Evaluating OLCI, MERIS, & MODIS ocean color products to advance watershed monitoring & time-series applications

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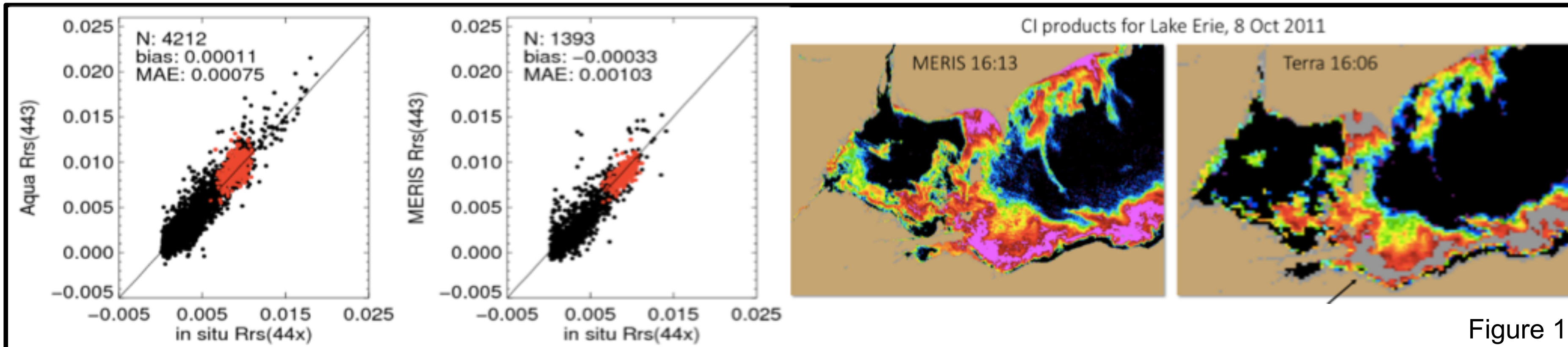

Figure 1

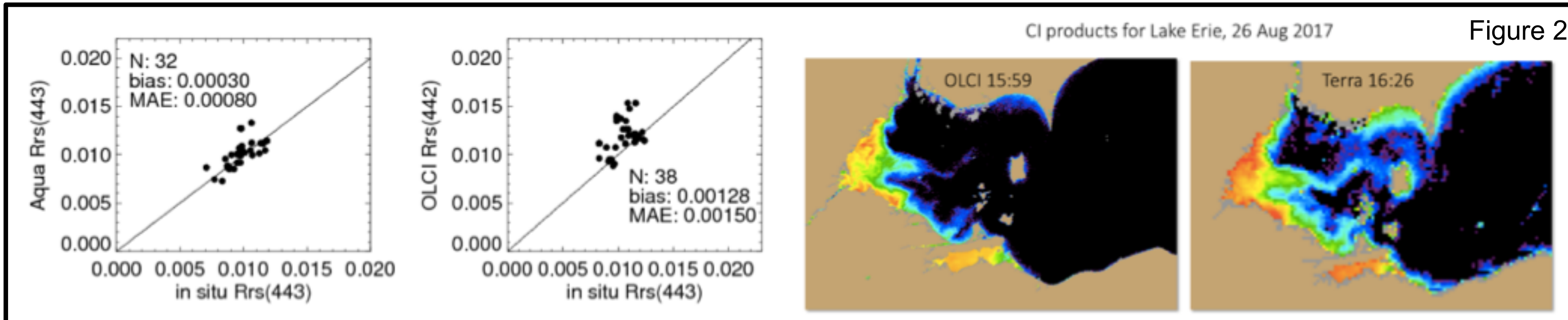

Figure 2

The CyAN Project (EPA, NASA, NOAA, USGS) uses ESA/Copernicus MERIS & OLCI data products to identify harmful cyanobacteria blooms in U.S. inland lakes. MERIS & OLCI data records do not overlap; thus, we use MODIS-Aqua & -Terra to infer their consistency. MERIS & MODIS radiometrically agree well, leading to cyanobacteria index (CI) products that also agree (Fig. 1). OLCI appears to have a high radiometric bias and, thus, produces cyanobacteria index products that are more conservative (fewer IDs) than MODIS (Fig. 2).

