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GOES-R Socioeconomic Benefits Study:
Phase 2 – Assessments of Additional Products and Services

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David G. Lubar and Michael L. Jamilkowski
Civil Spectrum Engineering and Management
Civil Systems Group Technology Office

and

Jeffrey K. Lazo
Jeffrey K. Lazo Consulting LLC

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- Jeffery E. Adkins, Contractor Economist, formerly of the Office of the NOAA Chief Economist, Silver Spring, MD

- Joseph E. Conran, Economist, Office of the NOAA Chief Economist, Silver Spring, MD

Executive Summary

The Aerospace Corporation (Aerospace) Civil Systems Group (CSG) Civil Spectrum Engineering and Management branch[1] was commissioned by the GOES-R Program Office to conduct a socioeconomic benefits study of the GOES-R Series system. Under this task, an Aerospace team developed initial estimates of the socioeconomic benefits of the GOES-R Series system in both qualitative and quantifiable terms for a limited number of NOAA products and services whose contributions from GOES-R data could be determined. These are primarily National Weather Service (NWS) products and services but also include other benefit areas attributable to GOES-R.

In the first phase of this study, previously published, the team selected an NWS forecast product area as a pathfinder for which there was significant monetary and human value from the GOES-R data contribution. The GOES-R contribution to four hurricane forecast attributes was estimated to be $8.4B (2020$) over the life of the system [*Lubar et al. 2021*].

In this second phase of the GOES-R Socioeconomic Benefits Study, our goal was to undertake preliminary assessments of multiple other GOES-R-related benefits areas. To accomplish this, our objectives were to pursue the additional product/benefit areas for analysis and valuation by (1) using benefit transfers from other existing relevant studies and (2) utilizing the NESDIS TPIO NOAA Observing Systems Integrated Analysis (NOSIA) GOES-R refresh data for the GOES-R contribution percentages. This assessment must be understood to be preliminary due to limited resources (manpower and time).

To facilitate our analysis, the NOSIA II GOES-R refresh data provided us with initial estimates of GOES-R contribution percentages for several NWS products based on NESDIS/TPIO's expert-elicitation-type survey process of numerous NWS Weather Forecast Office (WFO) and Center personnel.

For Phase 2 work we undertook analysis for the following benefit areas:

1. Extreme weather
    a. Wildfires
    b. Winter storms
    c. Flash flood and riverine flood warnings
    d. Severe thunderstorms and tornadoes
    e. Drought
2. General public forecasts and warnings
3. Air quality
4. Aviation weather
    a. Weather-related delays
5. Unique Payload Services (UPS)
    a. Search and rescue
    b. DCS data communication
        i. Riverine flooding
        ii. NOAA's Physical Oceanographic Real-Time System (PORTS®)
6. Climate policy
7. Benchmarking

Employing heuristically developed average percentages for loss and avoidance costs attributable to weather, in combination with the NOSIA II GOES-R refresh data, we make preliminary but reasonable

[1] Under NSEETS Contract # 80GSC19D0011

estimates of the value of GOES-R data to each benefit area. In addition, we assess overall GOES-R contribution values using “benchmarking” as a top-down approach to quantifying the total economic value of weather information across the entire economy.

Table 1 shows the benefit areas, the impact evaluated, the baseline annual benefits (in millions of 2020 dollars) derived for each benefit area and the baseline aggregated benefit (in billions of 2020 dollars). The last column in Table 1 shows estimates for all benefit areas and methods using the baseline parameters at a discount rate of 1.185%.

The work associated with the GOES-R Advanced Baseline Imager (ABI) is directly relevant to Geostationary Extended Observations (GeoXO), not accounting for the increased resolution of the GeoXO-era instrument.

Table 1. GOES-R Benefit Estimates for Various Benefit Areas
(Baseline Parameters with Discount Rate 1.185%)

	Impact Evaluated	Baseline Annual Benefits Millions 2020$	Present Value of Benefits Billions 2020$
Extreme Weather	n/a	n/a	n/a
Hurricanes (Phase 1)	Willingness to pay (WTP)	312.16	8.36
Wildfires	Reduced costs with early detection	316.57	9.68
Winter Storms	Reduced “billion-dollar” disasters	33.26	0.84
Flash Flooding—Riverine Flood Warnings	Reduced fatalities	18.44	0.55
Flash Flooding—Riverine Flood Warnings	Reduced damages	3.82	0.11
Severe Thunderstorms and Tornadoes	Reduced fatalities	64.60	1.94
Drought	Reduced billion-dollar disasters	60.70	1.82
General Public Forecasts and Warnings	WTP	875.26	26.24
Air Quality	Reduced fatalities	33.29	1.00
Aviation Weather	Reduced weather-related delays	470.34	19.67
Unique Payload Services	n/a	n/a	n/a
Search and Rescue	Reduced fatalities	44.34	1.30
Data Collection System (DCS) data communication	n/a	n/a	n/a
Riverine flooding	Reduced flood damages	0.42	0.01
PORTS®	Lower property losses and oil pollution remediation costs / reduced fatalities	2.64	0.08
Climate Policy	Reduced climate impacts	270.15	8.10
Benchmarking	Reduced negative / increased positive impacts on Gross Domestic Product (GDP)	1,872.99	45.66

We caution that these benefit estimates cannot be simply added across all the benefit areas to derive total socioeconomic benefit estimate of the GOES-R program. For several of these benefit areas there are overlaps with other benefit areas. For instance, benefits from reduced impacts in aviation may implicitly include benefits already partly assessed in other areas such as winter storms, severe weather, wildfire, and even public forecasts. In addition, some of the methods, such as benchmarking, are essentially different approaches to the same problem.

We emphasize a few "caveats" with respect to interpreting and using the benefit estimates derived at this point. For the most part, the results reported here should be considered preliminary as there are significant degrees of uncertainty due to limited information to quantify each step in the "value chain." We also note that, although several of the benefit estimates are reported to two digits, in general for most of the benefit areas, there is significantly more uncertainty as some of the initial factors used in the analysis are subjective and likely reliable only to an order of magnitude. In that sense, some of the benefit areas are "strawmen" intended to suggest potentially important or interesting benefit areas for future analysis. The logic model developed in some areas should be further discussed and evaluated to determine if it could be built upon to derive more valid and reliable benefit estimates.

Based upon our experience with executing this study, we submit the following ideas for future considerations and efforts:

- An effort to assess all GOES-R-related product values would be a considerably larger task (in time, manpower, and funding) than the effort in this study. As with any economic analysis, the resources to be applied to the analysis should be based on the desired use of the information and outcomes.

- Our team has made recommendations in each benefit area, especially for any socioeconomic assessment that refines the approach and additional evaluations to improve the methodologies used in Phase 2. These are summarized in the concluding discussion section.

- It is critical that NOAA not "reinvent the wheel" with every new socioeconomic benefits study. We hope this effort increases the body of socioeconomic knowledge on the GOES-R technical side and the understanding of the GOES-R program and products on the economics side that can better support future studies.

We also hope that our study will better inform the future GeoXO efforts on the benefits and values of capabilities potentially contributing to the NWS Weather Ready Nation (WRN) Mission Service Areas (MSAs) covered herein.

We have not assessed costs but feel the benefits evaluated here (even with reasonable uncertainty bounds), as well as the Phase 1 work on hurricanes, demonstrate that the benefits of GOES-R likely will outweigh the investment made by the government in this program. Finally, we note that we focus on the potential benefit domestically and thus underestimate the regional or global socioeconomic benefits.

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1. Introduction

1.1 Geostationary Operational Environmental Satellite – R Series (GOES-R) Overview

The ability of meteorologists and scientists to continuously view weather from space originated in the mid-1960s when the Spin-Scan Camera was flown as a payload on the Applications Technology Satellites (ATS) I and III. This camera, the invention of Dr. Verner E. Suomi (widely recognized as the "Father of Satellite Meteorology"), from the University of Wisconsin-Madison, allowed scientists to view the clouds moving across the planet (See Figure 1 made by Dr. Suomi's Spin-Scan Cloud Camera, December 11, 1966). Prior satellites, in non-geostationary orbit, were always moving with respect to the planet. Once this product was operationalized, "using these images, it was possible to measure and track air motion, cloud heights, rainfall, even pollution and natural disasters" *[University of Wisconsin – Madison, SSEC, 1996]*.

