (DT) method:

a supervised machine learning approach to find hidden relationships among multiple attributes/parameters.

DT algorithms tested:

- **the J48 (C4.5, originally proposed by Quinlan (1986)),**
- **NBTree, which is a Naïve Bayes/Decision Tree hybrid (Kohavi, 1996),**
- **Random Tree,**
- **Random Forest (Breiman, 2001),**
- **REP Tree,**
- **BFTree,**
- **Decision stump,**
- **and CART (Classification and Regression Trees) and FT (Final Tree) tree classifiers.**

The basic strategy is to select an attribute that will best separate the samples into individual classes by a measurement '*Information Gain Ratio*'.

Algorithm Description
Predictors Selected

Predictors selected:

CH_3/CH_2 , CH_3-CH_2 , NDVI, NDWI

According to the spectral characteristics, water has lower reflectance in near-infrared (GOES-R ABI Channel 3, 0.88 μm) than vegetation and other land cover types. On the contrary, water has slightly higher values than land features in ABI channel 2 (0.64 μm). Therefore, the ratio image and the difference image between CH_3 and CH_2 can be used to enhance the difference between water and land (*Sheng and Xiao, 1994*). In the ratio image, water has extremely low value, while land has relatively high value.

MODIS/SEVIRI data were used as the proxy data for the GOES-R ABI data. The MODIS CH2 corresponds to the ABI CH3, and MODIS CH1 is similar to ABI CH2.

Algorithm Description
DT Algorithms Comparison

Comparison of DT Accuracy Rate of Classified Instances in different types of Decision Tree Algorithms (Water/Land/Average)

Trees Types	ADTree	BFTree	J48graft /J48	Decision Stump	FT	Random Forest	Random Tree	REPTree	CART	NBTree
Water	97.0	97.6	97.8	97.0	97.0	93.7	93.9	97.7	97.7	94.6
Land	99.0	98.9	99.2	99.1	98.0	98.9	98.9	98.9	98.9	99.2
Average	**98.7**	**98.7**	**98.9**	**98.7**	**97.8**	**98.6**	**98.1**	**98.7**	**98.8**	**98.5**

The J48 (C4.5) was selected as our baseline algorithm in the ADR

DT Algorithm for Water Identification

Example using Decision Tree (DT) Algorithm for Water Identification

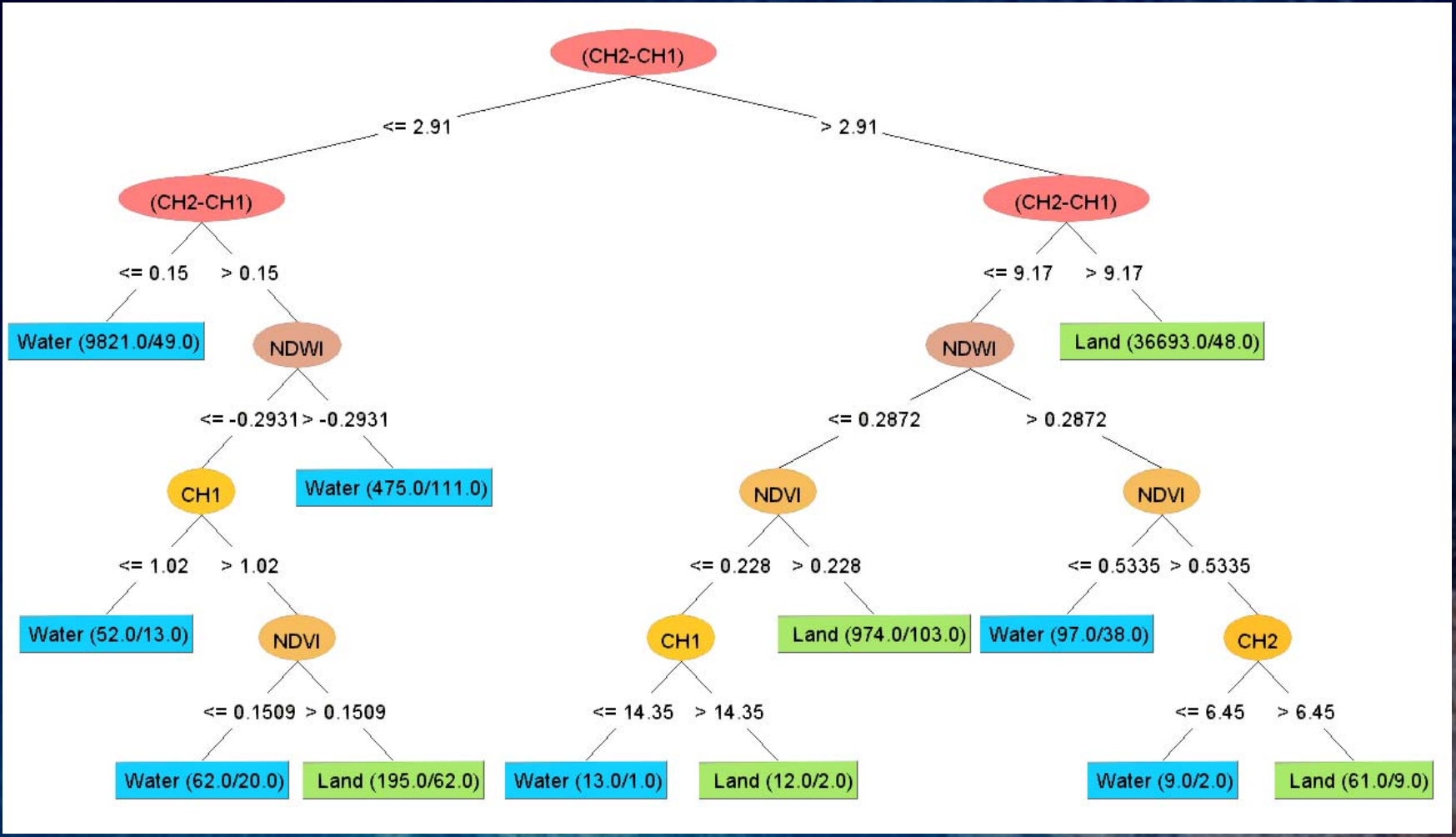
DT algorithms Water Types	NBTree	J48graft /J48	Random Forest	Random Tree	REPTree	CART	BFTree	FT
Water Mixed with land	69.6%	70.3%	76.8%	66.7%	63.8%	68.1%	66.7%	69.6%
Wetland	62.4%	66.7%	63.1%	56%	58.2%	57.7%	56%	48.9%
Pure River Water	82.1%	82.1%	84.6%	73.2%	82.1%	82.4%	79.7%	80.5%
Pure Lake Water	80.7%	82%	84%	81.3%	79.3%	86.9%	82%	80%
Average	73.4%	73.6%	75.95%	67.5%	71.7%	72%	70.4%	68.5%

