NAVOCEANO’s Use of GOES-R and JPSS Data

Danielle Carpenter, Melissa Dykman, Harron Wise, Paul Lyon, Dan Olzewsiz, Valinda Kirkland, Michelle Little, Bruce McKenzie

Naval Oceanographic Office, NP321 Remote Sensing Branch

The Remote Sensing Branch of the Oceanographic Data Collection Division at the Naval Oceanographic Office (NAVOCEANO) is responsible for providing near-real-time oceanographic measurements to the US Navy, as well as other government agencies. With developmental assistance from the Naval Research Lab (NRL), numerous sets of GOES and JPSS satellite data are processed in house for input to the Navy's Global Ocean Forecast System (GOFs) and the Navy Global Environmental Model (NAVGEM).

MMGPS

The Multi Mission Satellite Processing System (MMGPS) is a system that converts Suomi National Polar-orbiting Partnership (S-NPP), and joint Polar Satellite System (JPSS-1, now NOAA-20) Extended Application Packet (EAP) raw files for the Visible Infrared Imaging Radiometer Suite (VIIRS) and Advanced Technology Microwave Sounder (ATMS) sensors into Raw Data Records (RDRs). Those are then fed through the Community Satellite Processing Package (CSPP), developed by the University of Wisconsin, to create Sensor Data Records (SDRs). Those SDRs are used by the NRL Ocean Surface Flux System (NFLUX), the Ice Concentration Processing System (ICPS), the Multi Channel Sea Surface Temperature System (MCSSST), and the Automated Optical Processing System (AOPS) at NAVOCEANO for in-house data processing and product creation, to support naval operations.

MCSSST

MCSSST produces Sea Surface Temperatures (SST) using multiple polar orbiting and geostationary satellites with an in-house suite of software. GOES-16 data, acquired via NCEP College Park, is processed in-house utilizing channels 2, 3, 7, 13, 15, and 16, from the Advanced Baseline Imager (ABI). NAVO processes full disks every 10 minutes with 4km resolution SSTs (2x2 grid). VIIRS data is processed using channels 5, 7, 12, 15, 16, and associated geolocation data. NAVO processes 85 second granules in near-real-time resulting in daily global coverage with 1.5km resolution (2x2 grid of 750m). SST measurements are an important parameter assimilated into oceanographic and atmospheric forecasts, which constrain circulation model initial conditions and quantify the flux energy exchange between the ocean and atmosphere. Real-time ocean prediction systems readily assimilate SST, along with other oceanographic measurements, to generate mesoscale ocean forecasts for operational maritime activities.

AOPS

The Automated Optical Processing System (AOPS) produces in-water water clarity and visibility from multiple satellite-borne sensors, including VIIRS. The near-real-time products are used by warfighters in the Navy to accomplish their tasks more safely, efficiently and effectively. Historical climatology products are also generated for mission asset scheduling. The in-water optical products are implemented in mission planning and naval operations around the globe.

NFLUX

NFLUX is a data processing and assimilation system used to provide near-real-time satellite-based surface heat flux fields over the ocean. This system provides satellite-based 3-hourly gridded analysis fields over the global ocean for the near-surface parameters of air temperature, specific humidity, wind speed, solar radiation, and longwave radiation. NFLUX uses multiple inputs, including ATMS, from over a dozen different satellites to provide fluxes that will be used to determine NAVGEM bias corrections over the ocean in near-real-time.

ICPS

ICPS is a system for operationally producing near-real-time ice concentration products from S-NPP, NOAA-20, and Global Change Observation Mission – Water “Shizuku” (GCOM-W1) satellites. Using VIIRS and Advanced Microwave Scanning Radiometer 2 (AMSR2) inputs, it creates ice concentration products for the northern and southern hemispheres. Future updates include higher resolution products and implementation of NOAA-20.
SNPP and NOAA-20 VIIRS Day/Night Band Calibration Performance Monitoring and Applications

Xi Shao1, Sirish Uprety1, Yalong Gu2, Yan Bai2, Slawomir Blonski2, Wenhui Wang3 and Changyong Cao3
1. Cooperative Institute for Satellite Earth System Studies (CISESS), University of Maryland, College Park, MD
2. National Oceanic and Atmospheric Administration (NOAA), Silver Spring, MD
3. NOAA/NESDIS/STAR, College Park, MD

Abstract

- The VIIRS Day/Night Band (DNB) sensors onboard NOAA-20 and SNPP satellites, being 50 minutes apart along the same orbit, provide nighttime imagery of clouds, nocturnal lights, auroras etc., and have been used for a variety of studies involving both geophysical and socio-economic activities.
- Recent SNPP and NOAA-20 DNB calibration algorithm updates focused improving imagery quality of DNB by addressing the striping in high aggregation zones due to residual nonlinearity.
- To synchronize with the improved DNB calibration algorithm, monthly DNB stray light correction LUTs for SNPP and NOAA-20 have also been updated. This paper reports updates that have been performed for SNPP and NOAA-20 DNB stray light correction and evaluate the improvements in DNB imagery product.
- Examples of applications of DNB data products in observations of aurora activities during severe solar storms, deep convective cloud monitoring, observation of light emissions from lava flow, during volcanic eruptions and monitoring of impacts of global events on social activities are also given.

SNPP and NOAA-20 DNB Calibration Update and Stray Light Correction

- Details on recent updates and development of SNPP and NOAA-20 DNB calibration can be found in the papers by Gu et al. presented in this session. The calibration algorithm improvements are mainly to reduce strong striping at the end aggregation zone.
- DNB stray light has been observed over both the Northern and the Southern Hemispheres. Origin of the stray light may be due to the leakage of solar light near the extended zone and through the VIIRS Earth/solar and Earth/sun difference aperture.
- To maintain consistency between DNB stray light correction and calibration algorithm update, monthly DNB stray light correction LUTs have been routinely generated by NOAA/STAR for operational DNB data production.

SNPP DNB Stray Light Correlation

- There were remnant stray light of the magnitude ~1 nW/cm²sr in the SNPP DNB image over the southern hemisphere resulting from the use of static yearly-recycled stray light correction LUTs (twelve sets) generated during 2014 and 2015. To address this issue, the stray light correction algorithm was improved to support operational SNPP DNB calibration since May, 2019.

Applications of Day/Night Band

- Aurora Activities during Severe Solar Storm Observed by SNPP DNB

- Deep Convective Cloud Observation under Moon Light

- DNB Observation of Lava Flow during Hawaii Kilauea Volcano Eruption

Inter-Comparison of Radiometric Performance between SNPP and NOAA-20 DNB

- For NOAA-20 DNB, as the new improved DNB calibration algorithm and maintain consistency between DNB stray light correction and calibration algorithm update, monthly DNB stray light correction LUTs have been routinely generated for one additional full year until November, 2020.

Summary

- Maintained consistency between SNPP/NOAA-20 DNB stray light correction and recent DNB calibration algorithm update.
- Improved DNB stray light quality with updated stray light correction for SNPP by removing remnant stray light.
- Radiometric bias mapping of SNPP and NOAA-20 DNB over pseudo-irrelevant calibration sites under moon light shows the radiometric consistency between SNPP and NOAA-20 DNB is within 3-5% with SNPP being higher. Part of the bias is due to the spectral response differences and the use of different solar irradiance spectra for DNB calibration. The rest may be from the calibration uncertainties.
- DNB observation of Deep Convective Cloud enables inter-calibration between SNPP and NOAA-20 DNB using lunar radiances.
- SNPP and NOAA-20 DNB data enable applications in monitoring large spatial scale and temporal variation of aurora light during severe solar storms, nocturnal light variation during global socio-economic events, and monitoring light emission variation during global natural disaster events such as lava flow due to volcanic eruptions.

References:

- Cao, C. et al., Radiometric Inter-Consistency of VIIRS DNB on Suomi NPP and NOAA-20 from Observations of Reflected Lunar Lights over Deep Convective Clouds, Geosci. J., 2018, in press.
Abstract

The Day/Night Band (DNB) is a panchromatic visible and near-infrared band of the Visible Infrared Imaging Radiometer Suite (VIIRS) on board the Suomi National Polar-orbiting Partnership (S-NPP) and NOAA-20 satellites. Because of its three gain stage design, i.e., Low-Gain Stage (LGS) for daytime scenes, the Mid-Gain Stage (MGS) for twilight scenes, and the High-Gain Stage (HGS) for nighttime low light scenes, the DNB is capable of quantitative measurement of light radiances from $3 \times 10^{-9}$ W cm$^{-2}$sr$^{-1}$ to $2 \times 10^{-2}$ W cm$^{-2}$sr$^{-1}$. The extreme sensitivity to low light enables numerous applications of environmental remote sensing and anthropogenic activities monitoring in nighttime. However, the three gain stage design makes radiometric calibration of the DNB’s nighttime data complicated. Artifacts like striping are shown in the calibrated nighttime images. In this paper, we present our efforts for improving image quality of VIIRS DNB on-board both S-NPP and NOAA-20 by updating radiometric calibration algorithms. Our work is beneficial for applications that require high quality of DNB nighttime images.

