

# Global Satellite Observations for Smart Cities

Zhong Liu<sup>1,2</sup>, Menglin S. Jin<sup>3</sup>, Jacqueline Liu<sup>4</sup>, Angela Li<sup>1</sup>, William Teng<sup>1,5</sup>, Bruce Vollmer<sup>1</sup>,  
and D. Meyer<sup>1</sup>

<sup>1</sup>NASA Goddard Earth Sciences Data and Information Services Center, Godard Space Flight

Center, Greenbelt, Maryland, USA

<sup>2</sup>Center for Spatial Information Science and Systems, George Mason University, Virginia, USA

<sup>3</sup>Department of Atmospheric and Oceanic Science, University of Maryland at College Park,

Maryland, USA

<sup>4</sup>Urbana High School, Urbana, Maryland, USA

<sup>5</sup>Adnet Systems Inc., Greenbelt, Maryland, USA

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## 24 1. Introduction

25 Over the past several decades, the number of megacities (exceeding 10 million people in  
26 population) has been rapidly growing around the world as a result of rapid economic growth and  
27 unprecedented urbanization (United Nations 2014). For example, in Asia alone, more than 30  
28 cities (Fig. 1) are listed as megacities (e.g., Tokyo, Shanghai, Guangzhou), demanding effective  
29 management for city planning, operations, and disaster mitigation. The smart city approach  
30 requires data and information to be collected from multiple sources and to be integrated with  
31 modern technologies, providing a new and cost-effective way for decision makers to manage  
32 cities in different sizes around the world as well as making information publicly available for  
33 city residents.

34 Environmental information at different spatial and temporal scales (e.g., ranging from  
35 local to regional and from real time to climate) is one of critical sources for city planning,  
36 management, and disaster mitigation (Seto 2011). Each year, severe weather events (e.g., heavy  
37 rain or snowfall, tropical cyclones, heat waves) can strike a city around the world without  
38 warning and cause severe damage to a city's infrastructure as well as interrupt people's daily life.  
39 Effective management of water, air pollution, energy, etc. requires environmental data to be  
40 available at anytime and on demand. Nonetheless, making data available for timely and easy  
41 access is critically important for effective city planning and management activities (Seto 2011).

42 Climate change can have a profound impact on cities around the world. For example, for  
43 cities in tropical and sub-tropical regions, changes in heavy rainfall amount as well as tropical  
44 cyclone size, frequency, and intensity can impact a city's operations, infrastructure,  
45 development, and long-term planning. Sea level rise is another major concern for city managers  
46 and residents in coastal cities. To be able to monitor and predict such change is critical for a

47 city's planning and operations and all cannot be done without environmental data.

48         On the other hand, studies show that cities, especially large cities, can have an impact on  
49 local weather (e.g., Zhang et al. 2017; Jin et al. 2005, 2010, 2011; Shepherd and Jin 2004; Seto  
50 and Shepherd 2009; Kauffmann et al. 2007; Guo et al. 2016). Activities from urbanization and  
51 city development can dramatically modify its surrounding natural environment and landscape.  
52 For example, urban heat islands (UHI) provide manmade heat sources that can change its  
53 surrounding atmospheric environment and potentially fuel severe weather. Air pollution that is  
54 associated with automobiles, industries, etc. supplies the atmosphere with aerosols that could  
55 modify meteorological processes such as clouds and precipitation (Jin et al. 2005, 2011).

56         Nonetheless, the few examples above have shown the importance of environmental data  
57 in city's planning and management. Such data consist of multi-disciplines at multi-scales in  
58 space and time. Traditional ground-based observations (e.g. rain gauges, automatic weather  
59 stations) have limitations because it is costly and time-consuming to deploy such measurements,  
60 especially at regional and global scales. On the other hand, satellite-based measurements, in  
61 combination with ground-based measurements, can overcome many of these difficulties and  
62 provide environmental data at multiple-scales (Seto 2007, 2011; Boucher and Seto 2009).

63         As mentioned earlier, the smart city approach requires collection of interdisciplinary data  
64 and information from multiple sources and integration with modern technologies to provide a  
65 new and cost-effective way for researchers and decision makers to study and manage cities. In  
66 this book chapter, we introduce NASA satellite-based global and regional observations with  
67 emphasis on the hydrologic cycle (e.g., precipitation, wind, temperature, soil moisture) for smart  
68 cities. These products, consisting of both near-real-time and historical datasets, are publicly  
69 available free of charge and can be used for global and regional research and applications.

70 Examples of using these datasets in smart cities are included. The chapter is organized as  
71 follows, first, a brief overview of NASA global satellite-based data products, followed by data  
72 services and tools, two examples of using satellite-based datasets in megacities, and finally  
73 summary and future plans.

## 74 **2. Overview of NASA Satellite-based Global Data Products for Smart Cities**

75  
76 Significant progress has been made in satellite Earth's observations since the first  
77 successful launch of weather satellite, the Television Infrared Observation Satellite (TIROS), by  
78 NASA on April 1, 1960. In particular, NASA's Earth Observing System (EOS) is a coordinated  
79 series of polar-orbiting and low inclination satellites for long-term global observations of the  
80 land surface, biosphere, solid Earth, atmosphere, and oceans to enable an improved  
81 understanding of the Earth as an integrated system (NASA 2017a). At present, there are ~28  
82 active satellite missions currently in space to provide observations to scientific and application  
83 users around the world (NASA 2017a). The Earth Observing System Data and Information  
84 System (EOSDIS) currently hosts ~22 PB of Earth Observation (EO) data at twelve DAACs  
85 (Distributed Active Archive Centers) and it is expected to grow rapidly over the coming years, to  
86 more than 37 (246 PB) PB by 2020 (2025) (NASA 2017b). Such large EO data archive is an  
87 important asset for environmental research and applications around the world including smart  
88 cities because the smart city approach requires multidisciplinary datasets collected from multiple  
89 sources.

90 NASA's EOS and other past NASA satellite mission data are available and distributed by  
91 the EOSDIS, with major facilities at twelve DAACs located throughout the United States  
92 (NASA 2017b). Scientific disciplines at twelve DAACs include atmosphere, cryosphere, human  
93 dimensions, land, ocean, calibrated radiance, solar radiance, etc. Table 1 lists the twelve DAACs



94 and their discipline-oriented data archives (NASA 2017b). For example, ocean winds and sea  
95 surface temperature data are available at the Physical Oceanography DAAC in the Jet Propulsion  
96 Laboratory (JPL). Lighting data from the NASA-JAXA Tropical Rainfall Measuring Mission  
97 (TRMM) are archived at the Global Hydrology Resource Center (GHRC) DAAC. As of this  
98 writing, a large collection of datasets and services are available at the twelve NASA data centers.  
99 However, due to page limit, it is difficult to give a detailed description for each DAAC. Here we  
100 focus on the Goddard Earth Sciences and Data and Information Services Center (GES DISC),  
101 located in Greenbelt, Maryland, USA, because it archives a large amount of interdisciplinary  
102 datasets in comparison to other DAACs. Datasets used in the examples in this article are  
103 archived at the GES DISC.

## 104 **2.1. Satellite-based Data Products at the GES DISC**

105 The GES DISC hosts global and regional satellite-based interdisciplinary data products  
106 from these scientific disciplines: precipitation, solar irradiance, atmospheric composition and  
107 dynamics, global modeling, etc. Currently, over 2700 unique data products are archived at the  
108 GES DISC and distributed to the public. Given such a large collection of products and space  
109 limitation, we can only present a brief overview of several major projects that are closely related  
110 to research and applications for smart cities.

### 111 **2.1.1. Multi-satellite and Multi-sensor Merged Global Precipitation Products**

112 Over the years, algorithms that utilize multi-satellites and multi-sensors (i.e., microwave  
113 and geostationary infrared sensors), or blended methods, have been developed to overcome a  
114 very limited spatial and temporal coverage from any single satellite (Adler et al. 2003; Huffman  
115 et al. 2007, 2009, 2010, 2012, 2013; Joyce et al. 2004; Mahrooghy et al. 2012; Hong et al. 2007,  
116 Sorooshian et al. 2000; Behrangi et al. 2009; Aonashi et al. 2009) and products are widely used

117 in hydrometeorological research and applications. For example, the TRMM Multi-Satellite  
118 Precipitation Analysis (TMPA) products in Table 2 (Huffman et al. 2007, 2010, 2012, 2013),  
119 developed by the Mesoscale Atmospheric Processes Laboratory at NASA Goddard Space Flight  
120 Center, provide precipitation estimates at 3-hourly and monthly temporal resolutions on a 0.25-  
121 degree x 0.25-degree grid available from January 1998 to present. The TMPA consists of two  
122 products: near-real-time (3B42RT, spatial coverage: 60°N-60°S) and research-grade (3B42,  
123 spatial coverage: 50°N-50°S). The former is less accurate, but provides quick precipitation  
124 estimates suitable for near-real-time monitoring and modeling activities (e.g. Wu et al. 2012).  
125 The latter, available approximately two months after observation, is calibrated with gauge data,  
126 different sensor calibration, and additional post-processing in the algorithm. The resulting  
127 product is more accurate and suitable for research (Huffman et al. 2007, 2010). Over the years,  
128 the TMPA products have been widely used in various research and applications (e.g. Wu et al.  
129 2012, Bitew et al. 2012, Gourley et al. 2011, Su et al. 2011, Gianotti et al. 2012, Tekeli 2017,  
130 Engel et al. 2017, Tan and Duan 2017).

131 During the GPM era, the Integrated Multi-satellitE Retrievals for GPM (IMERG) product  
132 suite (Huffman et al. 2017) not only addresses limited spatial and temporal coverage issues in  
133 TRMM but also has been significantly improved comparing the TMPA products in terms of  
134 spatial and temporal resolutions, i.e., from 0.25 degree to 0.1 degree and from 3-hourly to half-  
135 hourly (Table 2). The IMERG suite contains of three output products, “Early satellites” (lag  
136 time: ~6 hours), “Late satellites” (lag time: ~18 hours), and the final “Satellite-gauge” (lag time:  
137 ~4 months) along with additional new input and intermediate files, creating a new opportunity  
138 for research and applications. The retro-processing of the IMERG product suite back to the  
139 TRMM era will be released in 2018.