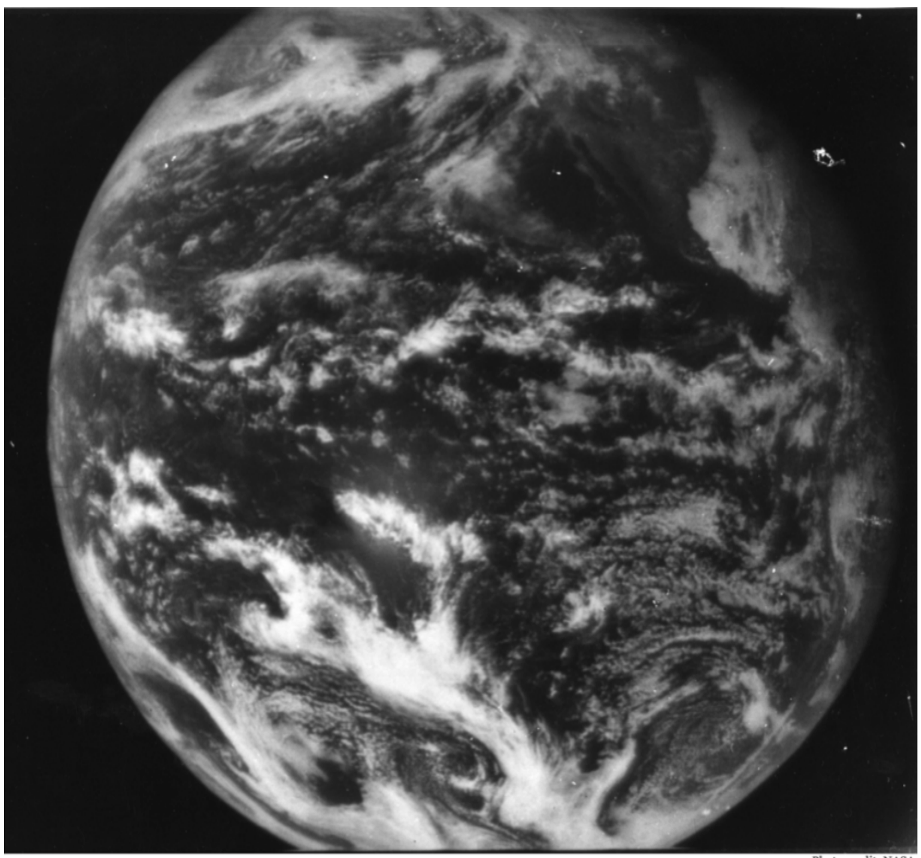
Photo credit: NASA

Figure 1. Spin-Scan Camera – A two-dimensional Image of Earth.

Following in succession were predecessor satellites to GOES-R, (e.g., Synchronous Meteorological Satellite [SMS], and earlier versions of GOES), that pursued similar objectives as today's satellites: "Provide the primary source of near-real-time visible / infrared observations for short term weather forecasting and imaging of severe weather events." [*Goodman, S.J., 2020*]

GOES-R series capabilities have continued this evolution from simple imagery to provide multiple bands of visible and IR imagery, numerous space weather observations, and lightning detection from the cloud-top view (Figure 2), "as it provides life-saving observations of high-impact environmental phenomena such as severe storms, hurricanes, fires, and volcanic eruptions across Earth's Western Hemisphere throughout the day and night." [*Goodman, S.J., 2020*]

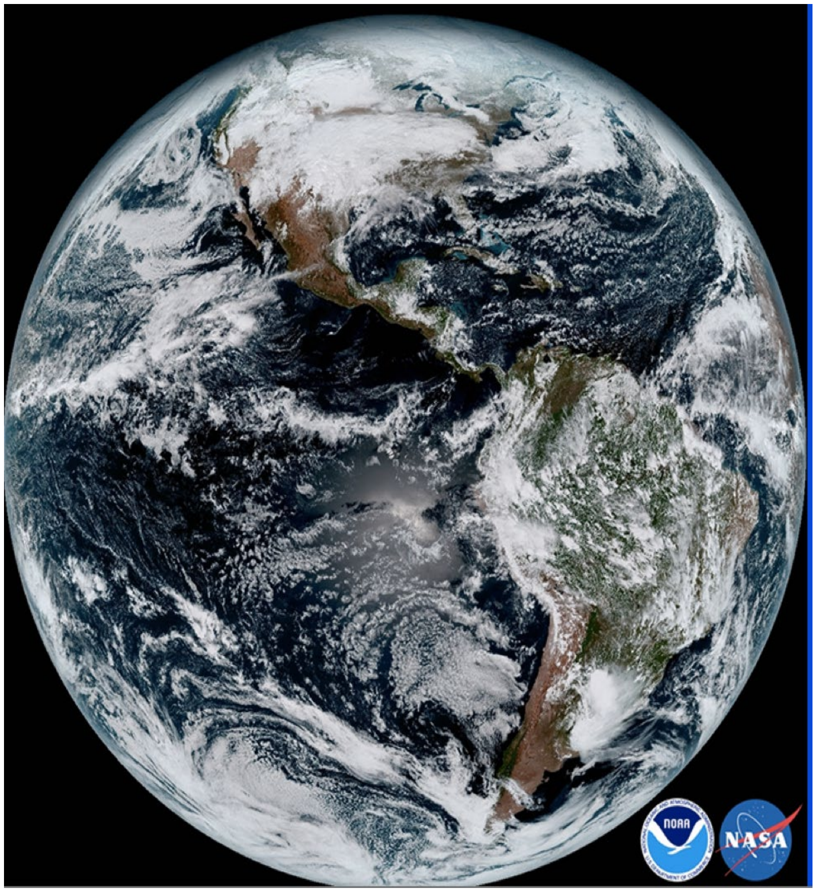

Figure 2. Full disk, first light image from GOES-16.

Today's GOES-R products contribute to understanding tropical cyclones, support to aviation operations, analysis of water vapor imagery to better understand large-scale weather patterns, tracking fires, obtaining cloud and fog information, understanding convective initiation and monitoring of convective events, aerosol products useful in determining impacts from particulate matter (especially from dust and smoke), surface features such as snow cover, understanding of cloud-to-cloud lightning structures, and space weather measurements. Imagery from GOES-R provides situational awareness and information to forecasters. GOES-R data are also used as one of many data inputs assimilated into several numerical weather prediction models.

The end users of GOES-R imagery can provide some of the best examples of how this system supports environmental and meteorological applications. For instance, this December 21, 2021, image across Florida from a National Weather Service (NWS) Jacksonville (FL) Weather Forecast Office (WFO) tweet compares the GeoColor image of the cloud tops from GOES-R (left), while the right includes Day Cloud-Phase Red Green Blue (RGB) to highlight details (Figure 3).

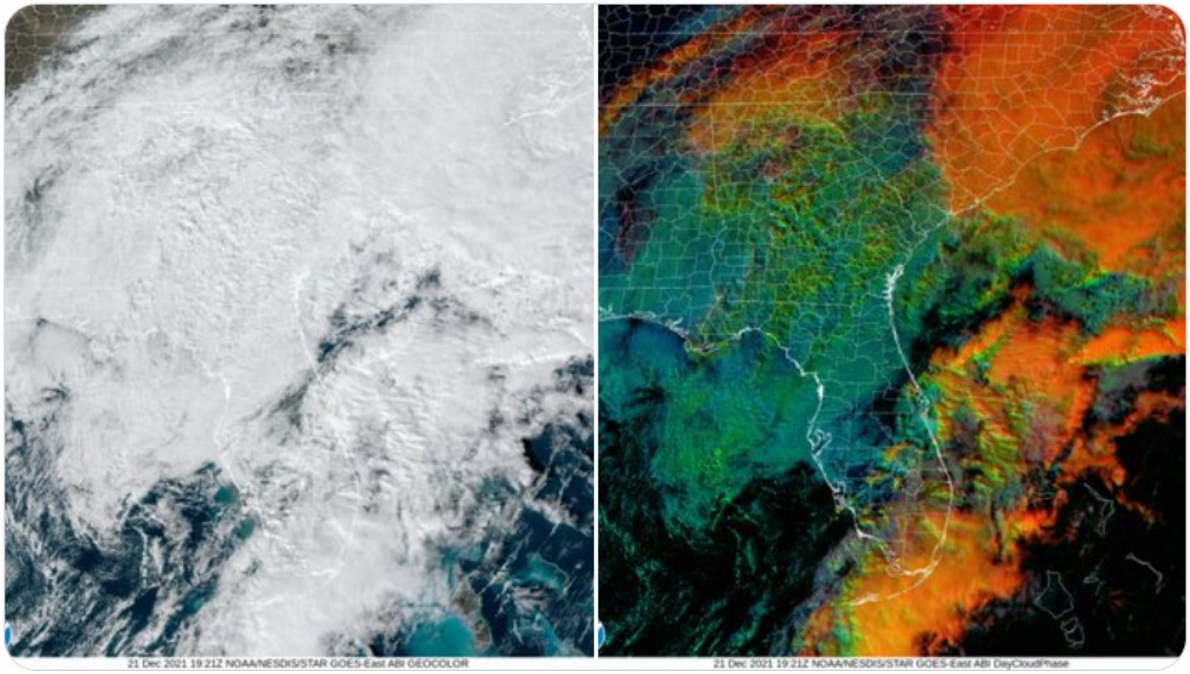

Figure 3. Comparison of GOES-R images using different instrument band combinations (source: NOAA).