Correction of Stripping due to Detector Nonlinearity

- Stripping has been found in many aggregation zones of both the S-NPP and NOAA-20 VIIRS DNB nighttime imagery.
- Aggregation zone 21 of NOAA-20 VIIRS DNB is a typical example, shown in Figure 1.
- Because of the special aggregation option known as Option 21, about 30% pixels of a NOAA-20 VIIRS DNB image are in aggregation zone 21.
- Striping severely degrades the quality of the NOAA-20 VIIRS DNB nighttime imagery.

Improved SNPP VIIRS DNB Image Quality after Reprocessing

Reprocessed SNPP VIIRS DNB SDRs from early mission to March 2017 accommodate calibration updates since launch.
- Continuous DNB LGS gain degradation using modulated relative spectral response (RSR) function, benefiting application of nighttime time series for study of socioeconomic changes (Figure 5).

Significantly improved quality of the DNB data collected before March 20, 2012 which were originally calibrated with the prelaunch LUTs.
- Straylight corrected DNB data available since early mission of SNPP.
- Enhanced low light detection by the deep space based HGS dark offset

Improved SNPP VIIRS DNB Image Quality after Reprocessing

- Significantly improved quality of the DNB data collected before March 20, 2012 which were originally calibrated with the prelaunch LUTs.
- Straylight corrected DNB data available since early mission of SNPP.
- Enhanced low light detection by the deep space based HGS dark offset

Summary

- This study summarized radiometric calibration updates for improving image quality of VIIRS DNB on-board both S-NPP and NOAA-20 satellites.
- Major improvements include:
  - Correction of stripping due to detector nonlinearity
  - Continuous DNB LGS gain degradation correction by modulated RSIs
  - DNB data collected during early mission calibrated with the postlaunch LUTs
  - Straylight corrected DNB data available since early mission
  - Enhanced low light detection by the deep space based HGS dark offset
- Reprocessed SNPP VIIRS SDR data including DNB from early mission to March 2017 are available at https://ncdc.noaa.gov/VIIRS/index.php

References:


Acknowledgment:

This study is funded by the Joint Polar Satellite System (JPSS) program. Poster contents are solely the opinions of the authors and do not constitute a statement of policy, decision, or position on behalf of NOAA or the U.S. government.
Enterprise VIIRS LST Production for JPSS Mission: Validation and Application

Yuling Liu¹, Yunyue Yu², Peng Yu¹, Heshun Wang¹

1. ESSIC/CISESS, University of Maryland, College Park, MD 2. STAR/NESDIS/NOAA, College Park, MD.

Enterprise JPSS VIIRS LST Product Introduction

- **NDE Land Surface Temperature Product**
  - Based on split window technique
  - \[ T_{l2} = C_1 + C_2T_{IR} + C_3T_{IR} + C_4 + C_5d(T_{IR} - T_0) + C_6\Delta e \]
  - Spatial and temporal variability of daytime land surface temperature
  - The long term monitoring is ready for both SNPP and NOAA 20 VIIRS LST
  - L2 VIIRS LST has been in operational and the L3 VIIRS LST was just put into operational.

- **NDE Land Surface Temperature access**
  - The L2 enterprise VIIRS LST is available at NOAA CLASS under group of “JPSS VIIRS Product (granule)” (JPSS-GRAN).
  - The L2 enterprise SNPP VIIRS data has been available since 06/06/2019 and J01 VIIRS LST has been available since 09/18/2019.
  - Also available at SCDC under data type “VIIRS-LST” for STAR internal users and interested groups.

Ground Validation

- **NOAA20 VIIRS LST**
  - NOAA20 VIIRS LST is used as a reference to provide subset data and global 5km composite data
  - Various output in graphics, table and log file
  - Weekly email notification with details for outliers beyond the threshold.

- **Snow surface**
  - L2 VIIRS LST (left) and L3 VIIRS LST (right)

Long Term Monitoring

- **Site monitoring**
  - Global LST monitoring for both SNPP and NOAA20
  - Provide subset data and global 5km composite data
  - Various output in graphics, table and log file
  - Weekly email notification with details for outliers beyond the threshold.

- **Global monitoring**
  - Cross-satellite Comparison
  - L3 NOAA 20 LST vs. MYD11A1
  - Night: 0.64 (1.18)
  - Daytime: 0.38 (2.04)

User Applications and feedback

- **AQUA MODIS LST Product**
  - MYD11A1: Split window algorithm
  - MYD21A1: TES algorithm

- **NOAA 20 VIIRS LST product**
  - The global L3 data in Jan, Feb, Mar and Apr. 2019 were used for the cross comparison between L3 N20 VIIRS LST and MYD11A1 LST and MYD21A1 LST. Global mean difference was analyzed for daytime and nighttime LST.

Cross-comparison with AQUA MODIS LST

- **Attribute**
  - Analysis/Validation
  - L3 NOAA 20 LST vs MYD11A1
    - Night: 0.64 (1.18)
    - Daytime: 0.38 (2.04)
  - Cross-satellite Comparison
    - L3 NOAA 20 LST vs MYD21A1
      - Nighttime: -0.38 (1.31)
      - Daytime: -1.20 (2.16)

Summary

- The enterprise VIIRS LST products has a pretty good agreement with the ground measurements from SURFRAD, BSRN and GMD stations based on multiple years of data validation.
- The enterprise NOAA 20 VIIRS LST is in between the L3 MYD11A1 and MYD21A1 LST for both daytime and nighttime.
- The long term monitoring is ready for both SNPP and NOAA 20 VIIRS LST.
- LST application has been used in model LST verification, data assimilation to adjust 2m Tair and 1 km soil moisture product development etc.
- Ready to provide long term climate data records for users.
Enterprise VIIRS LST Production for JPSS Mission: Validation and Application

Yuling Liu, Yunyue Yu, Peng Yu, Heshun Wang
1. ESSIC/CISESS, University of Maryland, College Park, MD 2. STAR/NESDIS/NOAA, College Park, MD.

Enterprise JPSS VIIRS LST Product Introduction

- NDE Land Surface Temperature Product
  - Based on split window technique
  - \[ T_s = C_0 + C_1 T_{SW} + C_2 T_{SW} + C_3 + C_4 (T_{SW} - T_{w}) + C_5 \Delta e \]
  - \( T_{SW} \) and \( T_w \) : the TIR split-window channel B Ts
  - \( \Delta e \) mean emissivity at the TIR spectrum, and the emissivity difference between urban and rural areas
- Granule (L2) and gridded (L3) LST product for both SNPP VIIRS and NOAA 20 VIIRS
- L2 VIIRS LST has been in operational and the L3 VIIRS LST was just put into operational.

NDE Land Surface Temperature access
- The L2 enterprise VIIRS LST is available at NOAA CLASS under group of "JPSS VIIRS Product (granule) [JPSS-GRAN1]" available at https://www.avl.class.noaa.gov/ssa/products/search/JPSS_GRAN
- The L2 enterprise SNPP VIIRS data has been available since 06/06/2019 and J01 VIIRS LST has been available since 09/18/2019. Both are in the updated version 4.1 with most recent updates implemented.
- Also available at SCDR under data type "VIIRS-LST" for STAR internal users and interested groups.

Ground Validation

- NOA20 VIIRS LST vs SNPP VIIRS LST
- Snow surface
- Surface

Long Term Monitoring

- Six sites from SURFRAD network in Continental US; two sites from BSRN network in Netherland and Namibia; one site in Summit, Greenland.
- For SNPP LST validation: over seven years of SURFRAD observations from Feb. 2012 to Oct. 2019; over four years of BSRN observations from January 2015 to Oct. 2019 were used. For NOAA 20 LST validation: the data covers the time period from Jan. 2018 to Oct. 2019.
- Overall good agreement; consistent performance between SNPP and NOAA20 LST data over snow surface is affected by cloud contamination

Cross-comparison with AQUA MODIS LST

- MYD11A1: Split window algorithm
- MYD21A1: TES algorithm
- NOAA 20 VIIRS LST product
  - The global L3 data in Jan, Feb, Mar and Apr. 2019 were used for the cross comparison between L3 N20 VIIRS LST and MYD11A1 and MYD21A1. Global mean difference was analyzed for daytime and nighttime LST.

Attribute Analyzed

- L3 NOAA 20 LST vs MYD11A1
  - Nighttime: 0.64 (1.18)
  - Daytime: 0.38 (2.04)

Cross-satellite Comparison

- L3 NOAA 20 LST vs MYD21A1
  - Nighttime: -0.30 (1.31)
  - Daytime: -1.20 (2.16)

User Applications and feedback

- NCEP/EMC Modeling
  - VIIRS NDE LST product is in operational need for model output verification purposes
  - RTMA/URMA system data assimilation
    - To assimilate VIIRS LST into RTMA system to adjust the 2m air temperature
  - Near real time 1 km SMAP soil moisture (SM) product development
    - VIIRS LST data is used as an input in the NRT 1 km SMAP Soil Moisture Data Product development
  - Temporal and spatial variability of daytime land surface temperature in Houston
    - SNPP VIIRS LST data is used as a reference to compare with aircraft LST observations during the NASA’s DISCOVER-AQ (Deriving Information On Surface Conditions from Column and Vertically Resolved Observations Relevant to Air Quality) field campaign in September, 2013.