## 140 **2.1.2. Global and Regional Land Data Assimilation Products**

141 Global and regional land data assimilation system data products include optimal fields of  
142 land surface states and fluxes (NASA 2017c). The fields are generated by ingesting satellite- and  
143 ground-based observational data products and using advanced land surface modeling and data  
144 assimilation techniques (NASA 2017c). A methodology is to implement a Land Data  
145 Assimilation System (LDAS) that consists of land-surface models (uncoupled from an  
146 atmospheric model). These land-surface models are forced with observations and thus the model  
147 results are not affected by Numerical Weather Prediction forcing biases (NASA 2017c). This  
148 research has been implemented using existing Surface Vegetation Atmosphere Transfer Schemes  
149 (SVATS) by NOAA, NASA/GSFC, NCAR, Princeton University, and the University of  
150 Washington at 1/8th-degree resolution across central North America and at 1/4th-degree  
151 resolution globally to evaluate these critical science questions (NASA 2017c). These LDAS  
152 systems have been run retrospectively starting in January 1979 and continue in near real-time,  
153 and are forced with gauge precipitation observations, satellite precipitation data, radar  
154 precipitation measurements, and output from numerical weather prediction models (NASA  
155 2017c). Model parameters are derived from the existing high-resolution vegetation and soil  
156 coverages. The LDAS model results support water resources applications, numerical weather  
157 prediction studies, numerous water and energy cycle investigations, and also serve as a  
158 foundation for interpreting satellite and ground-based observations (NASA 2017c). Eventually,  
159 in situ or remotely-sensed observations (soil moisture, temperature, snow) of LDAS storages and  
160 fluxes (including evaporation, sensible heat flux, runoff) will be used to further validate and  
161 constrain the LDAS predictions using data assimilation techniques (NASA 2017c). The GES

162 DISC hosts the archive of data products from GLDAS, NLDAS, NCA-LDAS, and FLDAS  
163 (NASA 2017c).

### 164 **2.1.3. Modern-Era Retrospective Analysis for Research and Applications (MERRA)** 165 **Products**

166 The Modern-Era Retrospective analysis for Research and Applications, Version 2  
167 (MERRA-2), has been developed at the NASA Global Modeling and Assimilation Office  
168 (GMAO) at the NASA Goddard Space Flight Center (NASA 2017d). MERRA-2 provides global  
169 data beginning in 1980 and runs a few weeks behind real time (NASA 2017d). Alongside the  
170 meteorological data assimilation using a modern satellite database, MERRA-2 includes an  
171 interactive analysis of aerosols that feed back into the circulation, uses NASA's observations of  
172 stratospheric ozone and temperature (when available), and takes steps towards representing  
173 cryogenic processes (NASA 2017d). The MERRA project focuses on historical analyses of the  
174 hydrological cycle on a broad range of weather and climate time scales and places the NASA  
175 EOS suite of observations in a climate context (NASA 2017d). Compared to the previous  
176 version, advances have been made in the assimilation system that enables assimilation of modern  
177 hyperspectral radiance and microwave observations, along with GPS-Radio Occultation datasets  
178 (Riencker et al. 2011; Reichie and Liu 2014; Suarez and Bacmeister 2015; Takacs et al. 2015).  
179 MERRA-2 also includes advances in both the Goddard Earth Observing System Model, Version  
180 5 (GEOS-5) and the GSI (Gridpoint Statistical Interpolation) assimilation system and NASA  
181 ozone observations after 2005. MERRA-2 begins from 1980 to present.

182 There are two types of precipitation parameters in MERRA-2: a) precipitation from the  
183 atmospheric model (variable PRECTOT in the MERRA-2 data collection) and b) observation-  
184 corrected precipitation (variable PRECTOTCORR; Reichle and Liu 2014; Bosilovich et al.

185 2015). Observational data are introduced in the latter parameter due to considerable errors that  
186 propagate into land surface hydrological fields and beyond (Reichle et al. 2011).

187 Bosilovich et al. (2015) have conducted a general evaluation of MERRA-2 precipitation  
188 estimates, including precipitation climatology, interannual variability, diurnal cycle, Madden-  
189 Julian Oscillation (MJO) events, global water cycle and U.S. summertime variability. Major  
190 findings (Bosilovich et al. 2015) are, 1) an overestimate of the modeled precipitation in the  
191 tropical west Pacific Ocean, the eastern tropical ITCZ (the Intertropical Convergence Zone) and  
192 the SPCZ (the South Pacific convergence zone) in DJF and JJA (Bosilovich et al. 2011, 2015); 2)  
193 Extreme values of modeled precipitation in the vicinity of high topography in the tropics; 3) An  
194 upward trend in the MERRA-2 time series exists and by contrast no trend is observed in GPCP  
195 (the Global Precipitation Climatology Project); 4) Larger modeled precipitation diurnal cycle  
196 (PDC) amplitude is found over the high mountains; 5) The phases of modeled PDC are not well  
197 reproduced in several regions such as the U.S. Great Plains; 6) MJO signal from modeled  
198 precipitation is stronger than GPCP; 7) MERRA-2 can reproduce the observed precipitation and  
199 anomalies in U.S. summertime, reasonably well. Although the preliminary evaluation provides a  
200 basic understanding of the MERRA-2 precipitation products, evaluation for extreme rainfall  
201 events is missing and as a result, it is not clear about MERRA-2 precipitation behavior and  
202 characteristics in extreme events.

203 The complete list of MERRA-2 products along with documentation and more is available  
204 on the official MERRA-2 Web site (NASA 2017d). To facilitate data access, the GES DISC has  
205 developed several data services and tools to be described in the next section.

### 206 **3. Data Services**

207 Although a large collection of NASA global satellite data is available for research and

208 applications around the world, many researchers find it challenging to discover, access, and use  
209 NASA satellite remote sensing data (Liu and Acker 2017). Heterogeneous data formats, complex  
210 data structures, large-volume data storage, special programming requirements, diverse analytical  
211 software options, and other factors often require a significant investment in time and resources,  
212 especially for novices (Liu and Acker 2017). Over the years, data services have been developed  
213 at NASA's EOSDIS DAACs to improve NASA data discovery and access. First, an EOSDIS  
214 Web search interface (NASA 2017e) has been developed and anyone, with a Web browser, can  
215 access NASA data products at twelve DAACs through this interface. Figure 2 is a screenshot of  
216 the EOSDIS Web search interface, showing a search box where users can type in a data variable  
217 name such as precipitation. User registration is required for downloading data from all EOSDIS  
218 data services. Users can also visit each individual DAAC and use their Web interfaces to access  
219 discipline-oriented data products and services. Furthermore, special discipline-oriented data tools  
220 have been developed at DAACs and they are organized in the following categories: Search and  
221 Order, Data Handling, Subsetting and Filtering, Geolocation, Reprojection, and Mapping, and  
222 Data Visualization & Analysis (NASA 2017f). EOSDIS DAACs also support Web services and  
223 various Web protocols for machine-to-machine data access and applications such as OPeNDAP  
224 (Open source Project for a Network Data Access Protocol), WMS (Web Map Service), GDS  
225 (GrADS Data Server), THREDDS, https, etc. To address data and science related issues and  
226 inquiries from users, DAACs provide user services including Frequent Asked Questions (FAQs),  
227 data recipes, user forums, email or phone inquiry, etc. Due to space limitation, it is difficult to  
228 describe all data tools and services at the DAACs in one article. Since we focus on datasets for  
229 the hydrologic cycle in this article, data services at the GES DISC and other well-known services  
230 are presented.

### 231 **3.1. Point-and-click Online Tools**

232 Over the years, surveys (e.g. Kearns 2017) and experience from user support services at  
233 the GES DISC show that non-expert users and those who occasionally use satellite-based  
234 products prefer point-and-click data tools in order to obtain graphic and data assessment results.  
235 As mentioned above, new dataset assessment activities may not be straight-forward and can be  
236 costly. Point-and-click tools provide fast and easy access to satellite-based data products for all  
237 users without the need of coding and downloading data and software. Here, we introduce two  
238 popular point-and-click online tools developed by NASA: the NASA Worldview and the NASA  
239 GES DISC Giovanni.

#### 240 **3.1.1. NASA's Worldview**

241 NASA's Worldview is a tool developed by the NASA's EOSDIS project (Fig. 3). It  
242 provides the capability to interactively browse global, full-resolution satellite imagery and then  
243 download the underlying data (NASA 2017g). Worldview contains 400+ NASA satellite-based  
244 products and most of them are updated within three hours of observation, essentially showing the  
245 entire Earth as it looks "right now" (NASA 2017g). Worldview is a user-friendly online tool to  
246 support time-critical application areas such as wildfire management, air quality measurements,  
247 and flood monitoring. Mobile access is also available for Worldview. Worldview is powered by  
248 the Global Imagery Browse Services (GIBS) to rapidly retrieve its imagery for an interactive  
249 browsing experience (NASA 2017g). Data in Worldview images can be exported as several  
250 popular image formats such as JPEG and PNG. Image data in GeoTIFF and KMZ are also  
251 available. Figure 3 is a screenshot of Worldview, showing the Web interface and Hurricane  
252 Harvey in Gulf of Mexico on August 24, 2017. Hurricane Harvey made landfall near Corpus  
253 Christ, Texas, USA. A record-breaking flood in Houston, Texas was reported due to heavy

254 rainfall from Hurricane Harvey's rainbands. Fatalities and enormous economic loss in Houston  
255 were reported as well.

### 256 **3.1.2. NASA GES DISC Giovanni**

257 Point-and-click tools can be further developed for in-depth data analysis and  
258 visualization. A new infrastructure system, the Geospatial Interactive Online Visualization and  
259 Analysis Infrastructure (Giovanni, NASA 2017h), has been developed by the GES DISC to assist  
260 a wide range of users around the world with data access and evaluation, as well as with scientific  
261 exploration and discovery (Liu and Acker 2017; Acker and Leptoukh 2007). There are 8  
262 disciplines and 74 measurements available in Giovanni and they are listed in Tables 3 and 4,  
263 respectively. Over 1800 variables are currently available in Giovanni as of this writing and more  
264 are being added. Data variables in Giovanni are multi-missions and multi-disciplinary (Fig. 4).  
265 Users can access these variables without downloading data and software (Liu and Acker 2017).  
266 Over the years, a wide range of activities of using Giovanni has been reported by users, ranging  
267 from classroom activities to scientific investigation. Over 1300 peer-reviewed papers across  
268 various Earth science disciplines and other areas were published with help from Giovanni.

269 Giovanni has both Keyword and Faceted Search capabilities in its Web interface (Fig. 4)  
270 for locating variables of interest. For example, a search for 'precipitation' returns over 100  
271 related variables (Fig. 4). By using facets, one can filter for variables based on satellite missions  
272 (TRMM, GPM), instruments, spatial or temporal resolution, etc.

273 Many commonly used analytical and plotting capabilities (Liu and Acker 2017), used to  
274 capture spatial and temporal characteristics of datasets, are available in Giovanni. Mapping  
275 options include time-averaging, animation, accumulation (precipitation), time-averaged overlay  
276 of two datasets, and user-defined climatology. For time series, options include of area-averaged,



277 differences, seasonal, and Hovmöller diagrams. Cross-sections include latitude-pressure,  
278 longitude-pressure, time-pressure, and vertical profile for 3-D datasets from AIRS (Atmospheric  
279 Infrared Sounder) and MERRA. For data comparison, Giovanni has built-in processing code for  
280 data sets that require measurement unit conversion and regridding. Commonly used comparison  
281 functions include map and time-series differences, as well as correlation maps and X-Y scatter  
282 plots (area-averaged or time-averaged). Zonal means and histogram distributions can also be  
283 plotted. Samples of the analytical and plotting features are shown in Figs. 4 and 5.

284 Visualization features (Liu and Acker 2017) include interactive map area adjustment;  
285 animation; interactive scatter plots; adjustments of data range; change of color palette;  
286 contouring; and scaling (linear or log). The on-the-fly area adjustment feature allows an  
287 interactive and detailed examination of a result map without re-plotting data. Animations are  
288 helpful to track evolution of an event or seasonal changes. Interactive scatter plots allow  
289 identification of the geolocation of a point of interest in a scatter plot. Adjustments of any of  
290 these plots provide custom options to users.