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References:

P.J. Werdell, T. Owens, C. Proctor, B. Seegers, R. Stumpf, B. Schaeffer, and K. Loftin (2018), Evaluating & achieving consistency in OLCI & MERIS ocean color products to advance watershed monitoring & time-series applications IS41A-04, *presented at 2018 American Geophysical Union Ocean Sciences Meeting, Portland, OR, 15 Feb 2018.*

B.A. Schaeffer, K. Loftin, R.P. Stumpf, and P.J. Werdell (2015), Agencies collaborate, develop a cyanobacteria assessment network. EOS Trans. AGU 96, 16–20.

Data Sources:

All satellite data were distributed and processed by the Ocean Biology Processing Group (616), NASA GSFC. Original data sources include NASA, ESA, and Copernicus. All in situ data were acquired from SeaBASS (616), NASA GSFC. MOBY data were collected by NOAA. AERONET-OC data originate from various AERNOT stations, coordinated by NASA GSFC.

Technical Description of Figures:

Figure 1: In situ (MOBY=red, AERONET-OC=black) vs. MODIS-Aqua remote sensing reflectance at 443 nm (left). In situ (MOBY=red, AERONET-OC=black) vs. MERIS remote sensing reflectance at 442 nm (center). Cyanobacteria index (CI) products for MODIS-Terra and MERIS in Lake Erie (right). MAE is the median absolute error.
Figure 2: In situ (MOBY) vs. MODIS-Aqua remote sensing reflectance at 443 nm (left). In situ (MOBY) vs. OLCI remote sensing reflectance at 443 nm (center). Cyanobacteria index (CI) products for MODIS-Terra and OLCI in Lake Erie (right).

Scientific significance, societal relevance, and relationships to future missions:

The CyAN Project (EPA, NASA, NOAA, USGS) uses 300-m ESA/Copernicus MERIS & OLCI data products to identify harmful cyanobacteria blooms in U.S. inland lakes. Stakeholders & collaborators include regional EPA offices, state departments of natural resources, & regional watershed managers. The CyAN Project distributes OLCI data to these collaborators. At this time, OLCI CI data products are conservatively low (fewer positive identifications of harmful algae). Ongoing & forthcoming calibration efforts will improve OLCIs radiometric accuracy and improve its harmful cyanobacteria detection capability. With future support, the Ocean Biology Processing Group (616) will continue to evaluate & improve OLCI data products.

Lake Chad Total Surface Water Area

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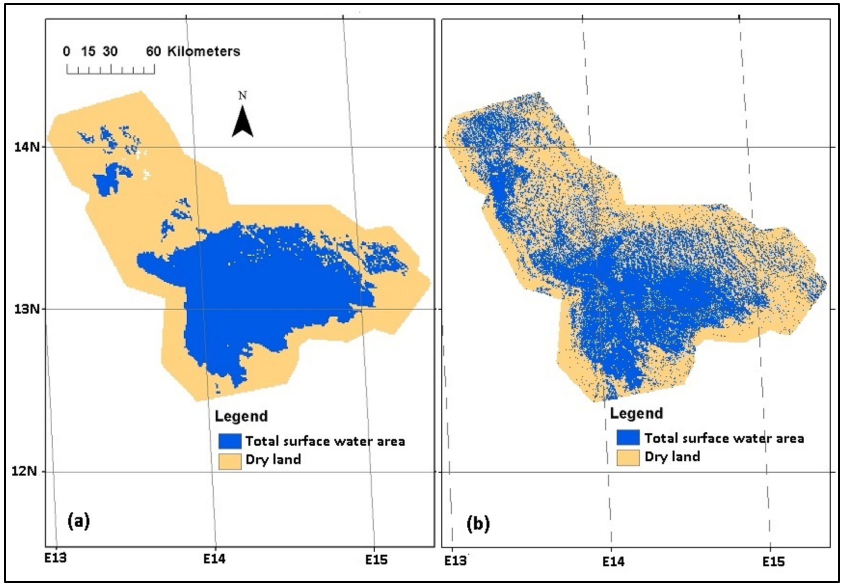