Summary

- The enterprise VIIRS LST products has a pretty good agreement with the ground measurements from SURFRAD, BSRN and GMD stations based on multiple years of data validation.
- The enterprise NOAA 20 VIIRS LST is in between the L3 MYD11A1 and MYD21A1 LST for both daytime and nighttime.
- The long term monitoring is ready for both SNPP and NOAA 20 VIIRS LST.
- LST application has been used in model LST verification, data assimilation to adjust 2m Tair and 1 km soil moisture product development etc.
- Ready to provide long term climate data records for users.
ABSTRACT

Surface Albedo (SURFALB), defined as the ratio between solar radiation reflected by Earth's surface and solar radiation incident at the surface, is a function of both solar illumination and the surface reflective properties.

NOAA provides operational daily mean shortwave albedo over land and sea-ice surface from VIIRS data. The latest version (v1r2) S-NPP and NOAA-20 VIIRS Albedo have been available since 09/19/2019 and can be accessed from CLASS.

The SURFALB products are also available at SCDR under data type "VIIRS-SURFALB" for STAR internal users and interested groups.

The NOAA VIIRS albedo algorithm deploys a single clear-sky observation to estimate daily mean albedo, which is straightforward and stable for online processing. For cloudy pixels, the albedo fill value comes from a temporal filtered result which integrates information from preceding 9-days and the climatology. The clear-sky retrievals are regarded as high-quality ones.

The SNPP and JPSS1 VIIRS albedos demonstrate slight difference due to the orbital difference, and the LUT sensitivity to angles. The inconsistency may cause some inconvenience for some users.

Blending VIIRS albedo from SNPP and JPSS1 would increase the clear-sky observations at most locations and the percentage of high-quality retrievals.

The current blending algorithm in test is an albedo-level-composition using L2 SURFALB data as input.

Current ALGORITHM

Direct estimation principle:

\[
LSA = a_0 + \sum a_i \alpha_i
\]

\(a_i\) is regression coefficient for Band i, which varies with surface cover type, solar-object-view geometry angles, latitude, and day of year. i is VIIRS band number, including the channels 1,2,3,4,5,6,7,8,10 and 11.

SITE LEVEL BLENDED

- Data period: Jan 01, 2018– Oct 16, 2019
- Fort Peck, MT

GLOBAL BLENDED

BLENDED VIIRS Global Albedo (L3 global), Feb 21 2020

BLENDED VIIRS Global Albedo Retrieval Path: Feb 21 2020

BLENDED VIIRS Global Albedo Retrieval Counts: Feb 21 2020

REFERENCE


ACKNOWLEDGEMENT

Thank all current and former group members for their contributions to the algorithm development and the NOAA ASSIST team for their assistance on integration.

LIMITATIONS

- The V2 climatology in framework is waiting to be applied in NDE in queue, which has more complete sea-ice surface coverage. The v3 climatology is in development, which would provide more continuous result over Greenland and Antarctic.

- The site blended result is reprocessed from IDPS snow mask, cloud mask, surface type, and ice concentration, as the NDE version EDRs is only available since Sep 2019.

CONCLUSIONS

- SNPP and JPSS1 VIIRS albedo provides high-quality, comparable, and continuous retrievals.

- The single-day directly-retrieved albedo difference between SNPP and JPSS1 is attributed to the orbit difference and the sensitivity of LUT to angle difference.

- The preliminary blended-VIIRS albedo product, from SNPP and JPSS1, is an example of data fusion to yield a unified and improved albedo product. The blended product has enhanced high-quality retrieval coverage, clear-sky observation coverage, and data accuracy compared to in-situ measurements.

- The blended albedo will be more friendly to users since it provides one better product instead of separate products from different sensors with slight inherent inconsistency.

- Various blending calculation methods would be further tested on the VIIRS daily mean albedo. The current blending algorithm is conducted at L2-albedo level, more blending algorithms at reflectance-level or L3-albedo level would also be considered.
NOAA-20 Green Vegetation Fraction (GVF) Product

Zhangyan Jiang1, Mingshi Chen1, Corinne Carter2, Yunyue Yu3

1 IMSG at NOAA/NESDIS/STAR. 2 ESSIC/ UMD/ NOAA. 3 NOAA/NESDIS/STAR, College Park, MD, 20740.

NOAA/GOES-R Proving Ground / Risk reduction Summit, Feb 24-28, 2020, College Park, MD 20740

VIIRS GVF

- Green Vegetation fraction (GVF) is defined as the fraction of a pixel covered by green vegetation if it were viewed vertically.
- Real-time GVF is needed in the numeric weather, climate and hydrological models.
- The Suomi National Polar-orbiting Partnership (SNPP) Visible Infrared Imager Radiometer Suite (VIIRS) GVF has been operationally produced since Feb 2015 at NOAA.
- GVF are produced as a daily rolling weekly composite at 4-km resolution (global scale) and 1-km resolution (regional scale).
- As NOAA-20 (JPSS-1) data became available, the new NOAA-20 GVF product is developed and introduced in this poster.

VIIRS GVF Algorithm

The GVF processing system generates daily rolling weekly GVF through the following steps:

Step 1: VIIRS swath surface reflectance data in bands I1 (red), I2 (NIR), and M3 (blue) during a calendar day (0000 – 2400 UTC) are mapped to the native GVF geographic grid (0.003 degree plate carree projection) to produce a gridded daily surface reflectance map.

Step 2: At the end of a 7-day period, the daily surface reflectance maps of the 7 days are composited to produce a weekly surface reflectance map using the MVA-SAVI compositing algorithm, which selects, at each GVF grid point (pixel), the observation with maximum view-angle adjusted SAVI (soil-adjusted vegetation index) value in the 7-day period. The 7-day compositing is conducted daily using data in the previous 7 days as input data, which is called daily rolling weekly compositing.

Step 3: EVI is calculated from the daily rolling weekly composited VIIRS surface reflectance data in bands I1, I2 and M3.

Step 4: High frequency noise in EVI is reduced by applying a 15-day digital smoothing filter (Sullivan, 1993) on EVI.

Step 5: GVF is calculated by comparing the smoothed EVI against the global maximum (EVI_g) and minimum EVI (EVI_m) values assuming a linear relationship between EVI and GVF.

Step 6: GVF is aggregated to 0.009 degree (1 km) and 0.036 degree (4 km) resolution for output maps. Potential gaps on the output maps at high latitudes are filled using monthly VIIRS GVF climatology.

Validation

- Reference GVF data derived from 107 Landsat ETM+ images distributed globally.
- Decision tree classification method used to classify the 30 m Landsat pixels into 3 vegetation levels (GVF=0, 0.5 or 1).
- Landsat classified images reprojected to the VIIRS GVF projection and 30 m GVF are aggregated to 4 km GVF.

Summary:

1) The NOAA-20 VIIRS GVF system produces a global 4-km resolution GVF map and a regional 1-km GVF map once a day.
2) NOAA-20 GVF time series showed similar seasonal variation as the ground measured greenness index (GCC).
3) VIIRS GVF accuracy, precision and uncertainty were lower than the specifications, indicating that the global and regional VIIRS GVF products meet the design requirements.
4) Operational NOAA-20 VIIRS GVF product has been available for the public at NOAA comprehensive large array-data stewardship system (CLASS) since 6/4/2019.

(https://www.bou.class.noaa.gov/saa/products/welcome)
Motivation: NOAA has undertaken a major effort to improve its hydrological forecast services through the development of a new National Water Model (NWM) at the National Water Center. Because of the uncertainties in model physics and input parameters, and potential errors in forcing data, the soil moisture (SM) estimates may be erroneous, resulting uncertainties in the output of the NWM. These type of model errors can be compensated for by assimilating fine resolution satellite SM observations. For operational users, the downscaling approach should be feasible for operational implementation, requiring limited ancillary information and primarily depending on readily available satellite observations. Thus, a near-real-time 1 km SMAP SM data product is proposed to be routinely generated at the NOAA-NESDIS using remotely sensed land surface temperature (LST) and enhanced vegetation index (EVI) observations.

**Fig. 1** Nine selected downscaling schemes for developing an optimal downscaling strategy.

<table>
<thead>
<tr>
<th>Metrics</th>
<th>SMAP (25 km)</th>
<th>VTCl (1 km)</th>
<th>UCLA (1 km)</th>
<th>TRIA (1 km)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DAY</td>
<td>NIGHT</td>
<td>DAY</td>
<td>NIGHT</td>
</tr>
<tr>
<td>R</td>
<td>0.642</td>
<td>0.582</td>
<td>0.584</td>
<td>0.596</td>
</tr>
<tr>
<td>RMSE</td>
<td>0.089</td>
<td>0.091</td>
<td>0.092</td>
<td>0.086</td>
</tr>
<tr>
<td>ubRMSE</td>
<td>0.054</td>
<td>0.060</td>
<td>0.059</td>
<td>0.054</td>
</tr>
</tbody>
</table>

Tab. 1. Summary of the statistical comparison results when averaged across the CONUS, including correlation coefficient ($r$), RMSE ($m^3/m^3$), and ubRMSE ($m^3/m^3$) over the 1 May 2017-30 April 2019 period. Italic bold indicates the optimal metric.