291 To support increasing socioeconomic and GIS activities in Earth sciences, vector  
292 shapefiles have been added for countries, states in the United States, and major watersheds  
293 around the world. Available functions for shapefiles are time-averaged and accumulated maps,  
294 area-averaged time series, and histogram. Land-sea masks have been recently added.

295 All data files involved in Giovanni processing are listed and available in the lineage page.  
296 Available image formats are PNG, GEOTIFF, and KMZ (Keyhole Markup Language) that can  
297 be used for different applications and software packages; for example, KMZ files can be  
298 conveniently imported into Google Earth where a rich collection of overlays is available. All  
299 input and output data are available in NetCDF, which can be handled by many off-the-shelf

300 software packages. Furthermore, users can bookmark URLs generated by Giovanni processing  
301 for reference, documentation, or sharing with other colleagues.

### 302 **3.2. Data Rod Services**

303 Providing long time series data to the hydrology community can be a challenge (Teng et  
304 al. 2012). In hydrology, earth surface features are expressed as discrete spatial objects such as  
305 watersheds, river reaches, and point observation sites; and time varying data are contained in  
306 time series associated with these spatial objects. Long-time histories of data may be associated  
307 with a single point or feature in space. Most remote sensing precipitation products are expressed  
308 as continuous spatial fields, with data sequenced in time from one data file to the next.  
309 Hydrology tends to be narrow in space and deep in time, which poses a challenge during the  
310 GPM era. For example, to generate a one-year time series, one needs to pull all the 0.1 deg., half-  
311 hourly IMERG product, which can be time consuming and not suitable for online data services  
312 due to the large volume of data.

313 The concept of data rods (Teng et al. 2012; Gallaher and Grant 2012; Rui et al. 2012,  
314 2013) can be applied to this challenge. Teng et al. (2012) proposed two general solutions: 1)  
315 retrieve multiple time series for short time periods and stitch the multiple time series into desired  
316 single long time series and 2) reprocess (parameter and spatial subsetting) and archive data as  
317 one-time cost approach. The resultant time series files would be geospatially searchable and  
318 could be optimally accessed and retrieved by any user at any time (Teng et al. 2012). One  
319 drawback for the data rod approach is that there are a lot of files to be generated and maintained.  
320 For example, for IMERG, the number of files will be  $1300 \times 3600 = 4,680,000$ . At present, the  
321 concept has been implemented in CUAHSI-HIS (Consortium of Universities for the  
322 Advancement of Hydrologic Science, Inc. - Hydrologic Information System) and other

323 hydrologic community tools (Rui et al. 2013) where TMPA data time series data can be  
324 accessed.

### 325 **3.3. Other Web Data Services**

326 NASA satellite-based data products at the GES DISC are also accessible (NASA 2017i)  
327 via other Web services and protocols including https (the data archive), OPeNDAP, WMS, GDS,  
328 etc. These protocols support for data downloading activities such as daily operations on the  
329 user's side. The https method provides direct access to product archives. OPeNDAP, WMS,  
330 GDS, etc. provide remote access to individual variables within datasets in a form usable by many  
331 tools and software packages such as IDV, McIDAS-V, Panoply, Ferret, GrADS, etc. OPeNDAP  
332 is a framework that simplifies all aspects of scientific data networking and makes local data  
333 accessible to remote locations regardless of local storage format (OPeNDAP 2017). OPeNDAP  
334 software is freely available to anyone. WMS is a standard Web protocol for serving  
335 georeferenced map images over the Internet generated by a map server using data from a GIS  
336 database and the specifications developed and published by the Open Geospatial Consortium  
337 (OGC) in 1999 (WMS, 2017). The GDS, is a stable, secure data server that provides subsetting  
338 and analysis services across the internet (GDS 2017). The core of the GDS is OPeNDAP, a  
339 software framework used for data networking that makes local data accessible to remote  
340 locations.

## 341 **4. Examples**

### 342 **4.1. The Pearl River Delta**

343 The Pearl River Delta (PRD) is located in Guangdong province, the People's Republic of  
344 China (PRC). The PRD is a low-lying area surrounding the Pearl River estuary where the Pearl  
345 River flows into the South China Sea (Wikipedia 2017a). The region has experienced an

346 economic boom and accelerated urbanization since the region was named as one of the three  
347 Special Economic Zones (SEZs) by the PRC, and is one of the most densely urbanized regions in  
348 the world (Wikipedia 2017a). The city of Guangzhou has become a mega city, the 3rd largest in  
349 PRC and the largest in southern China, with a population of over 15 million. Adding the nearby  
350 cities, the total population in PRD is over 40 million, forming the so-called the Pearl River Delta  
351 Mega City. Figure 6 is the PRD viewed from the 2016 annual NASA black marble, a nighttime  
352 view of the Earth derived from a composite of data from the Visible Infrared Imaging  
353 Radiometer Suite (VIIRS) instrument on board the joint NASA/NOAA Suomi National Polar-  
354 orbiting Partnership (Suomi NPP) satellite. UHI effect is also quite visible from the MODIS-  
355 Terra monthly nighttime land-surface temperatures averaged between December 2016 and  
356 February 2017 (Fig. 7). Giving economic activities at such scale, it is important to understand  
357 environment impacts that are associated with economic activities and EO data play an important  
358 role to provide such analysis and information. In this chapter, we present few examples regarding  
359 how NASA EO datasets are used in this region.

#### 360 **4.1.1. Typhoon Nida Rainfall**

361 Formed on July 28, 2016, Typhoon Nida struck the Philippines in late July and made  
362 landfall in the PRD as a Category-1 typhoon (Fig. 8) in early August (Wikipedia 2017b).  
363 According to news reports, Nida caused heavy economic loss in the affecting countries and  
364 regions including the Philippines, the mainland of PRC, Hong Kong, and Vietnam (Wikipedia  
365 2017b). In PRC alone, ~495,000 people in five southern provinces were affected and 37,000  
366 required evacuation and 2,100 needed emergency assistances (Wikipedia 2017b). Homes and  
367 crops were destroyed or damaged. People's lives in the region were severely disrupted,  
368 according to news reports (Wikipedia 2017b).

369 NASA EO data are available for Nida. At the GES DISC, precipitation from TMPA,  
370 GPM, IMERG, MERRA, GLDAS, etc. with different spatial and temporal resolutions are  
371 available for research and analysis. Figure 8 is an example of total rainfall in mm accumulated  
372 between August 1-5, 2016. It is seen that heavy rainfall was received in the western part of the  
373 PRD and the heaviest rainfall area is found in the adjacent ocean off the coast of the PRD (Fig.  
374 8). MERRA provides data such as wind, temperature, pressure, etc. for meteorological analysis.  
375 GLDAS provides data for hydrological research and analysis. Many of these datasets are  
376 available in the GES DISC Giovanni and ready for assessment, analysis, and visualization  
377 without the need to download data and software.

#### 378 **4.1.2. Atmospheric Composition Preliminary Analysis**

379 As mentioned, the PRD has experienced an unprecedented economic growth and  
380 urbanization since 1979. The environmental conditions in the region have also experienced the  
381 changes, which requires EO data for research and analysis. MERRA uses various NASA satellite  
382 observations and the chemistry model to generate reanalysis products for research and  
383 applications. Figures 9 and 10 are the time series plots of sample MERRA-2 atmospheric  
384 chemistry variables for the PRD: monthly aerosol optical depth, SO<sub>2</sub> surface mass concentration,  
385 CO surface concentration, and black carbon surface mass concentration, showing seasonal and  
386 inter-annual variations in the PRD over the past 30+ years. In Fig. 9, it is seen that aerosol  
387 optical depth experienced a large increasing trend since 2000, followed by a decreasing trend  
388 after mid-2000 or so. According to reports (Wikipedia 2017c), the PRD region's GDP in 2005  
389 was ~US\$221.2 billion, compared to US\$89 billion in 2000. Further investigation is needed to  
390 better understand and link these observation results with the economic growth in the region. The  
391 SO<sub>2</sub> surface mass concentration experienced a steady increase before 2000, followed a rapid

392 climb shortly after 2000 (Fig. 9). The increasing period ended near 2010 and the concentration  
393 still remained high with fluctuations afterwards (Fig. 9). The similar trends are also found in CO  
394 surface concentration (Fig. 10). The black carbon surface mass concentration (Fig. 10) is quite  
395 similar to the aerosol optical depth in Fig. 9. It is necessary to point out that these time series  
396 plots in Figs. 9 and 10 are preliminary and need to be verified independently with ground  
397 measurements to ensure that biases and other issues are addressed properly.

#### 398 **4.2. Estimation of Hurricane Contribution to Annual Precipitation in Maryland, USA**

399 The state of Maryland, USA is located in the Mid-Atlantic region near the nation's capital  
400 or the Washington D.C. According the 2016 report (Censor Bureau 2016) from the U.S. Censor  
401 Bureau, the population of the region that consists of Washington-Arlington-Alexandria and D.C.-  
402 Virginia-Maryland-West Virginia, reached over 6 million in 2015 and became the 6<sup>th</sup> most  
403 populous metro area in the U.S.

404 Despite the fact that major hurricanes (category 3 or above) rarely make landfall in the  
405 state, Maryland is indirectly influenced by hurricane remnants (NOAA 2017a) such as rainfall.  
406 Giving the global warming scenario, it is important to understand changes of hurricane size,  
407 track and intensity since all of them could have significant impacts on precipitation in Maryland.  
408 In this study, the TMPA precipitation products were used to assess hurricane precipitation.  
409 Unlike many land-only precipitation products, the TMPA products not only provide precipitation  
410 information over land but also over oceans, therefore, they are suitable for this type of study. The  
411 objectives of this study are to estimate hurricane contribution to annual precipitation in Maryland  
412 and its inter-annual variation (Liu and Liu 2015). The methodology could be applied to other  
413 states or regions as well.

##### 414 **4.2.1. Data and Methods**

415           The Version-7 3-hourly (3B42) and monthly (3B43) TMPA products are used in this  
416 study. 3B42 and 3B43 provide a near-global (50° N-S) coverage of both land and oceans and  
417 allow tracking of hurricane precipitation since some hurricanes can pass by Maryland over ocean  
418 without making landfall and influence the state with rain, winds, waves, etc.

419           The TMPA algorithm (Huffman 1997; Huffman et al. 2007, 2010; Huffman and Bolvin  
420 2014) consists of multiple independent precipitation estimates from the TMI (TRMM  
421 Microwave Imager), Advanced Microwave Scanning Radiometer for Earth Observing Systems  
422 (AMSR-E), Special Sensor Microwave Imager (SSM/I), Special Sensor Microwave  
423 Imager/Sounder (SSMIS), Advanced Microwave Sounding Unit (AMSU), Microwave Humidity  
424 Sounder (MHS), microwave-adjusted merged geo-infrared (IR), and monthly accumulated rain  
425 gauge analysis from the Global Precipitation Climate Centre (GPCC). The preprocessing  
426 (Huffman and Bolvin 2014) of the TMPA products is as follows: (a) all input passive microwave  
427 (PMW) products mentioned above are inter-calibrated to TRMM Combined Instrument (TCI)  
428 precipitation estimates (TRMM product 3B31); (b) the IR estimates are computed using monthly  
429 matched microwave-IR histogram matching; (c) then missing data in individual 3-hourly  
430 merged-microwave fields are filled with the IR estimates. When the preprocessing is complete,  
431 the 3-hourly multi-satellite fields are summed for the month and combined with the monthly  
432 GPCC gauge analysis using inverse-error-variance weighting to form the best-estimate  
433 precipitation rate and RMS precipitation-error estimates (Huffman and Bolvin 2014).