Figure 1

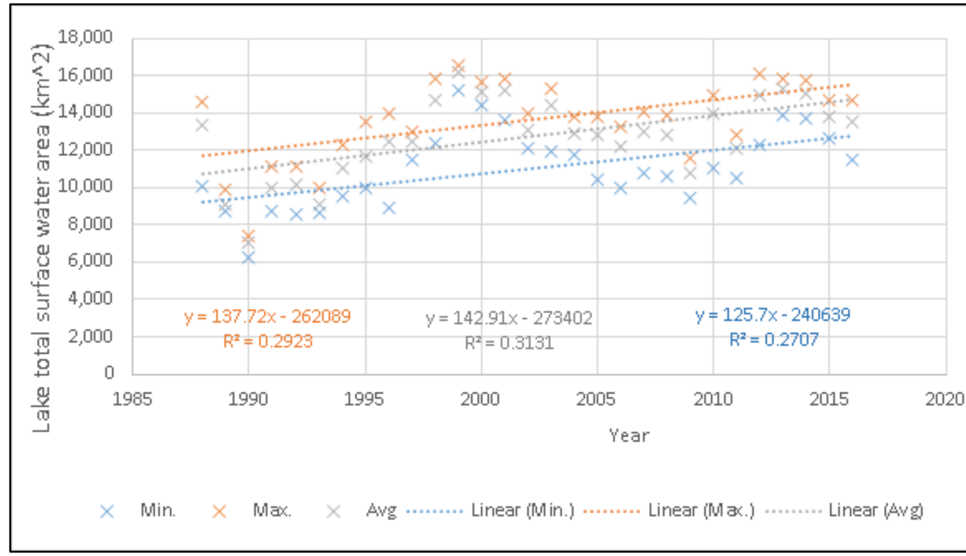

Figure 2

We extended an existing time series of Lake Chad total surface water area from 13 to 28 years using MODIS Land Surface Temperature and Sentinel-1a C-band radar data. We find for the dry seasons of 1988–1989 to 2016–2017 that the maximum total surface water area of the lake was approximately 16,800 sq. km (February and May, 2000), the minimum total surface water area of the lake was approximately 6,400 sq. km (November, 1990), and the average was approximately 12,700 sq. km. Further, we find the total surface water area of the lake to be highly variable during this period, with an average rate of increase of approximately 143 km^2 per year.

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Data Sources: NASA MODIS Land Surface Temperature data, ESA Sentinel-1a C-band radar data, Lake Chad total surface water area from Leblanc, et al., 2011.

Technical Description of Figures:
Figure 1: (**a**) Example NASA MODIS Land Surface Temperature (LST)-derived dry season water classification (31 October 2016–7 November 2016) (**b**) Example ESA Sentinel-1a C-band radar-derived dry season water classification (5 November 2016).
Figure 2: Annual mean, maximum, and minimum Lake Chad dry season total surface water area time series composite from Leblanc et al., 2011 and Policelli et al., 2018. Each data point represents a full month. Trend lines are included.

