Major revisions summary for: Reviews and syntheses: Ongoing and emerging opportunities to improve environmental science using observations from the Advanced Baseline Imager on the Geostationary Operational Environmental Satellites

We would like to thank the reviewers for their careful and helpful feedback and suggestions. We have provided a summary of the revisions we have made to specific sections to address the comments by the reviewers. We have also provided a response to referee comments with the changes that were made. Finally, we provide a version of the manuscript which tracks the changes made for the revisions.

- We included a specific discussion in the introduction that clarifies that the focus of the paper is on GOES. However, since GOES exists within a global constellation of geostationary satellites, we found it crucial to review the research applications that have been developing with data from satellites throughout the global constellation. We also added this point in the introduction in hope of providing clarity.

- Sections 3.3.2 and 4.4
    - We provided more clear separation between atmospherically correcting thermal data and retrieving Land Surface Temperature (LST),
        - We moved anything about LST and emissivity to LST section to provide a clearer separation between sections 3.3.2 and 4.4.
        - We kept the atmospheric correction section to atmospheric correction of thermal data and some efforts for atmospheric correction of GOES thermal data.

- Sections 4.4 – 5.2
    - In response to referee comments, we have provided a more detailed explanation of how GOES data is used in flash drought detection with an example.
        - Lines 490 – 495 were added to explain how GOES inputs are used in flash drought detection more clearly:
            - LST → ET → ESI → Flash drought detection
        - We added Figure 2 to show an example: Comparison between ESI and other drought classifications and indicators

- Section 5.3
    - We have added a paragraph starting at line 544 to acknowledge the importance of small fires to highlight the future importance of studies that will compare GOES biomass burning emissions with emissions from finer spatial resolution imagery.

- Section 5.4
    - We point readers to figures from papers that illustrate the advantage of geostationary satellites for phenology
        - We have added an additional example from Japan comparing the length of seasonal transitions between greenness trajectories derived from the Advanced Himawari Imager (AHI) and MODIS data.

    - Starting at line 587, we have added a brief discussion about improving dryland phenology as a potential application where GOES might be useful.

- Section 6.1
    - We have changed the discussion of LUE models to provide a brief summary of LUE models and a brief description of how vegetation indices are used in existing LUE models used with satellite data. This should hopefully provide a better connection with the “Data products”.
    - We have added a discussion on the potential of integrating GOES data with the ALEXI framework to estimate carbon and water fluxes and the potential for studying carbon-water-energy coupling using ALEXI.
    - We have included the Zhang et al. (2016) paper about incorporating diffuse radiation and carbon-water coupling in GPP models
- We have renamed “Working with ABI Data” to “ABI top-of-atmosphere data to surface reflectance and surface temperature”.
- Figures
    - We have added a figure about ESI to show a clear example of using ESI (an output from GOES inputs) to detect flash droughts.
    - We have added MODIS NBAR NDVI and NDII product values in figures 3 and 4
    - We have changed the order of figures so they match when they are mentioned in the text.

Point-by-point response to reviews: Below we provide a point-by-point summary of changes we made to address specific comments by reviewers.

- Referee 1 comments

  1) High frequency observations may be of great use for many different reasons: to follow rapidly evolving phenomena, such as weather systems; for surface monitoring purposes, high frequent observations in visible/infrared bands may be important in areas which are frequently cloud-covered, by increasing the probability of acquiring clear-sky observations; variables with strong diurnal cycles may not be properly represented by low-frequency observations; identification of rapid changes, such as phenology. Although the article touches some of these aspects, I think they should be further systematized and clearer with further examples of applications where GOES-R observations play a significant role.
  Author response: Thank you for this point. Our manuscript continuously points to the advantage of the availability of clear observations throughout the year in almost every section where the point is applicable. We have include some more specific examples for the importance of capturing rapid changes during phenological transitions. We have also pointed readers to existing figures from various papers that we cite that illustrate the advantage that geostationary imagers provide for phenology.

  2) It is acknowledged that some of the issues that one needs to deal with when using ABI or other similar instruments on geostationary satellites to monitor the Earth’s surface

are well covered – parallax, atmospheric correction, increasing pixel size towards the disk's edge. The article then lists a number of products that may be derived from ABI followed by a few examples of relevant applications of those data. Here, I suggest that the actual added-value of ABI observations/products with respect to other commonly used data should be further highlighted, namely:
2.1) the use of GOES/ABI observations and products, including LST, to derive evapotranspiration is well-known. Here I would expect to see an example of such an application including the input satellite data/products and respective evaporative fluxes. Showing the on-set of drought conditions highlighting the advantages of high frequency data would be of interest to users.
Author response: We have used the example of detecting flash droughts and further elaborated on this application to illustrate the advantage of thermal observations with high temporal resolution. We have also included an addition figure and a more detailed explanation of the process of going from the input required observations from GOES to the output ET and ESI and finally their use in detecting drought conditions.

2.2) Landscape fires usually present significant diurnal cycles and therefore high frequency observations are better positioned for their full characterization. However, small agricultural fires aimed at burning agricultural waste, are known to cause a significant amount of emissions and pollution, but often these are too small and weak to be "seen" by the relatively coarse geostationary satellites. This is especially the case as we move away from the sub-satellite point, as the minimum detectable fire radiative power scales with pixel area. Please consider these problems and address the potential benefits of the combined use of ABI/GEO's observations with higher spatial resolution.
Author response: Thank you for this point. We have added a discussion on the importance of detecting small fires in burned area estimates as. We have also noted the importance of studies that will compare GOES biomass burning emissions to those from higher resolution imagery.

2.3) the coarse resolution of vegetation products/indices derived from geostationary observations is a major caveat as often pointed by users, especially when compared with the same type of variables derived from MODIS or VIIRS. The phenology example presented is relevant application, but again the actual advantage of ABI with respect to other more commonly used data is far from being clear. The authors show two cases presenting post-fire disturbances and vegetation recovery in California. However, the comparison with MODIS is only shown for one of them; the time-series do not cover the full growing season. Furthermore, I would say that the most relevant contribution of geostationary/ABI observations would be to map phenological cycles in a consistent way (given the high number of observations) over large areas. So although zooming at a relatively small area affected by fires may be of interest, I think that that is not the most appropriate example to illustrate the benefits of those types of observations, especially when compared with others.

Author response: We have added a comparison to MODIS in all time series. We have expand on some phenology examples published in the literature to highlight the advantage of using geostationary observations in capturing phenological transitions.

2.4) Following the above, it should be noted that only TOA vegetation indices are shown, while several atmospherically corrected and BRDF-corrected vegetation properties can be also derived from both ABI (geostationary) and MODIS or VIIRS (polar-orbiting) instruments. Why not using those types of indices – in principle less noisy – than TOA values?
Author response: The purpose of sticking to TOA MODIS values was to compare TOA ABI values with TOA MODIS values. We have added NDVI and NDII values from the existing MODIS NBAR product which is BRDF-adjusted.

3) The combined use of multiple geostationary satellites is only very briefly mentioned. Given the high quality of current sensors, there's a great potential to build nearly global high frequency fields and derived products. The combination of geostationary data with high spatial resolution observations (from MODIS/VIIRS to Sentinel-2/Landsat) targets a different set of users and applications, with the latter usually more focused on regional-to-local applications. Both global (or large scale) and regional/local scale applications are relevant and worth addressing.
Author response: We include the few existing examples in the literature that combine geostationary sensors to provide global coverage (for ex: Photosynthetically Active Radiation).

4) I would encourage the authors to improve the examples given in section 5 and to better link these to section 6. Evapotranspiration and energy fluxes are deeply linked to plant's carbon up-take and ecosystem dynamics. A brief reference is already made to "diurnal land attributes" – I suggest the authors further explain what is meant by that and how ABI observations can address those.
Author response: We have linked section 6 and section 5 more completely by elaborating on the potential application of GOES observations for estimating coupled carbon-water-energy fluxes simultaneously through the ALEXI framework which can estimate canopy latent heat and assimilation fluxes with stomatal, boundary layer, and aerodynamic resistances.

5) Editorial
- line 51 – please clarify what is meant by "diurnal behavior of land surface function".
- line 280 – by "effective surface temperature" do the authors mean brightness temperature? I find it unclear what the authors are mean as a physical surface temperature. Whatever temperature you consider, it will most likely have a physical meaning, being radiometric temperature, aerodynamic temperature, brightness temperature,
- line 314 – S. Ha et al, 2020?
- lines 379-380 – this is not shown here, since the time-series does not cover April.

-line 391 – please refer to European satellites as “Meteosat” instead of METEOSAT.
Done
- line 449 – Fig. 2 is called after Figs 3 and 4 – so why this figure order?

Author response: Thank you for the careful read, we have made these changes and clarified terminology in the LST section.

- Referee 2 comments

-Line 112: I might choose a different heading here. This section seems less about working with ABI data (which I had initially interpreted as being from the perspective of a typical environmental science user) than about some of the issues and uncertainties in ABI data that need to be corrected before you can even start working with it.
Author response: We have change the title of this section.

-Section 3.3.2: This section is kind of general and could be more specifically focused on LST from ABI (or others of the newer generation of geostationary sensors).
Author response: We have moved the entire discussion of retrieving land surface temperature with land emissivity estimates to section 4.4. We kept section 3.3.2 focused on the removal of atmospheric effects on thermal band data and mention earlier efforts with GOES data.

-Lines 231-232: It might also be worth noting that EVI has a soil background correction factor built in that may also make it more suitable for open canopy systems (Huete et al., 2002).
Author response: We have added this advantage of EVI.

-Lines 356-358: There’s a really good article from Zhang et al. (2009) on the impact of temporal resolution on vegetation phenology retrieval (as well as the impacts of missing data around vegetation transitions) that might be useful here. It might be worth expanding a bit on where and how much geostationary data could improve on the composite data (typically 8- to 16-day) that are often currently used for vegetation phenology retrieval. The authors specifically mention how it could be useful where cloudy conditions occur around seasonal transitions, but another thing to highlight might be the utility of geostationary observations in some dryland systems, where phenological transitions can occur very rapidly and unpredictably in response to rainfall pulses (Smith et al., 2019), which might be either missed by polar orbiting sensors or washed out in the composite. Monitoring phenology in these regions has definitely been a long-standing problem (e.g., the White et al. 2009 and Ganguly et al. 2010 articles that are already cited by the authors). Of course, there are other challenges aside from temporal resolution that make dryland phenology difficult to model/detect (Smith et al., 2019), but any potential improvement from geostationary observations in these regions could be worth noting.
Author response: We have incorporated ideas about dryland phenology into the revised manuscript and noted it as an area where ABI observations could be beneficial.