Comparison of Accuracy Rates of Classified Different Water Instances

FSW Description

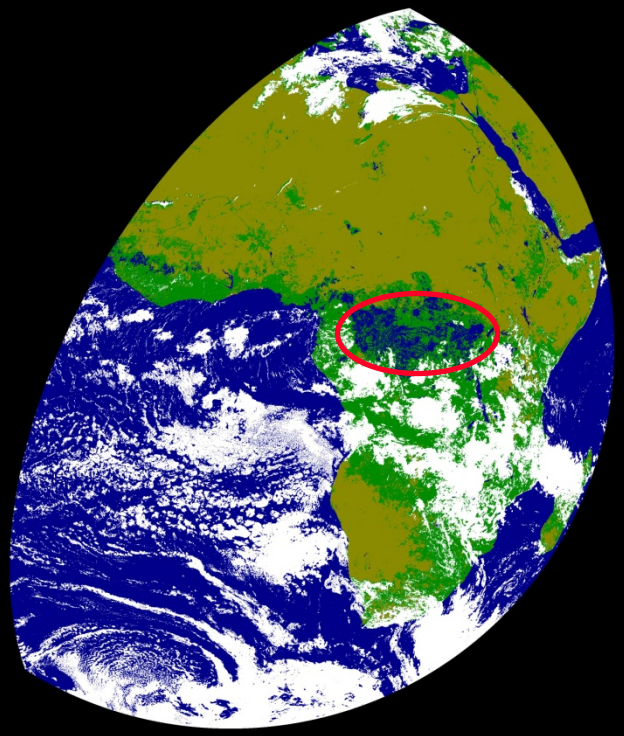
DT Algorithm for Water/Land (or yes/no) Identification

An example of tree structure from C4.5 for water/land classification with the proxy MODIS data