434           On April 15, 2015, TRMM was decommissioned after 17 years of continuously  
435 collecting data from space. Although the TMPA is still in production using the remaining  
436 satellites in the constellation, the changes and impact of the loss of TRMM on the TMPA  
437 characteristics are expected to be small since TRMM only covers a band of 38° N-S and most of

438 Maryland is located north of this band. In addition, the use of gauge data from GPCC will correct  
439 biases due to the loss of TRMM. The TMPA data between 1998 and 2013 are used in this study.

440 TMPA (Version 7) products were downloaded from the GES DISC (Liu et al. 2012).  
441 There have been few processing issues (Huffman and Bolvin 2014) before, but all the TMPA  
442 data used in this study are current.

443 Hurricane track data were obtained from the Best Track Data (HURDAT2), available at  
444 the NOAA National Hurricane Center (NOAA 2017b). The radius for hurricane influence is set  
445 to 500 km (Jiang and Zipser 2010), given typical

446 When tropical cyclones make landfall, they leave moist tropical and sub-tropical oceans  
447 and enter drier land in mid-latitudes. As a result, water vapor as energy supply from underneath  
448 is cut off and they quickly lose strength and become remnants. When the remnants interact with  
449 frontal systems in mid-latitudes, rainfall is often enhanced when tropical warm and moist air  
450 collides with cooler and drier air from north and extra lifting is generated. Meanwhile, it is  
451 difficult to separate rainfall areas between tropical cyclones and frontal systems. In this study, we  
452 do not attempt to separate the two rain regimes when they collide together. As long as the track  
453 data are still available, rainfall within the 500-km radius is considered as hurricane rainfall (Jiang  
454 and Zipser 2010).

455 The terrain of Maryland is characterized with the Appalachian Mountains in the west,  
456 running through the panhandle (can obstruct passing cold fronts and cause rain shadow) and the  
457 flat area in the east adjacent to the Atlantic Ocean (exposes area to coastal weather systems).

#### 458 **4.1.1. Preliminary Results**

459 From 1998 to 2014, Hurricane Floyd, Charley, Ernesto, and Irene influenced the state of  
460 Maryland. Our preliminary results from Fig. 11 show that Maryland experienced relatively high



461 amounts of precipitation in years 2003 and 2011 and relatively low amounts precipitation in the  
462 year 2001. In addition, further calculations show the average annual precipitation in Maryland is  
463 about 1200 mm/year. Figure 11 shows how much precipitation that hurricanes have contributed  
464 to annual precipitation. The highest contribution of precipitation (35%) occurred in 2011, due to  
465 major hurricanes passing through Maryland such as Hurricane Irene. Additionally, in 2001 when  
466 Maryland was experiencing a drought, no hurricanes passed through the state. The average  
467 contribution of precipitation by hurricanes to annual precipitation is about 15%. Figure 11 shows  
468 the average of the average annual precipitation compared against each year's precipitation with  
469 and without precipitation contributed by hurricanes. Results show that when precipitation  
470 contributed by hurricanes is removed, most annual precipitations fall below the average. Some  
471 exceptions occur such as in year 2003, where Maryland was receiving relatively high monthly  
472 precipitation in general throughout the year. As a result, one could conclude that precipitation  
473 contributed by hurricanes does affect Maryland's precipitation.

## 474 **5. Summary and Future Plans**

475 In this chapter, we introduce NASA satellite-based data and services with emphasis on  
476 the hydrologic cycle and data products at the GES DISC. Significant progress has been made in  
477 satellite Earth's observations since the first successful launch of weather satellite, TIROS, by  
478 NASA on April 1, 1960. In particular, NASA's EOS project is a coordinated series of polar-  
479 orbiting and low inclination satellites for long-term global observations of the land surface,  
480 biosphere, solid Earth, atmosphere, and oceans to enable an improved understanding of the Earth  
481 as an integrated system. NASA's EOS and other past NASA satellite mission data are available  
482 and distributed by the EOSDIS, with major facilities at twelve DAACs located throughout the  
483 United States. Science disciplines at twelve DAACs include atmosphere, cryosphere, human

484 dimensions, land, ocean, and calibrated radiance and solar radiance, etc. Datasets are emphasized  
485 and used in the examples in this article are archived at the GES DISC.

486         The GES DISC hosts global and regional satellite-based data products from these science  
487 disciplines: precipitation, solar irradiance, atmospheric composition and dynamics, global  
488 modeling, etc. There are over 2700 unique data products archived at the GES DISC. In this  
489 chapter, we only present several major projects that are closely related to smart cities.

490         Multi-satellite and multi-sensor merged global precipitation products are available at the  
491 GES DISC. In particular, The IMERG suite contains of three output products, “Early satellites”  
492 (lag time: ~4 hours), “Late satellites” (lag time: ~18 hours), and the final “Satellite-gauge” (lag  
493 time: ~2 months) along with additional new input and intermediate files. The retro-processing of  
494 the IMERG product suite back to the TRMM era will be released in late 2018.

495         Global and regional land data assimilation system data products include optimal fields of  
496 land surface states and fluxes. They are generated by ingesting satellite- and ground-based  
497 observational data products and using advanced land surface modeling and data assimilation  
498 techniques. Both forcing data and model results support water resources applications, numerical  
499 weather prediction studies, numerous water and energy cycle investigations, and also serve as a  
500 foundation for interpreting satellite and ground-based observations.

501         The Modern-Era Retrospective analysis for Research and Applications, Version 2  
502 (MERRA-2), has been developed at the NASA Global Modeling and Assimilation Office  
503 (GMAO) at the NASA Goddard Space Flight Center. MERRA-2 provides global data beginning  
504 in 1980 and runs a few weeks behind real time. Alongside the meteorological data assimilation  
505 using a modern satellite database, MERRA-2 includes an interactive analysis of aerosols that  
506 feed back into the circulation, uses NASA's observations of stratospheric ozone and temperature

507 (when available), and takes steps towards representing cryogenic processes. The MERRA project  
508 focuses on historical analyses of the hydrological cycle on a broad range of weather and climate  
509 time scales and places the NASA EOS suite of observations in a climate context.

510 Two popular point-and-click tools are presented. First, NASA's Worldview provides the  
511 capability to interactively browse global, full-resolution satellite imagery and then download the  
512 underlying data (NASA 2017g). Worldview contains 400+ NASA satellite-based products and  
513 most of them are updated within three hours of observation, essentially showing the entire Earth  
514 as it looks "right now" (NASA 2017g). On the other hand, NASA's GES DISC Giovanni is  
515 designed for in-depth data analysis and visualization. There are 8 disciplines and 74  
516 measurements available in Giovanni and they are listed in Tables 3 and 4, respectively. Over  
517 1700 variables are currently available in Giovanni as of this writing and more are being added.  
518 Data variables in Giovanni are multi-disciplinary and users can access them without  
519 downloading data and software (Liu and Acker 2017). Over the years, a wide range of activities  
520 of using Giovanni has been reported by users, ranging from classroom activities to scientific  
521 investigation. Over 1300 peer-reviewed papers across various Earth science disciplines and other  
522 areas were published with help from Giovanni.

523 NASA satellite-based data products at the GES DISC are also accessible (NASA 2017i)  
524 via other Web services and protocols including https (the data archive), OPeNDAP, WMS, GDS,  
525 etc.

526 Two examples were presented regarding the use of satellite-based data products in  
527 understanding environment changes and conditions in megacities. In Example 1, the TMPA  
528 precipitation dataset was presented with the accumulated rainfall map for Typhoon Nida that  
529 made landfall in the PRD region. Time series plots of several atmospheric composition datasets

530 from MERRA-2 were plotted and analyzed, showing significant changes in the atmospheric  
531 environment in PRD, which could be associated with the unprecedented economic growth and  
532 urbanization in the region, especially since 2000. It is necessary to mention that these  
533 preliminary results need to be verified independently with ground or other measurements to  
534 address biases and other issues.

535 In Example 2, the effect of hurricanes on annual precipitation in Maryland was  
536 investigated. From 1998 to 2014, Hurricane Floyd, Charley, Ernesto, and Irene influenced the  
537 state of Maryland. Our preliminary results from Fig. 11 show that Maryland experienced  
538 relatively high amounts of precipitation in years 2003 and 2011 and relatively low amounts  
539 precipitation in the year 2001. In addition, further calculations show the average annual  
540 precipitation in Maryland is about 1200 mm/year. Figure 11 shows how much precipitation  
541 hurricanes have contributed to annual precipitation. The highest contribution of precipitation  
542 (35%) occurred in 2011, possibly due to major hurricanes passing through Maryland such as  
543 Hurricane Irene. Additionally, in 2001 when Maryland was experiencing a drought, no  
544 hurricanes passed through the state. The average contribution of precipitation by hurricanes to  
545 annual precipitation is about 15%. Figure 11 shows the average of the average annual  
546 precipitation compared against each year's average precipitation with and without precipitation  
547 contributed by hurricanes. Results show that when precipitation contributed by hurricanes is  
548 removed, most annual precipitations fall below the average for each. Some exceptions occur  
549 such as in year 2003, where Maryland was receiving relatively high monthly precipitation in  
550 general. As a result, one could conclude that precipitation contributed by hurricanes does affect  
551 Maryland's precipitation.

552 As of this writing, EOSDIS hosts ~22 PB of Earth Observation (EO) data at twelve  
553 DAACs and it is expected to grow to more than 37 (246 PB) PB by 2020 (2025) (NASA 2017a).  
554 Such large EO data archive is an important asset for environmental research and applications  
555 around the world. Over the years, NASA EOSDIS has developed data services and tools to  
556 facilitate data discovery and access in twelve discipline-oriented DAACs. For complex issues of  
557 smart cities, it often requires a multi-disciplinary approach which needs an information system  
558 that can integrate all these data products archived at twelve DAACs as well as other related data  
559 products from users, providing a one-stop shop for data and services by removing obstacles such  
560 as data discovery, access, interoperability, etc. and better address environmental issues  
561 encountered in city planning, operations, research, etc. (Güneralp and Seto 2008). The NASA  
562 GES DISC Giovanni is an example that makes multi-discipline data variables available in one  
563 place and efforts are being carried out to include additional datasets from other DAACs and  
564 make them available in Giovanni. The ongoing NASA EOSDIS Cloud Evolution Project (NASA  
565 2017j) will have the potential for developing an information system that supports multi-  
566 disciplinary data products and services. Moving from discipline-oriented to multi-discipline-  
567 oriented data services is not a simple task, which will involve in a team of data scientists from  
568 NASA and other organizations as well as from end users of smart cities due to many obstacles to  
569 be overcome such as data formats, data volume, data structures, terminology in different  
570 disciplines, etc. Nonetheless, still a lot of work needs to be done to develop better information  
571 systems and services for efficiently solving problems in smart cities.

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838

839 **Table 1.** EOSDIS DAACs and their archived products (NASA 2017b).