-Line 416: I think this should say “linear relationship between absorbed PAR (APAR) and _gross_ primary production,” right? The MODIS algorithm first models GPP at an 8-day frequency then estimates annual NPP as the annual integral of GPP minus the annual integral of autotrophic respiration (modeled from allometric relationships and air temperature).
Author response: We have revised the discussion on LUE models to a more generalized summary of these models and then certain specifics related to the use of vegetation indices. Since there are a number of LUE models, we thought it would be beneficial to not solely focus on MODIS.

-Lines 417-420: There are a couple (admittedly nitpicky) details of the MODIS algorithm that I think are incorrect here and should be double-checked. First, in the operational MODIS GPP/NPP product, NDVI is not the primary way that APAR is estimated (though in principle, it certainly could be). APAR is estimated from the MODIS FPAR product (MOD15), which is itself based primarily on an inversion of a radiative transfer model, with the NDVI~FPAR relationship only being used as a backup algorithm in case the full inversion fails (Knyazhikin et al. 1999; Myneni et al. 2002). Second, and this is merely a technicality, there are five (not three) biome-specific parameters in the model since Tscale and Wscale require two parameters each: a lower Tmin/VPD threshold and an upper Tmin/VPD threshold. (If you also include the allometry and Q10 parameters needed for the NPP estimates, then there are even more than five.)
Author response: We have added the updated MODIS FPAR (MOD15) input for APAR to clearly delineate the line of reasoning that leads to the MODIS carbon cycle products. We have also removed specifics about the stressors developed in one model and present a bigger overview of LUE model formulations.

-Lines 429-432: Maybe here, or maybe elsewhere, it might be worth noting possible synergies with other satellite-based sensors. Here, for example, I’m thinking of possible synergies with soil moisture estimates from microwave sensors (e.g., SMAP or AMSR-E/AMSR-2) given the widespread importance of soil moisture for primary production and the known deficiencies in existing LUE models’ ability to represent soil moisture stress (Stocker et al. 2018, 2019).
Author response: Thank you, we have added some discussion of modeling techniques that have been able to capture the impacts of soil moisture on carbon assimilation and have also added the need to test ABI carbon uptake estimates for their response to soil moisture conditions.

-Lines 434-435: This is very true, and worth noting that there is at least one relatively new LUE model that does indeed include effects of diffuse irradiance (Zhang et al., 2016).
Author response: We have included this paper in our discussion on including the effects of diffuse radiation on GPP in models.

Editorial suggestions/corrections:
-Line 113: I would suggest changing “certain” to “given” and deleting “on the Earth”.
-Line 131: This should be section 3.2, not 3.1.
Author response: We have made the above editorial suggestions.

Author response references

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Smith, W. K., Dannenberg, M. P., Yan, D., Herrmann, S., Barnes, M. L., Barron-Gafford, G. A., et al. (2019). Remote sensing of dryland ecosystem structure and function: Progress, challenges, and opportunities. Remote Sensing of Environment, 233.
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Zhang, Y., Song, C., Sun, G., Band, L. E., McNulty, S., Noormets, A., et al. (2016). Development of a coupled carbon and water model for estimating global gross primary productivity and evapotranspiration based on eddy flux and remote sensing data. Agricultural and Forest Meteorology, 223, 116–131.

Reviews and syntheses: Ongoing and emerging opportunities to improve environmental science using observations from the Advanced Baseline Imager on the Geostationary Operational Environmental Satellites

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Abstract. Environmental science is increasingly reliant on remotely-sensed observations of the Earth's surface and atmosphere. Observations from polar-orbiting satellites have long supported investigations on land cover change, ecosystem productivity, hydrology, climate, the impacts of disturbance, and more, and are critical for extrapolating ("upscaling") ground-based measurements to larger areas. However, the limited temporal frequency at which polar-orbiting satellites observe the Earth limits our understanding of rapidly evolving ecosystem processes, especially in areas with frequent cloud cover. Geostationary satellites have observed the Earth's surface and atmosphere at high temporal frequency for decades, and their imagers now have spectral resolutions in the visible and near-infrared regions that are comparable to commonly-used polar-orbiting sensors like the Moderate Resolution Imaging Spectroradiometer (MODIS), Visible Infrared Imaging Radiometer Suite (VIIRS), or Landsat. These advances extend applications of geostationary Earth observations from weather monitoring to multiple disciplines in ecology and environmental science. We review a number of existing applications that use data from geostationary platforms and present upcoming opportunities for observing key ecosystem properties using high-frequency observations from the Advanced Baseline Imagers (ABI) on the Geostationary Operational Environmental Satellites (GOES), which routinely observe the Western Hemisphere every 5 - 15 minutes. Many of the existing applications in environmental science from ABI are focused on estimating land surface temperature, solar radiation, evapotranspiration, and biomass burning emissions along with detecting rapid drought development and wildfire. Ongoing work in estimating vegetation properties and phenology from other geostationary platforms demonstrates the potential for expanding ABI observations to estimate vegetation greenness, moisture, and productivity at high temporal frequency across the Western

Hemisphere. Finally, we present emerging opportunities to address the relatively coarse resolution of ABI observations through multi-sensor fusion to resolve landscape heterogeneity and to leverage observations from ABI to study the carbon cycle and ecosystem function at unprecedented temporal frequency.

1 Introduction

Modern environmental science would be unrecognizable without satellite remote sensing, which has revolutionized our field since its advent over a half-century ago (Kerr and Ostrovsky, 2003). The platforms by which we observe the Earth system are increasingly diverse and now include miniaturized satellites (CubeSats), sensors like ECOSTRESS traveling onboard the International Space Station (Hulley et al., 2017), and even lidar systems (Coyle et al., 2015; Qi et al., 2019), yet most environmental science applications employ polar-orbiting satellites, namely Landsat and the Moderate Resolution Imaging Spectroradiometer (MODIS). The Landsat and MODIS programs have radically improved the ability of ecologists to track vegetation change and its impacts on habitat, biogeochemical cycling, and other ecosystem services (De Araujo Barbosa et al., 2015). Like all remote sensing platforms, polar-orbiting satellites must make compromises with respect to spectral resolution, spatial scale, and temporal scale that limit their ability to 'measure all things, all the time'. Notably, the 1-to-2 day cadence of MODIS and VIIRS and 3-to-5 day cadence of the combined Landsat- and Sentinel-2-class sensors may be insufficient to track ecological phenomena that occur at shorter time scales, including the timing of rapid environmental change (White et al., 2009) and the diurnal behavior of land surface function such as sub-hourly variations in ecosystem carbon and water fluxes (Chudnovsky et al., 2004; Grant et al., 2000).

As a part of the European Organization for the Exploitation of Meteorological Satellites (EUMETSAT), the Satellite Application Facility for Land Surface Analysis (LSA SAF) has leveraged high frequency observations from the Spinning Enhanced Visible and Infrared Imager (SEVIRI) onboard the Meteosat Second Generation (MSG) geostationary satellites to provide operational products relevant for studying vegetation, wildfires, the surface radiation budget, and the carbon and water cycle (Trigo et al., 2011) at sub-daily time scales. These opportunities are also available in the Western Hemisphere. Focusing on the Advanced Baseline Imager (ABI), a joint effort by the National Oceanic and Atmospheric Administration (NOAA) and the National Aeronautics and Space Association (NASA), onboard the Geostationary Operational Environmental Satellites (GOES), we argue that the GOES constellation – commonly used as weather satellites – represents an under-explored opportunity for environmental science in situations where spatial resolution can be compromised in favor of more frequent imagery, especially now that ABI's spectral sensitivity has approached that of Landsat and MODIS (Table 1; Fig. 1). Given the constellation of geostationary satellites around the world, extending environmental science applications to ABI and generating relevant data products is crucial for achieving near-global coverage of satellite environmental data available at the time scale of minutes. Developing algorithms that can be applied to data from multiple geostationary satellites will be an important component for achieving near-global coverage.

Here, we detail a number of applications by which GOES and other geostationary satellites have enhanced or could enhance our understanding of ecological phenomena that occur at time scales as short as minutes. We keep our focus on the GOES constellation, but we also discuss research and applications from various satellites in the global constellation of geostationary satellites to provide the larger context for emerging applications from GOES ABI. We outline the technical steps necessary to make imagery from ABI more useful for environmental science with an eye toward near real-time monitoring of environmental phenomena across the globe. We also note complementarity between GOES, other geostationary platforms including Japan's Himawari-8&9, South Korea's GEO-KOMPSAT-2A, and European Union Meteosat satellites – especially the forthcoming third-generation (MTG) – all of which have similar spectral resolution that make near-global observation possible (Table 1). We first review the recent efforts regarding geolocation and atmospheric correction to produce surface reflectance from ABI and other geostationary imagers. We then describe new data products that can be created using state-of-the-art geostationary satellite data with a brief description of existing data products that are providing key insight into Earth surface processes. Finally, we outline existing and emerging applications of observations from geostationary satellites that are ushering in the era of 'hyper-temporal' remote sensing (Miura et al., 2019) for environmental science.

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2 Background

2.1 Geostationary satellites: Past, present, and future

Geostationary remote sensing began with the launch of six Applications Technology Satellites (ATS) starting in 1966 (Suomi and Parent, 1968). The subsequent successful launches of the Synchronous Meteorological Satellites (SMS) were the precursor to the GOES mission, which began in 1974 and continues to the present (Menzel, 2020). By 1979, the global constellation of geostationary satellites included the European Space Agency's Meteosat, the Japanese Geostationary Meteorological Satellite (GMS), and two GOES (Menzel, 2020). Seventeen GOES have been successfully sent to space as of 2018, two of which – GOES-16 positioned at 75.2 W (currently GOES-East) and GOES-17 positioned at 137.2 W (currently GOES-West) – arise from the GOES-R Series that include additional visible and near-IR channels that are commensurate with channels observed by Landsat and MODIS (Table 1, Fig. 1). The GOES-R Series has an expected operational lifetime to 2036 which promises multiple years of continuous data availability. This will be followed by the Geostationary and Extended Orbits program, which is planned for operation in 2030-2050 and is anticipated to include "GOES-R-class" imagers (Sullivan et al., 2020).

