Quality Assessment of S-NPP VIIRS Land Surface Temperature Product

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Introduction

Land Surface Temperature (LST) is a baseline product of the JPSS mission, which is the measurement of the skin temperature over global land coverage including coastal and inland-water. It is measured by the Visible and Infrared Imager Radiometer Suite (VIIRS) using a split-window regression algorithm in which the algorithm coefficients are surface type dependent, referring 17 International Geosphere-Biosphere Programme (IGBP) types. In this study we present validation results of the VIIRS LST product using two approaches including the conventional temperature-based (T-based) approach by comparisons between the VIIRS LSTs and in-situ LSTs, and the radiance-based (R-based) validation approach. The ground observations are from the SURFRAD network in US and Gobabeb in Africa. Time span of the SURFRAD data are from Feb. 2012 to Aug. 2014 and the Gobabeb data is for the whole year of 2012. The ground validation results show an overall good agreement between the VIIRS LSTs and ground LST estimates, with the agreement level varied among the sites and land cover types and it presents a diurnal as well as monthly and seasonal features. The R-based validation is conducted at granule level; areas are selected at a global scale for different time periods representing a variety of land cover types and seasonal changes. The validation results from both the T-based and the R-based methods demonstrate that VIIRS LST marginally meets the mission's requirements with the limited datasets. A theoretical analysis of the VIIRS LST uncertainty is also performed, taking into account the uncertainty from surface type input and sensor data input. It shows that an uncertainty of 0.9K is given by the surface type commission error and sensor noise level. However, the LST uncertainty is found much larger when using real data particularly the uncertainty caused by the surface type input.

VIIRS LST Algorithm

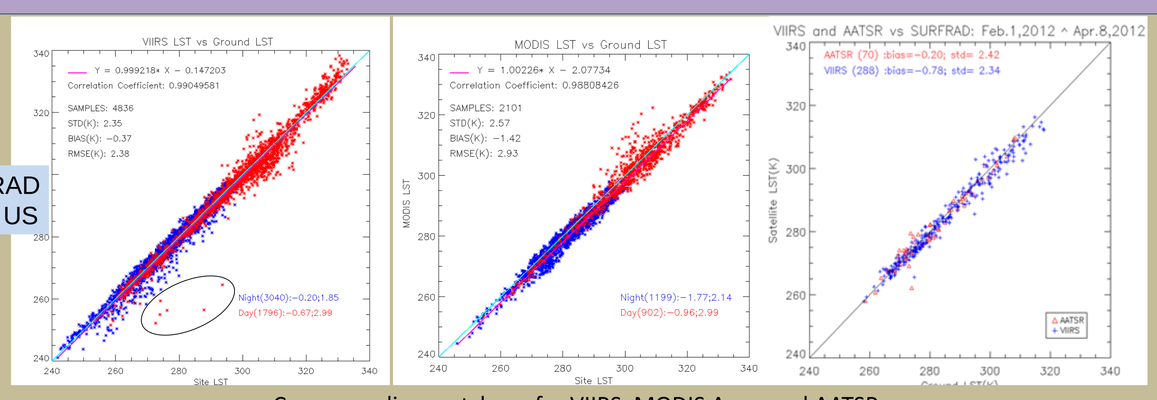
Establish the 2-band 10.76µm(M15) and 12.01µm(M16) split window algorithm for both day and night based on regression equation for each of the 17 IGBP surface types.

$$LST_{i,j} = a_0(i,j) + a_1(i,j)T_{15} + a_2(i,j)(T_{15} - T_{16}) + a_3(i,j)(\sec\theta - 1) + a_4(i,j)(T_{15} - T_{16})^2$$

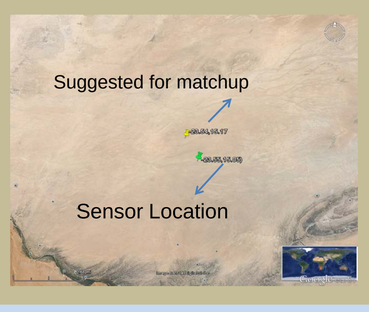
Where $a_k(i,j)$ (with k=0 to 4) are coefficients depending on surface type (with i =0 to 16 for 17 IGBP surface types) and day/night condition (with j=0 to 1), and θ is satellite viewing zenith angle.