**Fig. 2** With respect to the quality controlled SCAN SM observations, left column shows the metrics for SMAP/Sentinel 3 km SM product (SPL2SMAP), while the right column shows the metric differences between SPL2SMAP and 3 km UCLA DTRup during the 1 May 2017-30 April 2019 period. Top, middle and bottom rows are for correlation coefficients ($r$), RMSE ($m^3/m^3$) and ubRMSE ($m^3/m^3$), respectively.

**Fig. 3** Process flow of producing a NRT 1 km downscaled SMAP soil moisture map using the UCLA DTR method.

**Fig. 4** Longitude-averaged data availability over the CONUS domain.

**Fig. 5** Sample maps for (a) 25 km SMAP and (b) the downloaded 1 km SMAP SM retrievals over the sub-region from -118°E, 37.5°N to 115°E, 39°N on August 3, 2018.

Conclusions:

1. The advantages of the downscaling technique include simplicity, feasibility of operational implementation, pure reliance on remote sensing measurements, computationally fast and limited ancillary information requirements.
2. With respect to the quality controlled SCAN observations, the UCLA DTR method showed the most successful performance out of the 9 downscaling schemes. As expected, the accuracy level is significantly improved with the advance of the fine scale satellite SM measurements.
3. Compared to the NASA 3 km SMAP/Sentinel product, the accuracy level was significantly improved. The downscaled 1 km SMAP SM data product also provides larger data availability, although the VIIRS observations used as ancillary information can be affected by cloud coverage.
4. Building on the results shown in this paper, a near-real-time 1 km SMAP SM data product is proposed to be developed at NOAA-NESDIS.
Introduction

Land Surface Temperature (LST) is one of the key variables in the weather and climate system controlling surface heat and water exchange at the land atmosphere interface. Satellite measured LST is mostly based on thermal infrared band observations which theoretically gives the temperature at some nominal skin depth of the surface. Knowledge of the LST gives critical information on temporal and spatial variations of the surface equilibrium state and is of fundamental importance to many aspects of geosciences, e.g., the net radiation budget at the Earth surface and to monitoring the state of crops and vegetation, as well as an important indicator of both the greenhouse effect and the energy flux between the atmosphere and the land.

The first Geostationary Operational Environmental Satellite-R Series (GOES-R) satellite, the GOES-16, was launched in November 2016, joined by its successor, the GOES-17, in March 2018. The Advanced Baseline Imager (ABI) onboard both platforms has 16 spectral bands (compared to five from previous GOES satellite imagers), including the Split-window (SW) channels used for LST retrieval. The LST product, as one of the baseline ABI products, has been operationally produced since January 2017. The GOES-16 LST was validated with the in-situ surface temperature estimates from the SURFRAD network and results show that the bias and precision required by the mission were met for all three LST products (CONUS, FD, and Meso). As a result, the GOES-16 LST reached its Provisional maturity in March 2018. Its GOES-17 counterpart during “cool” period reached the Provisional maturity in June 2019.

This presentation will provide detailed information about the product’s validation and evaluation results, their current status, and future direction.

Validation Results

<table>
<thead>
<tr>
<th>GOES-16 CONUS LST Validation Results</th>
<th>GOES-17 CONUS LST Validation Results</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Product Timeline</strong></td>
<td><strong>Product Timeline</strong></td>
</tr>
<tr>
<td>GOES 16</td>
<td>GOES 17</td>
</tr>
<tr>
<td>GOES 17</td>
<td>GOES 17</td>
</tr>
<tr>
<td>Sep. 2018</td>
<td>Sep. 2018</td>
</tr>
</tbody>
</table>

Hourly Output Frequency

<table>
<thead>
<tr>
<th>Land Surface Temperature at Fort_Park, MT</th>
<th>Land Surface Temperature at Fort_Park, MT</th>
</tr>
</thead>
<tbody>
<tr>
<td>GOES 16</td>
<td>GOES 17</td>
</tr>
<tr>
<td>100</td>
<td>700</td>
</tr>
</tbody>
</table>

GOES-R ABI Land Surface Temperature Product

**GOES-R mission requirements for LST**

<table>
<thead>
<tr>
<th>Requirements</th>
<th>GOES-16</th>
<th>GOES-17</th>
<th>Requirements</th>
<th>GOES-16</th>
<th>GOES-17</th>
</tr>
</thead>
<tbody>
<tr>
<td>LST</td>
<td>11</td>
<td>10</td>
<td>LST</td>
<td>11</td>
<td>10</td>
</tr>
<tr>
<td>LST</td>
<td>11</td>
<td>10</td>
<td>LST</td>
<td>11</td>
<td>10</td>
</tr>
<tr>
<td>LST</td>
<td>11</td>
<td>10</td>
<td>LST</td>
<td>11</td>
<td>10</td>
</tr>
<tr>
<td>LST</td>
<td>11</td>
<td>10</td>
<td>LST</td>
<td>11</td>
<td>10</td>
</tr>
<tr>
<td>LST</td>
<td>11</td>
<td>10</td>
<td>LST</td>
<td>11</td>
<td>10</td>
</tr>
</tbody>
</table>

**GOES-R ABI LST Product**

- GOES-16 is at GOES-East
- GOES-17 is at GOES-West
- Two platforms overlap at the CONUS
- 2 minutes temporal frequency and more detailed temporal evolution compared to sensors onboard polar orbiting missions, e.g., TPS and NPOESS

**Advanced Baseline Imager Scan Modes**

- Mode 1: Full disk images (~45 km)
- Mode 2: Continuous Full disk (~45 km)
- Mode 3: Full disk (~45 km)
- Mode 4: Continuous Full disk (~45 km)
- Mode 5: Full disk (~45 km)
- Mode 6: Full disk (~45 km)

**Advanced Baseline Imager Scan Modes**

- GOES-16 LST is used in numerical weather forecast model output verification.
- GOES Evapotranspiration and Drought System
- Urban air surface temperature model

**Application Examples**

- Scatter and difference plots for ground station and satellite-predicted air temperature for three individual stations in Dallas, TX (top), Elizabeth, NJ (middle), and Sacramento, CA (bottom). Each station is at least 70% urban. The scatter shows the adherence of the prediction algorithm to the true ground station temperatures. The distribution shows the distribution of the scatter.

Summary

- GOES-16 LST and GOES-17 LST (during “cool” period only) reached provisional maturity in March 2018 and June 2019, respectively. All products, FD, CONUS, and MesoS, meet the mission requirement based on the validation results.
- An enterprise LST retrieval algorithm applicable to multiple sensors has been developed and delivered to ASSISTT. The evaluation results indicate it outperforms the current baseline algorithm.
- To address the loop heat pipe overheating issue, an mitigation algorithm has been developed to improve the product quality and increase its usable period during “warm” period. The preliminary evaluation results are satisfactory.
- The Enterprise/Mitigation package are expected to be implemented in the ground system in August 2020.
- The product has been widely used in different applications
A Novel Re-Compositing Approach to Create Continuous and Consistent Cross-Sensor/Cross-Production Global NDVI Datasets

Wenze Yang¹, Felix Kogan², Wei Guo¹, and Yong Chen³

1. IMSG at NOAA/NESDIS/STAR, College Park, MD *Email: Wenze.Yang@noaa.gov; 2. NOAA/NESDIS/STAR, College Park, MD; 3. GST, Greenbelt, MD

Introduction

The longest Normalized Difference Vegetation Index (NDVI) time series, produced from the Advanced Very High Resolution Radiometer (AVHRR) has ended in 2017, and there will be no continuation of AVHRR on-board afternoon satellites. NDVI from other sensors, especially the operational Visible Infrared Imaging Radiometer Suite (VIIRS), is imperative to elongate this global data set while maintaining the continuity and consistency. NDVI could be de-composed into two components: the multi-year climatology and vegetation condition index (VCI), with the former contains climate information and a majority of sensor noise, and the latter contains weather information and residual sensor noise. With the assumption that VCI from different sensors are similar, we re-composited the cross-sensor/cross-production NDVI with original VCI and the cross-sensor/cross-production climatology, and compared various cross-converted datasets with the three base NDVI datasets: two NDVI productions derived from AVHRR observation and another from VIIRS observation. As a result, the re-composited NDVI agrees well with the original NDVI spatially and temporally, with an accuracy of 0.02 NDVI unit at a global scale.

Methodology

NDVI could be de-composed into its climatology and VCI. The climatology stores Ecosystem Component and major part of Observing Noise Component, while the VCI contains Weather Component and some residual of Observing Noise Component. Similarly, NDVI from different sensor and/or different production suite could be de-composited into its distinctive climatology and VCI. With the assumption that the discrepancy of VCI from different sensors/productions could be neglected, and given corresponding sets of climatology, we can back-project, or re-compose VCI to sensor/production-specific NDVI.

Sensor Specific Differences

(a) Relative spectral response function of VIIRS (S-NPP), AVHRR-2 (NOAA-11) and AVHRR-3 (NOAA-19) red and NIR bands. The transmittance spectra of some selected gases are also plotted; (b) Local equatorial crossing time (LECT) of polar satellites which carry either the sensor VIIRS (S-NPP and NOAA-20) or AVHRR (the rest). In the figure, NPP is short for Suomi NPOESS Preparatory Project (S-NPP), rest N is short for National Oceanic and Atmospheric Administration (NOAA), and M is short for MetOP.