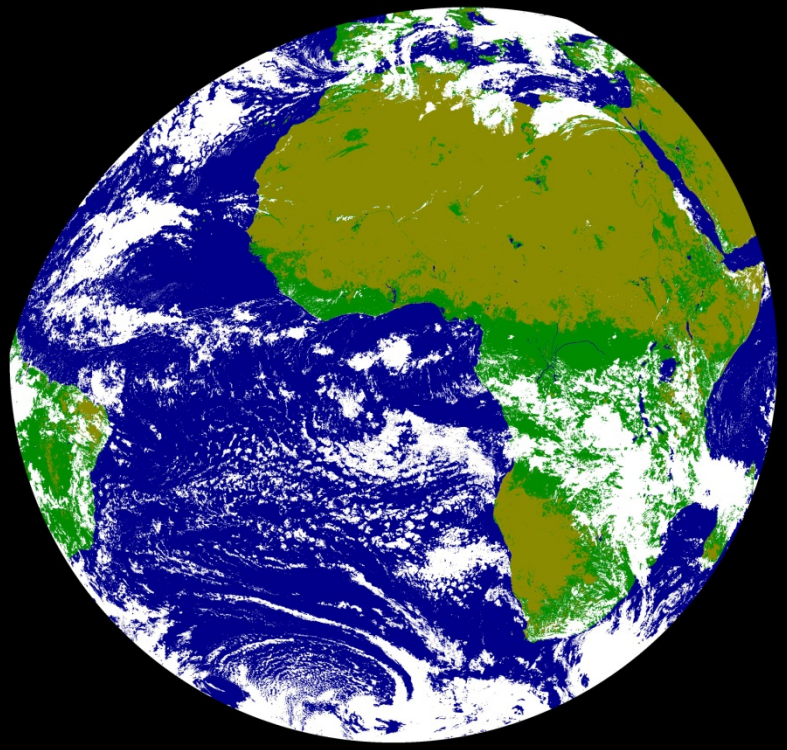


Challenges: Solar Zenith Angle Correction

08: 45 UTC, Dec 26, 2007



11: 00 UTC, Dec 26, 2007

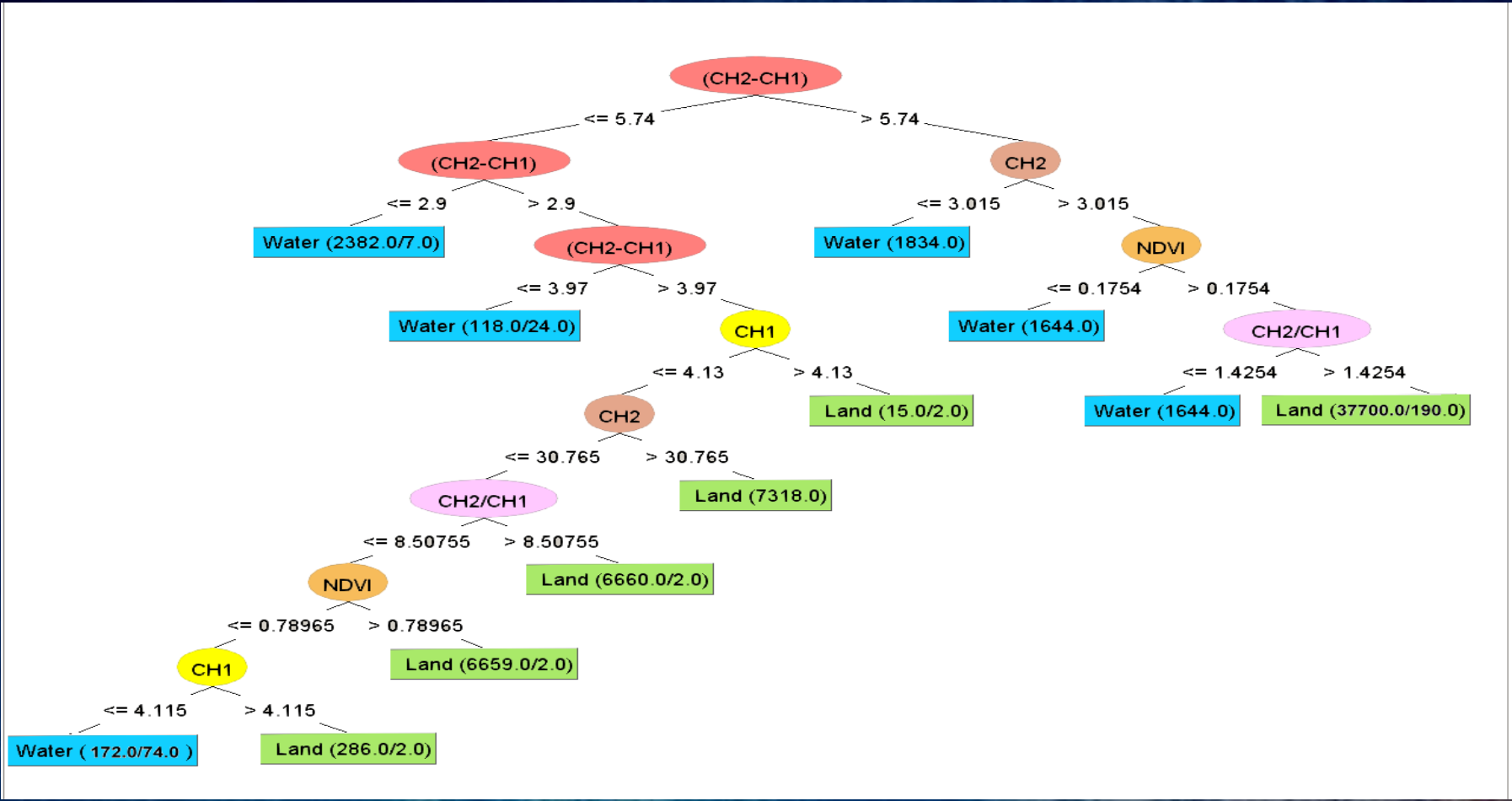


The low reflectance over vegetation during early morning and late afternoon may cause vegetated surface misclassified as