<b>Distributed Active Archive Center (DAAC)</b>	<b>Data Products</b>
Alaska Satellite Facility (ASF) DAAC	SAR products, sea ice, polar processes, geophysics, etc.
Atmospheric Science Data Center (ASDC)	Radiation budget, clouds, aerosols, tropospheric chemistry, etc.
Crustal Dynamics Data Information System (CDDIS)	Space geodesy, solid Earth, etc.
Global Hydrology Resource Center (GHRC) DAAC	Hydrologic cycle, severe weather interactions, lightning, atmospheric convection, etc.
Goddard Earth Sciences Data and Information Services Center (GES DISC) Land Processes DAAC (LP DAAC)	Global precipitation, solar irradiance, atmospheric composition and dynamics, global modeling, etc. Surface reflectance, land cover, vegetation indices, etc.
Level 1 and Atmosphere Archive and Distribution System (LAADS) DAAC	MODIS and VIIRS Level-1 and atmosphere data products
National Snow and Ice Data Center (NSIDC) DAAC	Snow and ice, cryosphere, climate interactions, sea ice, etc.
Oak Ridge National Laboratory (ORNL) DAAC	Biogeochemical dynamics, ecological data, environmental processes, etc.
Ocean Biology DAAC (OB.DAAC)	Ocean biology, sea surface temperature, etc.
Physical Oceanography DAAC (PO.DAAC)	Gravity, sea surface temperature, ocean winds, topography, circulation and currents, etc.
Socioeconomic Data and Applications Data Center (SEDAC)	Human interactions, land use, environmental sustainability, geospatial data, etc.

840  
841 **Table 2.** Global gridded multi-sensor and multi-satellite precipitation products (Liu et al. 2012,  
842 2017).

<b>Dataset</b>	<b>Description</b>	<b>Date Range</b>	<b>Spatial Resolution and coverage</b>	<b>Temporal Resolution</b>
The Integrated Multi-satellite Retrievals for GPM (IMERG) – “Early, Late, and Final”	Rain rate from multi-satellite, multi-sensor and gauge measurements	1998-01-01 - present	Gridded 10 km, global, initially 60°N-60°S	Half-hourly, daily, and monthly
TRMM Multi-satellite Precipitation Analysis (Near-real-time, Research)	Rain rate from multi-satellite and multi-sensor measurements	1998-01-01 - present	Gridded 25 km, 60°N-60°S (Research: 50°N-50°S)	3-hourly, daily and monthly

843 **Table 3.** Disciplines and variables in Giovanni (NASA 2017h).

<b>Disciplines (No. of Variables)</b>
Aerosols (183)
Atmospheric Chemistry (79)
Atmospheric Dynamics (385)
Cryosphere (15)
Hydrology (997)
Ocean Biology (44)
Oceanography (48)
Water and Energy Cycle (1065)

844

845 **Table 4.** Measurements and variables in Giovanni (NASA 2017h).

<b>Measurement (No. of Variables)</b>							
Aerosol Index (3)	Buoyancy (2)	Dust (23)	Height, Level (12)	OLR (19)	Runoff (63)	Soil Temperature (105)	Water Storage (1)
Aerosol Optical Depth (83)	CH4 (16)	Emissivity (4)	Incident Radiation Anomaly (2)	Organic Carbon (8)	SO2 (4)	Statistics (24)	Wind Stress Magnitude (4)
Air Pressure Anomaly (1)	CO2 (2)	Erythemat UV (4)	Incident Radiation (70)	Ozone (28)	SO4 (4)	Streamflow (1)	Wind Velocity (7)
Air Pressure (51)	Canopy Water Storage (6)	Evaporation Anomaly (1)	Iron (2)	Particulate Matter (42)	Scattering Angle (4)	Surface Runoff (1)	Wind (72)
Air Temperature (84)	Chlorophyll (11)	Evaporation (44)	Irradiance (6)	Phytoplankton (16)	Sea Salt (5)	Sea Surface Temperature (3)	Surface Temperature (55)
Albedo (21)	Cloud Fraction (32)	Evapotranspiration (41)	Latent Heat Flux (5)	Precipitation Anomaly (2)	Sensible Heat Flux (5)	Total AOD Climatology Anomaly (6)	Total Aerosol Optical Depth (49)
Altitude (8)	Cloud Properties (75)	Flooding (3)	Latent Heat (1)	Precipitation (107)	Sensible Heat (1)		UV Exposure (1)
Angstrom Exponent (17)	Component Aerosol Optical Depth (7)	Geopotential (11)	Mixed Layer Depth (2)	Quality Info (1)	Radiation, Net (56)	Snow/Ice (37)	Vegetation (9)
Atmospheric Moisture (114)		Heat Flux (102)	NO2 (2)	Radiation, Net (56)	Reflectivity (25)	Soil Moisture (203)	Vorticity (2)
Black Carbon (5)	Diffusivity (1)		Nitrate (2)				

846 **Figure captions:**

847

848 Figure 1. Cities in Asia viewed from the 2016 annual NASA black marble, a nighttime view of  
849 the Earth , derived from a composite of data from the Visible Infrared Imaging Radiometer Suite  
850 (VIIRS) instrument on board the joint NASA/NOAA Suomi National Polar-orbiting Partnership  
851 (Suomi NPP) satellite (Lee et al. 2006). (Credit: NASA Worldview).

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853 Figure 2. NASA Earthdata (NASA 2017b) provides a Web interface for searching and accessing  
854 NASA data at twelve EOSDIS DAACs.

855

856 Figure 3. The NASA Worldview Web interface (NASA 2017g) showing Hurricane Harvey in  
857 Gulf of Mexico on August 24, 2017.

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859 Figure 4. Top: The Web portal of NASA GES DISC Giovanni (NASA 2017h) with many  
860 features for easy locating a variable of interest, data analysis, and visualization; Middle:  
861 Corrected reflectance (true color) from MODIS Aqua on September 4, 2017, showing smoke  
862 from forest fires spreads across the United States and Canada (More detailed story is available at,  
863 <https://earthobservatory.nasa.gov/IOTD/view.php?id=90899>). Bottom: The combined dark target  
864 and deep blue aerosol optical depth (AOD) at 0.55 micron for land and ocean from MODIS  
865 Aqua on September 4, 2017. Combined with NASA Worldview, Giovanni provides analysis and  
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868 Figure 5. Sample graphics from Giovanni. Top: Accumulated rainfall (the GPM IMERG Late  
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881 product).

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883 Figure 9. Time series from MERRA-2 showing seasonal and internal variations of monthly  
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890 contributed precipitation highlighted. Bottom: Average annual precipitation (in red) in Maryland

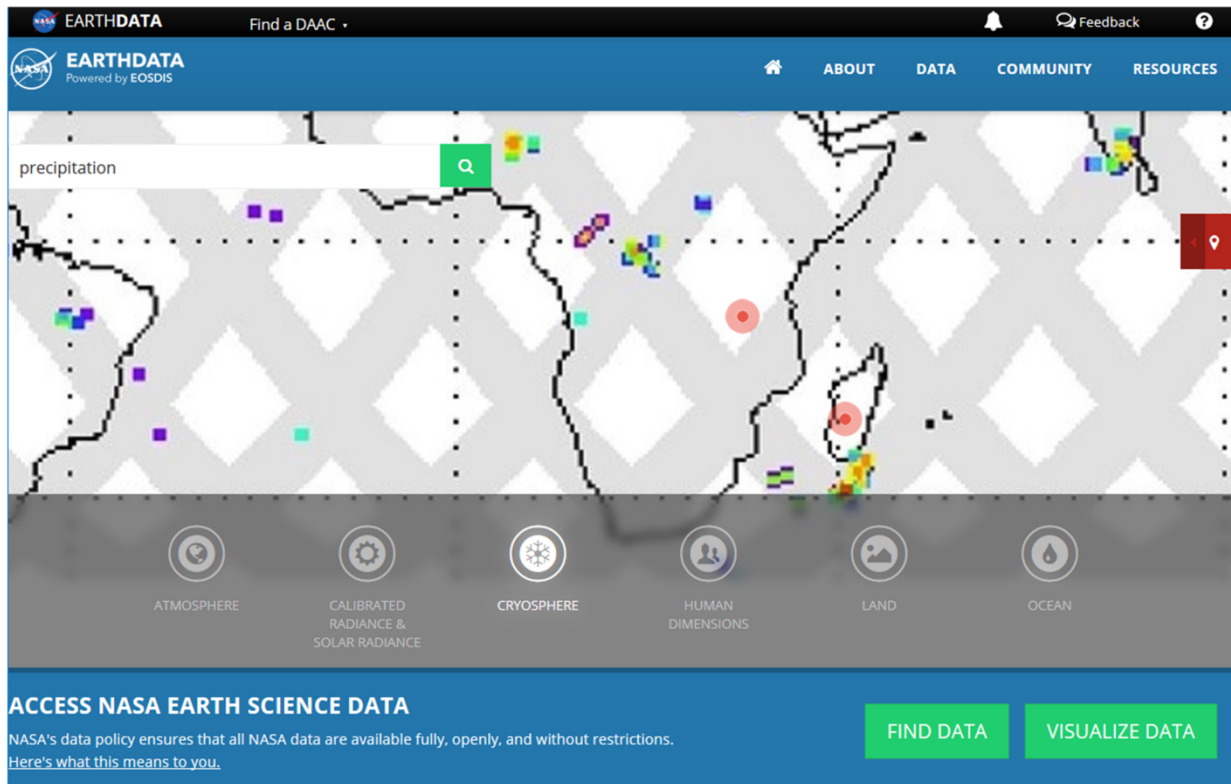


891 compared against annual precipitation with (in green) and without (in blue) hurricane contributed  
892 precipitation (units: mm).  
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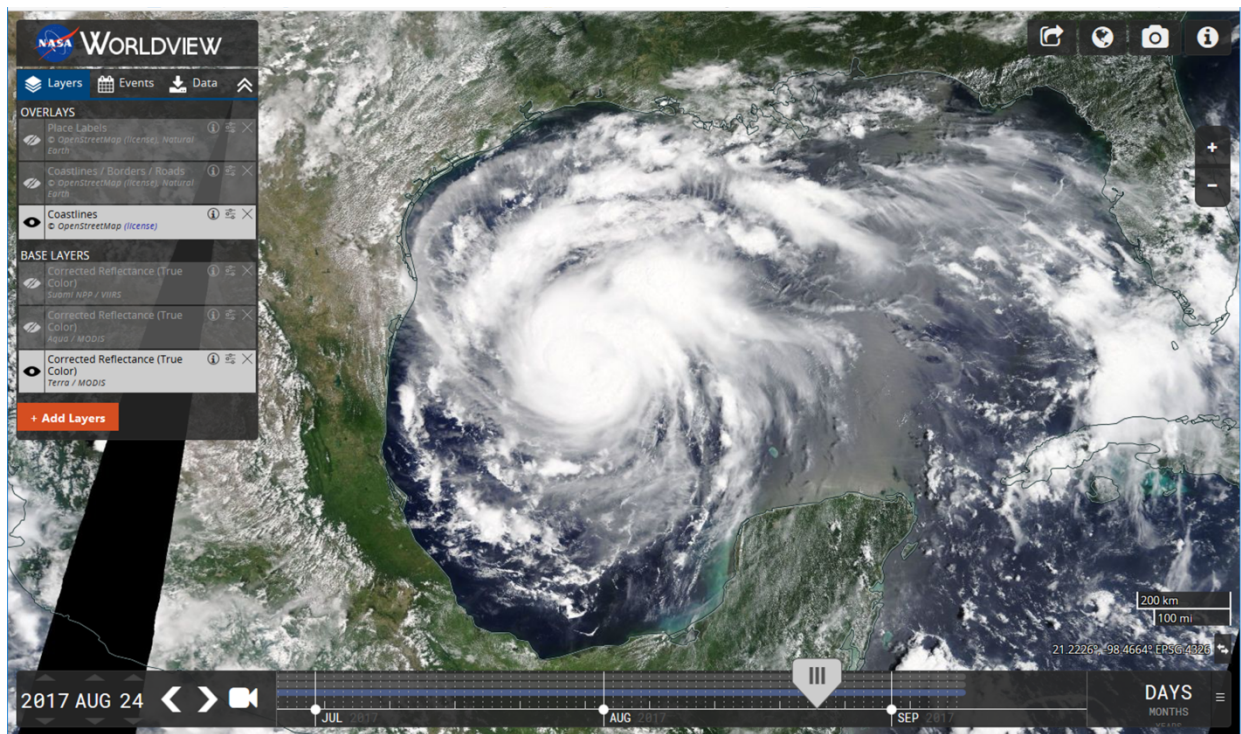
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908



**GIOVANNI** The Bridge Between Data and Science v 4.23 [Release Notes](#) [Browser Compatibility](#) [Known Issues](#)  
 MODIS OPeNDAP server continuing problem ... [1 of 2 messages] [Read More](#)

Select Plot  
 Maps: Time Averaged Map  Comparisons: Select...  Vertical: Select...  Time Series: Select...  Miscellaneous: Select...

