



Miami Update: VIIRS Sea-Surface Temperatures: pathways for improvements

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Focus of studies



- VIIRS Continuity with heritage sensors
- Improving and evaluating algorithm performance at higher viewing angles
 - Response versus scan angle corrections
- Sensor validation
 - Analysis of global fields and matchups with in situ data from NOAA IQUAM.
- Improving Cloud screening algorithms
 - machine learning ensemble algorithms
- Impact of Sampling Bias in gridded Level 3 products

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Algorithm Continuity



- Coefficients tuned to atmospheric conditions AVHRR Pathfinder wet/dry atmospheres monthly C6 MODIS/VIIRS – latitude and month of year
- Extend retrievals towards edge of VIIRS & MODIS swaths

SST _{sat} =
$$a_0 + a_1 T_{11} + a_2 (T_{11} - T_{12}) T_{sfc}$$

+ $a_3 (sec(\theta) - 1) (T_{11\mu m} - T_{12\mu m})$
+ $a_4 (mirror.side) + a_5(\theta) + a_6(\theta^2)$

- Cloud/anomalous atmosphere detection

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Regional versus global accuracy 1km matchups +- 30 minutes of over pass



1.0

MODIS TERRA mean 16 year average 1 degree resolution





Longitude 1 degree resolution grid

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_atitude





Cloud mask

- IR algorithms are only accurate in cloud free and atmospherically "clean" pixels
- Decision Tree misclassification errors.
 - Sensitivity versus specificity
 - Good classified as bad and bad classified as good.
- Persistent clouds and differences in ability to detect clouds between day and night can impact sampling/binning of higher level products.
 - Differences in gap free fraction
- Ensemble classification using boosting and alternating decision trees (ADTree) methods reduce both the gap fraction and misclassification errors.



L3 Method used to evaluate sampling bias and cloud mask



MUR

MUR Sampled by MODIS



MODIS 4km-daily L3 Cloud mask

D: SST mask N: SST4 mask

1 day... 4km map Base resolution

Averaging

Temporal: 3d,1w,2w,mon Spatial: 12k, 0.25°,0.5°,1°,2.5°,5°

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MODIS SST Zonal Mean Sampling error



Temporal **Spatial** a. b. 0.6 0.6 [12k,1d] [0.25°,1d] [0.5°,1d] [2.5°,1d] [5°,1d] [4k,3d] [4k,1w] [4k,2w] [4k,mon] [1.0°,1d] 0.5 0.5 0.4 0.4 0.3 0.3 $\overline{\epsilon_{A,r}}(K)$ $\overline{\epsilon_{A,r}}(K)$ 0.2 0.2 0.1 0.1 0.0 0.0 -0.1 -0.1 70.0°S 50.0°S 30.0°S Eq 30.0°N 50.0°N 70.0°N 70.0°S 50.0°S 30.0°S Eq 30.0°N 50.0°N 70.0°N Latitude Latitude

Mean of the 4 months data

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NASA SST Science Meeting, Dec 3-5, 2014, Annapolis, MD, USA,



Temporal averaging MODIS SST Difference from MUR

Mean of the 4 months data









ROSEN

ATMO

Spatial averaging Difference from

Mean of the 4 months data









Improved cloud classification for VIIRS reduces sampling bias compared to products from heritage sensors

Alternating Decision Trees * are an ensemble collection both weak and strong classifiers with each binary decision nodes ending with a prediction node containing vote. Each vote is scaled to the predictive power of the test.

The combined vote from a collection of weak prediction nodes when voting together as a block can modify or over ride the vote of a single strong prediction node.

Combined with boosting algorithms a very accurate ensemble classification model can be developed.

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* Freund and Mason 1999, Pfahringer et. al . 2001)



Branch of SST ADTree cloud classifier



(crowd sourcing classification with the help of experts)



Classification is based on sum of community vote across all tree stumps and branches.

A positive sum is classified as good/clear and a negative is bad/cloud. The absolute magnitude of the sum provides an estimate of the confidence in the classification.

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Classifier Ensemble Vote



An ensemble of 4 Alternating Decision Trees classifiers were trained to classify VIIRS SST retrievals as either clear or cloudy, using 10 foldcross validation and boosting. The training sets consisted of a subset of randomly selected records in the VIIRS buoy Matchup Database (MUDB).