water, so BRDF corrected surface reflectance is desired.

FSW Description

DT Algorithm for Water/Land (or yes/no) Identification

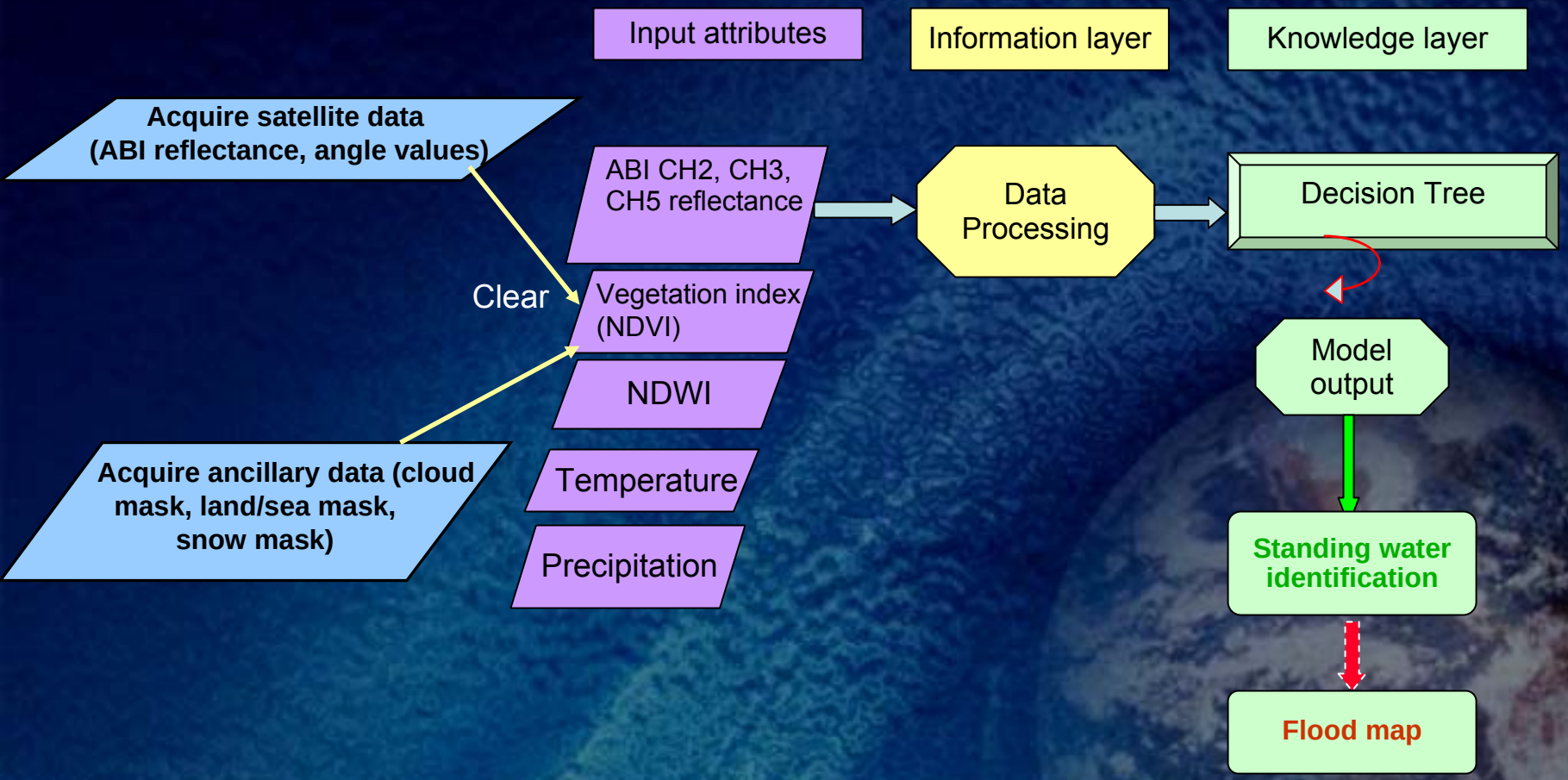
An example of tree structure from C4.5 for water/land classification with the proxy MODIS BRDF corrected surface reflectance data