Temperature based Validation

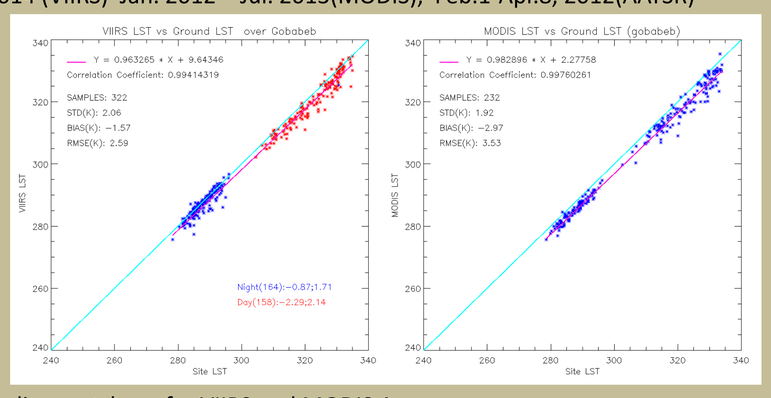
SURFRAD data in US



Corresponding matchups for VIIRS ,MODIS Aqua and AATSR:
Time span: Feb. 2012 – Aug. 2014 (VIIRS) Jan. 2012 – Jul. 2013(MODIS), Feb.1-Apr.8, 2012(AATSR)



Ground data in Gobabeb, Namibia



Corresponding matchups for VIIRS and MODIS Aqua:
Time span: Jan. 2012 – Dec. 2012

Radiance based Validation

Global Scale

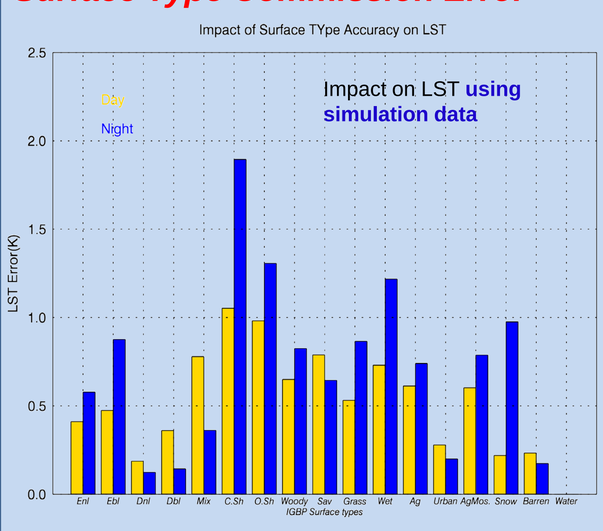
The radiative transfer model MODTRAN is used for the radiance based validation of the VIIRS LST at the granule level. NCEP GFS analysis data are used as the atmosphere profile for model input.
Total 9 areas are selected to represent the global coverage. Considering that some IGBP types particularly vegetation types may have seasonal variability, granules representing each season are selected for this study.

SurfaceType	Overall			Day			Night		
	Samples	Bias	STD	Samples	Bias	STD	Samples	Bias	STD
Evergreen Needleleaf Forests	216593	0.19	0.54	70324	-0.22	0.54	146269	0.38	0.41
Evergreen Broadleaf Forests	207839	-0.4	0.97	107698	-0.68	1.02	100141	-0.09	0.82
Deciduous Needleleaf Forest	13554	0.25	0.74	5932	-0.44	0.46	7622	0.78	0.42
Broadleaf Forests	385231	0.22	0.55	204843	-0.05	0.56	180388	0.54	0.32
Mixed Forests	597413	-0.02	0.8	359702	-0.42	0.76	237711	0.59	0.34
Closed Shrublands	92393	0.94	1.13	30537	-0.21	0.97	61856	1.5	0.69
Open Shrublands	5906708	0.72	1.29	3305495	-0.22	0.85	2601213	1.92	0.53
Woody Savannahs	917791	0.31	0.7	407793	-0.12	0.65	509998	0.66	0.52
Savannahs	3142202	0.48	0.81	1008898	-0.22	0.81	2133304	0.81	0.56
Grasslands	1124800	-0.07	1.42	517457	-1.2	1.25	607343	0.9	0.6
Permanent Wetlands	28282	0.02	0.54	4013	0.09	0.91	24269	0.01	0.45
Croplands	4072551	0.15	1.2	1491236	-1.02	1.21	2581315	0.82	0.44
Urban Built-Up	190876	0.27	0.52	89295	0.04	0.5	101581	0.47	0.45
Croplands/Natural Vegetation Mosiacs	1276644	0.31	0.56	543193	-0.08	0.45	733451	0.59	0.45
Snow Ice	1142843	0.04	0.51	336615	0.54	0.55	806228	-0.17	0.31
Barren	2389775	1.29	0.89	699333	0.54	0.75	1690442	1.6	0.75
Water Bodies	161468	-0.22	0.86	45826	-0.35	1.35	115642	-0.16	0.55