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2.2 Advanced Baseline Imager (ABI)

The ABI is the primary instrument onboard GOES-16/17 and is designed for monitoring land and ocean surfaces, the atmosphere, and cloud formation (Schmit et al., 2017, 2018). The ABI has 16 spectral bands that measure solar reflected radiance in the visible and near-infrared wavelengths and emitted radiance at infrared wavelengths (Schmit and Gunshor,

2020). With multiple infrared bands positioned in atmospheric absorption regions and in atmospheric windows, the ABI can collect information from the Earth's surface and multiple levels in the atmosphere (Schmit and Gunshor, 2020). Multiple scan modes are used to provide near-hemispheric geographic coverage with spatial resolutions between 0.5 and 2 km. The full disk scene consists of near hemispheric coverage centered at the equator and the longitude of the sensing satellite (D O C et al., 2019). The ABI also scans a scene of the contiguous United States (CONUS) and two mesoscale scenes (1000 km by 1000 km). Operating in the flex mode, the ABI collected a full disk image every 15 minutes until April 2019 but now collects a full disk image every 10 minutes (with the exception of GOES-17 during parts of the year). The ABI also collects a CONUS scene every 5 minutes, and two mesoscale scenes every minute in the flex mode (Schmit and Gunshor, 2020).

In late April 2018, an issue with the GOES 17 ABI cooling system was detected due to malfunctioning of the loop heat pipe which transfers heat from the ABI detectors and helps maintain adequate temperatures for proper functioning (Yu et al., 2019). This results in the loss of infrared data during some nighttime hours around 13:30 UTC during parts of the year due to the sun heating the seven ABI detectors faster than they can be cooled resulting in infrared emissions from the overheated detectors (NOAA and NASA, n.d.; NOAA, n.d.). This nighttime data loss can also fluctuate seasonally depending on how much solar radiation the instrument absorbs (NOAA, n.d.). A data quality flag in the metadata of the Level 1b radiances and Level 2 Cloud and Moisture Imagery can identify the faulty nighttime data (NOAA and NASA, n.d.). This malfunction will result in the loss of some nighttime data for data products that utilize the infrared bands and are relevant for observing the full diurnal cycle.

3 ABI top-of-atmosphere data to surface reflectance and surface temperature

ABI top-of-atmosphere data to surface reflectance and surface temperature

The ABI collects top-of-atmosphere (TOA) data from a given location at a constant view zenith angle (VZA) and varying solar zenith angles (SZA) throughout the day. While the increased sampling of SZA creates opportunities in surface Bidirectional Reflectance Factor (BRF) modeling (Ma et al., 2020), the large VZA at off-nadir locations can present challenges for studying the land surface including coarsened resolution, potentially degraded locational accuracy, and more complex atmospheric compensation due to longer slant paths. Below, we review the existing efforts to address these challenges and make ABI imagery more suitable for studying the land surface.

3.1 Geolocation

The geolocation accuracy of ABI on GOES-16 and GOES-17 has been tracked and improved throughout its provisional and operational stages using the Image Navigation and Registration Performance Assessment Tool Set (IPATS) (Tan et al., 2018, 2019, 2020). IPATS quantifies the navigation error, the difference between the location of a pixel in ABI imagery and a reference location (Tan et al., 2020). Some of the largest navigation errors, calculated from correlations between subsets of ABI and Landsat 8 imagery concentrated along the coast of North and South America, were 10 - 13 μrad less than the mission requirement of 28 μrad (1 km at nadir) in October 2019 (Tan et al., 2020). In addition to IPATS, the Geostationary-

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NASA Earth Exchange (GeoNEX) processing chain adjusts the geolocation of ABI imagery using a reference map from the Shuttle Radar Topographic Mission (SRTM) Digital Elevation Model (DEM) and more than 30,000 landmarks along coastlines (Wang et al., 2020). The shift in the geolocation of the red band (500 m at nadir) between IPATS and the GeoNEX algorithm was under 0.5 pixels for a majority of the time throughout the full disk scene but can be as large as 1 - 2 pixels for short periods of time (Wang et al., 2020).

3.2 Parallax

Geostationary satellites observe most of the hemisphere at an angle relative to the zenith, which introduces a challenge due to parallax: the effect of observing an object from a large VZA. Parallax can result in uncertainties in land surface observations in mountainous terrain and can introduce errors in the mapped location of clouds (Bieliński, 2020). These errors vary by VZA and the height of the feature and are largest for high VZA and high feature altitude relative to the surface (Bieliński, 2020; Zakšek et al., 2013). For example, the parallax shift at 49 degrees latitude from GOES-16 ABI can be as large as 51 km for an object that is 15 km high (Whittaker, 2014). Since the mapped location of the clouds detected depends, in part, on the VZA, parallax shifts can also complicate comparing the location of clouds between sensors with different VZA (Zakšek et al., 2013). However, it is possible to correct for parallax shifts with knowledge of VZA and feature (cloud or surface) altitude (Kim et al., 2017; Yeom et al., 2020).

3.3 Atmospheric correction

3.3.1 Surface reflectance

Correcting for atmospheric attenuation of radiation to derive surface reflectance from TOA reflectance is a crucial prerequisite to studying surface processes from satellite platforms. Current efforts to estimate surface reflectance from the ABI, the Advanced Himawari Imager (AHI), and the Geostationary Ocean Color Imager (GOCI) onboard the Communication, Ocean, and Meteorological Satellite (COMS) include generating lookup tables from the Second Simulation of the Satellite Signal in the Solar Spectrum (6S) radiative transfer model (He et al., 2019; Tian et al., 2010; Vermote et al., 1997; Yeom and Kim, 2015; Yeom et al., 2018, 2020). Optimal estimation methods that estimate surface BRF from SEVIRI have been extended to estimate surface broadband albedo and surface reflectance from the ABI and the AHI on Himawari-8 (Govaerts et al., 2010; He et al., 2019, 2012; Wagner et al., 2010). These algorithms estimate surface reflectance and broadband surface albedo by minimizing the difference between TOA BRF estimated through radiative transfer modeling and measured by the satellite (He et al., 2019, 2012). Unlike the surface reflectance algorithm currently used for SEVIRI, the algorithm for the ABI and the AHI takes the diurnal variation of aerosol optical depth into account (He et al., 2019). Originally developed for atmospheric correction of MODIS imagery, the Multi-Angle Implementation of Atmospheric Correction (MAIAC) has also been adapted to provide provisional daytime surface reflectance every 10 minutes for bands 1 - 6 of the AHI with plans to extend the algorithm to ABI (Li et al., 2019b). The surface reflectance from the AHI showed

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less variation compared to surface reflectance from MODIS and the differences in surface reflectance between the AHI and MODIS were smaller for the red, near-infrared (NIR), and shortwave infrared (SWIR) bands compared to the blue and green bands (Li et al., 2019b). ABI channels 1, 3, 5, and 6 are accurate to within 2% but channel 2 has a bias error of up to 5% (McCorkel et al., 2020). With geolocation, parallax, atmospheric correction, and sensor accuracy taken into account, imagery from the ABI can provide sub-hourly estimates of various land surface variables.

3.3.2 Surface temperature

Atmospheric attenuation due to water vapor requires atmospheric correction of thermal data collected from satellites, and also limits surface temperature retrieval to thermal bands that have the lowest atmospheric absorption (Sun and Pinker, 2003). A single-channel approach requires the use of one thermal channel within an atmospheric window at around 10 μm and radiative transfer modeling to simulate atmospheric transmittance and emission of longwave radiation (Li et al., 2013; Pinker et al., 2019). With known land surface emissivity and atmospheric profiles and simulated atmospheric transmittance/emission, surface temperature can be retrieved through the inversion of a radiative transfer equation that explains the different components of at-sensor radiance (Li et al., 2013). Since accurate atmospheric profiles over a study area can be difficult to obtain, a split-window technique can be used to correct atmospheric absorption to estimate surface temperature from at-sensor radiance in two thermal bands with differential water vapor absorption (Li et al., 2013; Ulivieri and Cannizzaro, 1985). Split-window techniques were used in earlier estimates of surface temperature from GOES thermal data and they are based on the relationship between surface temperature and the difference in temperature between two adjacent thermal bands with high emissivity and low atmospheric absorption typically centered at 11 and 12 μm (Li et al., 2013; Sun and Pinker, 2003). The split window techniques used to generate the GOES-R hourly LST product is discussed in section 4.4 which further expands on surface temperature retrieval from GOES. In section 4.4, we also discuss the importance of emissivity for estimating land surface temperature (LST) and current sources of emissivity estimates used in LST retrievals from geostationary satellites.

Similar to surface reflectances, the directional thermal radiation recorded by sensors on satellites can also be impacted by the VZA of the sensor (Diak and Whipple, 1995). Products that utilize diurnal thermal data from GOES have used the difference in surface radiometric temperature during the morning hours which has shown to be less sensitive to changes in VZA compared to absolute surface radiometric temperature (Anderson et al., 1997; Diak and Whipple, 1995). Other methods to address the impacts of varying VZA include adding zenith angle correction terms to split window algorithms in order to address the large path lengths at high VZA (Sun and Pinker, 2003; Yu et al., 2009)

4 Data products

Geostationary satellites can now measure a number of common vegetation indices used for ecological applications and make measurements that support derived products including land surface temperature as noted, incident solar radiation, and more.

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Deleted: knowledge about the fractional cover of vegetation in a pixel (Li et al., 2013). Furthermore, land surface emissivities can be estimated by using surface temperature-emissivity separation techniques applied to multi-spectral thermal

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We describe these measurements with an eye toward explaining the benefits and challenges of using geostationary platforms such as the ABI for ecology and environmental science.

4.1 Incident solar radiation and Photosynthetically Active Radiation (PAR)

Geostationary satellites are equipped to estimate incident solar radiation at the Earth's surface (Diak, 2017; Pinker et al., 2002), critical for the surface energy balance, photosynthesis, and solar power applications. Earlier efforts to do so include a simple physical model by Gautier et al. (1980) which estimated incident solar radiation during clear and cloudy conditions using the reflectance from the visible band of the Visible Infrared Spin Scan Radiometer (VISSR) on GOES-2. The model included Rayleigh scattering and water vapor absorption of downwelling and reflected shortwave radiation. Cloud albedo and absorption were estimated from a linear relationship with the satellite-measured cloud reflectance, and estimates of incident solar radiation were subsequently improved by including ozone absorption of shortwave radiation in the atmosphere (Diak and Gautier, 1983; Diak, 2017). Continued improvements in both the physical model and the spatiotemporal resolution of the GOES imagery have resulted in higher accuracy of hourly and daily insolation estimates when compared to pyranometer measurements (Diak, 2017; Otkin et al., 2005). More recent models of the transmittance of direct and diffuse shortwave radiation through aerosol extinction by different aerosol components, gaseous absorption, and Rayleigh scattering have provided estimates of the surface shortwave radiation flux and its diffuse fraction from SEVIRI observations at 15-min resolution (Carrer et al., 2019) and could also be applied to ABI observations. Applying algorithms for estimating incident solar radiation to data from multiple geostationary satellites can lead to near-global coverage and be beneficial for near-global estimates of evapotranspiration and gross primary productivity that are driven in part by solar radiation.