The GOES-R series features multiple image and data products, including 16 bands of visible or IR images of either the full Earth disk, the continental United States (CONUS) or 1000 km × 1000 km mesoscale sectors, space weather products, and lightning mapper optical transients of total lightning. There are approximately 43 separate product categories from GOES-R, some of which produce more than 1 type of product. All of these contribute to hundreds of meteorological end-user-derived products.

The path from GOES-R satellite product or products to end-user-derived meteorological products is not always straightforward, with some data being used directly and other inputs from in situ measurements and radar outputs used in conjunction with satellite data.

1.2 NESDIS/Technology, Planning and Integration for Observation (TPIO) NOAA Observing Systems Integrated Analysis (NOSIA) II

This Phase 2 assessment utilizes data on the GOES-R series as collected by the NOSIA 2.1 study conducted by NOAA's TPIO Office to arrive at an estimated percent contribution from GOES-R to a given area. Our team worked with National Environmental Satellite Data and Information Services (NESDIS)/TPIO NOSIA 2.1 team for this effort. We resolved that NOSIA 2.1 data would be useful to our Phase 2 efforts since they had been refreshing their analysis data to include GOES-R (the original NOSIA II only included GOES N-O-P series [Geostationary Operational Environmental Satellite – R, O, and P Series] data). The NOSIA 2.1 data provided us an initial best alternative to performing expert elicitations of GOES-R-related contributions to each benefit area given our limited study resources (people, time, and funding).

The NESDIS/TPIO NOSIA analysis process utilizes surveys of NWS members from various WFOs and Centers to evaluate, document, and create a database for the impact and importance of various NOAA observing systems to NWS products and services. To classify these data, TPIO used the NOAA Value Tree and derived Weather Ready Nation (WRN) Mission Service Areas (MSAs) depicted in Figure 4 [*Yapur, 2020*]. A primary element of the NOAA Value Tree (left) is the MSAs of which the NWS WRN MSAs are shown on the right.

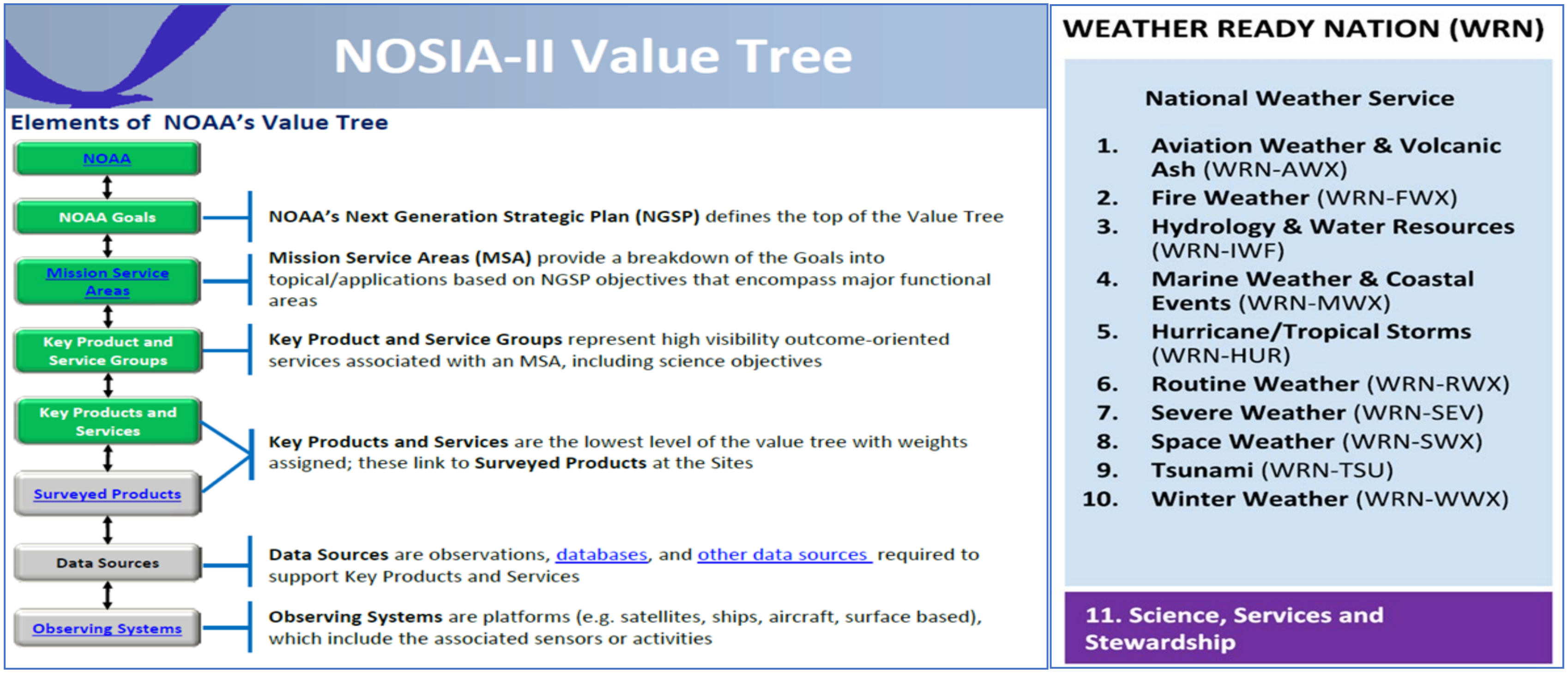

Figure 4. NOAA Value Tree and NWS WRN MSAs [*Yapur 2020*].

TPIO examines all the models that directly contribute to products in the NOAA MSAs as indicated in Figure 5. Then they identify all GOES-based data sources used by those models specifically. They also look at non-model use of GOES for products. TPIO calculates the impact of those specific GOES data sources and then determines the difference in impact across all MSAs, outcomes, and key products associated with those MSAs. While our analysis focuses primarily on WRN MSAs, which represent most of the NWS missions, we also examine portions of other MSAs, including Marine Transportation (RC-MTS) and Climate Policy (CLI).

NOAA Mission Service Areas (MSAs)			GOES-R Socioeconomic Benefits Study Areas
Applicable NOAA Org.	Applicable MSA Category	Applicable Mission Service Area	
NWS	Weather Ready Nation	Aviation Weather & Volcanic Ash (WRN-AWX)	Aviation Weather
NWS	Weather Ready Nation	Fire Weather (WRN-FWX)	Wildfires
NWS	Weather Ready Nation	Hydrology & Water Resources (WRN-IWF) (Integrated Water and Prediction Information focus)	Flood Warnings Drought
NWS	Weather Ready Nation	Hurricanes/Tropical Storm (WRN-HUR)	Hurricane Products
NWS	Weather Ready Nation	Routine Weather (WRN-RWX)	General Public Forecasts & Warnings
NWS	Weather Ready Nation	Severe Weather (WRN-SEV)	Severe Thunderstorms & Tornadoes
NWS	Weather Ready Nation	Advanced Systems Performances Evaluation tool for NESDIS (WRN-ASPEN)	Air Quality
NWS	Weather Ready Nation	Winter Weather (WRN-WWX)	Winter Storms
NOS	Resilient Coasts	Marine Transportation (RC-MTS)	Transportation
NOS	Resilient Coasts	Resilience to Coastal Hazards & Climate Change (RC-RCC)	Climate
OAR	Climate	Assessments of Climate Changes & Its Impacts (CLI-ACC)	
OAR	Climate	Climate Mitigation & Adaptation Strategies (CLI-CMA)	
OAR	Climate	Climate Science & Improved Understanding (CLI-SIU)	
OAR	Climate	Climate Prediction and Projections (CLI-CPP)	

Figure 5. NOAA's MSAs and GOES-R benefit areas assessed here [*Yapur 2020*].

Figure 5 cross-references applicable NWS WRN MSAs with most of the GOES-R benefit areas we assessed in this study.

As is evident from the Sankey Diagram[2] in Figure 6, the GOES-R relationships and connections with the various MSAs and sub-areas are varied and complex but also very extensive. There are three columns in the Sankey diagram. From left to right, they are Program Groups, MSAs, and Societal Benefit Areas. Any connection from GOES to the second column or from anything with a connection to GOES in the second column that is connected to the third is colored blue.

[2] "A *Sankey diagram* is a visualization used to depict a flow from one set of values to another. The things being connected are called *nodes* and the connections are called *links*." (text from https://developers.google.com/chart/interactive/docs/gallery/sankey) The key to reading and interpreting Sankey diagrams is remembering that the width is proportional to the quantity represented. The Sankey diagram displays how quantities are distributed among items between two or more stages.)