Select Date Range (UTC) Select Region (Bounding Box or Shape)  
 YYYY-MM-DD HH:mm Format: West, South, East, North  
 - - - - - to - - - - -  
 Valid Range: 1948-01-01 to 2017-09-08

Please specify a start date.

Select Variables

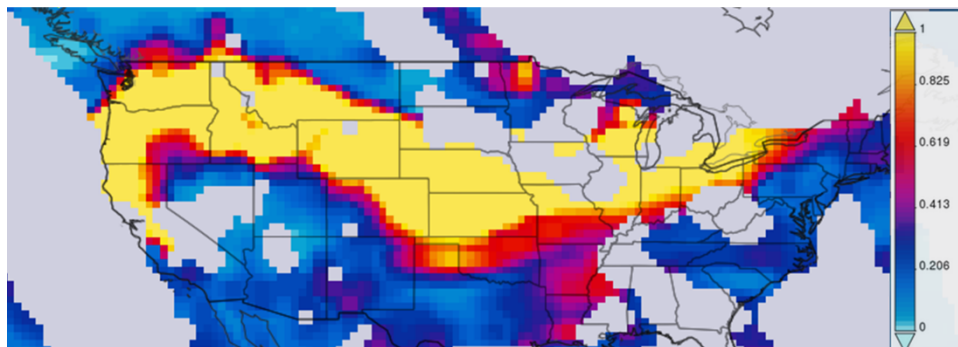
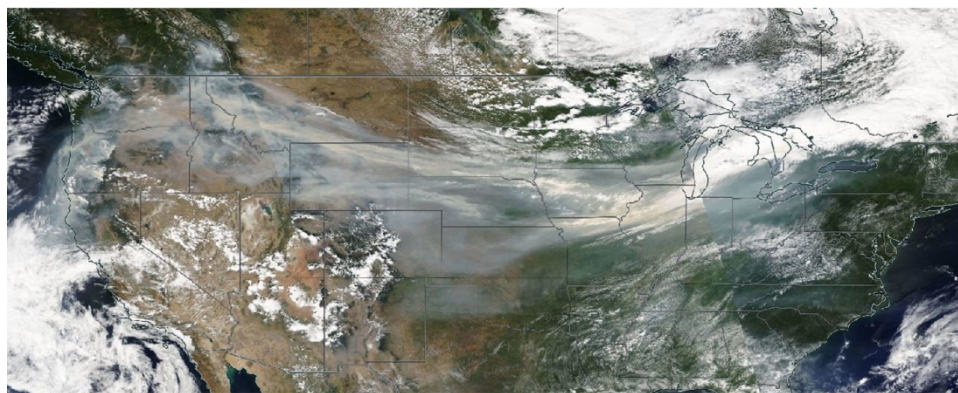
**Disciplines**  
 Atmospheric Dynamics (16)  
 Cryosphere (1)  
 Hydrology (98)  
 Water and Energy Cycle (82)

**Measurements**  
 Atmospheric Moisture (1)  
 Cloud Properties (1)  
 Precipitation Anomaly (2)  
 Precipitation (107)  
 Snow/ice (5)

► Platform / Instrument  
 ► Spatial Resolutions

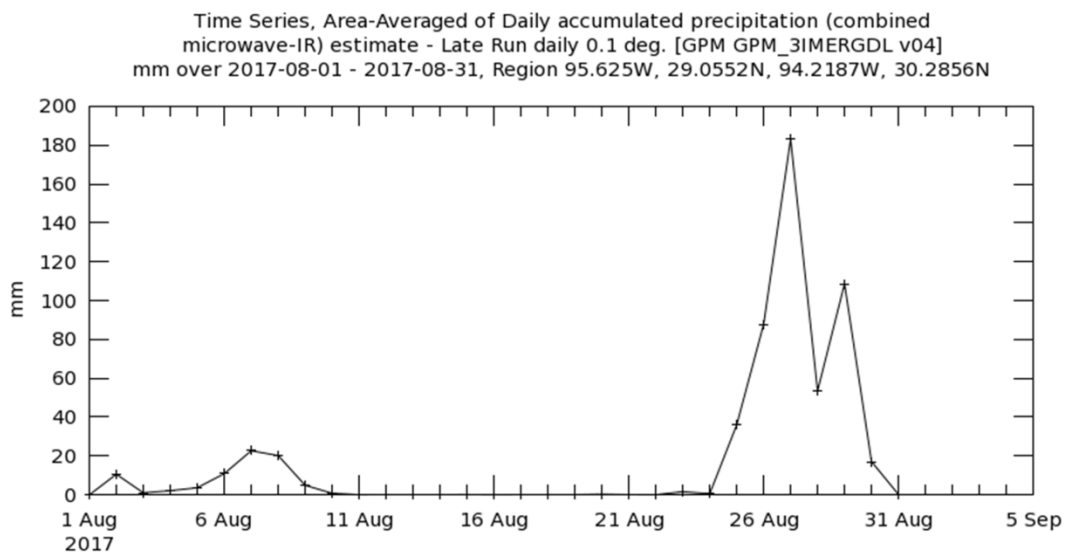
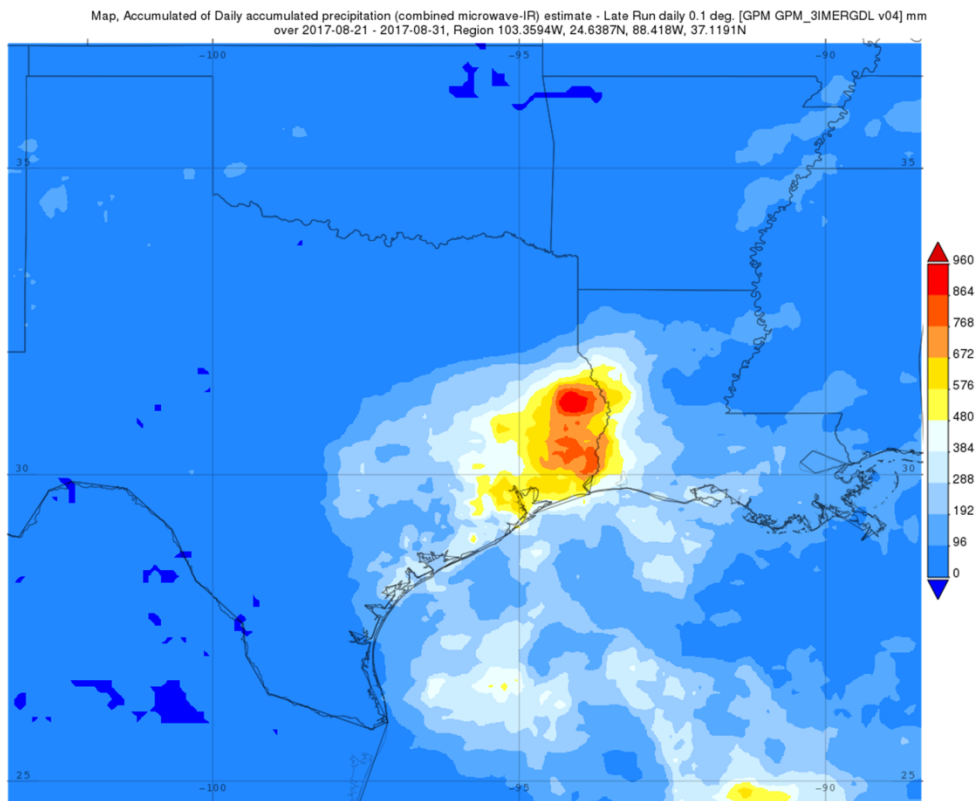
Number of matching Variables: 112 of 1735 Total Variable(s) included in Plot: 0  
 Please select at least 1 variable  
 Keyword: precipitation

Variable	Source	Temp. Res.	Spat. Res.	Begin Date	End Date	Units	Vert. Slice
<input type="checkbox"/> Cloud.Ice (TRMM_3A12.v7)	TRMM	Monthly	0.5 °	1997-12-01	2015-03-31	g/m <sup>3</sup>	0.5 km
<input type="checkbox"/> Rain.Rate (TRMM_3A12.v7)	TRMM	Monthly	0.5 °	1997-12-01	2015-03-31	mm/hr	-
<input type="checkbox"/> Precipitation.Rate (TRMM_3A12.v7)	TRMM	Monthly	0.5 °	1997-12-01	2015-03-31	mm/hr	-
<input type="checkbox"/> Precipitation.Snow (TRMM_3A12.v7)	TRMM	Monthly	0.5 °	1997-12-01	2015-03-31	g/m <sup>3</sup>	0.5 km
<input type="checkbox"/> Precipitation.Rain (TRMM_3A12.v7)	TRMM	Monthly	0.5 °	1997-12-01	2015-03-31	g/m <sup>3</sup>	0.5 km
<input type="checkbox"/> Graupe (TRMM_3A12.v7)							
<input type="checkbox"/> Precipitation (TRMM_3A12.v7)							