Incident solar radiation in the wavelengths of photosynthetically active radiation (PAR, 400 - 700 nm) can also be estimated using the visible bands of geostationary satellites (Janjai and Wattan, 2011). Specifying a range of SZA, VZA, cloud types, aerosol types, cloud extinction coefficient, and atmospheric visibility, lookup tables generated from simulations of Moderate Resolution Atmospheric Transmission (MODTRAN) have been used to estimate downwelling PAR from at-sensor radiance (Zhang et al., 2014; Zheng et al., 2008). These methods have been extended to multiple geostationary satellites including GOES-11 and GOES-12 and MODIS surface reflectance data to generate global incident PAR estimates (Zhang et al., 2014).

Although these methods account for elevation, validation efforts have shown that satellite-derived PAR in high-altitude areas can be biased when compared to ground measurements, possibly due to inaccurate specification of atmospheric profiles governing water vapor corrections (Zhang et al., 2014). Furthermore, PAR estimated from satellites has been reported to underestimate PAR measured on the ground when the model assumed urban aerosol absorption over areas where maritime aerosols were more dominant (Janjai and Wattan, 2011). Despite these limitations, frequent estimates of PAR and incident solar radiation from geostationary satellites may be uniquely suited to drive the land surface models that are operating at increasingly fine spatial and temporal resolutions, providing a natural link for using geostationary satellite observations to improve our understanding of the carbon, water, and energy cycles (Williams et al., 2009).

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Terrestrial photosynthesis is particularly responsive to diffuse PAR, which penetrates plant canopies more efficiently than direct PAR (Emmel et al., 2020; Gu et al., 2003). The diffuse fraction of incoming PAR is well-described as a linear function of transmissivity, or a clearness index, through the atmosphere within certain inflection points (Erbs et al., 1982; Oliphant and Stoy, 2018; Weiss and Norman, 1985). Estimates of cloud height, optical depth, and particle size along with aerosols from GOES can be used to further partition incoming PAR into direct and diffuse beam fractions as currently provided by EUMETSAT at 15-minute intervals (Carrer et al., 2019). Such observations could ultimately prove useful for analyses of the diurnal pattern of carbon cycling (see section 6.1), given that the variability in terrestrial carbon cycling is often most sensitive to the variability of PAR at time scales from minutes to days (Stoy et al., 2005).

4.2 Vegetation greenness

The Normalized Difference Vegetation Index (NDVI) – the normalized difference between the reflectance in red and near-infrared wavelengths – is strongly correlated to chlorophyll content, green biomass, leaf area index (LAI), and the fraction of incoming PAR absorbed by leaves (fAPAR) (Gamon et al., 1995; Jordan, 1969; Rouse et al., 1974; Running et al., 1986; Tucker, 1979; Tucker et al., 1985) and therefore is a critical variable for monitoring the land surface. The ABI also has the ability to measure the Enhanced Vegetation Index (EVI) which is beneficial in areas (and periods) of dense vegetation cover where, unlike NDVI, EVI does not saturate and in open canopy areas because of a correction factor applied for canopy background (Huete et al., 2002; Zhou et al., 2014). The near-infrared reflectance of vegetation (NIRv) is strongly correlated to the amount of incoming PAR absorbed by plants and therefore photosynthesis at half-hourly to annual timescales and has shown stronger relationships with photosynthesis compared to NDVI (Badgley et al., 2017, 2019; Baldocchi et al., 2020; Wu et al., 2020), and can also in principle be measured by GOES (Table 1).

LAI from SEVIRI is produced on a daily and 10-day basis through the LSA SAF program (Trigo et al., 2011). High temporal estimates of LAI from ABI will have widespread utility in the Western Hemisphere by providing an important variable needed for modeling seasonal vegetation dynamics and energy, water and carbon fluxes (Anderson et al., 2011; Guan et al., 2014; Robinson et al., 2018). An ABI LAI product can provide harmony in temporal scales and data sources needed to estimate fractional vegetation cover needed for a two-source energy balance model used for estimating evapotranspiration from GOES thermal data (further discussion in section 5.1) (Anderson et al., 2011). Similarly, the ABI LAI product can provide a data source for plant respiration modeling (see further discussion in section 6.1) (Robinson et al., 2018).

The increased temporal frequency of measurements available from geostationary satellites compared to polar-orbiting satellites provide more opportunities for measuring NDVI, EVI, LAI, and NIRv in areas with frequent cloud cover (Miura et al., 2019). However, the geostationary position captures reflected radiation at varying SZA throughout the day and these novel sun-sensor geometries, not previously captured by polar orbiting satellites, can cause diurnal variation in vegetation indices calculated from TOA reflectance (Tran et al., 2020). EVI shows less SZA-induced diurnal variation compared to NDVI and is less impacted by the midday hot spot effect during times of the year (spring and autumn equinox)

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when the SZA and AHI VZA are aligned (Tran et al., 2020). NDVI measurements can be normalized to a reference sun-target-sensor geometry by estimating bidirectional reflectance distribution functions (BRDF) to address the impacts of varying sun-sensor geometry (Fensholt et al., 2006; Seong et al., 2020; Tian et al., 2010; Yeom and Kim, 2015; Yeom et al., 2018). Given the SZA sensitivity of NDVI measurements, Wheeler and Dietze (2019) demonstrated a Bayesian model to estimate a daily midday NDVI value from diurnal NDVI calculations using ABI observations.

4.3 Vegetation moisture

Liquid water absorption influences reflectance by plants in the atmospheric windows of shortwave infrared (SWIR) wavelengths (1.3 - 2.5 µm). Reflectance by plants in the SWIR has a negative relationship with leaf water content (Chen et al., 2005; Gao, 1996; Tucker, 1980), and multiple vegetation indices have been developed from bands in the SWIR wavelengths to capture these phenomena, especially in the 1.55 - 1.75 µm range (Fensholt and Sandholt, 2003; Tucker, 1980). Some notable vegetation indices that use SWIR wavelengths are the Normalized Difference Infrared Index (NDII) and the Normalized Difference Water Index (NDWI) which have been formulated from the difference in reflectance (ρ) in the NIR (0.76 - 0.9) and SWIR (1.55 - 2.5 µm) bands as: (ρNIR - ρSWIR) / (ρNIR + ρSWIR) (Chen et al., 2005; Fensholt and Sandholt, 2003; Gao, 1996; Hardisky et al., 1983; Tucker, 1980). NDII has been used to improve global estimates of canopy water content and provided more realistic estimates of canopy water content in semiarid shrublands when compared to regression models without NDII (García-Haro et al., 2020). NDWI has been useful in estimating the water content of corn (maize) fields because it saturates at higher values than NDVI in response to changing vegetation water content during the growing season (Chen et al., 2005; Jackson et al., 2004). The shortwave infrared water stress indices derived from MODIS have stronger correlations with growing season soil moisture than NDVI in the semiarid grasses of northern Senegal, Africa (Fensholt and Sandholt, 2003). Many of these indices and their changes over time can now in principle be measured by geostationary satellites (Table 1).

The ABI, along with the Advanced Meteorological Imager (AMI) on GEO-KOMPSAT-2A, the AHI, and SEVIRI, all offer bands in the SWIR regions, with ABI band 5 placed in the refined interval of 1.55 - 1.75 µm identified by Tucker (1980) (Table 1). Atmospherically corrected surface reflectances from ABI, SEVIRI, AHI, and AMI can provide near-real-time and near-global coverage for vegetation water content. This remains a relatively unexplored opportunity given the potential benefits of near-real-time monitoring of vegetation status (Verger et al., 2014).

4.4 Land surface temperature

The ABI features three longwave infrared bands with spatial resolutions of about 2 km for measuring land surface temperature (LST) – the skin temperature of the uppermost layer of the land surface – including correction for atmospheric moisture (Yu et al., 2012). Since the emission from the land surface diverges from a blackbody, the knowledge of land surface emissivity is a crucial component of retrieval of LST from at-sensor radiance (Li et al., 2013; Sun and Pinker, 2003). Global emissivity data may be gathered by consulting compiled tables of emissivities for various land covers along with land

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cover classifications of the landscape (Li et al., 2013). Land surface emissivity can also be estimated through its relationship with the NDVI. This method only applies to vegetation and soil and requires knowledge about the fractional cover of vegetation in a pixel (Li et al., 2013). Furthermore, land surface emissivities can be estimated by using surface temperature-emissivity separation techniques applied to multi-spectral thermal satellite observations (Li et al., 2013). Data sources for land surface emissivity in LST retrievals from geostationary satellites can include spectral libraries given a specific type of environmental surface (Peres and DaCamara, 2005), the MODIS operational land surface emissivity product (MOD11) or the Combined ASTER and MODIS Emissivity over Land (CAMEL) product (Pinker et al., 2019).

The hourly ABI LST product uses the difference between the brightness temperatures of ABI bands 14 (11.2 μm) and 15 (12.3 μm) in a split-window algorithm with an added term to correct for path length at high view zenith angles (Yu et al., 2009, 2012). These bands were chosen because they are placed in regions of maximum surface emission with low atmospheric absorption (Yu et al., 2009). However, water vapor absorption in a more moist atmosphere (e.g. a water vapor content greater than 2 g cm-2) at large view zenith angles (> 45°) remains an issue for the ABI LST algorithm (Yu et al., 2009).

For the generation of a consistent long-term record of LST, a single channel approach has also been proposed for LST retrieval from GOES 12 channel 4 (10.7 μm) in order to develop an algorithm that can be applied to data from multiple GOES satellites including for time periods from mid-2004 - 2017 when only one thermal channel was available (Pinker et al., 2019). Diurnal LST time series available from geostationary platforms have a wide range of applications in environmental monitoring, from mapping surface-atmosphere fluxes of heat, water, and carbon dioxide to tracking drought and fire dynamics. These and other applications are discussed further in the following sections.