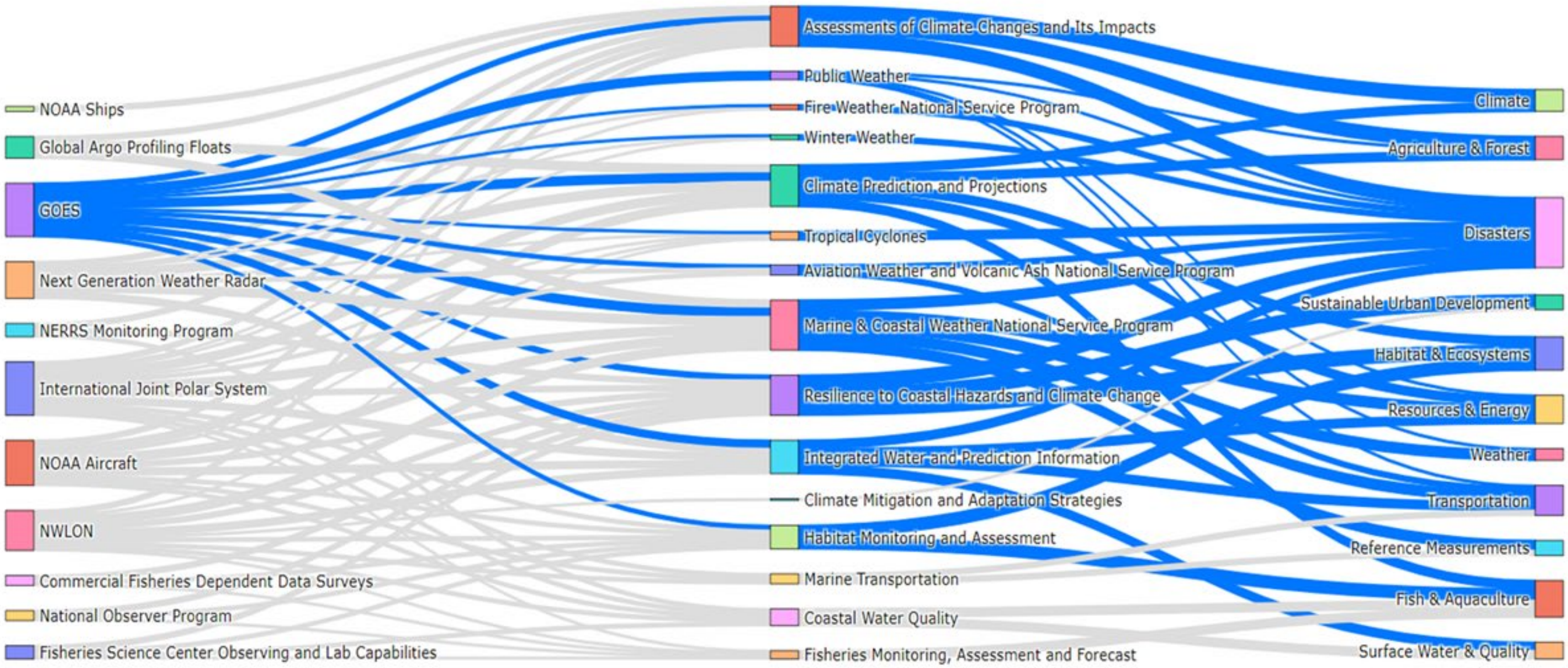

Figure 6. Sankey diagram of the NOAA observing systems, MSAs, and societal benefit areas. GOES-R relationships highlighted in blue [*TPIO 2021*].

Table 2 shows the GOES-R contribution percentages to specific benefit areas used in this analysis. The NESDIS TPIO NOSIA II team surveyed hundreds of NWS Center and WFO personnel over several years and compiled all their survey data into a GOES-R refresh we refer to as “NOSIA 2.1.” Furthermore, our study team had the TPIO NOSIA II team perform several analyses of their GOES-R data to synthesize it down to the single GOES-R contribution/impact percentage for the first seven focus (or benefit) areas listed in Table 2 below.

Table 2. TPIO Data on GOES-R Contributions

Focus Area	TPIO GOES-R Contribution
Fire Weather	14.02%
Winter Weather	11.19%
Integrated Water and Prediction Information	10.24%
Severe Weather	13.96%
Public Weather	6.38%
Air Quality	8.16%
Aviation Weather	20.47%

1.3 Phase 2 GOES-R Benefit Assessments

This study is a follow on to our Phase 1 effort, which focused on hurricane products (Lubar et al. 2021). As it is not feasible to develop a comprehensive list of applications for which GOES-R products and data are used, we selected several that we expected to make the greatest socioeconomic contributions and/or had data available that could be used in our socioeconomic assessment. As outlined more in section 2.3, we elected to investigate these following benefit areas for the Phase 2 study.

1. Extreme weather including:
    a. Wildfires
    b. Winter storms
    c. Flash floods
    d. Severe thunderstorms and tornadoes
    e. Drought
2. General public forecasts and warnings
3. Air quality
4. Aviation weather
5. Unique Payload Services (UPS)
    a. Search and rescue (SARSAT)
    b. Data Collection System (DCS)
        i. Riverine flooding
        ii. NOAA’s Physical Oceanographic Real-Time System (PORTS®)
6. Climate policy
7. Benchmarking

2. Benefit Estimation Methods for Phase 2

2.1 Phase 1 Assessment Methods

During the Phase 1 assessment, our team conducted extensive meetings and interviews and obtained input from GOES experts, weather forecasters, researchers, and existing literature to characterize the contribution of GOES-R to end-user products and services.

We used input from Phase 1 to identify several potential benefit areas for this Phase 2 assessment. We selected additional areas where the GOES-R series contributes to specific impactful meteorological events or supports a particular industry or segment of the economy.

2.2 Assessment Approach

Our team's overall assessment approach is depicted in Figure 7:

1. (Far-left column) We derived candidate benefit areas mostly from NOAA's MSAs (see section 1.2) and selected the ones for assessment as described in section 2.1.

2. (Second column from left) For each selected area, we examined the available literature to determine what, if any, socioeconomic impacts data exist (e.g., number of events, deaths/mortality numbers and costs, flight delays, and damage costs).

3. (Center column) Next, we assigned a percentage of what portion of the impacts could/would be reduced with weather information (mostly heuristic determinations but a few derived from actual data).

4. (Second column from right) We then applied a percent of weather information that was attributable to GOES-R data, which we obtained from TPIO analyses of the NOSIA II data.

5. Based on these calculations, for each benefit area, we derived a baseline annual benefit estimate that we adjusted to 2020$ to maintain consistency across benefit areas and derive benefits in constant (real) dollars.

6. (Far-right column) Finally, we calculated a total GOES-R benefit present value for each selected area by aggregating the data [from steps (2) through (5) above] over the expected lifetime of the GOES-R series and taking into account a number of socioeconomic factors (e.g., affected population numbers and growth, discount rates, growth of weather variability, income growth, and inflation adjustments). See section 2.3 for a more detailed explanation of these factors.

At the end of each benefit analysis, we identified constraints in our work and recommendations for future, more comprehensive efforts.