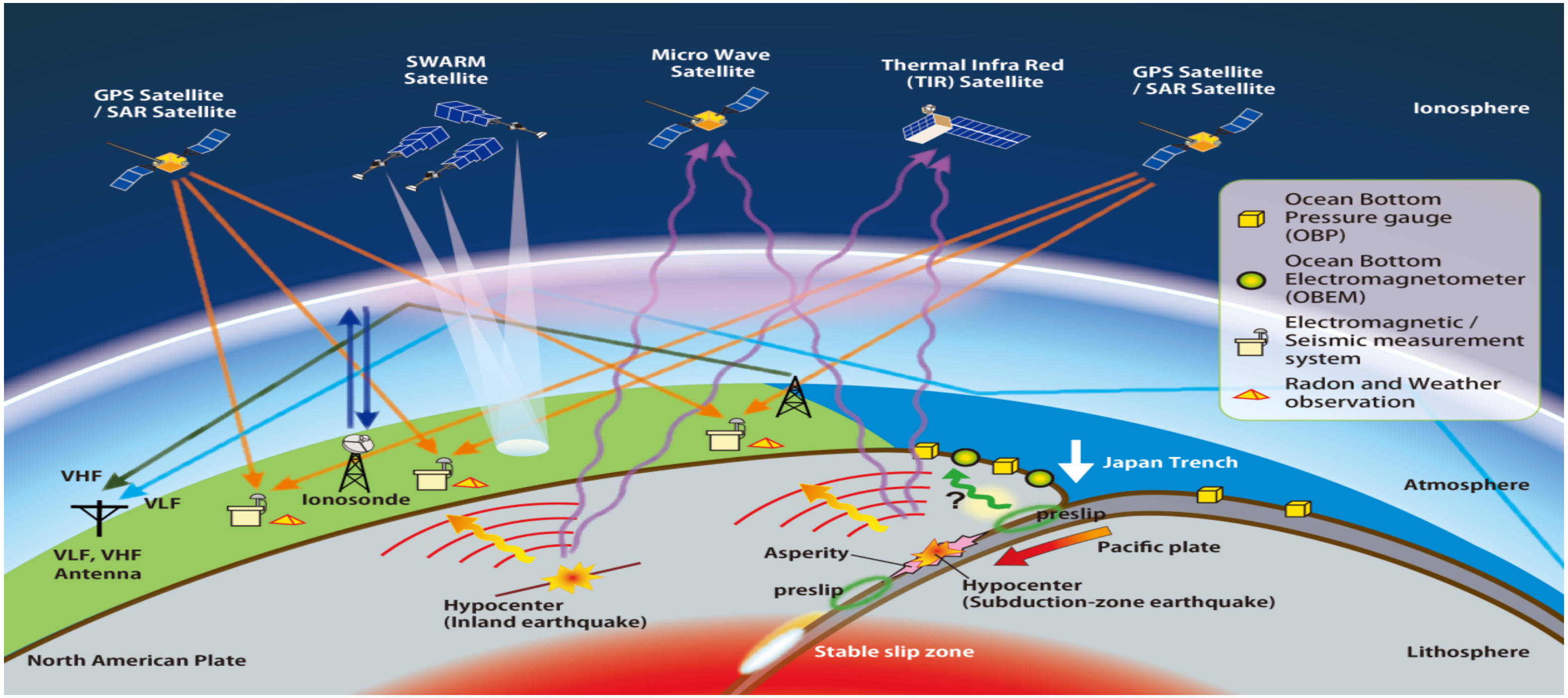
In Figure 1 Inundated area is shown in blue and dry land in tan. The total area of water is very similar in 1a (LST-derived water classification) and 1b (radar-derived water classification), however the distribution is different. Given the maturity of the use of radar for classifying water, we used the radar-derived classification to adjust the LST-derived classification. This allowed us to develop a longer time series (28 years) of adjusted LST-derived water extent than was possible with radar alone. In figure 2, the time series of Lake Chad total surface water area is shown, with the maximum monthly area for each year shown in orange, the minimum monthly area for each year shown in blue, and the average monthly area for each year shown in gray. Trend lines indicate the average rate of increase of lake area.

Scientific significance, societal relevance, and relationships to future missions: The time series of Lake Chad total surface water area is being used in follow-on research to develop a statistical model of Lake Chad's annual flooding cycle. The flooding extent and timing are unpredictable and important to the estimated 2 million people living along the lake's shoreline (Magrin, G., 2016); a significant part of their livelihoods derives from "recession farming" in the fertile soil of previously flooded lake bed (Sarch and Birkett, 2000). Without good forecasts of the flooding cycle, poor timing or location of planting can result in the loss of crops (Okpara et al., 2016). This research demonstrates the importance of future NASA radar missions such as NISAR for monitoring water beneath flooded vegetation.