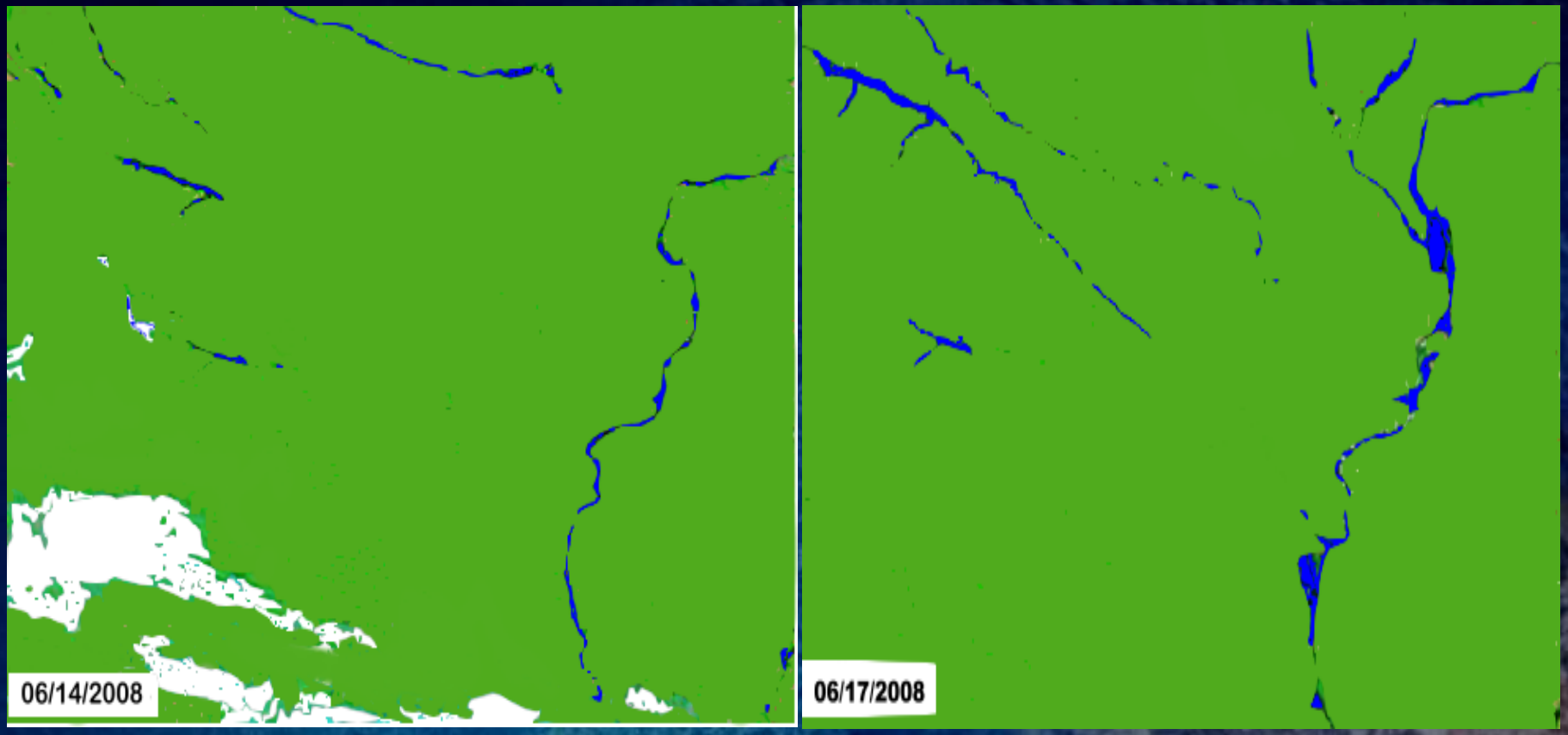
Algorithm Summary

- For binary yes/no detection of standing water, we select decision tree (C4.5) algorithm. This algorithm can integrate all useful predictors, and gives accuracy estimates.
- Input Datasets: Proxy ABI data are used to test the algorithm: 1) 1 km MODIS, 2) 3 km MSG SEVIRI.
- Water/Land are firstly identified.
- Flood detections can then be made based on the difference in water/land classification map before and after flooding
- A series of tests are performed to ensure that the algorithm can meet the accuracy requirements