5 Existing applications of geostationary satellites for environmental science

5.1 Evapotranspiration, latent heat flux, and sensible heat flux

Diurnal observations from GOES provide multiple estimates of directional surface radiometric temperature and downwelling solar radiation each day to estimate water and energy fluxes from the soil and canopy (Diak and Stewart, 1989). One approach for estimating evapotranspiration (ET) that is well-suited for geostationary implementation is the Atmosphere-Land Exchange Inverse (ALEXI) model (Anderson et al., 1997, 2007a; Mecikalski et al., 1999), which estimates the bulk surface energy balance (net radiation, sensible heat flux, latent heat flux, and soil heat flux) as well as the nominal partitioning of these fluxes between the soil and canopy. ALEXI is a time-integrated model based on the two-source (vegetation and soil) energy balance (TSEB) approach of Norman et al. (1995). ALEXI models the growth and sensible heating of the atmospheric boundary layer based on the morning rise in surface radiometric temperature that can be measured by GOES, estimating time-integrated latent heat flux (or ET in units of mass flux) as a residual to the overall energy balance (Anderson et al., 1997). The model performs best when the insolation inputs are also derived from geostationary satellite data (Sec. 4.1), giving optimal spatial and temporal correspondence between net radiation forcings and

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surface temperature response signals. In comparison with other sources of insolation data, geostationary-based insolation could significantly improve ET retrievals particularly in areas of frequent cloud cover where reanalysis estimates may not accurately capture the timing and spatial extents of clouds (Anderson et al., 2019; Wonsook et al., 2020).

ALEXI-based ET estimates are produced routinely at 4 km resolution for the United States (Anderson et al., 2020). Also, daily 2-km resolution ALEXI-based ET estimates have been generated from ABI observations as a part of the GOES ET and Drought (GET-D) product system (Fang et al., 2019). A surface energy balance approach has also been used to estimate 30-minute ET from albedo and downwelling radiation from MSG SEVIRI over the areas covered by MSG and 3-hourly ET in the Haihe River Basin in China from hourly LST observations from MTSAT, a Japanese geostationary satellite (Ghilain et al., 2011; Zhao et al., 2019). By measuring LST, geostationary satellites can estimate sensible heat flux and therefore also the Bowen ratio, which can give insight into atmospheric boundary layer heat and moisture transport as well as plant water stress (Diak and Whipple, 1995). Applications of ALEXI-based ET and energy fluxes for drought monitoring and modeling carbon fluxes are discussed below.

5.2 Drought monitoring

Drought indicators based on remotely sensed thermal observations can improve the effectiveness of drought early warning systems due to their high spatial resolution and the tendency for large decreases in ET to precede visible reductions in vegetation biomass during early stages of drought development (Anderson et al., 2013a; Otkin et al., 2015). The Evaporative Stress Index (ESI; Anderson et al., 2013a) is a drought indicator based on standardized anomalies in the actual-to-reference ET ratio, where actual ET is retrieved with ALEXI using the morning LST rise signal, typically obtained from GOES. ESI has demonstrated ability to provide early signals of developing vegetation stress (Anderson et al., 2007b, 2013a, 2016; Otkin et al., 2015, 2018a).

A recent prominent application of the ESI has been in the detection of flash droughts (Otkin et al., 2013). Flash drought conditions are characterized by a period of rapid drought intensification and typically include warm air temperature and low cloud cover anomalies, with dew point suppressions and high winds that can increase ET and hasten the removal of water from ecosystems (Gerken et al., 2018; Otkin et al., 2014, 2016, 2018b). ESI has proven to be an effective indicator of moisture stress in vegetation and the onset of flash drought conditions (Otkin et al., 2014, 2016, 2018b). For example, rapid temporal changes in the ESI toward increasing vegetation stress appeared several weeks earlier than the point at which the US Drought Monitor (USDM) classified regions of the central United States to be experiencing moderate to exceptional drought in 2003 and 2012 (Otkin et al., 2014). The ESI was also able to capture the onset of vegetation stress and the subsequent vegetation recovery during the flash-drought and flash-recovery sequence of 2015 in the south central United States (Otkin et al., 2019).

Drought indices based on precipitation and atmospheric demand highlight areas with potential for vegetation stress, but these stresses may not materialize due for example to beneficial rainfall, management (e.g., irrigation), or plant root access to groundwater. ESI uses LST to diagnose actual stress materializing on the ground, and therefore has been used as a

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moisture stress indicator for estimating drought impacts on crop yields (Anderson et al., 2016; Mladenova et al., 2017). ESI is routinely generated at 4 km resolution over the CONUS, and 5 km globally, or can be downscaled to sub-field or stand scales (30 m) using higher resolution thermal data from Landsat (Yang et al., 2018, 2020). The ability of ESI to detect drought stress earlier than USDM and other indices is shown in Fig. 2 adapted from Anderson et al. (2013b).

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5.3 Wildfire detection and biomass burning emissions

The Automated Biomass Burning Algorithm (ABBA) was developed from the 4 μm and 11 μm bands of the GOES visible infrared spin scan radiometer atmospheric sounder (VAS) to identify fire pixels (Prins and Menzel, 1994) based on the differential increases in emitted radiation with increases in temperature between the two bands. The ABI fire algorithm has adapted ABBA to detect fires from differences in the brightness temperatures of the 3.9 μm and 11.2 μm bands and provides the location, sub-pixel size, temperature, and radiative power of fires (Schmidt et al., 2012; Schmit et al., 2015). Fire Radiative Power (FRP) is the rate at which radiation is emitted from a fire and, for a 600 - 1400 K temperature range, FRP is proportional to the difference between radiance in the middle infrared (MIR) at 3.9 μm and the regional background radiance in MIR (Schmidt et al., 2012; Wooster, 2003; Xu et al., 2010). Fire Radiative Energy (FRE) is the time-integrated FRP during the course of a fire. Emissions of trace gasses and aerosols from biomass burning can be estimated using FRE, a biomass combustion rate, and an emission factor specific to land cover and emitted species (Zhang et al., 2012). The diurnal FRP cycles of various ecosystems have been estimated from GOES and from fusion of FRP estimates from GOES and MODIS to provide biomass burning emissions at hourly, daily, and monthly scales (Li et al., 2019a; Zhang et al., 2012).

While GOES-R thermal observations can provide biomass burning emissions at a fine temporal scale, the coarse spatial resolution of GOES-R presents a challenge in detecting small sub-pixel fires and emissions. Differences between medium (20 m) and coarse resolution (500 m) imagery can result in substantial differences in total detected burned area, estimated emissions, and the length of the fire season (Ramo et al., 2021). Small fires can make up a great portion of total burned area, emissions, and they can result in a lengthening of the fire season in regions where anthropogenic fires are prevalent (Ramo et al., 2021). Similar to other coarse spatial scale emissions datasets, emissions from GOES-R should be considered conservative in areas with substantial undetected small fires (Ramo et al., 2021). Similar to (2021), studies comparing biomass burning emissions from GOES-R with emissions from finer spatial resolution satellite imagery should reveal the magnitude of differences and trade-offs between high temporal and spatial resolution in estimating emissions.

5.4 Plant phenology

Plant canopies have unique and observable events that occur annually as a part of their phenology. The phenology of photosynthesis and plant growth is sensitive to temperature, precipitation, and photoperiod (Bauerle et al., 2012; Fu et al., 2017; Piao et al., 2019; Stoy et al., 2014b), and shifts in the phenology of carbon uptake and plant growing season in response to changing climate have important implications for ecosystems (Bradley et al., 1999; Xu et al., 2020). These shifts often occur on time scales that cause uncertainty from polar-orbiting satellites, especially when cloudy conditions are present

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during spring in the temperate zone (Richardson et al., 2013) and dry-to-wet (and wet-to-dry) seasonal transitions in tropical forests (Ganguly et al., 2010). Research on land surface phenology to date has used a combination of satellite remote sensing and near-surface remote sensing via webcams to detect seasonal transitions in vegetation greenness and photosynthesis such as the start, peak, and end of the growing season (Dannenberg et al., 2020; Gamon et al., 2016; Seyednasrollah et al., 2019; Wong et al., 2019; Zhang et al., 2003). These observations have varying spatial and temporal resolutions depending on the method and instrumentation used (Brown et al., 2016; Filippa et al., 2018; Liu et al., 2017).

Geostationary satellites such as GOES have unique capabilities that could further enhance plant phenology research. Compared to polar-orbiting satellites, the large number of diurnal observations from geostationary satellites capture greater variation in sun-angle geometries. This increased variability allows for better BRDF adjustments and improved investigations about the impact of the SZA on the vegetation indices used for extracting phenological transitions (Ma et al., 2020). Time series of LAI, NDVI, and the two-band Enhanced Vegetation Index (EVI2) from SEVIRI, AHI, and GOCI show increased observations during cloudy conditions and improved estimates of phenological cycles and transitions (Guan et al., 2014; Miura et al., 2019; Yan et al., 2016; Yeom and Kim, 2015; Yeom et al., 2018). Figures of time series from various papers cited above demonstrate the value of geostationary imagers in capturing greenness trajectories as a complement to polar orbiting satellites. NDVI from BRDF-adjusted reflectance from GOCI has demonstrated an improved ability to monitor the growth of rice paddies in North Korea and South Korea compared to MODIS NDVI from BRDF adjusted reflectance, especially during the monsoon season with frequent cloud cover that limits the ability of polar-orbiting sensors to observe the surface (Yeom et al., 2015, 2018). In the Congo Basin, the multiple annual phenological cycles of greenness in evergreen broadleaf forests were better captured by the increased observations from SEVIRI compared to MODIS (Yan et al., 2016). In Japan, the greenness trajectories from an EVI2 time series revealed differences in the length of seasonal transitions (timing between start of spring to end of spring) between AHI and MODIS (Yan et al., 2019).

GOES-R can also provide increased observations for the remote sensing of dryland phenology which can include multiple growing cycles per year and where phenological transitions can be triggered by pulses of rainfall and present an ongoing challenge for the remote sensing of land surface phenology (Smith et al., 2019). However, since drylands feature heterogeneous vegetation, studies will need to investigate whether increases in temporal resolution with coarse spatial resolution are enough to offer an improvement in dryland phenology (Smith et al., 2019). Leveraging diurnal observations from GOES to estimate greenness trajectories and phenological transitions (Hashimoto et al., 2021; Wheeler and Dietze, 2021) across the Western Hemisphere coupled with the ability to extract these transitions from AHI, SEVIRI, and GOCI can result in a near-global improvement in estimating seasonal vegetation growth and decline. The capacity of GOES to track events in plant phenology is shown in Figs. 3 and 4 for pixels within and outside of the Kincade Fire scar with notable increases in vegetation greenness and moisture during March and April at the end of the typical rainy season in California's Mediterranean ecosystems.