Original Base NDVI Time Series

NDVI time series of 6 sites from three base datasets: GIMMS NDVI1g (1981-2015) vs. AVHRR VHP (VHP-SMN, 1981-2017) vs. VIIRS (VIIRS-SMN, 2013-2018). The 6 sites are (a) East Sahara in Libya, (b) Saratov in Russia, (c) Illinois in USA, (d) South Queensland in Australia, (e) Maine in USA, and (f) Amazon in Brazil.

Converted vs. Original NDVI Time Series

After converting AVHRR VHP and VIIRS NDVI to GIMMS NDVI1g, we compared their time series with the original NDVI1g. Note if converting to other two datasets, the comparison results are similar.
Global Surface Type Products from VIIRS
Chengquan Huang, Jiaming Lu, Weishu Gong, Zhenhua Zou, Xiwu Zhan
1. Department of Geographical Science, University of Maryland, College Park, MD 20742 2. STAR/NEDIS/NOAA, College Park, MD 20740

Summary
VIIRS observations from S-NPP have been used to generate global surface type maps on an annual basis. The primary product is an Annual Surface Type (AST) map derived using VIIRS observations acquired within one full calendar year. This product uses 17 IGBP classes to characterize the Earth’s surface at approximately 1-km spatial resolution. To facilitate product use in specific applications, two additional maps are produced by reclassifying the IGBP map using the classification schemes required by those applications.

The overall accuracies of the IGBP classifications for the years between 2012 and 2018 varied between 76% and 79%, exceeding the JPSS L1RD requirement of 70%. The 2019 product is being developed with a planned release date in late summer/early fall. Future products will be produced by incorporating VIIRS data from NOAA-20 and VIIRS-like observations that will be available when the planned EUMETSAT Metop Second Generation (Metop-SG) satellite is launched. Together, these observations will greatly improve the feasibility to monitor sub-annual dynamics important for weather/climate processes, including rapid changes in surface inundation, snow/ice cover, and vegetation conditions. The VIIRS Surface Type team will explore and demonstrate capabilities for monitoring such changes.

Methods

<table>
<thead>
<tr>
<th>Overall Approach</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bridging</td>
</tr>
<tr>
<td>Gridded surface reflectance data</td>
</tr>
<tr>
<td>Compositing</td>
</tr>
<tr>
<td>Global composites (daily)</td>
</tr>
<tr>
<td>Global composites (32-day)</td>
</tr>
<tr>
<td>Metrics generation</td>
</tr>
<tr>
<td>Other surface type products</td>
</tr>
<tr>
<td>Annual metrics (global)</td>
</tr>
</tbody>
</table>

Improved Image Compositing Method

Self-Adaptive Compositing (SA-Comp) method produces clear view composites for both vegetated and non-vegetated (water, snow/ice, desert, etc.) surfaces.

Advanced Classification Algorithm

The support vector machines (SVM) method is designed to find optimal boundaries between classes, and hence is more resistant to noises and typically produces more accurate results than other classification algorithms.

Reference Data
Large quantities of reference samples have been derived based on Google Earth and other available high resolution imagery. Well distributed across the globe, highly reliable class labeling. Training samples: > tens of thousands, add as needed. Validation samples: ~6000 selected following a probability based sampling design.

Accuracy Assessment
Accuracy estimates are derived following well-established accuracy assessment protocol (Olodsson et al. 2014).

Major Characteristics of Primary Product
- 17 IGBP Surface Types
- 1 km spatial resolution
- Mapped annually
- Available in both Sinusoidal projection and Lat/Long

Future Directions

We will focus in the following areas in our future research:
- Continue to produce the VIIRS Annual Surface Type (AST) product
- Incorporate VIIRS continuity and VIIRS-like observations
- VIIRS continuity: NOAA-20, future JPSS missions
- VIIRS-like observations: METImage onboard METOP-SG, AM mission by Europe
- Explore and demonstrate capabilities for monitoring sub-annual surface type dynamics
- Focus on changes important for weather/climate processes:
  - Snow/ice, surface inundation, vegetation
  - Leverage existing/planned products/capabilities

Surface type maps updated daily with snow cover change by integrating snow cover maps generated through the Interactive MultiSensor Snow and Ice Mapping System (IMS) and other advanced algorithms.

Conclusion

Surface Type map with classes needed to support NCEP modeling

Landscape image showing fire and burnt areas, Oct. 20, 2017 (NOAA)
Surface type map showing snow/ice areas, Oct. 20, 2017 (NOAA)
High-resolution images showing status of the fire

Product Dissemination

2012
2018
An Evapotranspiration Data Product at 2km resolution from NOAA GOES-16

Li Fang1,2,*, Xiwu Zhan2, Mitchell A. Schull1,2, Satya Kalluri2, Istvan Laszlo2, Peng Yu1,2, Corinne Carter1,2, Christopher Hain3, Martha Anderson4

1 Cooperative Institute for Satellite Earth System Studies (CISESS)/Earth System Science Interdisciplinary Center, University of Maryland
2 NOAA-NESDIS Center for Satellite Applications and Research
3 NASA Marshall Space Flight Center
4 USDA Agricultural Research Service* Li Fang 1fang1@umd.edu

INTRODUCTION

- GOES Evapotranspiration (ET) and Drought (GET-D) has been operationally generating ET and Evaporative Stress Index (ESI) data products at 8km resolution for NCEP NWP model validation and drought monitoring.
- Continuation of GET-D operation using the current high-resolution thermal observations of the Advanced Baseline Imagers (ABI) from GOES-R series is in high demand.
- This study introduces the architecture of the upgraded GET-D system, the core model (Atmosphere-Land Exchange Inversion model; ALEXI) and preliminary validation results of ET product.

ALEXI MODEL

- Atmosphere-Land Exchange Inversion (ALEXI) model exploits the mid-morning rise in LST from GOES to deduce the land surface fluxes, including evapotranspiration.
- Implementation of the two-source energy balance (TSEB) model which balances components of energy budgets for the soil and canopy components separately.

SYSTEM OUTPUTS

- Two ET products were generated from the GOES-16 ABI L1b radiance product: GOES-16 ET product (from Channel 13 (GET-D) and GOES-16 ET product (from LST). The second option uses GOES LST observations to generate ET and Evaporative Stress Index (ESI) data products at 8km resolution for CONUS NCEP NWP model validation and drought monitoring.

PRODUCT

ET retrieval comparison between operational GOES-13/15 based 8km product and upgraded GOES-16 8km ET product; Monthly composite of July 2017 (mm/day)

RESULTS

- MEAD, NE Amelillus site (J. Varno, 2010) Rainfed and irrigated corn and soybean
  - Field #1: 41°09’54.2” N, 96°28’35.9” W
  - Field #2: 41°09’53.5” N, 96°28’12.3” W
  - Field #3: 41°10’46.8” N, 96°26’22.7” W

CONCLUSIONS

- The GET-D system has been upgraded successfully to generate ET at much improved spatial resolution of 2km over CONUS using GOES-16 observations.
- The comparison proves ET estimates from the upgraded GET-D system to be very consistent with the current operational products.
- The spatial correlation between the two products reaches 0.946 averaged over CONUS domain for the studying period.
- Upgrade GET-D is validated against MEAD in situ observations.
- Accuracy of the new GET-D ET product is satisfactory with the bias of 0.588 mm/day and the correlation of 0.914 averaged from three Mead sites.

Error Statistics

<table>
<thead>
<tr>
<th>Variables</th>
<th>Source</th>
<th>Spatial Resolution</th>
<th>Unit</th>
<th>Format</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ET</td>
<td>GOES-13 Based</td>
<td>2km</td>
<td>mm day⁻¹</td>
<td>NetCDF, GRIB2</td>
<td>Daily ET</td>
</tr>
<tr>
<td>Flux QC</td>
<td>GOES-13 Based</td>
<td>2km</td>
<td>W m⁻² day⁻¹</td>
<td>NetCDF, GRIB2</td>
<td>Quality control flag for retrieved ET</td>
</tr>
<tr>
<td>Flux QC</td>
<td>GOES-16 Based</td>
<td>2km</td>
<td>W m⁻² day⁻¹</td>
<td>NetCDF, GRIB2</td>
<td>Quality control flag for retrieved ET</td>
</tr>
</tbody>
</table>

MEADsites1

<table>
<thead>
<tr>
<th>Variables</th>
<th>Source</th>
<th>Spatial Resolution</th>
<th>Unit</th>
<th>Format</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>MEADsites1</td>
<td>GOES-13 Based</td>
<td>2km</td>
<td>mm day⁻¹</td>
<td>NetCDF, GRIB2</td>
<td>Daily ET</td>
</tr>
</tbody>
</table>

MEADsites2

<table>
<thead>
<tr>
<th>Variables</th>
<th>Source</th>
<th>Spatial Resolution</th>
<th>Unit</th>
<th>Format</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>MEADsites2</td>
<td>GOES-16 Based</td>
<td>2km</td>
<td>mm day⁻¹</td>
<td>NetCDF, GRIB2</td>
<td>Daily ET</td>
</tr>
</tbody>
</table>