FSW Processing Schematic

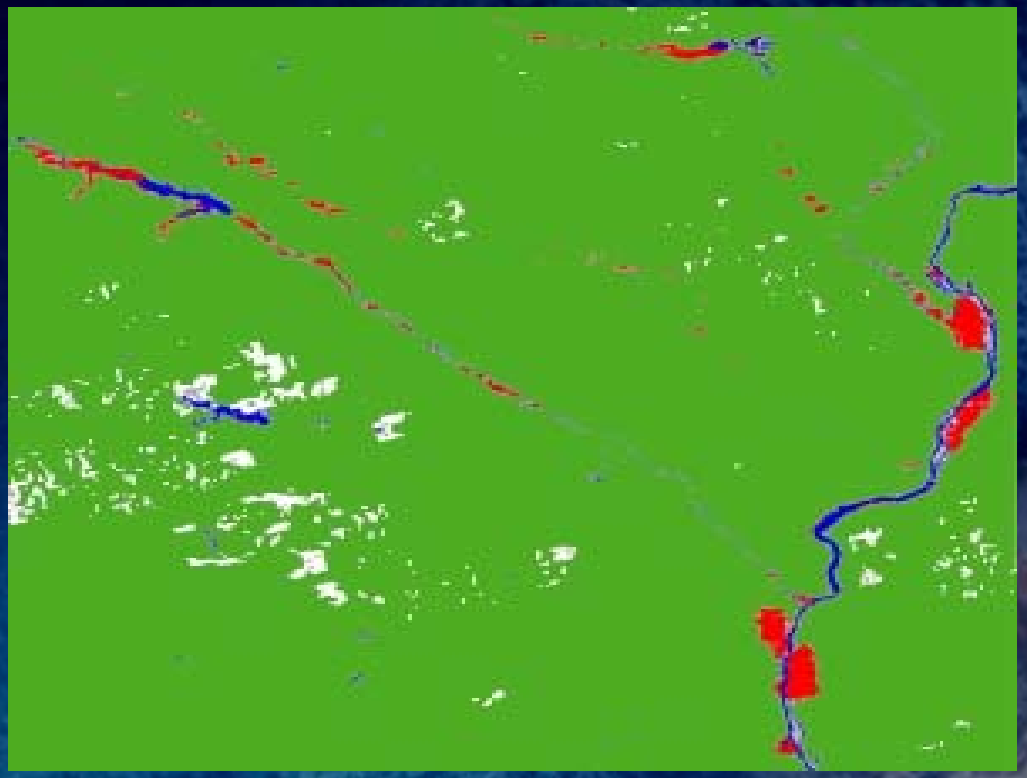


Sample FSW Product Output
Proxy MODIS Data (1)



In June 2008, unusually heavy rains from the 17th to the 19th in the upper Midwest triggered flooding throughout the upper Mississippi basin. Water (blue/Land (green) classification from the decision tree C4.5 algorithm with the proxy MODIS data for the Midwest flood case on 6/14/2008 (left) before and on 6/17/2008 (right) after the flooding.

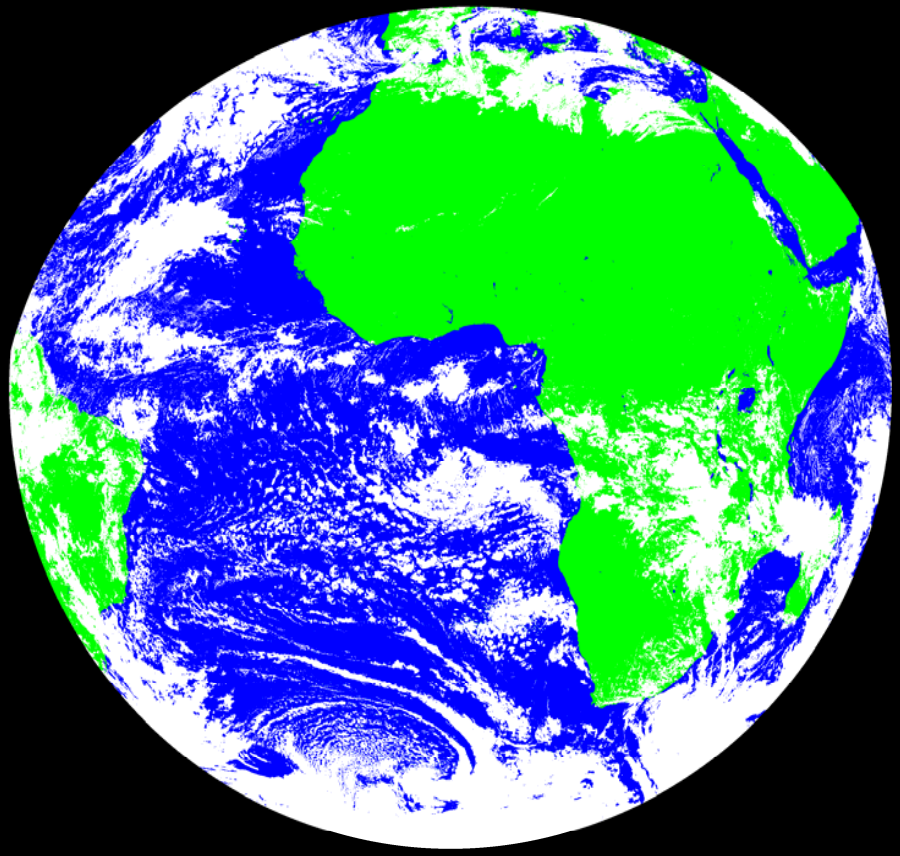
Sample FSW Product Output
Proxy MODIS Data (2)