Classification model cases:

Night
Day non glint coeff < 0.005
Day moderate glint coeff 0.005 - 0.01
Day high glint coef > 0.01

~ 30-40 nodes/leaves for each model

classification model validation data set: Correctly Classified 29732 91.0015 % Incorrectly Classified 2940 8.9985 %

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Ensemble of ADTree classifier improves retention of good quality pixels at frontal boundaries







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June 19 2014 L2 over Gulf Stream

NOAA JPSS annual VIIRS SST Science Team Meeting

11 August 2016 Greenbelt, MD



Ensemble ADTree classifier Increases number of valid retrievals







Difference in Miami cloud free fraction Best quality VIIRS – MODIS-A 2014



V6 V_SST - A_SST : Cnt_q0 (%)(q0)





Full swath

Scan angles < 55

dCnt_q0 (%)



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dCnt_q0q1 (%)

0



Monthly 4km SST difference VIIRS ADtree cloud mask-MODIS-A

10.0

3.0

1.0

-1.0

-3.0

-10.0



Scan angle < 55 degrees quality 0







VIIRS L3 is often cooler than MODIS-A in regions where MODIS A showed a warm sampling bias relative to MUR and the converse warmer for persistently cloudy regions



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Full swath comparisons VIIRS 3band-MODISA 4um

V6 V_SST3 - A_SST4 : SST(K)(q0q1)



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Summary



 Continued excellent agreement at 1km between VIIRS LWIR SST and both MODIS sensors using an NLSST continuity algorithm

 ✓ VIIRS Cloud identification using an ensemble of Alternating Decision Trees reduces misclassification in frontal zones and cloud edges

 ✓ Increased number of valid retrievals at 1 km better captures SST geophysical variability reducing L3 sampling bias in IR SST products

✓ Together MODIS, VIIRS and NOAA PFSST produce 36



Buoy SST accuracy characterization



Is the accuracy and stability of buoy SST measurements good enough for Satellite SST CDR validation?

 Study calibration drift and accuracy over a 1 to 2 year deployment in Bear cut

 1-2 years of monthly comparison to thermometers calibrated against the RSMAS black body



12 moored buoys - 3 each of 4 designs

- 3 designs SIO
- I design NOAA/AOML

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Thank you.

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VIIRS Alternating decision tree Model for day non glint:



Instance where the Glint coef < 0.005 Decision node:vote += confidence good clear -= confidence bad cloud Final sum votes all TRUE nodes <0 flag as cloud Tree size (total number of nodes): 46

:0 (1)rho 1610 >= 0.16: -1.755 (1) rho 1610 < 0.16: 0.805 (6)rho 1610 < 0.266: 0.642 (2) rho 748 < 0.062: 0.393 (6)rho 1610 >= 0.266: -0.19 (3)rho 1380 < 0.004: 0.287 (14)max-min rho 678 5x5 box < 0.103: 0.425 (9)BT deficit 11um < 0.002: -0.681 (14) max -min rho 678 5x5 box >= 0.103: -0.195 (9)BT deficit 11um >= 0.002: 0.026 (10)11um-12um BT < 0.235: -0.189 (13)rho 748 < 0.039: 0.364 (10) 11um-12um BT >= 0.235: 0.411 (13)rho 748 >= 0.039: -0.21 (15)water vapor NCEP Kg/m2 < 2.946: 0.038 (3)rho 1380 >= 0.004: -1.244 (15) water vapor NCEP Kg/m2 >= 2.946: -1.137(2)rho 748 >= 0.062: -0.572 (7)max -min 11um BT 5x5 box < 0.762: 0.156 (5)min rho 610 5x5 box < 0.032: 0.455 (7) max -min 11um BT 5x5 box >= 0.762: -0.188 (5)min rho 610 5x5 box>= 0.032: -0.395 (11) water vapor NCEP Kg/m2 < 1.315: 0.327(4)sensor zenith angle < 64.994: 0.216 (11) water vapor NCEP Kg/m2 >= 1.315: -0.054(8)rho 1380 < 0.007: 0.065 (12)sst < 278.171 K°: -0.679 (8)rho 1380 >= 0.007: -1.077 (12)sst >= 278.171 K°: 0.05 (4)sensor zenith angle >= 64.994: -0.708

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rho= visible band reflectance BT= brightness temperature H