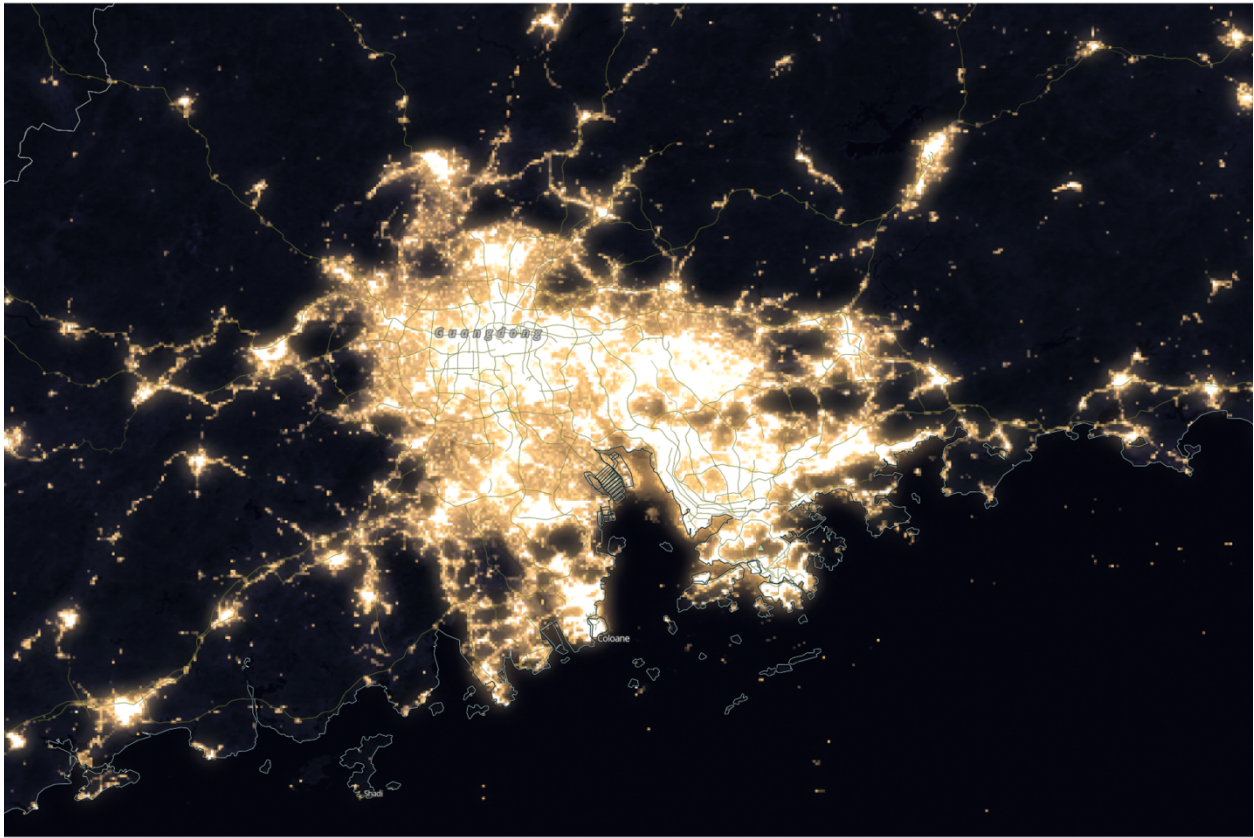
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 916 Aqua on September 4, 2017. Combined with NASA Worldview, Giovanni provides analysis and  
 917 visualization of the smoke aerosol for the event.  
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919

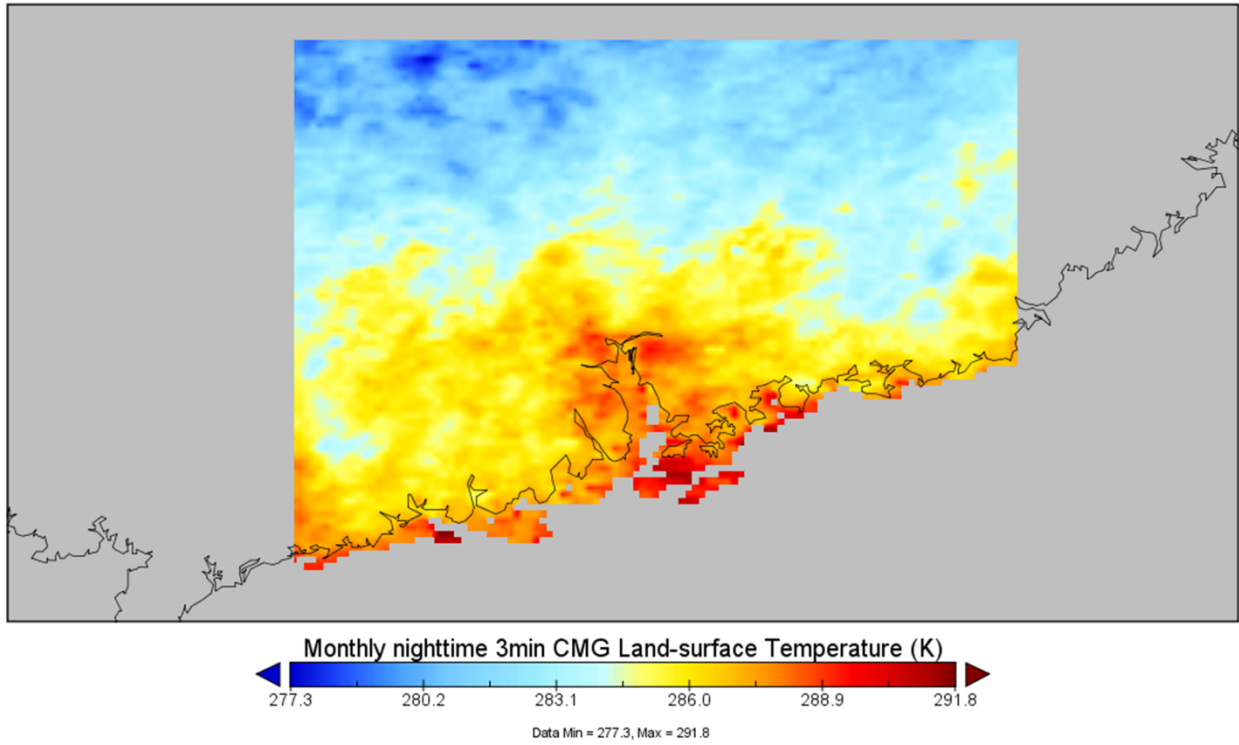
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928

Monthly nighttime 3min CMG Land-surface Temperature

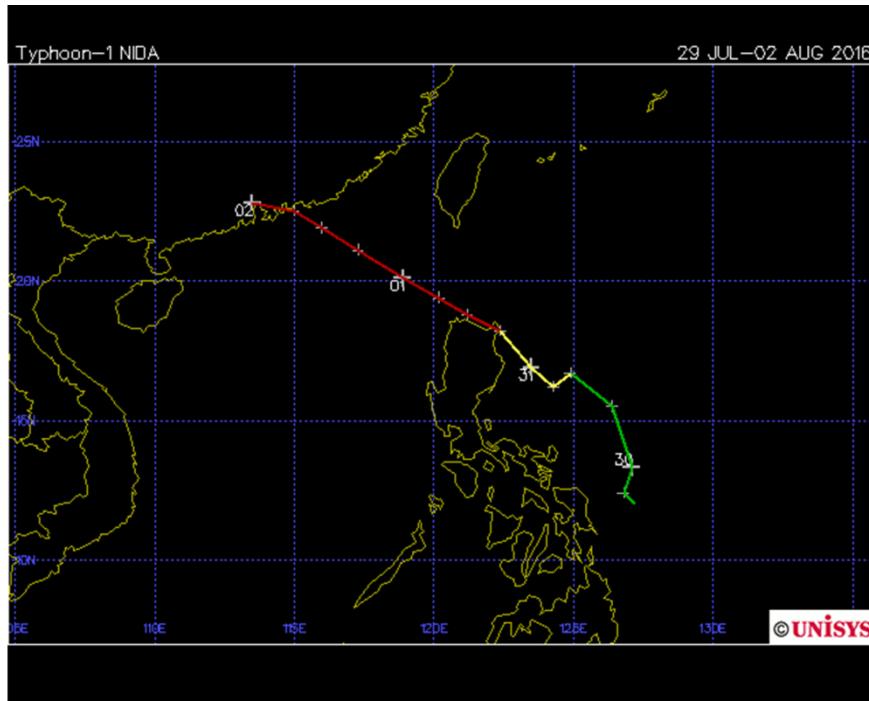


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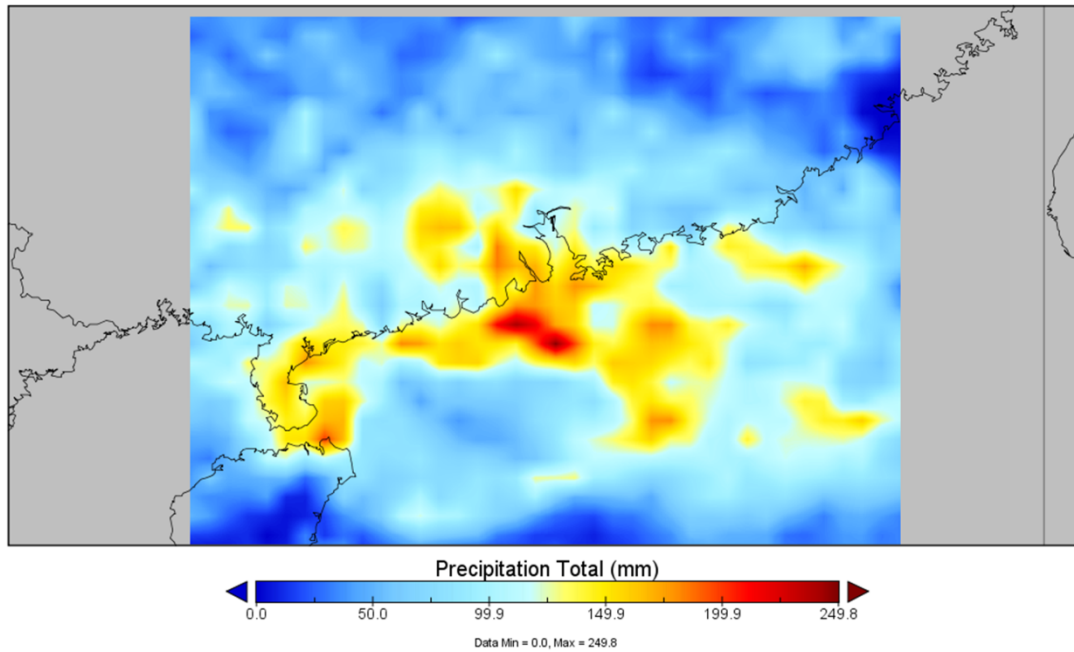
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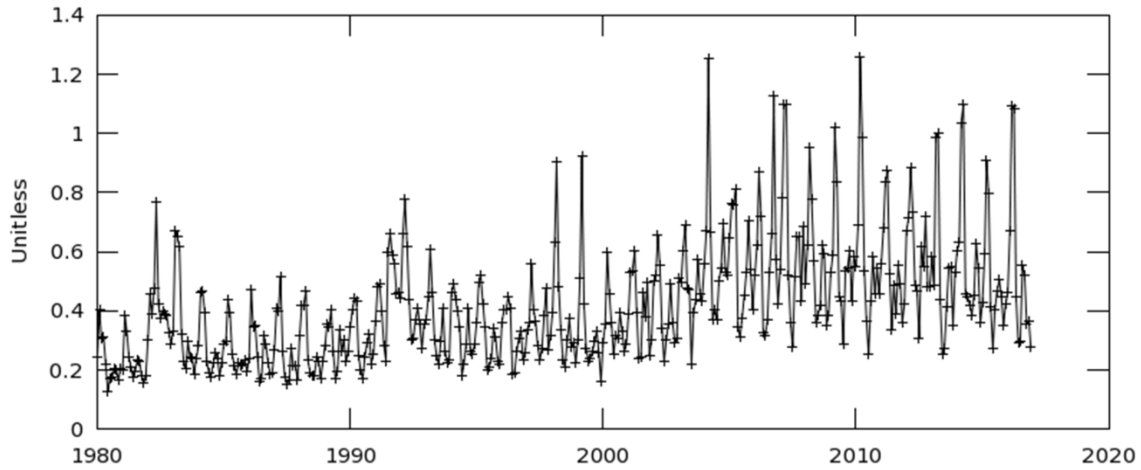
Precipitation Total