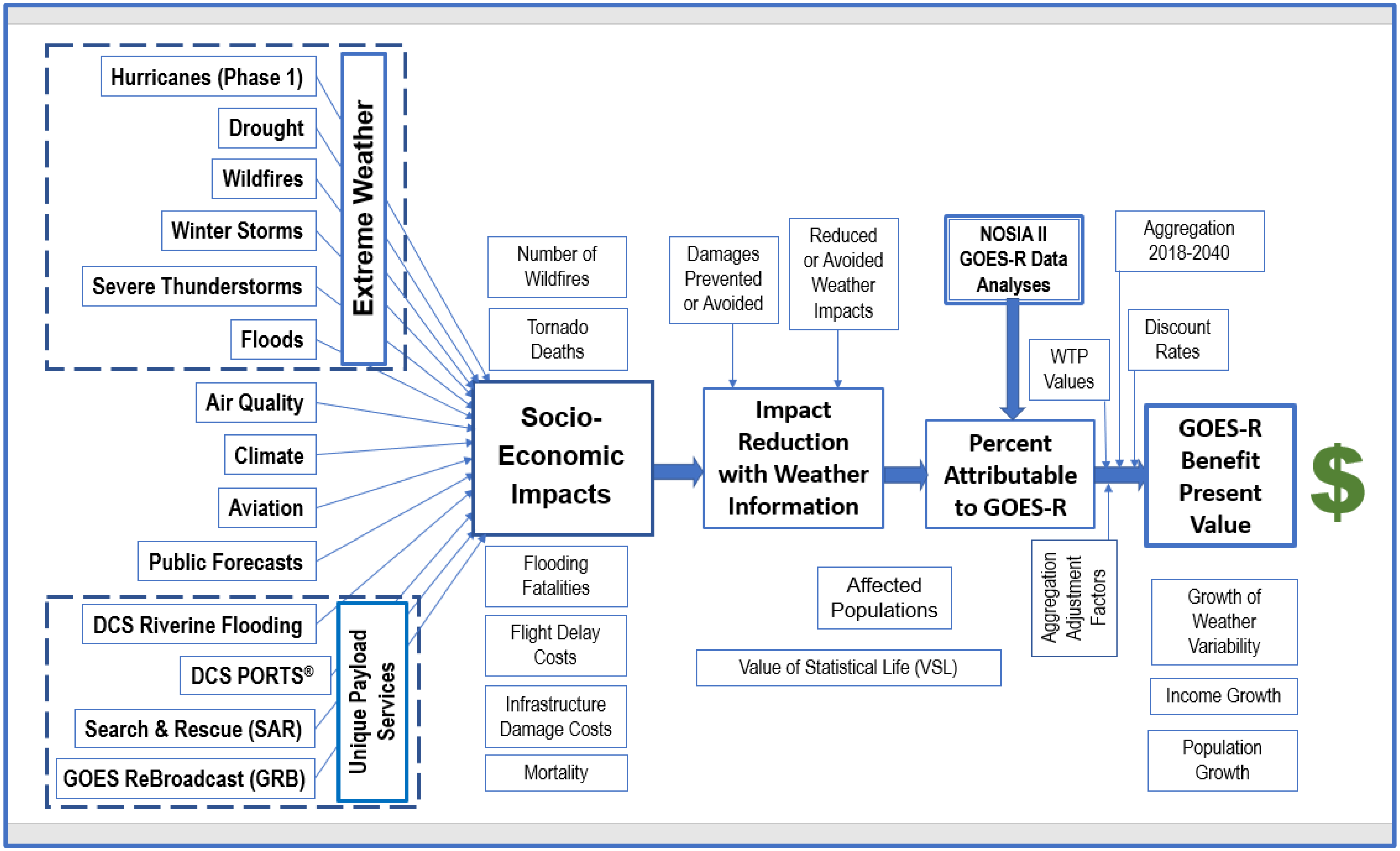

Figure 7. Processes for GOES-R benefit estimation (source: Aerospace).

2.3 Assessment Benefit Areas

The primary assessment benefit areas were selected because of indications that these areas likely had significant use for GOES-R data and derived products and services. Our team derived this input during discussions, webinars, and interviews during Phase 1 as well as through reviewing the extant literature on GOES-R products and services. Undertaking any specific analysis was then dependent on the availability of economic data or prior studies in those areas. Recognizing that other GOES-R contribution areas may not be included in our Phase 2 topics, such as space weather, selections are based upon the availability of data and adequate resources from our team. It was also felt that GOES-R observations that have a broader applicability, likelihood of occurrence, and impact to larger populations or multiple economic areas have the potential to drive most of the socioeconomic contributions and thus we have not included some highly specific products and services at this time.

For purposes of "framing" the benefit areas, we refer to the "Weather Information Value Chain" concept as discussed in our Phase 1 report, section 3.1, and copied here as Figure 8 [*Lazo 2018b*; *Lubar et al. 2021 p.15*].

Figure 8. Weather Information Value Chain.

As discussed in our Phase 1 report, building on prior value chain work [*Lazo and Mills 2021*] and the NOAA Fleet Study [*Abt et al. 2018*] framework, we developed a customized GOES-R value chain for hurricane products and services as shown in Figure 9. We have not developed value chain models for each of the benefit areas discussed in Phase 2 but feel it would be worthwhile to do so as additional effort is applied to refine and better validate analysis in these areas.

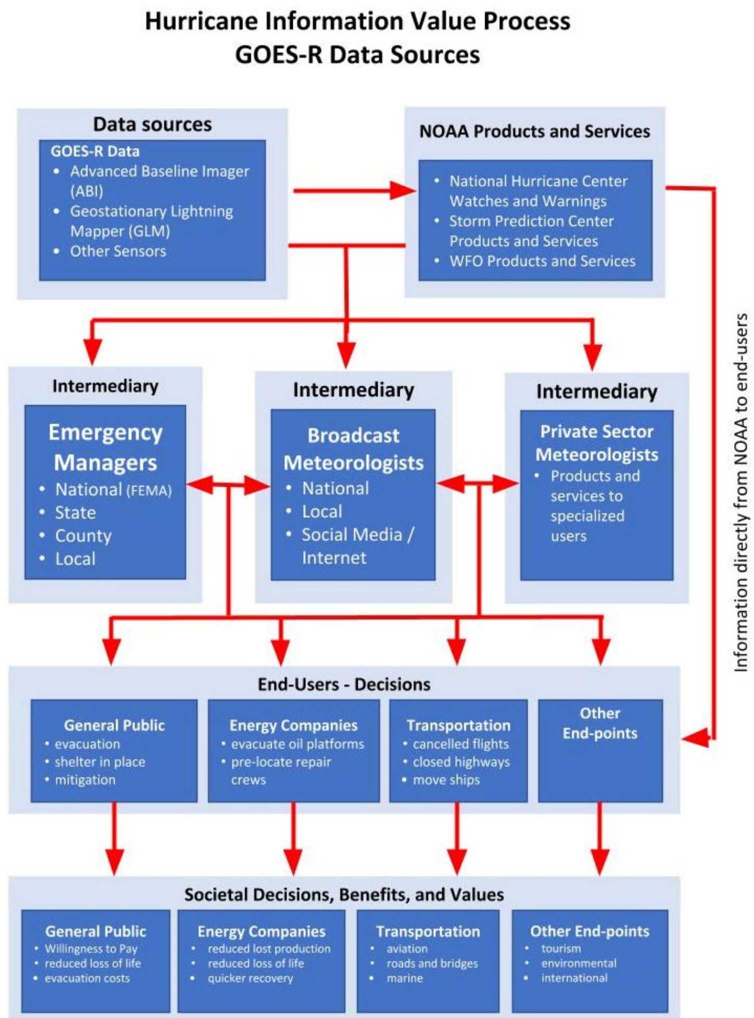

Figure 9. GOES-R hurricane information value chain model (source: Aerospace).

In these value chain models, observations, data, information, products, and services generally flow from the left to the right (Figure 8) or top to the bottom (Figure 9). We recognize that there are, or at least should be, feedback loops from users to early steps in the process to help inform decisionmaking and thus enhance information value. In the following explanation of our organization of the benefit areas, we refer to where in the value chains the focal point is for that benefit area. Regardless of where this focal point is, we note that GOES-R's input is at the beginning of the chain and the realization of the benefits is at the very endpoint of the chain. Uncertainties in our analyses generally lay in identifying the flow of information through the chain and contributions or attribution of value at each step. Better identification and refinement of parameter estimates at these points would improve the reliability and validity of this analyses as discussed in the last section of this report and individually within each benefit area.

Our organization of the analysis fell into several general benefit categories, including:

1. Extreme weather: These topics are generally specific weather events or phenomenon. In terms of the value chain concept, these would fall on the far-left side of the value chain (Figure 8). We start with an overview of the extreme weather area based on data from NOAA and the "Billion-Dollar Weather and Climate Disasters" [*NCEI-NOAA, 2022*] framework. This general benefit category includes:

a. Wildfires

b. Winter storms

c. Flash flood and riverine flood warnings

d. Severe thunderstorms and tornadoes

e. Drought

2. General public forecasts and warnings: While information in this area may be considered benign, routine, non-severe, everyday, or garden-variety, it can also include information supporting the forecast of extreme weather events. This is also more of an end-point benefit area rather than being a specific weather phenomenon. Finally, this benefit area encompasses the entire United States (U.S.) population, whereas the extreme-weather-affected populations tend to be smaller sub-populations that are vulnerable to those weather events. In terms of the value chain concept, the general public falls on the far-right side of the value chain as the ultimate end-user group.

3. Air quality: As a somewhat unique but obvious benefit area, air quality is not a specific NWS MSA. The NWS does, though, produce and issue many GOES-R data-fed operational air-quality-related forecast guidance products such as:

   a. 1-hour and 8-hour average ozone concentration

   b. Daily 1-hour and 8-hour ozone concentration

   c. 1-hour average surface smoke concentration

   d. 1-hour average vertical smoke integration

   e. 1-hour averaged surface dust concentration

   f. 1-hour averaged column-integrated dust concentration

   These products become part of the National Digital Guidance Database (NDGD).[3] More importantly, they contribute to the air quality products of other agencies (primarily the Environmental Protection Agency [EPA]).