New Book: Pre-Earthquake Processes-A Multidisciplinary Approach to Earthquake Prediction Studies,

Editors: D. Ounounov[1], S. Pulinets[2], K. Hattori[3], and P. T. Taylor[4]

[1]Chapman Univ., [2]Space Res. Inst., [3]Chiba Univ., [4]Geodesy & Geophysics Lab. GSFC/NASA



The first scientific treatise to report comprehensively about earthquake-associated phenomena. This volume highlights some twenty recent studies that present current research and progress reports on pre-earthquake investigations. They are globally distributed with a majority coming from China, Japan, Russia, Taiwan and Italy. They describe the various observations being recorded and their relationship to pre-seismic activity. Some of these monitored parameters (shown above) include: observing crustal motion; radon; thermal infra red/ (VLF); magnetic anomalies; atmospheric effects including ionospheric total electron content (TEC); and recording regional seismicity in active areas.

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Reference: AGU/Wiley Geophysical Monograph 234. Pre-Earthquake Processes-A multidisciplinary approach to earthquake prediction studies, Dimitar Ouzounov, Sergey Pulinets, Katsumi Hattori, Patrick Taylor, Editors.

Data Source: The data for this volume came from various NASA and non-NASA satellites (GPS, Swarm, SAR) and other non-satellite sources (ionosondes, ocean bottom seismometers and pressure gauges, seismology stations, electro-magnetometers, radon and weather monitoring stations.)

Technical Description of Figure:

Figure *1.* This figure is a cartoon of the various and numerous data sources, both satellite and Earth based, used by the researchers in this volume. They come from over seven countries. The crustal cross section depicts the different tectonic processes that produce earthquakes at an idealized subduction zone or trench.

Scientific Significance:
This book was designed to introduce the inter-disciplinary approach towards pre-earthquake studies. Our goal is to document the latest progress made in studying pre-earthquake processes and provide a snapshot of the latest international development on a wide range of research. The peer-reviewed studies can be cited in the future journal publications and hopefully this will help satisfy skeptical scientists about the existence of physical phenomena preceding earthquakes.

We expect that this book will entice others to study pre-earthquake phenomena and continue developing the inter-disciplinary physical approach in exploring our changing planet and towards earthquake prediction and facilitating the education of new generation of scientists.

The Arctic sea ice cover of 2016: a year of record-low highs and higher-than-expected lows

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[1]Cryospheric Sciences Lab, NASA GSFC , [2]ESSIC, University of Maryland, [3]CPOM, University of Reading, UK, [4]National Snow & Ice Data Center, [5]BAS, Cambridge, UK, [6]AORI, Tokyo, Japan.

We analyzed the seasonal state and evolution of the Arctic sea ice cover of 2016. This was a highly noteworthy year featuring record low ice extents at the start and end of the year (Figure 1), but summer ice extents that were higher than expected by most seasonal forecasts.

The August sea ice was extremely unconsolidated, due in-part to two major Arctic storms. September saw a rapid refreeze in this region (Figure 2), although further south, warm fall SSTs resulted in record late refreeze.

We highlighted the benefits of forecasting sea ice area, instead of extent, considering these low summer ice concentrations.