MEADsites3

<table>
<thead>
<tr>
<th>Variables</th>
<th>Source</th>
<th>Spatial Resolution</th>
<th>Unit</th>
<th>Format</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>MEADsites3</td>
<td>GOES-16 Based</td>
<td>2km</td>
<td>mm day⁻¹</td>
<td>NetCDF, GRIB2</td>
<td>Daily ET</td>
</tr>
</tbody>
</table>

Average

<table>
<thead>
<tr>
<th>Variables</th>
<th>Source</th>
<th>Spatial Resolution</th>
<th>Unit</th>
<th>Format</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average</td>
<td>GOES-13 Based</td>
<td>2km</td>
<td>mm day⁻¹</td>
<td>NetCDF, GRIB2</td>
<td>Daily ET</td>
</tr>
</tbody>
</table>

NOAA’s National Environmental Satellite, Data, and Information Service (NESDIS) generates operational geostationary Level-2P (L2P) Sea Surface Temperature (SST) products in GHRSST GDS 2.0 format GOES-16 East and GOES-15 West, Meteosat Second Generation (MSG) 11 and 8, and Himawari-8. SST product accuracy for the heritage geostationary sensors was improved with the implementation of a physical retrieval algorithm based on a Modified Total Least Squares algorithm (Koner et al., 2015). Additionally, the operational geostationary SST products are then blended with the polar operational SSTs to produce daily global, 5-km resolution SST analyses in GHRSST L4 format (Maturi et al., 2017).

**OPERATIONAL SST RETRIEVAL**

- History of GEO SST retrieval algorithms at NOAA/NESDIS
  - 2000/12: GOES SST becomes operational, empirical regression + threshold cloud tests
  - 2006/8: Add SST retrieval from MSG/VIIRS
  - 2004/6: Bayesian cloud detection for clear sky (Koner et al., 2015, Merchant et al., 2005)
  - 2015/8: Physical SST retrieval using modified least square method becomes operational

Current geostationary SST retrieval: MTLS physical retrieval + Bayesian cloud detection for clear sky (Koner et al., 2015, Merchant et al., 2005)

Geo-Polar Blending: A multi-scale OI with data-adaptive correlation length scale, giving a ~5-km global L4 product (Maturi et al., 2017)
  - Analysis is performed at 3 different scales
  - Final result is interpolated from these analyses based on data density
  - Preserves fine-scale features without introducing excessive noise

**GEOSTATIONARY SST COVERAGE**

The image is a 24 hour merged composite of the Operational geostationary SST products generated by NOAA (GOES-W (15), GOES-E (16), Meteosat-11, Meteosat-8, Himawari-9). N.B. The addition of Meteosat-8 has improved coverage over the Indian Ocean – important for NOAA Coral Reef Watch

**EFFECT OF DIURNAL ADJUSTMENT**

Diurnal warming amplitude calculated using turbulence model, including a parameterization for Stokes’ drift

**BLENDED SST ANALYSIS**

These 5-km blended SST analyses are produced daily from 24 hours of polar and geostationary sea surface temperature satellite retrievals (NPP, Metop-B, GOES-E/W, Himawari-9, and Meteosat-11). Meteosat-8 is being added over the Indian Ocean.
  - Day & Night
  - Night-only
  - Diurnally adjusted Day & Night

**SUMMARY**

The analysis product validates to 0.3 K RMS against independent ARGO data (see https://www.star.nesdis.noaa.gov/sod/sst/squam/analysis/l4/74sst=CMC&ref=IQ2_AG&aggtime=monthly&stats=SD#timeseries_dyn). The physically retrieved SST L2P inputs from the heritage geostationary imagers are an important component of the SST Analysis products. The temporal and increased data coverage of the geostationary satellites generated by a high quality SST with Standard Deviation of 0.3-5 makes this a uniquely powerful product for many ocean applications requiring mesoscale temperature information.

INTRODUCTION
The first geostationary ocean color satellite (GOCI) has the unique capability with hourly measurements during daytime to provide short–long–term environmental monitoring in the marine ecosystem over the western Pacific region. In this presentation, we show results of GOCI-derived ocean color products from 2012 to 2019 using the Multi-Sensor Level-1 to Level-2 (MSL12) ocean color data processing system to characterize diurnal, seasonal, and interannual variations in water property. In addition, water quality and bio-optical products from the polar-orbiting ocean color satellite sensors, e.g., the Visible Infrared Imaging Radiometer Suite (VIIRS) onboard the Suomi National Polar-orbiting Partnership (SNPP) and the Ocean and Land Colour Instrument (OLCI) on the Sentinel-3A, derived using the MSL12 are compared with those from GOCI. Comparison results with the in-situ measurements from the two AERONET-OC sites located in the Yellow Sea show that over open oceans ocean color products are quite accurate and highly stable, and reasonable water property data can be derived over turbid coastal and inland waters. Furthermore, we show that GOCI measurements provide important diurnal information, while the polar-orbiting satellites provide large scale spatial coverages. Thus, measurements from the geo and polar-orbiting satellites are complementary to provide more complete picture/information of water optical, biological, and biogeochemical variations over the open ocean and coastal/inland waters.

DATA & METHODS
• The Multi-Sensor Level-1 to Level-2 (MSL12) ocean color data processing system has been used for VIIRS, OLCI, and GOCI data processing.
• Various parameters and lookup tables are generated, and a new atmospheric correction algorithm has been developed and implemented in MSL12 for GOCI data processing in the region (Wang et al., 2012, 2013).
• GOCI and OLCI Level-1B data were processed to derive Level-2 ocean color products using the new atmospheric correction algorithm (Jiang & Wang, 2014).
• VIIRS ocean color Environmental Data Records (EDR or Level-2 data) were processed from the VIIRS science quality Sensor Data Records (SDR or Level-1B data) routinely using MSL12 with the NIR-SWIR combined atmospheric correction algorithm (Wang & Shi, 2007).

Performance of GOCI Ocean Color Products
• Comparison results show that the GOCI-derived $n_{L}(\lambda)$ data are reasonably well corresponding to the in situ measurements in the optically complex waters (Fig. 2), which are similar to those with VIIRS data.
• $n_{L}(\lambda)$ spectra from GOCI (at noon), VIIRS, and OLCI climatology composites are similar in the five areas (Bohai Sea, middle of Yellow Sea, Yangtze river mouth, Japan East Sea, and off shore waters) (Fig. 3).

GOCI, VIIRS, and OLCI Climatology Images
• Overall, the GOCI-derived ocean color images are generally very similar to those from VIIRS and OLCI.
• However, there is still the boundary issue between slots in GOCI data, and significantly high values appear in the northern area in the GOCI-derived Chl-a images.

Interannual Variation of GOCI-, VIIRS-, and OLCI-derived Products
• GOCI-, VIIRS-, and OLCI-derived Chl-a images show similar seasonal and spatial distributions over the Northwestern Pacific Ocean.
• In general, Chl-a values are high in spring and low in summer in most waters.

SUMMARY
• The GOCI ocean color products for the GOCI coverage region have been derived using an iterative NIR-water reflectance corrected atmospheric correction algorithm (i.e., the BMW algorithm from Jiang and Wang (2014)). Time series of the monthly composite images were produced for the entire GOCI region.
• VIIRS and OLCI ocean color products were also generated using MSL12 with the NIR-SWIR combined and NIR atmospheric correction algorithms, respectively. The VIIRS and OLCI ocean color data over the entire GOCI coverage region were compared with the GOCI ocean color data.
• Matchup results show that GOCI ocean color data are reasonably well correlated to the in situ optical measurements in the Korean coastal waters.
• In general, the temporal and spatial patterns of the GOCI-derived ocean color products are comparable to those from VIIRS and OLCI although there are still some differences. More efforts are required to improve the VIIRS, OLCI, and GOCI ocean color data quality over highly turbid coastal/inland waters.

Reference:

Acknowledgments: The GOCI Level-1B data study were provided by Korea Institute of Ocean Science & Technology (KIOST) and in situ data were obtained from the NASA AERONET-OC sites. This study was supported by the NOAA Product Development, Readiness, and Application (PDRA)/Ocean Remote Sensing (ORS) Program funding and JPSS funding.
Remote sensing of shallow-water bathymetry: Leveraging multispectral satellite ocean color observations

Jianwei Wei¹, Menghua Wang², Zhongping Lee³, Henry O. Briceno⁴, Xiaolong Yu⁵, Lide Jiang⁶, Junwei Wang⁶, Kelly Luis⁶, Rodrigo Garcia⁷
1. NOAA/STAR; 2. NOAA/STAR; 3. University of Massachusetts Boston; 4. Florida International University; 5. NOAA/STAR; Colorado State University; 6. Xiamen University

**Question and Objective**

Ocean color satellites allow for derivation of important biogeochemical properties for global oceans. Limited to multispectral resolution, however, it remains difficult to generate geophysical properties, e.g., water depth, over global shallow waters with the satellite remote sensing reflectance ($R_s(\lambda)$). This study evaluates a new algorithm for practical application of multispectral ocean color observations to the retrieval of water depth for optically shallow waters.