4. Aviation weather: In terms of the value chain concept, aviation weather could fall in the middle as a set of weather phenomenon that then can impact a variety of end-user groups. We note that there are likely several other mid-points that we have not evaluated, such as energy, recreation, or other transportation modes.

5. UPS – "The GOES-R Series Unique Payload Services (UPS) consists of transponder payloads providing communications relay services in addition to the primary GOES mission data. Although other resources may exist for satellite communication, the specialized nature of

[3] The NDGD is a companion to the National Digital Forecast Database (NDFD) and provides access to computer-generated forecasts that are used by the NWS to create the official forecasts published in the NDFD. The Real-Time Mesoscale Analysis (RTMA) supports NDFD operations and provides analyses to NWS field forecasters. Many NDGD products are experimental, and none of them are official NWS forecasts. (https://www.ncei.noaa.gov/products/weather-climate-models/national-digital-guidance-database)

coverage at specific parts of the radio spectrum, and the importance of data latency drive the need for the UPS capability on the GOES-R spacecraft. The UPS suite consists of the Data Collection System (DCS), the High-Rate information Transmission/Emergency Managers Weather Information Network (HRIT/EMWIN), GOES Re-Broadcast (GRB), and the Search and Rescue Satellite-Aided Tracking (SARSAT) system." [*GOES-R Program Office, 2022*] In this analysis, we include assessment of a very small portion of UPS products and services related to:

a. SARSAT

b. DCS

i. Riverine flooding

ii. NOAA's PORTS[4]

6. Climate policy: Climate is one of the four primary MSAs identified by TPIO [*NOAA Technical Report, 2016*]. We undertook a demonstration of an order-of-magnitude benefit assessment in terms of how GOES-R information supports policy analysis in climate decisionmaking to reduce long-term reductions in Gross Domestic Product (GDP).

7. Benchmarking: Benchmarking, as applied here, is based on a method developed by World Bank [*WMO, et al, 2015*] for assessing total national value of investment in hydro-met services. It is not an additional benefit area but a top-down calculation that could be compared to the order-of-magnitude results in the benefit areas. Similar to the climate policy benefit area assessment, we undertook a demonstration of an order-of-magnitude benefit assessment in terms of how GOES-R information could lower negative impacts or enhance positive impacts on the U.S. GDP.

2.4 Baseline Parameters for Benefit Analyses and Aggregation

We applied several parameters in multiple benefit areas and discuss them here. To the extent possible, we attempted to maintain consistency across benefit areas by using the same parameter estimates where relevant. We included these parameters in our "Control Parameters" sheet of the analysis spreadsheet and subsequently linked them to the individual benefit areas. In this manner, any given "general" parameter can be changed as desired and the subsequent change in benefit estimates were flowed through to all areas consistently. Where applicable, we used the following information:

- *Population*: We obtained population projections for the United States from the U.S. Census International Database "Population estimates and projections for 227 countries and areas" for the years 2017 through 2040 [*Census Bureau 2022*]. From these data, we derived a simple average of the annual growth rates in U.S. population of 0.5725% to apply to future populations. Assuming increasing population is commensurate with increases in benefits from GOES-R applications, we increased the benefits each year in the analysis by this percent. We also used the 2018 population as the baseline for the United States when this is used in the benefit area analysis (e.g., in the public forecast benefits analysis). Appendix A shows the projected population estimates and growth rates and average of these growth rates.

- *Increase in weather variability*: To account for future changes in weather variability, we factored in an increasing impact of 1.5% per year. We applied this factor to the benefit estimates across the analysis period, but it is meant to reflect the fact that the impacts of weather variability will

[4] PORTS® is a registered trademark of NOAA's National Ocean Service.

likely increase in all benefit areas. The 1.5% factor is a subjective evaluation based on information from a range of sources including [*EPA 2021*], [*Neumann, 2020*], and [*Sarofim, 2021*]. Future ongoing analysis should confirm or refine this factor.

- *Increase in wealth and income*: Similar to increasing population, an increase in wealth (or income) would be associated with an increase in the benefits. We implicitly apply a "unit income elasticity"[5] of benefits by assuming that benefits increase at the same rate as income. As noted in our Phase 1 report: "To estimate average annual increase in income over time, we use historical data from the Bureau of Economic Analysis (BEA) interactive data tables. We accessed Table SAGDP10N for 'Per capita real GDP by state (Percent change from preceding period)' for the years 1997 through 2019 (22 years) and a simple average indicates 1.469% of annual real increased in per capita GDP" [*Lubar et al. p.50*].

- *Value of Statistical Life (VSL)*: The VSL is the economic measure applied to the reduction in potential fatalities related to information provided by GOES-R. VSL is not a measure of the economic value of any one individual but rather a measure of the socioeconomic benefit of reducing the risk of loss of life in a population. It is an ex ante measure of the benefit of risk reduction. As stated in the U.S. Department of Transportation (USDOT) guidance document on the use of VSL in policy analysis, "The benefit of preventing a fatality is measured by what is conventionally called the Value of a Statistical Life, defined as the additional cost that individuals would be willing to bear for improvements in safety (that is, reductions in risks) that, in the aggregate, reduce the expected number of fatalities by one" [*USDOT 2021, p.1*]. For the current analysis we used the VSL value recommended by the USDOT for the year 2020 of $11.6M [*USDOT VSL 2022*]. [6]

Consumer Price Index (CPI): We adjusted benefit estimates to 2020$ as applicable using the CPI. We used the CPI for All Urban Consumers (CPI-U) [7] using the U.S. city average across all items for the years 1913 to 2021 with the base period of 1982 to 1984 = 100. We used this measure primarily to adjust benefit estimates from prior years into 2020$. For instance, to update the benefit estimates in the wildfire benefit area from 2016$ to 2020$, we used the ratio of the 2016 CPI to 2020 CPI as shown in Table 3. We recognize that, for specific sector groups, there may be more directly relevant price indexes (e.g., for aviation or in the benchmarking exercise) but suspect that using these, any changes would be well within the broad margin of error of the overall analyses. Note that we undertook inflation adjustments from prior years to convert all estimates to 2020$. Then we undertook the analysis using real 2020$ dollars (i.e., not factoring in inflation).

- Table 3 is based on the CPI values for 1913 to 2018 shown in Appendix B.

[5] This means we assume that a 1% increase in income induces a 1% (unit increase) increase in benefits however benefits are measured.
[6] For instance, suppose a city council was considering improvements in traffic safety in a town that would on average lead to one fewer traffic fatality per year. To evaluate this, the council conducts a study and finds that each of the 100,000 households in the city is willing to have their taxes increase by $100 a year to pay for this safety program. The households are not paying to save any particular person in advance but to reduce the risk, so the value of the annual reduction in risk for one life is 100,000 households times $100 per household, or $10,000,000 per "statistical life."
[7] Source: https://data.bls.gov/timeseries/CUUR0000SA0 Series Id: CUUR0000SA0; Series Title: All items in U.S. city average, all urban consumers, not seasonally adjusted

Table 3. Example of Inflation Adjustment to 2020$

Year	CPI
2016	240.01
2020	258.81
Ratio applied to benefit estimate to adjust to 2020$	1.078

- *Discount rates*: For the choice of discount rates for aggregating to present value, we used the same set of discount rates as we used in the Phase 1 report. We indicate these in Table 4.

Table 4. Discount Rates (Real Rates)

Level	Rate	Reference
Low/Undiscounted[8]	0.000%	[*OMB 2003, Circular A-4*]
Medium Low	0.300%	[*0MB 2019, Circular No. A-94*]
Baseline	1.185%	Based on discount rate analysis from Phase 1 report
Medium High	3.000%	[*OMB 2003, Circular A-4*]
High	7.000%	[*OMB 2003, Circular A-4*]

Our baseline discount rate of 1.185% is based on our analysis of average decadal real 30-year treasury rates over four decades as discussed in section 8.3, Notes on Choice of Discount Rate, of the Phase 1 report [*Lubar et al. 2021*]. We believe that at the time of analysis, the 1.185% represented an appropriate measure of long-term real rates of return on 30-year treasury bonds, and thus would be an up-to-date estimate of an applicable discount rate for benefit analysis. The other discount rates are presented as "reference rates" to show the impact of using different rates in our analysis and to provide the present value estimates for those discount rates should others need those for policy implementation. These "references" are indicated as various OMB circulars in which these rates are noted as of the time of the analysis.