The resulting flood (red) extent map (17-19, June 2008) derived based on the difference of water/land classification from the proxy MODIS data after and before the flooding. Red color show the flooding, while blue color show the original rivers (green: land, white: clouds)

Validation Approach (1)

Water/land classification from the C4.5 DT algorithm with the SEVIRI data at 11:45 UTC on 12/25/2007

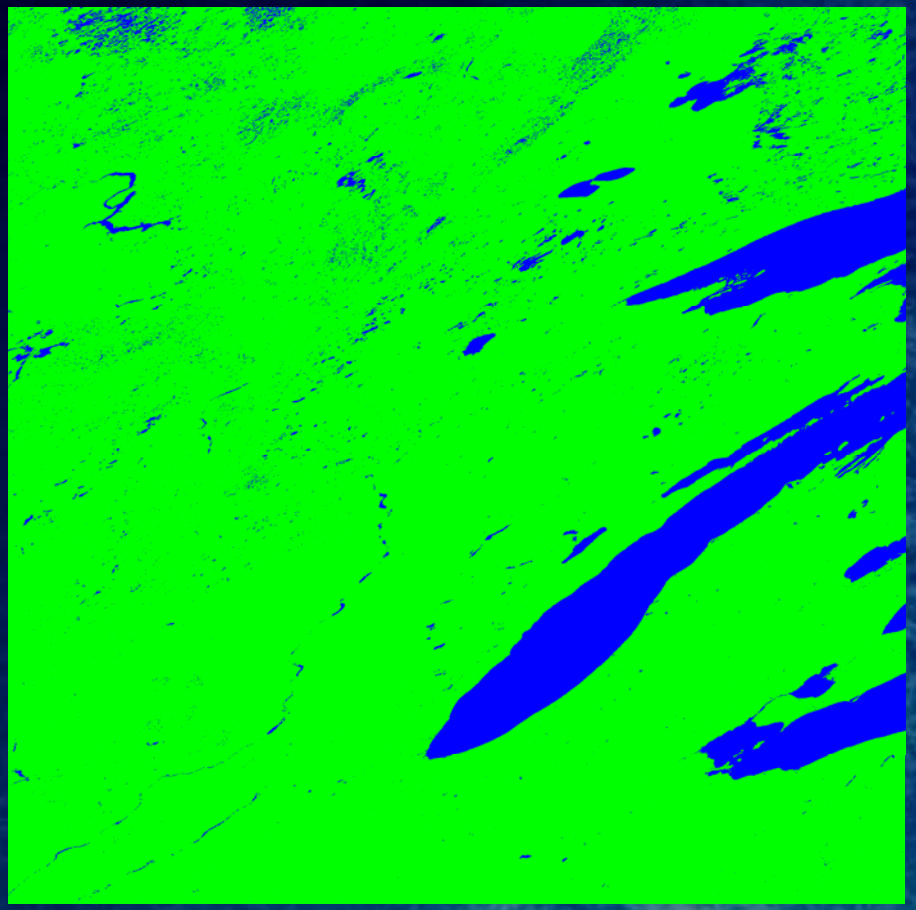


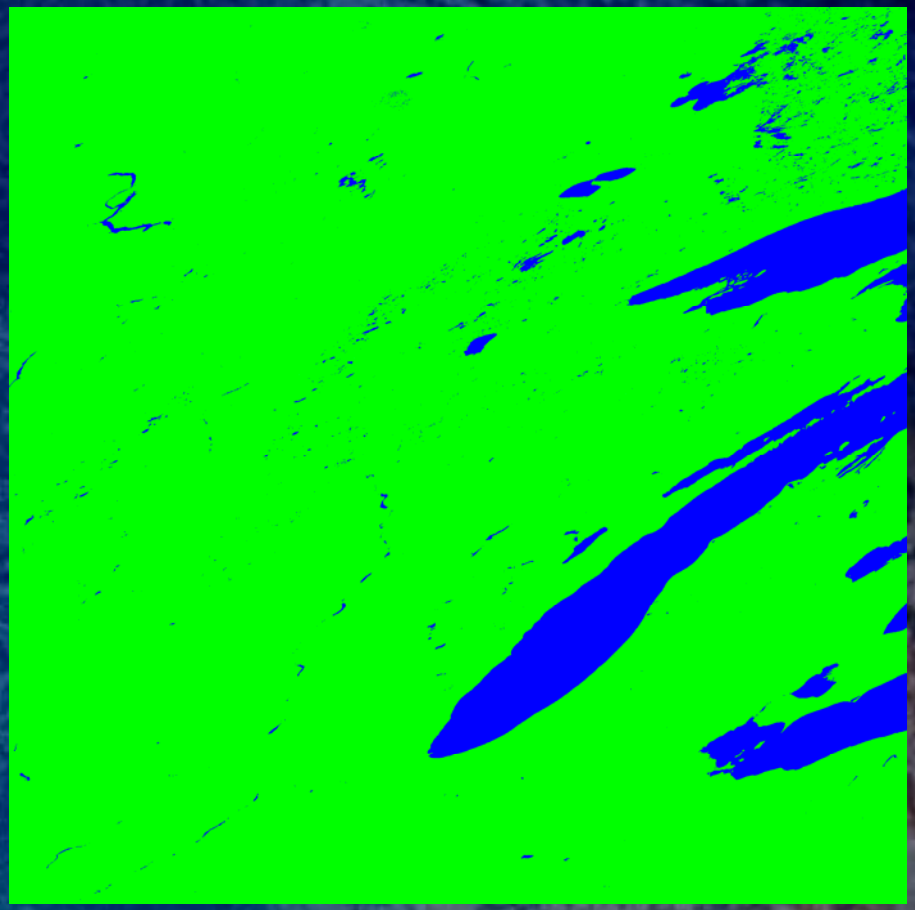
Ground truth of water/land classification

Validation Approach (2)

Water/land classification from the C4.5 DT algorithm with the MODIS surface reflectance data on 05/20/2008

Ground truth of water/land classification





Validation Results (1)

Validation Data: SEVIRI IGBP Land Cover Map				
MODIS Classification 12/25/2007		Classified Not Water (0)	Classified Water (1)	Producers Accuracy
	Validation Not Water (0)	(2445680 /2448826) 99.87%	(29528 /2728485) 1.08%	99.87%
	Validation Water (1)	(3146 /2448826) 0.13%	(2698957 /2728485) 98.92%	98.92%
	Users Accuracy	98.81%	99.88%	
			Total Accuracy	99.3689%
			Kappa Correlation Coefficient	0.9873

Validation Results (2)

Validation Data: MODIS IGBP Land Cover Map				
MODIS Classification 05/20/2008		Classified Not Water (0)	Classified Water (1)	Producers Accuracy