**Method and Algorithm**

- **Semi-analytical approach designed for hyperspectral $R_s(\lambda)$**
  Ocean color community has invested great effort in shallow water remote sensing with semi-analytical algorithms. An extensively tested algorithm is the so-called hyperspectral optimization processing exemplar (HOPE) (Lee et al., 1998; 1999). A shallow-water reflectance model is established as:

  $$r_s(\lambda) = r_p(\lambda) \left[1 - \exp \left( \frac{1}{\cos \theta} \frac{D_1(1 + D_2 r_p(\lambda))}{\cos \theta} \sin \theta \right) \right]$$

  Five unknowns of $P, G, X, B,$ and $H$ can be determined by quantifying the difference between the observed spectrum, $R_{obs}(\lambda)$, and modeled spectrum, $R_{mod}(\lambda)$.

  $$error = \sum \left( R_{mod}(\lambda) - R_{obs}(\lambda) \right)^2$$

- **Two-spectrum optimization approach (2-SOA) for multispectral $R_s(\lambda)$**
  Our new algorithm incorporates two independent $R_s(\lambda)$ spectra measured at the same location in the spectral optimization, thus allowing to generate much improved estimation for water depth with multispectral satellite ocean color observations. The work-flow is schematically shown in below:

  ![Two-spectrum optimization approach (2-SOA) for multispectral $R_s(\lambda)$](image)

**Performance Evaluation**

- **Error statistics for model-estimated water depth (0.5-30 m)**

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Range (interval)</th>
<th>Levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P$</td>
<td>0.001-0.19 (0.03)</td>
<td>7</td>
</tr>
<tr>
<td>$G$</td>
<td>0.001-0.19 (0.03)</td>
<td>7</td>
</tr>
<tr>
<td>$X$</td>
<td>0.5-20.5 (1)</td>
<td>30</td>
</tr>
<tr>
<td>$B$</td>
<td>0.5-20.5 (1)</td>
<td>30</td>
</tr>
<tr>
<td>$H$</td>
<td>0.001-0.05 (0.001)</td>
<td>5</td>
</tr>
<tr>
<td>$R_s$</td>
<td>0.01-0.10 (0.01)</td>
<td>10</td>
</tr>
<tr>
<td>$W_a$</td>
<td>0.01-0.10 (0.01)</td>
<td>10</td>
</tr>
<tr>
<td>$W_b$</td>
<td>0.01-0.10 (0.01)</td>
<td>10</td>
</tr>
</tbody>
</table>

  Cost function

  $$\text{MAPE} = \frac{\sum |r_{mod}(\lambda) - r_{obs}(\lambda)|}{\sum r_{obs}(\lambda)}$$

  **MAPE**: median absolute percentage error; **RMSE**: root mean square error

- **Depth-specific error statistics for model-estimated water depth**

  ![Depth-specific error statistics for model-estimated water depth](image)

  The algorithm performance varies with the range of water depth under study. Improved performance is observed for water depths over ~3-20 m in comparison to the “standard” approach.

**Conclusions**

- A new algorithm is developed for shallow-water bathymetric estimation for multispectral satellite ocean color sensors.
- Evaluation shows substantial improvement in the estimated depth product over 0-30 m.

Acknowledgment: [http://www.soest.hawaii.edu/coasts](http://www.soest.hawaii.edu/coasts)
Wildfire smoke forecasts using HYSPLIT-based emission inverse modeling system and GOES observations

Tianfeng Chai1,2, Hyun Cheol Kim1,2, Ariel Stein1, and Shobha Kondragunta3

1. NOAA Air Resources Laboratory, College Park, MD;
2. Cooperative Institute for Satellite Earth System Studies (CISESS), University of Maryland, College Park, Maryland;
3. National Environmental Satellite, Data, and Information Service, National Oceanic and Atmospheric Administration, College Park, Maryland

Motivation

Wildfire smoke forecasts have been challenged by high uncertainty in fire emission estimates, such as the BlueSky emission used in the current NOAA smoke forecasts (Fig. 1). We develop an inverse modeling system, the HYSPLIT-based Emissions Inverse Modeling System for wildfires (or HEIMS-fire) to estimate wildfire emissions from the smoke plumes measured by satellite observations.

Methodology

In this top-down approach, the unknown emission terms are obtained by searching the emissions that would provide the best model predictions closely matching the observations. The wildfire emission locations are identified by HMS, the unknown emission rates and the release heights are left to be determined. The emission rates may vary significantly with time. Thus, the unknowns of the inverse problem are the emission rates \( q_\text{ikt} \) at each location \( i \), different height \( k \) and period \( t \). The cost function \( F \) is defined as,

\[
F = \frac{1}{2} \sum_{n=1}^{N} \sum_{m=1}^{M} \left( q_\text{ikt} - q_\text{ikt}^0 \right)^2 + \frac{1}{2} \sum_{n=1}^{N} \sum_{m=1}^{M} \left( \epsilon_\text{k1m}^2 - \epsilon_\text{k2m}^2 \right) + F_{\text{other}}
\]

where \( q_\text{ikt}^0 \) is the \( m \)-th observed concentration or mass loading at time period \( n \) and \( c_\text{ikt}^0 \) is the HYSPLIT counterpart. As shown in Equation (1), a background term is included to measure the deviation of the emission estimation from its first guess \( q_\text{ikt}^0 \). The background terms ensures that the problem is well-posed even when there are not enough observations available in certain circumstances. The background error variances \( \sigma_k^2 \) measure the uncertainties of \( q_\text{ikt}^0 \). The observational error variances \( \epsilon_\text{km}^2 \) represent the uncertainties from both the model and observations as well as the representative errors. \( F_{\text{other}} \) refers to other regularization terms that can be included in the cost function. The optimization problem can be solved using many minimization tools, such as L-BFGS-B package, to get the final optimal emission estimates.

HEIMS-fire system

The HEIMS-fire system is shown in Fig. 2. The extensive fires in the southeastern U.S. region in November 2016 is studied here. (Fig.3).

Reconstructed smoke results

As smoke may come from distant sources, four domains of fire source inputs are considered (Fig.4). Sensitivity tests show that only including the domain 1 would generate comparable results. Using the HEIMS estimated emissions, the smoke plume predicted match the observation pretty well (Fig.5).

Summary and future work

Wildfire emission inversion system HEIMS-fire has been built based on HYSPLIT model, its TCM, and a cost function;
A case study using real GOES data has been performed;
High resolution GOES-16/17 data will be tested;
More evaluation will be performed using VIIRS AOD and surface PM2.5 observations;
Estimated emissions will be tested in other models, such as CMAQ and HRRR-smoke.

Contact information: Tianfeng.Chai@noaa.gov
Introduction

- Burned landscapes present difficult hydrologic forecasting challenges for National Weather Service Offices
- Burned soils and landscapes can be conducive to the development of flash flooding and landslides from heavy precipitation events (Ramsmeier and Arrowmith 2001)
- The severity of the burn scar can be directly related to the risk for debris flows (Cannon and DeGraff 2009)
- The severity of the burn scar can be directly related to the risk for debris flows (Cannon and DeGraff 2009)
- The severity of the burn scar can be directly related to the risk for debris flows (Cannon and DeGraff 2009)
- To help remedy this lapse in knowledge, NASA
  - Cannon, Susan & De Graff, Jerome. (2009). The increasing wildfire and post
- Landsat imagery, for example, may only be available about once every eight days, and cloudy
  - NBR imagery takes advantage of the fact that spectral
- Fire Severity Assessment by Using NBR and NDVI Derived from LANDSAT TM/ETM Images,
- This presentation will discuss the development of the GOES
- Ongoing fires will generally show up as red to dark brown colors due to higher emissions in the 2.2 µm band
- False returns at edges of water bodies occur in GOES-16/17 imagery due to differences in spatial resolution of 0.86 µm band (1 km) and 2.2 µm band (2 km)

Background/Methodology

- NBR imagery takes advantage of the fact that spectral responses of near-infrared and shortwave-infrared are opposite for burned areas vs healthy vegetation.
- For near-infrared (~0.86 µm): Burned areas have low reflectance, while healthy vegetation has high reflectance.
- For shortwave-infrared (~2.2 µm): Burned areas have high reflectance, while healthy vegetation has low reflectance.

\[ \text{NBR} = \frac{\text{Prefire NBR} - \text{Postfire NBR}}{\text{Prefire NBR}} \]

A couple of examples:

- **Healthy Vegetation:**
  - Prefire NBR = 0.86 (
  - Postfire NBR = 0.86 (18%)
  - NBR = (38-15)/(38+15) = 0.43
  - NBR = (18-32)/(18+32) = -0.28
- **Burned Vegetation:**
  - Prefire NBR = 2.25 (32%)
  - Postfire NBR = 2.25 (32%)
  - NBR = (38-15)/(38+15) = 0.43
  - NBR = (18-32)/(18+32) = -0.28

- The change in pre-fire and post fire NBR is known as dNBR.

\[ \text{dNBR} = \text{Prefire NBR} - \text{Postfire NBR} \]