- *Duration of GOES-R benefits:* As noted in our Phase 1 report, based on guidance from the NOAA GOES-R program office, we assume capability for the GOES-R series starting in 2018 and continuing until 2040. This timeline is supported by the formal "fly-out" chart graphic from NOAA/NESDIS. "NOAA Geostationary Satellite Programs Continuity of Weather Observations" (January 2022) [*NOAA/NESDIS Web Page 2022*] that shows the GOES-R (GOES-16/GOES-East) satellite became operational in late 2017 and will continue at least through 2032 and that other GOES-R series satellites will continue seamless operations at least through 2040. We used this "fly-out" chart to establish the duration period for this study. The benefit analysis thus aggregates over 23 years (2018 to 2040 inclusive). Table 5 summarizes the parameters and factors used in the benefit analysis. Where applicable, these are used consistently in each analysis.

[8] Our "Low" discount rate is officially referred to as "Undiscounted" in OMB Circular A-4, but for the remainder of this report, we will refer to it as the "Low" discount rate.

Table 5. Methods and Analysis Summary

Discount Rates (DRs) (Real Rates)	**Rate**	**Source**
Zero	0.000%	"Undiscounted," [*OMB 2003, Circular A-4*]
Low	0.300%	[*OMB 2019, Circular A-94*]
Baseline	1.185%	Analysis from Phase 1 report [*Lubar et al. 2021*]
Medium High	3.000%	[*OMB 2003, Circular A-4*]
High	7.000%	[*OMB 2003, Circular A-4*]
Analysis Factors	**n/a**	**n/a**
VSL	$11,600,000	Recommended VSL from USDOT (2020$) [*USDOT VSL 2022*]
Growth in weather variability	1.500%	Subjective summary multiple websites, peer-reviewed articles on projected socioeconomic impacts of climate change to derive estimate of growth of impacts over next 30 years
Population growth	0.572%[9]	U.S. Census-projected population growth 2018-2040 - average annual projected growth rates
Income growth per capita	1.469%	Historical Bureau of Economic Analysis interactive data tables. Table SAGDP10N simple average of 1.469% of annual real increase in per capita GDP.
CPI	See appendices	Historical CPI for urban areas to adjust all studies from year of analysis to 2020$ constant dollars—U.S. Bureau of Labor Statistics
Duration of benefits	2018 to 2040	Guidance from the NOAA GOES-R program office—graphic [*NOAA GEO Flyout 2021*]

[9] The exact number calculated from the census data is 0.572487826086957%, which is the percent applied in the benefit analysis spreadsheet but referred to throughout this report as 0.572%. Again, as noted above, the number of significant digits is much fewer than that indicated.

3. Extreme Weather: Overview

3.1 Overview

This section provides an overview and introduction to several benefit areas related to extreme weather and related NWS MSAs, including:

- Wildfires
- Air quality
- Winter storms
- Flash flood and riverine flood warnings
- Severe thunderstorms and tornadoes
- Drought

3.2 Impacts of Extreme Weather

Table 6 shows the CPI-adjusted United States billion-dollar disaster events over 41 years as tracked by NOAA's National Centers for Environmental Information [*NCEI 2022*]. This shows only those events exceeding NCEI criteria for a billion-dollar disaster and thus does not account for smaller events, which may in aggregate constitute significantly higher total socioeconomic impacts.

Table 6. Billion-Dollar Events to Affect the United States from 1980 to 2021 (CPI-Adjusted) [*NCEI 2022*]

Disaster Type	Events	Events/ Year	Precent Frequency	Total Costs	Percent of Total Costs	Cost/ Event	Cost/ Year	Deaths	Deaths/ Year
Drought	29	0.7	9.0%	$291.1B	13.2%	$10.0B	$6.9B	4,139†	99†
Flooding††	36	0.9	11.1%	$168.4B	7.7%	$4.7B	$4.0B	634	15
Severe Storm	152	3.6	47.1%	$344.8B	15.7%	$2.3B	$8.2B	1,972	47
Tropical Cyclone	57	1.4	17.6%	$1,157.1B	52.6%	$20.3B	$27.6B	6,708	160
Wildfire	20	0.5	6.2%	$123.6B	5.6%	$6.2B	$2.9B	418	10
Winter Storm	20	0.5	6.2%	$81.0B	3.7%	$4.1B	$1.9B	1,314	31
Freeze	9	0.2	2.8%	$33.7B	1.5%	$3.7B	$0.8B	162	4
All Disasters	323	7.7	100.0%	$2,199.7B	100.0%	$6.8B	$52.4B	15,347	365

Source: https://www.ncei.noaa.gov/access/monitoring/billions/summary-stats Accessed April 12, 2022.

†Note from NCEI: Deaths associated with drought are the result of heat waves, and not all droughts are accompanied by extreme heat waves.

††Flooding events (river basin or urban flooding from excessive rainfall) are separate from inland flood damage caused by tropical cyclone events.

We show a time series of events from 1980 to 2021 in Figure 10 (accessed January 10, 2022). There is a gradual upward trend in this time series. The growth of extreme weather events, as evidenced by NCEI's billion-dollar disaster statistics, indicates that GOES-R benefits in specific areas, some covered by other chapters in this report, will continue to increase. We attempt to capture these trends in our analysis by including the "increase in weather variability" factor of 1.5% per year to account for future changes in weather variability. The 95% confidence interval (CI) represents the uncertainty associated with the disaster cost estimates. Monte Carlo simulations were used to produce upper and lower bounds at these confidence levels [*Smith and Matthews 2015*].[10]

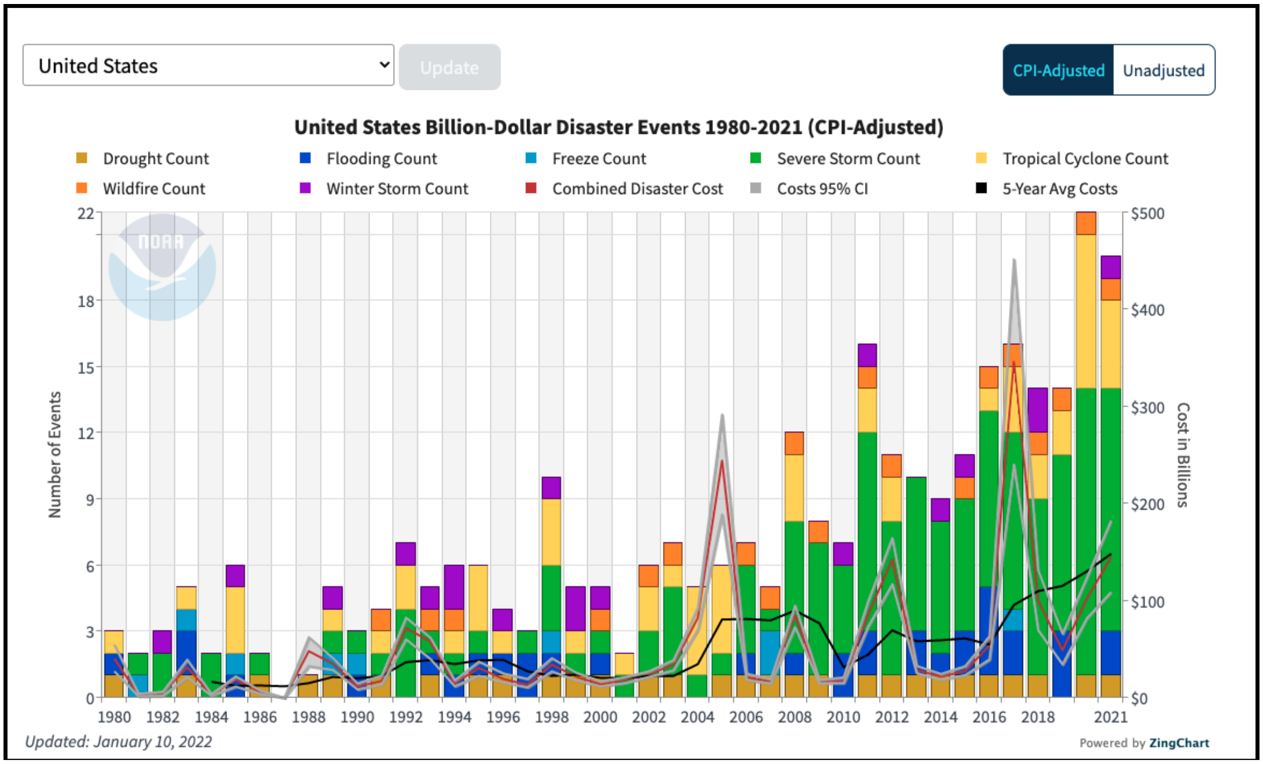

Figure 10. Time-series graph of U.S. billion-dollar disaster events (1980–2021) [*NCEI 2022A*].