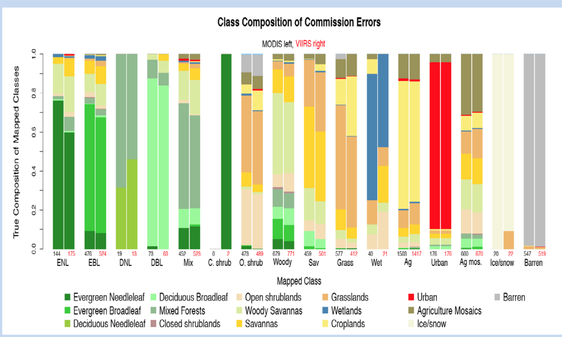
VIIRS LST overall agrees well with the radiance calculated LST. The bias varies from 0.07 K to 1.41 K with an average of 0.53K, the STD varies from 0.55 K to 1.53 K with an average of 1.03 K. It also demonstrates a regional difference and day/night difference: the best agreement is found over Greenland with a bias of 0.08 K and STD of 0.55 K; a smaller bias and a larger STD is found at daytime compared to that at nighttime.

VIIRS LST Uncertainty Estimation

Surface Type Commission Error



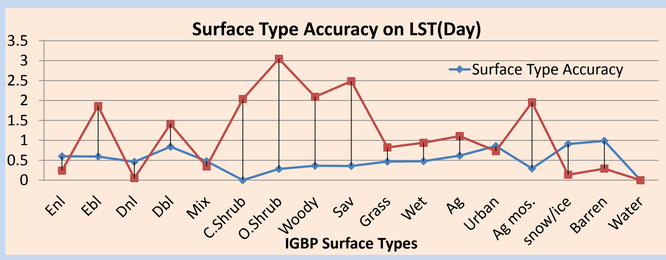
Overall Statistics	Impact on LST
All	0.73

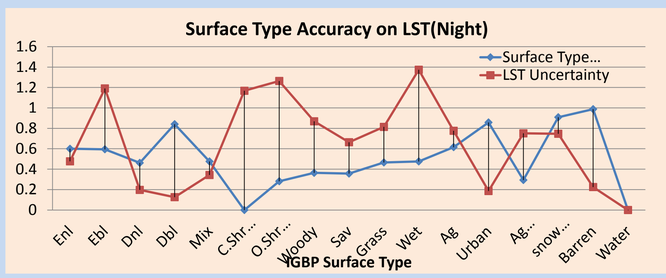


*Reference: Damien Sulla-Menashe, VIIRS ST V1 Quality Assessment April 02, 2014 EDR meeting

$$S_i^2 = \sum_{j=1}^{17}(p_{ij} * Rmse^2(\varepsilon_{ij})) \qquad S_{sf}^2 = \sum_{i=1}^{17}\left(\frac{S_i^2 * N_i}{N_t}\right)$$

p_{ij} is the probability of misclassification of surface type i (i=1,2…17) to be j (j=1,2…17)
ε_{ij} is the LST difference between LST calculated with the equation for surface type i and with the equation for surface type j for each pixel with i surface type
S_i^2 represents the error for each IGBP type i under either day or night condition
S_{sf}^2 represents the error for all IGBP types and all day/night conditions
N_i represents the number of samples for surface type IGBP i
N_t represents the total number of samples for all cases