	Validation Not Water (0)	(5185738 /5270950) 98.38%	(9433 /489050) 1.93%	98.38%
	Validation Water (1)	(85212 /5270950) 1.62%	(479617 /489050) 98.07%	98.07%
	Users Accuracy	99.82%	84.91%	
			Total Accuracy	98.3569%
			Kappa Correlation Coefficient	0.9012

Future Plan

What are going to from now (80% readiness) to 100% readiness?

- Anistropic correction to surface reflectance data
- Prep 80% algorithm package with AIT
- **Complete 80% algorithm Package with AIT**
- Develop version 4 algorithm
- Testing version 4 algorithm
- **Deliver version 4 algorithm to AIT**
- Final testing of version 5 algorithm
- **Delivery of version 5 algorithm to AIT**
- Prep 100% algorithm package with AIT
- **Complete 100% algorithm package with AIT**

Summary

- The ABI Flood/Standing Water Algorithms provide a new capability for objective detection and prediction of flood hazards
- Improved ABI temporal resolution offer a significantly better detection capability, since flood is usually rapid change event.
- Algorithms are applied to real SEVIRI and MODIS observations as proxy ABI data, and got accuracy of over 80% for water classification, and meet all performance and latency requirements of 60% accuracy.
- We are working with anistropic correction to surface reflectance data, preparing 80% ATBD, and develop version 4 algorithm.