- dNBR is used to assess burn severity and vegetation regrowth
  - Prefire imagery will have very high near infrared band values and very low mid infrared band values.
  - Postfire imagery will have very low near infrared band values and very high mid infrared band values.
  - It can be difficult to distinguish between burned and non-vegetated areas in dNBR imagery

- Developed a process in collaboration with NWS to assess burn scar severity with new generation satellites in the early stages of fire development and growth
- Limited feedback due to lack of fires in initial test WFO (ABO), but future users in ABO and AFRIC have provided feedback that data are sufficient to aid in decision-making.
- Continued testing with and feedback from NWS Western Region HQ and Albuquerque Forecast Office, planned discussions this fall
- Refine a technique for processing and disseminating GOES and S-NPP dNBR imagery in GIS format, minimizing cloud effects

Conclusions

- Continued testing with and feedback from NWS
- New images of fire scars may help mitigate
- Landsat/Sentinel
- GIS format, minimizing cloud effects

Next Steps

- Field Validation of Burned Area Reflectance Classification (BARC) Products for Fire
- To help remedy this lapse in knowledge, NASA
  - Cannon, Susan & De Graff, Jerome. (2009). The increasing wildfire and post
  - Landsat imagery, for example, may only be available about once every eight days, and cloudy
  - NBR imagery takes advantage of the fact that spectral
  - Fire Severity Assessment by Using NBR and NDVI Derived from LANDSAT TM/ETM Images,
  - This presentation will discuss the development of the GOES
  - Ongoing fires will generally show up as red to dark brown colors due to higher emissions in the 2.2 µm band
  - False returns at edges of water bodies occur in GOES-16/17 imagery due to differences in spatial resolution of 0.86 µm band (1 km) and 2.2 µm band (2 km)

Timeline of Analysis for Burn Scar Severity

- GOES-16/17 NBR Image available first, minutes to hours (clouds permitting)
- Higher-res dNBR imagery (e.g., Landsat, Sentinel), based on satellite, but typically days to weeks (clouds permitting)
- S-NPP NBR and/or dNBR imagery, once per day (clouds permitting)
- High-res BARC map produced from high-res satellite imagery

References

- Field Validation of Burned Area Reflectance Classification (BARC) Products for Fire Awareness, Hooker et al. 2020
- Fire Severity Assessment by Using NBR and NDVI Derived from LANDSAT TM/ETM Images, Susan et al. 2007
- Cannon, Susan & De Graff, Jerome. (2009). The increasing wildfire and post
- Landsat imagery, for example, may only be available about once every eight days, and cloudy
- NBR imagery takes advantage of the fact that spectral
- Fire Severity Assessment by Using NBR and NDVI Derived from LANDSAT TM/ETM Images,
- This presentation will discuss the development of the GOES
- Ongoing fires will generally show up as red to dark brown colors due to higher emissions in the 2.2 µm band
- False returns at edges of water bodies occur in GOES-16/17 imagery due to differences in spatial resolution of 0.86 µm band (1 km) and 2.2 µm band (2 km)

Woodbury Fire in Arizona June-July 2019

- Since NBR imagery are generated from GOES-16/17 and S-NPP bands in AWIPS, information about the burned vegetation can be observed in real-time
- Low values (bright yellow-orange-red) indicate burned vegetation severity, colors shifted to red with increased negative difference in NIR and SWIR
- High values (light green-dark green) indicate healthy vegetation, colors shifted to darker green with increased positive difference in NIR and SWIR
- Ongoing fires will generally show up as red to dark brown colors due to higher emissions in the 2.2 µm band
- False returns at edges of water bodies occur in GOES-16/17 imagery due to differences in spatial resolution of 0.86 µm band (1 km) and 2.2 µm band (2 km)

In the GOES-17 NBR images above, notice the spread of the burn scar from 17 June to 27 June. Burn scar severity in SW portion of the Woodbury Fire remains fairly stable through the period, but the scar has spread due to the ongoing fire and the worst burn severity developed after 17 June. The fire perimeter is also shown for this fire (right) as of 27 June 2019. False NBR returns can be seen along Theodore Roosevelt Lake to the north of the Woodbury Fire. However, other burn scars can be seen in the imagery on the 27 June image (right).

In this comparison between GOES-17 NBR imagery (left) and S-NPP NBR imagery (right), notice the higher spatial resolution of the S-NPP imagery. Also, issues with false returns, such as those along Theodore Roosevelt Lake to the north of the Woodbury Fire do not occur in the S-NPP imagery as is the case with GOES imagery. However, GOES imagery has the advantage of higher temporal resolution (every 5 min), vs the S-NPP imagery, which will only generally be available once per day at any given location (clouds permitting).

Timeline of Analysis for Burn Scar Severity

- GOES-17 NBR image with visible (0.64 µm) imagery overlays provides context for clouds and smoke, and makes the imagery appear more intuitive.
- Notice that smoke can be observed from the ongoing fire. The visible imagery is set to partial transparency (75%).
Satellite Perspectives on Western US Wildfires in 2019: Comparison of Aerosol Retrievals from GOES and MISR, with Ground-Based Validation

Michael J. Garay and Olga V. Kalashnikova
Jet Propulsion Laboratory, California Institute of Technology, Pasadena, CA 91109

On 12 February 2019 the Geostationary Operational Environmental Satellite-17 (GOES-17) became operational as GOES-West, providing detailed observations of the Western United States from the Advanced Baseline Imager (ABI), which is the primary instrument on the latest GOES-R series of satellites. The summer and fall 2019 wildfire season in the Western US provided the first test of the aerosol retrieval capabilities of the new instrument, especially aerosol optical depth (AOD), associated with extreme fire events. At the same time, the Multi-angle Imaging SpectroRadiometer (MISR) instrument remains operational on the NASA Terra EOS satellite, yielding an unprecedented opportunity to compare simultaneous aerosol retrievals from both ABI and MISR. Validation of these retrievals is further enhanced by the deployment of additional Aerosol Robotic Network (AERONET) sun photometer sites as part of the joint NASA/NOAA FIREX-AQ field campaign, which took place in the summer of 2019.

GOES comparisons with AERONET

GOES data were also matched with ground-based AERONET sites for times close to the overpass time of Terra (1800–1900 UTC) for the entire time period from 3 August to 21 August 2019. The AERONET AODs were interpolated to the 550 nm reference wavelength of GOES. Some of the AERONET sites experienced heavy smoke (see photos) during the FIREX-AQ time period. Regression plots and associated statistics are more limited due to the restricted time period. These results show that the GOES aerosol products perform fairly well relative to AERONET, but the GOES aerosol retrievals tend to overestimate the AOD. However, the GOES observations provide important information on the seasonal development and downward transport of smoke during FIREX-AQ.

References


© 2020. Government sponsorship acknowledged. Support for this research was provided by the NASA Earth Science Directorate.
A system has been set up to produce in near real-time nowcasting and forecast model input data from combined Direct Broadcast Satellite (DBS) Polar Hyperspectral (PHS) CrIS/IASI and GOES ABI (PHSnABI) Data. The data is made available to potential users via the internet and through the NWS AWIPS. Studies are being performed to demonstrate severe and precipitation forecast improvements using these data. The PHSnABI observation and forecast products will be provided to weather forecasters for evaluation during the NOAA spring 2020 Hazardous Weather Testbed (HWT).

**PHS and ABI Characteristics**

- **MetOp IASI**: Vertical Res. 1-2 km
  - Horizontal Res. 14 km
  - Time Res. 50 min to 7 hrs
- **GOES ABI**: Vertical Res. 5-10 km
  - Horizontal Res. 2 km
  - Time Res. 5-15 mins.

**Assimilating PHSnABI**

- NOAA RAP-like configured 9-Km WRF Model

**PHS and ABI Sounding Fusion**

**PHS Sounding Retrieval Process**

- Dual Regression + De-Alias (DRDA)*
  - Alias = Forecast Retrieval – Forecast Profile
  - DRDA Retrieval = DR Retrieval – Alias

**PHS and ABI Sounding Fusion Example**

**Nowcast Website (194116 UTC)**

http://dbps.cas.hamptonu.edu/development/
What Do Forecasters Currently Use Operationally for Blended TPW?

Forecaster Surveys from Hazardous Weather Testbed (HWT) and Flash Flood and Intense Rainfall Experiment (FFaIR)

Questions posed to forecasters in 2019 at Hazardous Weather Testbed (HWT - NSSL) and Flash Flood and Intense Rainfall Experiment (FFaIR - WPC)

1. Is the merged TPW product preferable to the operational blended TPW?
2. How important is it that blended TPW be independent of forecast model TPW?
3. Is hourly temporal resolution sufficient?

Cloud-Free Water Vapor Imagery

Derived from Passive Microwave Data

Summary and Future Work

Summary

- A new blended TPW product which uses advection and GOES-16 in clear skies has been developed.
- Comparisons of the GOES-16 TPW versus surface GPS and OCO-2 show low error (RMS ~2 mm) with good temporal stability.
- Forecasters rated the new product higher than the current operational product.
- Open Question: How much model input is too much?

Future Work

- Transition the new merged TPW into operations, including CIMSS MIMIC product.
- Survey users for applications of cloud-free water vapor imagery.

This work is supported by the NOAA GOES-R Risk Reduction and JPSS Proving Ground and Risk Reduction Programs.