Figure 1

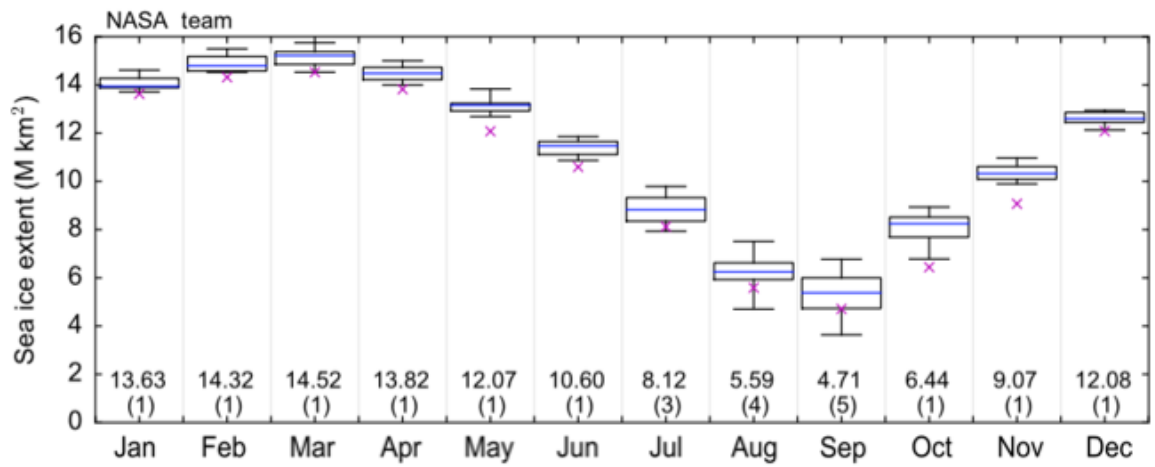
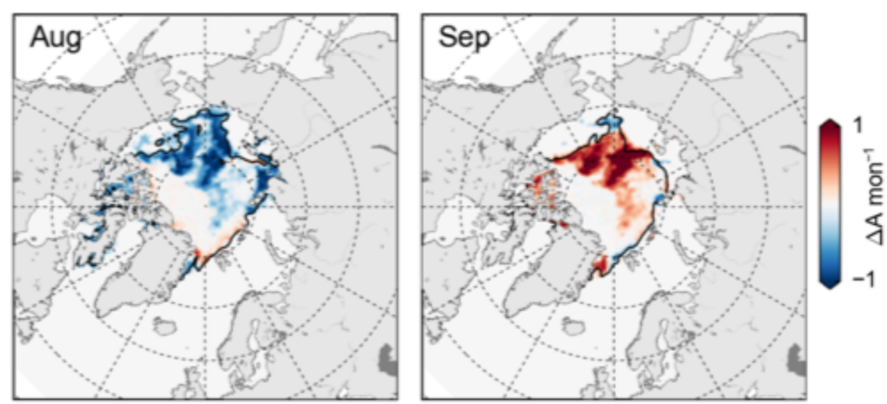


Figure 2



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Petty, A. A., D. Schroeder, J. C. Stroeve, T. Markus, J. Miller, N. T. Kurtz, D. L. Feltham, D. Flocco (2017), Skillful spring forecasts of September Arctic sea ice extent using passive microwave sea ice observations, *Journal of Geophysical Research Earth's Future*, 4, doi:10.1002/2016EF000495.

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Comiso, J. C.: Bootstrap Sea Ice Concentrations from Nimbus-7 SMMR and DMSP SSM/I-SSMIS, Version 2 [January 2000– December 20160], NASA National Snow and Ice Data Center Distributed Active Archive Center, Boulder, Colorado, USA, doi:10.5067/J6JQLS9EJ5HU, 2000 (updated 2017).

Data Sources: Sea ice concentration data using the NASA Team (Cavalieri et al., 1996, updated 2017) and Bootstrap (Comiso, 2000; updated 2017) processing of satellite passive microwave brightness temperature. NASA Cryospheric Sciences derived melt onset and freeze onset data (Markus et al., 2009).

Technical Description of Figures:

Figure 1: Box-and-whisker plots for the period 2000–2015 of observed monthly sea ice extent (SIE) calculated using the NASA Team sea ice concentration data. The magenta crosses and the number above the brackets (in million km^2) denote the monthly 2016 SIE, while the number in brackets gives the rank of the 2016 SIE across the 2000–2016 period (1 represents a record low in 2016).

Figure 2: August and September 2016 sea ice intensification anomalies, relative to the 2000-2015 mean calculated using Bootstrap data. Ice intensification represents the change in concentration through the month. The black contour is the 15% ice edge.

Scientific significance, societal relevance, and relationships to future missions: Providing an accurate assessment of the Arctic sea ice state, and better communicating sea ice variability/uncertainty, is of paramount importance considering the role of Arctic sea ice as an indicator of global climate change. Improving sea ice forecasts are also urgently needed for those living and operating in the Arctic. NASA sea ice data are providing crucial insight into sea ice variability and are improving sea ice forecasts, but need to be used with care.