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5.5 Ocean color

Geostationary satellites have been used for nearly a decade for monitoring the dynamics of ocean color. The ocean color signal can identify suspended particulate matter and phytoplankton (Neukermans et al., 2009; Ruddick et al., 2014) including harmful algal blooms (Choi et al., 2014; Noh et al., 2018) and may be a sentinel for the impacts of climate change on marine ecosystems (Dutkiewicz et al., 2019). Most research to date has involved the Geostationary Ocean Color Imager (GOCI), which has transmitted eight images per day since 2010 in six visible (412, 443, 490, 555, 660, and 680 nm) and two infrared channels (745 and 865 nm) with 20 nm bandwidth at 500 m spatial resolution centered around the Korean Peninsula at 128.2 °E (Ahn et al., 2012; Choi et al., 2012; Ryu and Ishizaka, 2012; Ryu et al., 2012) (Table 1). GOCI has been used to estimate ocean biogeochemical dynamics (Wang et al., 2013) including photosynthesis via chlorophyll-a absorption (Concha et al., 2018; Park et al., 2012) at diurnal time scales. Other geostationary sensors including SEVIRI on the 2nd generation of Meteosat (Schmetz et al., 2002) and (forthcoming) flexible combined imager (FCI) on the 3rd generation of Meteosat (Ouaknine et al., 2013) are not designed explicitly for ocean color monitoring but have proven useful for monitoring marine suspended particulates and PAR attenuation in water (Neukermans et al., 2009; Ruddick et al., 2014) as has GOES (Jolliff et al., 2019). All of these sensors provide an important complement to ocean color monitoring from polar-orbiting satellites like MODIS-AQUA, MERIS, and the Ocean Land Color Instrument (OLCI) on Sentinel-3 (Nieke et al., 2012; Peschoud et al., 2017). The persistent and consistent atmospheric characterization afforded by the geostationary sensors is critical for interpreting the relatively weak marine color signature (Ruddick et al., 2014).

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6 Emerging Applications

6.1 Carbon cycle science

Estimates of surface-atmosphere carbon flux from polar-orbiting instruments like MODIS are usually produced on eight-day to annual time steps (Zhao et al., 2005). The impact of rapidly evolving meteorological conditions on terrestrial carbon uptake has gained recent attention, suggesting that more frequent observations will improve our understanding of the carbon cycle. Precipitation events and the resulting short-term changes in meteorological conditions on the order of days result in local anomalies in canopy photosynthesis and respiration that influence seasonal ecosystem exchange (Randazzo et al., 2020). Fluctuations in carbon uptake can result from upwind climate extremes through heat and moisture advection, revealing more complexity in how climate extremes impact ecosystem carbon fluxes (Schumacher et al., 2020). Smoke from large wildfires can result in a short-term decrease in incoming PAR but an increase in the diffuse fraction of incoming PAR which, under the right circumstances, can increase seasonal carbon uptake through changes in Light-Use Efficiency (LUE, Hemes et al., 2020). The resulting daily anomalies in gross primary productivity (GPP) from sudden changes in limiting resources have been shown to disproportionately affect longer-term ecosystem carbon uptake (Kannenberg et al., 2020). Multi-day positive anomalies in GPP are critical for explaining its interannual variation at ecosystem and global scales (Fu et

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al., 2019; Zscheischler et al., 2016). All of these recent findings point to the importance of more frequent observations of ecosystem carbon cycling to improve our understanding of global carbon cycling.

Now that geostationary satellite imagers, such as the ABI, measure similar spectral bands to MODIS (Fig. 1, Table 1), they can be used to monitor the carbon cycle in similar ways but at higher temporal frequency. Estimates of GPP often rely on LUE models which are rooted in a linear relationship between absorbed PAR (APAR) and net primary production (Medlyn, 1998; Monteith, 1972). An ideal LUE in the absence of environmental stresses is specified and attenuated with the use of stress functions that describe the relationship between LUE and environmental stressors (Anderson et al., 2000; Mahadevan et al., 2008; Robinson et al., 2018; Running et al., 2004; Yuan et al., 2007; Zhang et al., 2016; Zhao et al., 2005). The most widely used environmental stressors include functions to describe temperature and moisture stress on LUE. Multiple approaches for estimating GPP from space exist based on the LUE approach with differences arising from the spatio-temporal resolution of the inputs, the meteorological data used, incorporating the impacts of CO_2 fertilization, environmental scalars used for adjusting LUE, and the treatment of LUE as a constant or specific to biome, plant functional type, or photosynthetic pathway (McCallum et al., 2009; Robinson et al., 2018; Sims et al., 2006; Xiao et al., 2019).

Vegetation indices calculated from GOES-R observations will provide spatiotemporal harmony with other GOES-R inputs such as downwelling shortwave radiation in estimating APAR. Various remotely sensed vegetation indices have been used for both estimating fAPAR to estimate APAR and in formulations of environmental stresses on LUE. The MODIS GPP algorithm uses NDVI and the MODIS fAPAR/LAI product to estimate APAR. The Vegetation Photosynthesis and Respiration Model (VPRM) (Mahadevan et al., 2008) uses a similar approach and estimates gross ecosystem exchange (GEE, similar to GPP) using the Enhanced Vegetation Index (EVI) instead of NDVI. The Land Surface Water Index (LSWI), the normalized difference between satellite-derived reflectance in near-infrared and shortwave infrared, is used to adjust LUE in response to water stress and leaf phenology (Mahadevan et al., 2008).

Implementing a model to estimate carbon uptake from ABI presents opportunities to improve LUE-based models by using emerging variables, as opposed to the commonly used air temperature and vapor pressure deficit, to represent environmental stressors on LUE such as soil moisture, diffuse radiation, LST, and the evaporative fraction (Anderson et al., 2000; Li et al., 2021; Yuan et al., 2007; Zhang et al., 2016). Ecosystem GPP increases with increases in diffuse radiation if light does not limit photosynthesis because diffuse radiation penetrates plant canopies more readily resulting in a more even distribution of light among shaded and sunlit leaves. (Hemes et al., 2020; Mercado et al., 2009). Incorporating the diffuse component of incoming PAR has been noted as a priority for improving LUE models (McCallum et al., 2009; Yuan et al., 2014). Recent attempts at incorporating diffuse radiation into LUE models as a stress on GPP have demonstrated an enhancement of LUE during overcast skies (Zhang et al., 2016). Fog events can be identified using GOES and increase both diffuse fraction of radiation and ecosystem water use efficiency (Baguskas et al., 2021). Partitioning estimates of PAR from ABI into diffuse and direct components along with the ABI LST product and ALEXI based estimates of sensible and latent heat flux can provide harmony between inputs for environmental stressors on LUE, PAR, and vegetation indices by not

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having to rely on estimates from sources other than ABI. Furthermore, estimates of LAI from GOES can contribute to respiration modeling data needs for estimating NPP (Robinson et al., 2018).

Estimating GPP with ABI data can also benefit from various LUE model formulations that incorporate the coupling between carbon uptake and water loss through stomatal processes and water use efficiency (Anderson et al., 2000; Zhang et al., 2016). Estimates of APAR from ABI can be used in existing carbon-water coupled models through the ALEXI framework which can estimate hourly fluxes which respond to diurnal variations in solar radiation and VPD along with capturing the effect of soil moisture stress on LUE (Anderson et al., 2000). The ALEXI framework presents an opportunity to use both ABI thermal data as previously mentioned in section 5.1 and ABI reflectance data to estimate carbon, water, and energy fluxes simultaneously (Anderson et al., 2008). Diurnal estimates of carbon uptake and water loss from ABI will enhance our understanding of ecosystem water-use efficiency and its response to environmental variation across geographic space. Furthermore, there are various opportunities to study the response of carbon fluxes estimated from ABI data to soil moisture variability with soil water content measured at various ground locations. This could be an important investigation considering the noted limitations of satellite GPP estimates in their ability to capture soil moisture effects on carbon uptake (Stocker et al., 2019). Observations from geostationary satellites could also, in principle, be used to assimilate instantaneous carbon flux observations from eddy covariance towers into ecosystem models (LeBauer et al., 2011).

6.2 Disturbance and recovery

Remotely sensed data have made it possible to map regional burn severity from wildfires, while time series of measures of greenness and primary productivity enable monitoring of vegetation disturbance and recovery (Bolton et al., 2017; Goetz et al., 2006; Meng et al., 2018). Mapping damage from hurricanes and the resulting impact to the carbon cycle has also been possible using remotely sensed data through the use of various vegetation indices related to greenness and moisture (Chambers et al., 2007; Wang et al., 2010). The difference in NDVI from pre- and post-fire imagery from GOES-16 shows the potential to detect variation in burn severity and recovery from wildfires as demonstrated for the notable Kincade Fire in 2019 in California (Fig. 5). High-frequency estimates of NDVI (Fig. 3) and NDII (Fig. 4) from GOES-16 can track vegetation disturbance and recovery from wildfire in a similar manner to MODIS although the magnitude of the vegetation indices differs between the two due to the atmospheric corrections and BRDF-adjustments of the MODIS TOA reflectance (Fig. 3 and 4). Variations in SZA and VZA can lead to differences in NDVI values between GOES, MODIS, and other sensors (Fensholt et al., 2006; Pinker and Ewing, 1985) with MODIS having the advantage of a low SZA during its overflight. These differences in viewing geometry need to be resolved to reconcile differences between sensors. Imagery from ABI also has the potential to estimate the regional decline in vegetation indices after hurricanes (Fig. 6) which can potentially be converted into the decline in GPP using methods described in section 6.1. A recent review has also highlighted the use of geostationary imagers in monitoring landslides and flooding (Higuchi, 2021).

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6.3 Ecosystem thermodynamics

Observations of the diurnal behavior of land surface attributes can also be used to improve our understanding of the thermal properties of ecosystems. Large-scale changes to ecosystems, such as logging, the conversion of grasslands or forests to farmland, and wildland fires alter the mechanisms by which ecosystems regulate their energy acquisition and heat exchange, thought to be related to the degree of complexity of the system (Kay and Schneider, 1992). The process of ecological succession modifies the structure of an ecosystem over time by gradually increasing its complexity (Odum, 1969). Ecosystems should therefore develop an increasing ability to dissipate incoming solar radiation as succession proceeds (Schneider and Kay, 1994) and, due to a higher order of complex structures, will improve cooling by transferring solar radiation into latent heat and metabolic energy (Norris et al., 2011). Effective energy dissipation results in a cooler surface (with less waste heat) for biological processes to occur. Diurnal patterns of LST can be used to quantify ecological complexity (Lin et al., 2009) and entropy production (Brunsell et al., 2011; Holdaway et al., 2010; Stoy et al., 2014a; Wiesner et al., 2019) and may be useful for monitoring the success of ecological restoration projects that seek to re-establish ecological function (Aerts et al., 2004).