Overall Statistics	Impact on LST
All-Day	1.5K
All-Night	0.8K
All	1.2K

Impact on LST **using real orbit data** on Oct. 22, 2014, daytime (top) and nighttime(bottom)

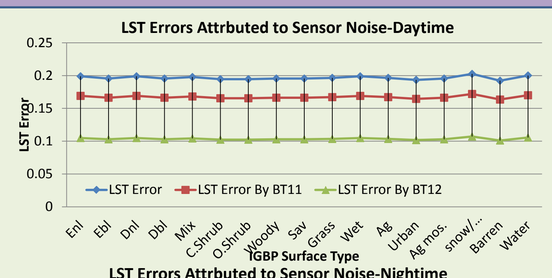
Sensor Noise

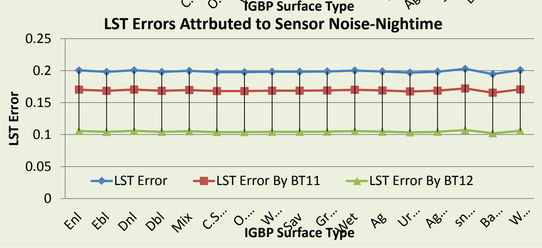
$$S_{(ij)bt}^2 = S_{(ij)bt11}^2 + S_{(ij)bt12}^2$$

Where $S_{(ij)bt11}^2 = \left(\overline{\frac{\partial f(ij)}{\partial Bt11}}\right)^2 \sigma_{bt11}^2 \qquad S_{(ij)bt12}^2 = \left(\overline{\frac{\partial f(ij)}{\partial Bt12}}\right)^2 \sigma_{bt12}^2$

$$S_{bt}^2 = \sum_{i=1}^{17}\frac{S_i^2 * N_i}{N_t}$$

$S_{(ij)bt}^2$ represents the error caused by sensor noise from both BT11 and BT12 for each IGBP type I under either day or night condition i (i=1,2…17) j(0:night,1:day)
$S_{(ij)bt11}^2$ represents the error caused by sensor noise from BT11
$S_{(ij)bt12}^2$ represents the error caused by sensor noise from BT12
σ_{bt11} and σ_{bt12} represents noise requirements for emissive band at 11micron and 12micron, onboard the VIIRS, respectively
S_{bt}^2 represents the overall error caused by sensor noise
N_i represents the number of samples for surface type IGBP i
N_t represents the total number of samples for all cases





Overall Uncertainty

$$S_{lst} = \sqrt{S_{sf}^2 + S_{bt}^2 + \delta_{alg}^2}$$

S_{lst} represents the overall LST uncertainty
S_{sf} represents the uncertainty caused by surface type
S_{bt} represents the uncertainty caused by sensor noise
δ_{alg} is the algorithm uncertainty, estimated in the coefficients regression procedure based only on the simulation data.

Overall Statistics	Uncertainty by Surface Type Accuracy	Uncertainty by Sensor Noise	Algorithm Uncertainty	Overall LST product Uncertainty **
All	0.73	0.198	0.46	0.88
All-Day	0.61	0.197	0.42	0.77
All-Night	0.83	0.199	0.51	0.99

Summary

- Cross comparisons against the ground observations from SURFRAD indicate an overall good agreement among VIIRS LST, MODIS LST and AATSR LST. The result over one field measurement dataset in Africa suggests that both VIIRS and MODIS underestimate the LST by 1.6K and 3K, respectively.
- The R-based validation indicates that the VIIRS LST overall agrees well with the radiance calculated LST. It also demonstrate a regional difference, day/night difference as well as the difference over surface types.
- Cloud contamination, particularly the cloud detection error over snow/ice surface, show significant impacts on LST validation quality therefore additional cloud filter is strongly recommended for LST validation and applications.
- VIIRS LST quality is strongly dependent on a correct classification of the surface type, which suggests that the ST dependent algorithm should be replaced with an Emissivity explicit algorithm for future satellite. e.g. J1.
- The sensor noise, surface type accuracy as well as algorithm uncertainty causes an overall LST uncertainty of 0.9K.
  - *VIIRS LST V1 result is based on limited in-situ data.*
  - *VIIRS LST EDR is ready for scientific use of the data*