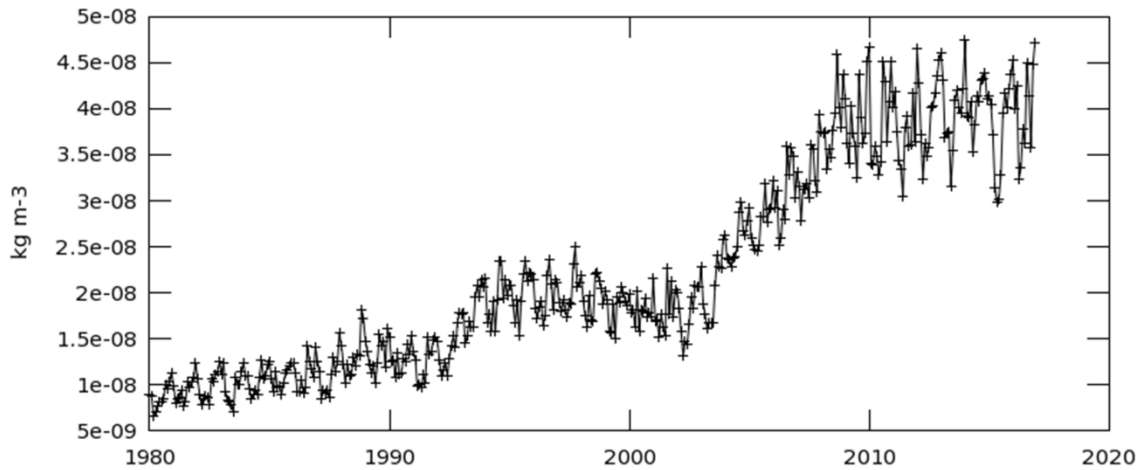
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Time Series, Area-Averaged of Aerosol Optical Depth Analysis monthly 0.5 x 0.625 deg. [MERRA-2 Model M2IMNXGAS v5.12.4] over 1980-Jan - 2016-Dec, Region 112.2803E, 22.0679N, 114.7852E, 23.9136N



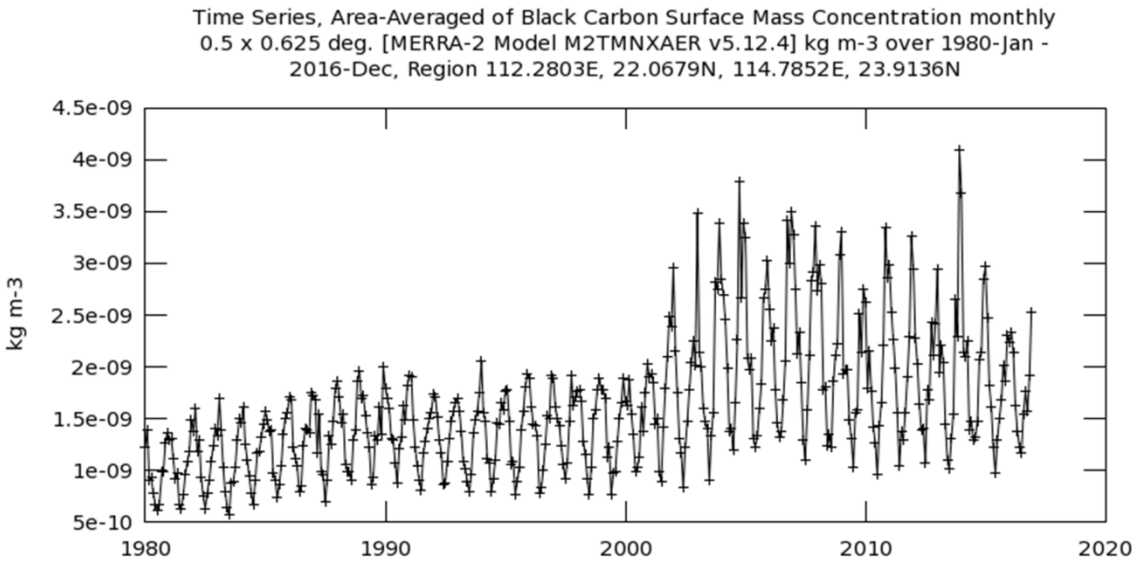
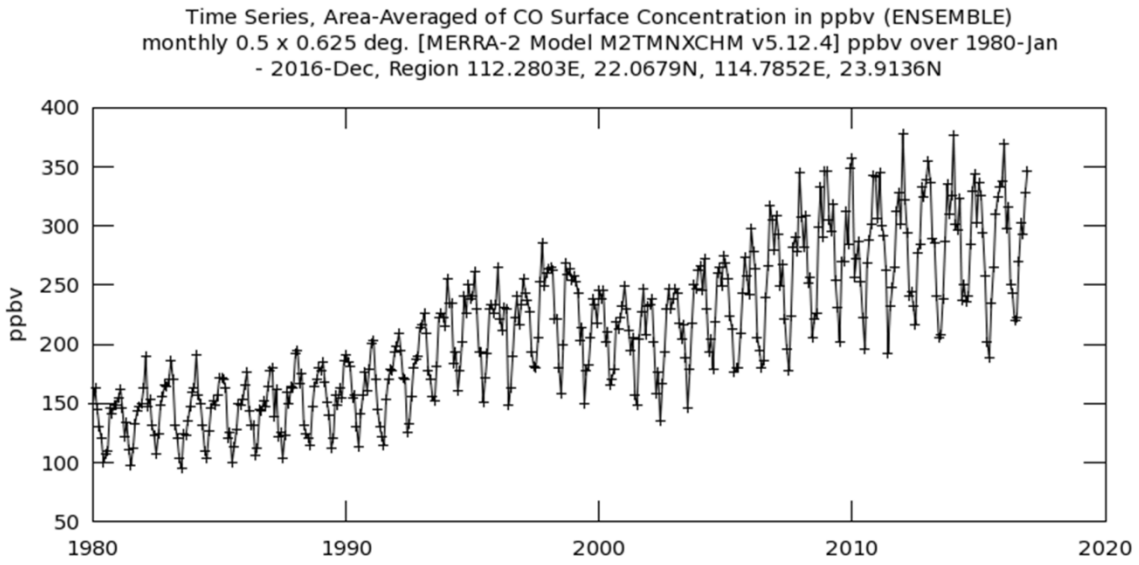
Time Series, Area-Averaged of SO2 Surface Mass Concentration (ENSEMBLE) monthly 0.5 x 0.625 deg. [MERRA-2 Model M2TMNXAER v5.12.4] kg m-3 over 1980-Jan - 2016-Dec, Region 112.2803E, 22.0679N, 114.7852E, 23.9136N



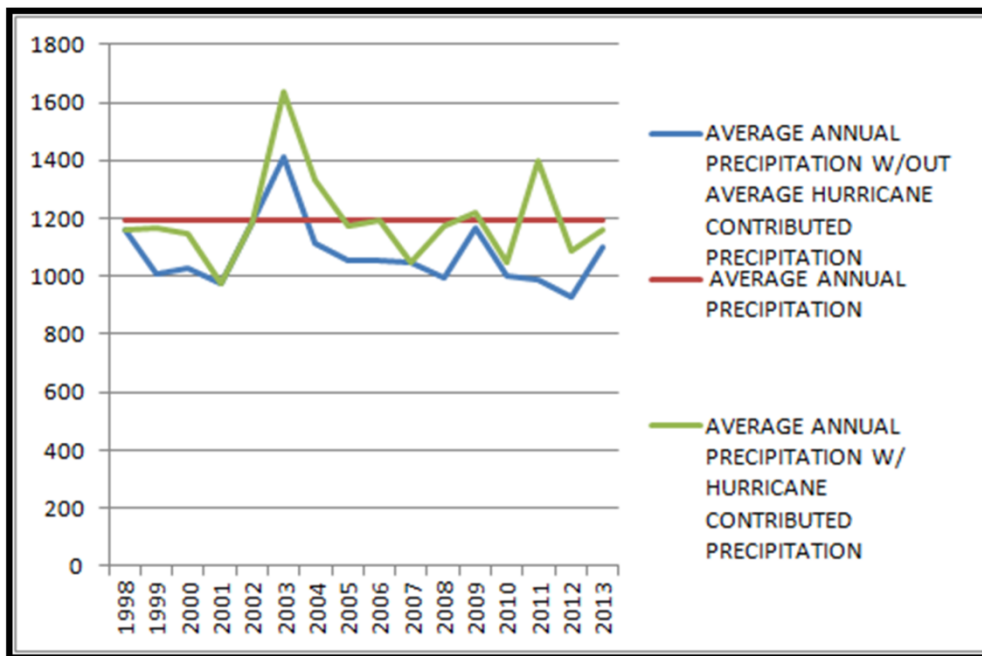
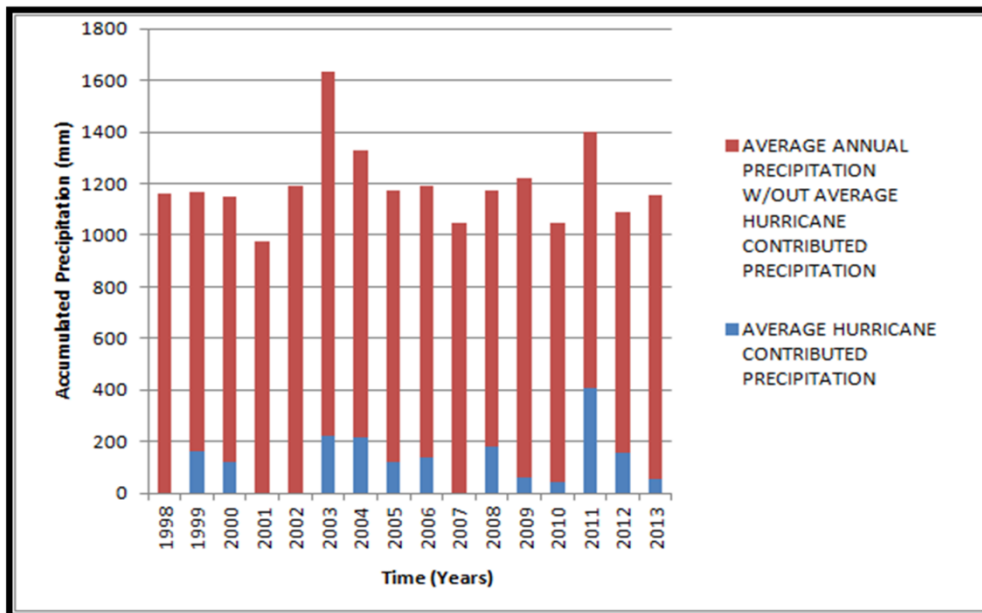
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