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6.4 Satellite data fusion products

One of the most promising applications of geostationary satellites for land surface science may simply be their ability to provide temporally dense observations that can be combined ("fused") with spatially dense observations from polar-orbiting or other satellite platforms. Such fusion products take advantage of the best features of different platforms, for example by exploiting the finer spatial resolution of observations from Landsat, Sentinel-2, MODIS, VIIRS, or the recently harmonized Landsat Sentinel-2 surface reflectance and the temporal resolution of GOES observations. Based on the assumption that changes in a Landsat pixel are equivalent or proportional to the changes in the co-located MODIS pixel between two dates, fusion algorithms are able to predict the surface reflectance of a Landsat pixel between acquisition dates using the change observed in MODIS pixels between the reference and prediction date (Gao et al., 2015). Multi-sensor fusion using polar-orbiting and geostationary satellites have provided higher spatiotemporal resolution for estimates of forest disturbance, NDVI, phenology, LST, ET, and water management, yield estimation, and fire radiative power (Cammalleri et al., 2013, 2014; Gao et al., 2015; Hilker et al., 2009; Knauer et al., 2016; Li et al., 2019a; Semmens et al., 2016; Wu et al., 2015; Yang et al., 2018; Zhao and Duan, 2020). Given the importance of considering landscape heterogeneity in using satellite data to estimate various ecosystem variables and model processes such as LUE, carbon flux and storage, phenology, and ET (Ahl et al., 2004; Cammalleri et al., 2014; Leitão et al., 2018; Zeng et al., 2020), multi-sensor data fusion offers a way to address the relatively coarse spatial scale of imagery from geostationary satellites as we expand their use in studying ecosystem function and surface-atmosphere exchange.

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7 Conclusions

The recently increased spectral and spatial resolution of imagers onboard geostationary satellites creates new opportunities to use remotely sensed observations in environmental science, especially when combined with ongoing and forthcoming improvements to the spectral sensitivity of other geostationary imagers. The increased diurnal sampling from the ABI can find cloud-free observations when polar-orbiting satellites may be hindered by cloud cover to improve time series of vegetation greenness, canopy water content, LST, and energy-water-carbon fluxes. Temporally dense geostationary observations have been crucial in detecting moisture stress and wildfires. Extending the use of these observations to measure more land surface variables can capture sudden changes in ecosystem fluxes due to changing atmospheric conditions and extreme events. Furthermore, estimations of vegetation phenological cycles can be improved using geostationary satellites, especially by taking advantage of short periods of clear skies occurring during times of otherwise persistent cloud cover. Studying ecosystem disturbance events should also benefit through increased availability of observations pre- and post-disturbance to estimate burned area and vegetation recovery. Multi-sensor fusion between relatively coarse geostationary satellite observations and observations from platforms with finer spatial resolution offers a way to resolve within-pixel spatial variability in heterogeneous landscapes.

The ongoing efforts to improve the geolocation and radiometric quality of imagery and providing higher level collections of data with surface reflectance, similar to the MODIS or Landsat program, will be a crucial component of using imagery from geostationary sensors. Furthermore, increased collaboration between the National Science Foundation, NASA, and NOAA with increased funding opportunities to pursue research utilizing imagery from geostationary sensors for investigations in the science topics we have detailed here will help realize the potential of these data. Leveraging the high-frequency observations from geostationary sensors for investigations in environmental science where they have been largely untapped will expand the scope of hyper-temporal remote sensing of the environment.

Data and code availability

The GOES-16 ABI Level 2 Cloud and Moisture Imagery (ABI-L2-MCMIPC) used to make the figures is available through https://registry.opendata.aws/noaa-goes/ . The GOES-16 ABI Level 2 Clear Sky Mask (ABI-L2-ACMC) is available through NOAA's Comprehensive Large Array-Data Stewardship System (CLASS). The MODIS (Terra and Aqua) Nadir Bidirectional Reflectance Distribution Function-Adjusted Reflectance (NBAR) product (MCD43A4) was accessed thought the Level-1 Atmosphere Archive & Distribution System (LAADS) Distributed Active Archive Center (DAAC). The code to produce Figs. 3 - 6 is available at https://github.com/anmikhan/envirogoes.git

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Author contribution

AMK and PCS conceived of the study and all authors contributed to writing the manuscript.

Competing interests

The authors declare that they have no conflict of interest.

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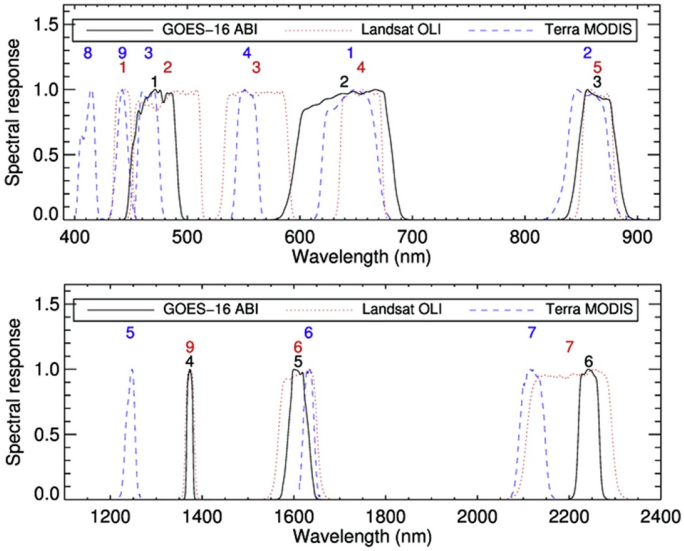

Figure 1: A comparison of the spectral sensitivity of the Advanced Baseline Imager (ABI) with the Landsat Operational Land Imager (OLI) and MODIS Terra (McCorkel et al., 2020).

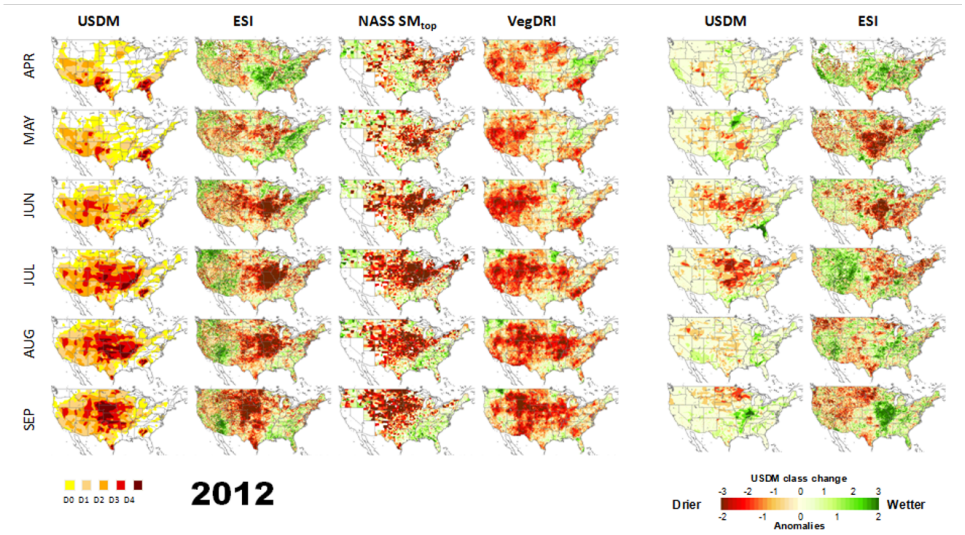

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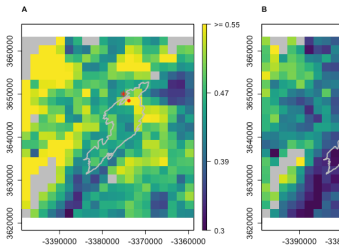
Figure 2: Comparison of drought evolution between the US Drought Monitor classification, the Evaporative Stress Index (ESI), and the Vegetation Drought Response Index (VegDRI). The figure is adapted from Anderson et al. (2013b) and distributed under a CC BY-NC-ND-3.0 license.



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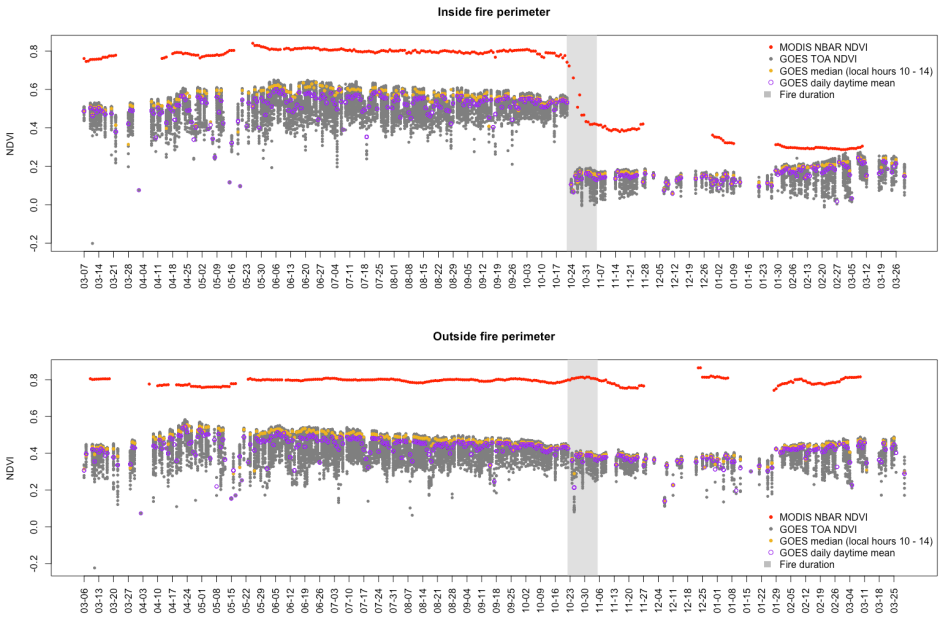
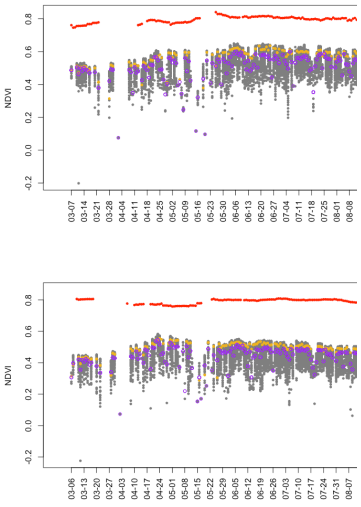


Figure 3: Normalized Difference Vegetation Index (NDVI) calculated using TOA reflectance factor from ABI on GOES-16 and Nadir Bidirectional Reflectance Distribution Function-Adjusted Reflectance (NBAR) from MODIS on the Terra and Aqua satellites for pixels inside and outside the Kincade fire (Oct. 23, 2019) perimeter in northern California for the period March 2019 to March 2020. The GOES Clear Sky Mask was applied to observations from GOES, MODIS NBAR with good quality flags were used. All observations are daytime with solar zenith angle < 70°. The locations of the points inside and outside of the fire perimeter are displayed in Figure 5.



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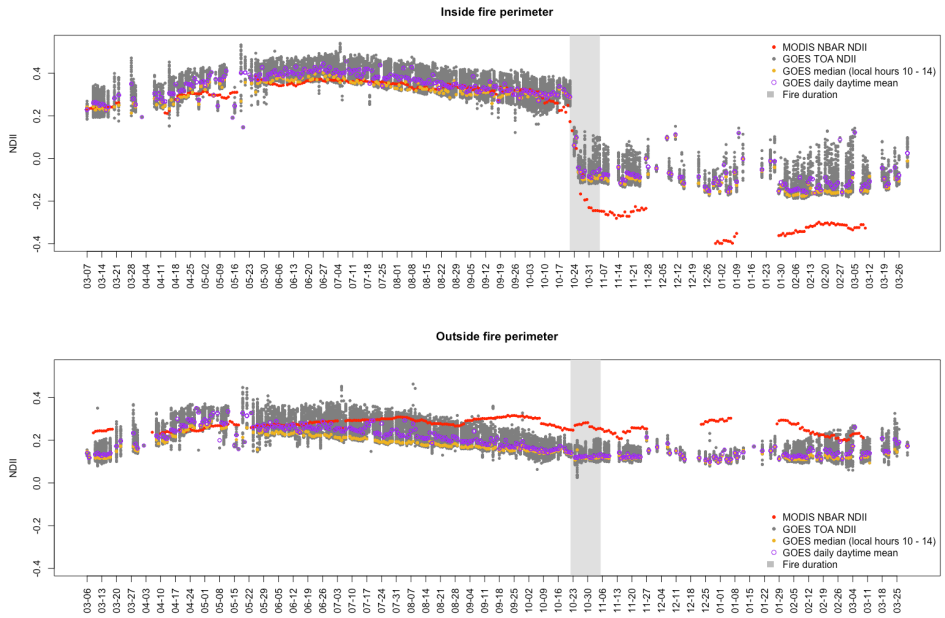

Figure 4: Normalized Difference Infrared Index (NDII) calculated using TOA reflectance factor from ABI on GOES-16 and Nadir Bidirectional Reflectance Distribution Function-Adjusted Reflectance (NBAR) from MODIS on the Terra and Aqua satellites for pixels inside and outside the Kincade fire (Oct. 23, 2019) perimeter in northern California for the period March 2019 to March 2020. The GOES Clear Sky Mask was applied to observations from GOES. MODIS NBAR with good quality flags were used. All observations are daytime with solar zenith angle < 70°. The locations of the points inside and outside of the fire perimeter are displayed in Figure 5.

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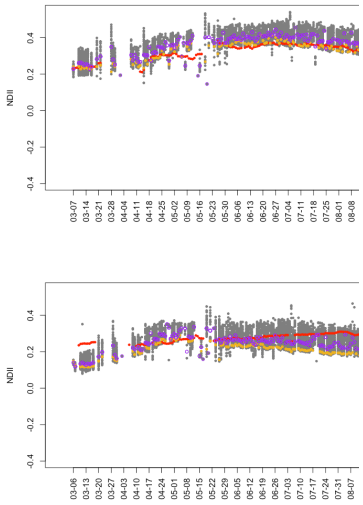

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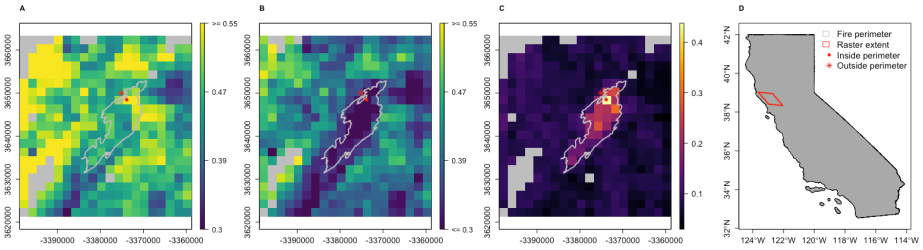

Figure 5: Top-of-Atmosphere (TOA) Normalized Difference Vegetation Index (NDVI) calculated using TOA reflectance factor from GOES-16 imagery for (A) DOY 295 (Oct. 22, 2019) 21:00 UTC and (B) DOY 312 (Nov. 8, 2019) 21:00 UTC and their difference (C) for the Kincade fire perimeter in northern California (D) (Oct. 23, 2019, DOY 296). Gray pixels were identified as cloudy from the GOES Clear Sky Mask. The points inside and outside of the fire perimeter correspond to the time series in Figure 3 and 4.

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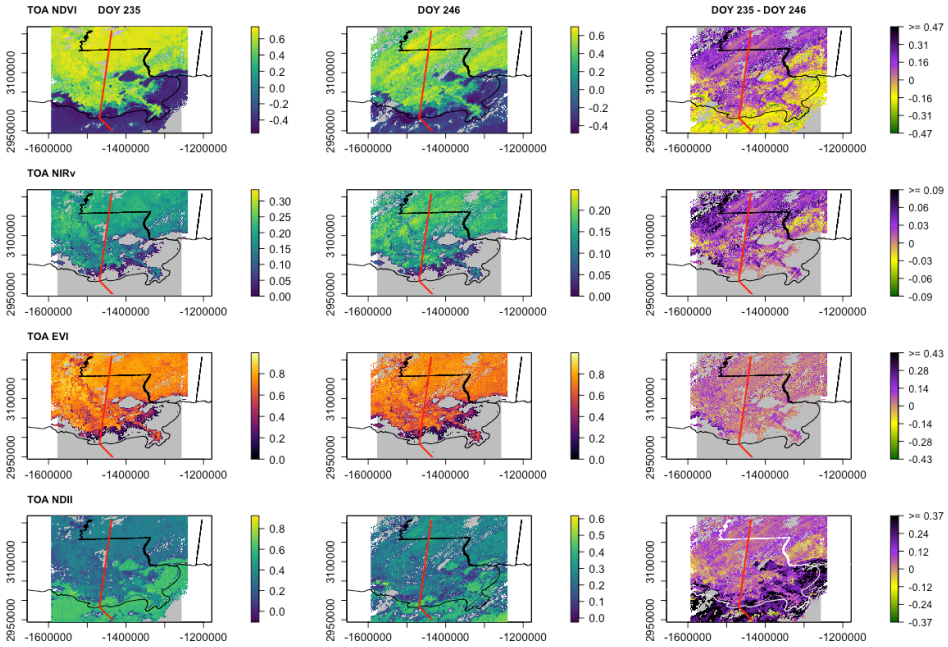

Figure 6: Top-of-Atmosphere (TOA) Normalized Difference Vegetation Index (NDVI), near-infrared reflectance of vegetation (NIRv), Enhanced Vegetation Index (EVI) and Normalized Difference Infrared Index (NDII) calculated using TOA reflectance factors from GOES-16 imagery for day of year (DOY) 235 (Aug. 22, 2020) 16:00 UTC, DOY 246 (Sep. 2, 2019) 16:00 UTC and their difference around the advisory track for Hurricane Laura (red line) in southern Louisiana (Aug. 26, 2020, DOY 239). Gray pixels represent cloudy pixels from the GOES Clear Sky Mask or vegetation index values below 0 for NIRv and EVI.

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Table 1: Instrument characteristics for the GOES-R Advanced Baseline Imager, Advanced Himawari Imager on Himawari-8/9, and the Advanced Meteorological Imager on the Geostationary - Korea Multi-Purpose Satellite-2 (GEO-KOMPAST-2A) (a) and The Global Ocean Color Imager-II (GOCI-II) on GEO-KOMPSAT-2B (b)

a.

GOES-16/17 Advanced Baseline Imager (ABI)			**Himawari-8/9 Advanced Himawari Imager (AHI)**			**GEO-KOMPSAT 2A Advanced Meteorological Imager (AMI)**		
Band	**Central Wavelength (µm)**	**Spatial Resolution (km)**	**Band**	**Central Wavelength (µm)**	**Spatial Resolution (km)**	**Band**	**Central Wavelength (µm)**	**Spatial Resolution (km)**
1	0.47	1	1	0.47	1	1	0.47	1
			2	0.51	1	2	0.51	1
2	0.64	0.5	3	0.64	0.5	3	0.64	0.5
3	0.86	1	4	0.86	1	4	0.86	1
4	1.37	2				5	1.4	2
5	1.6	1	5	1.6	2	6	1.6	2
6	2.2	2	6	2.3	2			
7	3.9	2	7	3.9	2	7	3.8	2
8	6.2	2	8	6.2	2	8	6.2	2
9	6.9	2	9	6.9	2	9	6.9	2
10	7.3	2	10	7.3	2	10	7.3	2
11	8.4	2	11	8.6	2	11	8.6	2
12	9.6	2	12	9.6	2	12	9.6	2
13	10.3	2	13	10.4	2	13	10.4	2
14	11.2	2	14	11.2	2	14	11.2	2
15	12.3	2	15	12.4	2	15	12.4	2
16	13.3	2	16	13.3	2	16	13.3	2

b.

GEO-KOMPSAT-2B Global Ocean Color Imager-II (CGOCI-II)		
Band	**Central Wavelength (nm)**	**Spatial Resolution (m)**
1	380	250
2	412	250
3	443	250
4	490	250
5	510	250
6	555	250
7	620	250
8	660	250
9	680	250
10	709	250
11	745	250
12	865	250
13	Wideband	250

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