[10] Data from https://www.ncdc.noaa.gov/billions/summary-stats/US/1990-2021. Technical paper: A. B. Smith, J. L. Matthews, "Quantifying Uncertainty and Variable Sensitivity within the U.S. Billion-dollar Weather and Climate Disaster Cost Estimates," Natural Hazards, 77 (2015), pgs., 1829-1851 See https://www.ncdc.noaa.gov/monitoring-content/billions/docs/smith-and-matthews-2015.pdf

4. Wildfires

4.1 Summary

To estimate benefits of GOES-R related to impacts of wildfires, we calculated reductions in socioeconomic impacts from fires due to potential early satellite detection. Building on existing information resources, we implemented the following steps to derive an annual benefit estimate:

- Obtained upper- and lower-bound estimates of total economic impacts of wildfires from Thomas et al. paper ($71M–$348M/year) and adjusted to 2020$
- Obtained the average total number of wildfires per year from Congressional Research Service (CRS) 2021 (62,805 fires/year)
- Divided impact estimates by number of wildfires to get average cost per fire ($1.2M–$6.0M/yr)
- Assumed 1% of fires are or could be avoided because of weather observation, modeling, and forecasting early detection. **(Note we feel this is a key unknown parameter)**
- Applied 14.02% factor as weather information attributable to GOES-R (TPIO number)
- Derived annual benefit estimates (upper and lower bound in 2016$) of early detection of wildfires using GOES-R information

This provided us with a baseline year annual benefit from GOES-R. We then aggregated these over the lifetime of the GOES-R series, accounting for increases in wealth, population, and weather variability (using a baseline discount rate of 1.185%), and took the average of the upper- and lower-bound estimates. Our baseline estimate is an aggregated present value benefit of **$9.68B** (in 2020$).

4.2 Introduction to Application Area

GOES-R fire detection and characterization-related data make Advanced Baseline Imager (ABI) products extremely useful to determine the detection of fire pixels in imagery and to monitor the growth or rapid changes of fires. As discussed here, wildfire-related GOES-R information covers a range of products and services at distinct phases of a wildfire. In our analysis, we focus only on the benefits of early detection and thus do not attempt to assess potential benefits for many other phases of wildfire information.

ABI allows heat signature detection with significantly improved time and spatial resolution over GOES-N, -O, -P. ABI can now also detect smaller fires. Features derivable from the GOES-R ABI are:

- Fire size
- Fire temperature
- Radiative power

The differential response between the 4-micron and the 11-micron channels is the basis for the Fire Detection and Characterization (FDC) product from GOES-R. One can also combine RGB visualizations with Geo Color enhancements to show hotspots and smoke side by side on the same product.

GOES-R also monitors smoke from wildfires by providing smoke-plume tracking in near realtime. GOES products can guide firefighting aircraft and helicopters to avoid areas of poor visibility. The movement of smoke can also affect visibility and airport operations. Additionally, GOES-R can monitor burn scarring in areas previously subjected to wildfires and denuded of vegetation so that flash flooding may be predicted from rain events.

Also related is biomass burning from "controlled" fires (e.g., forest dry-debris clearing and intentional agricultural burning), which is one of the largest "known-unknown" sources of potentially harmful U.S. airborne emissions.[11] Primary fire and smoke applications of GOES-R data include:

- Hotspot thermal detection
- Multi-spectral composites
- Hotspot identification and characterization (fire detection and characterization from ABI)
- Smoke and aerosol characterization
- Daytime smoke

Geostationary satellites provide more frequent coverage than non-geostationary satellite systems (NGSOs)[12] but provide only limited coverage of polar regions due to the large viewing angles at those higher latitudes. Therefore, wildfire detection performance may vary with higher latitudes.

GOES-R data contributes to the beneficial warnings of fires, based on the operational Fire Detection and Characterization product. High-intensity wildfires, often exacerbated by high winds, can create "megafires," which can be extremely hazardous[13] in the Plains regions of New Mexico, Texas, Oklahoma, and Kansas.

Wildfires also threaten lives and properties that are situated in areas where they can be impacted directly by wildfires. When temperature, drought, and wind conditions are optimal, wildfires can threaten lives, homes, and structures. Fire suppression costs, such as those from tanker-equipped airplanes and helicopters, can consume significant amounts of local, state, and federal agency budgets.

> Economic impacts … reach beyond the primary indicators of suppression costs and homes or structures loss. … Among other negative economic effects for communities, wildfires can burn timber, make recreation and tourism unappealing, and affect agricultural production. Local communities often become concerned about the effects of smoke on health and safety, as well. … Depending on the severity and location of a wildfire, post-disaster recovery can come with a considerable price tag. Factors that affect state and local budgets in the long-term include:
>
> - replacement of lost facilities and associated infrastructure
> - watershed and water quality mitigation
> - sensitive species and habitat restoration [*Diaz 2012*][14]

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[11] While we have not directly tied air quality impacts to wildfire, we do consider the benefits of improved air quality information based on GOES-R data in a following discussion.

[12] "Non-GSO satellites at medium Earth orbits (MEO) altitudes are between 8 000 and 20 000 kilometres above the Earth and low Earth orbits (LEO) altitudes are between 400 to 2 000 kilometres above the Earth. Since non-GSO satellites move across the sky during their orbit around the Earth, non-GSO operators must deploy a fleet of satellites, generally called "constellations", to provide continuous service from these altitudes." https://www.itu.int/en/mediacentre/backgrounders/Pages/Non-geostationary-satellite-systems.aspx Accessed April 12, 2022. Sensors on LEO satellites can detect smaller fires, but they only overfly the continental United States a few times during daytime or nighttime. A geostationary (GEO) satellite would not detect smaller fires but would offer near continuous visibility of a given point.

[13] For a good account of the dangers of wildfires on the plains, see Hollandsworth, Skip, 2017, "The Day the Fire Came," Texas Monthly, July 2017, located at https://features.texasmonthly.com/editorial/the-day-the-fire-came/

[14] Diaz, J.M., 2021. Economic Impacts of Wildfire. Southern Fire Exchange, SFE Fact Sheet 2012-7 located at https://fireadaptednetwork.org/wp-content/uploads/2014/03/economic_costs_of_wildfires.pdf

Figure 11 is an example of fire devastation to a local community. The arrow in Figure 11 indicates the former residence of Dr. Jeffrey Lazo, a co-author of this report.[15]

Figure 11. Burned-out neighborhood after the December 2021 Marshall Colorado Fire (source: J. Lazo).

4.2.1 GOES Fire Detection

GOES-R products that can flag the existence of a fire hotspot (sometimes well in advance of other techniques) to first responders and allow fire suppression efforts to begin sooner, help to reduce the economic impacts from that fire. Other GOES-R products can help identify smoke resulting from wildfires and support air quality determinations. The 1-minute scan from the GOES-R ABI mesoscale scans can rapidly identify the heat signature of early-phase wildfires under certain conditions.

Prior to the launch of GOES-16, experiments that simulated the capabilities of GOES-R using super rapid scan techniques with GOES-14 demonstrated that initial detection, coupled with Short Message Service (SMS) message text notices to Oklahoma emergency managers, often indicated a fire before it had been called into 911. Using appropriate wavelength detection, it allowed for rapid detection of hotspots. Participants during wildfire notifications in February 2016 indicated that "the dissemination of this information enhanced situational awareness and permitted contact with a few [fire] departments in advance of 911 calls...It was additionally noted that 'fire location often plays a role in resource allocation

[15] Photo credit: screen capture by Dr. Lazo from an indeterminate website such as https://www.youtube.com/watch?v=WK63zjsBl7Q.

priority' and the text messages enabled a timely dispatch of resources and aided in prioritization of fires with structures and improvements at risk" [*Lindley et al. 2016*].

GOES-R provides 5-minute observations over the conterminous U.S. and 10-minute observations over the entire Western Hemisphere. The automated Active Fire Product algorithm uses an approach primarily driven by data from GOES-R ABI mid-wave infrared (MIR) and long-wave infrared (LWIR) channels building on the legacy Wildfire Automated Biomass Burning Algorithm (WF-ABBA) (see the original concept [*Prins and Menzel 1992*]). The higher saturation temperature (+400 K) of the current MIR channel on the ABI makes it especially suited for active fire detection applications. The GOES-R fire product is named "Fire / Hot Spot Characterization (FDC)." FDC is, in fact, a suite of tools that can monitor large areas and routinely detect hundreds of fires at a time. FDC products are available every 5 and 15 minutes.

The NOAA/NESDIS Hazard Mapping System (HMS) is an analyst-integrated fire and smoke product used to analyze hotspots and smoke plumes for possible fire locations in near realtime. The NWS produces a blended product using output from automated fire detection algorithms that use both geostationary and polar-orbiting satellite data. The resulting display of fires and smoke plumes are generated daily for North and Central America. Users of these data include federal, state, and local agencies as well as private companies and universities.

Similarly, EPA's AirNow Fire and Smoke Map provides additional information on levels of particle pollution (particulate matter [$PM_{2.5}$]) in the air during fires (see an example in Figure 12).

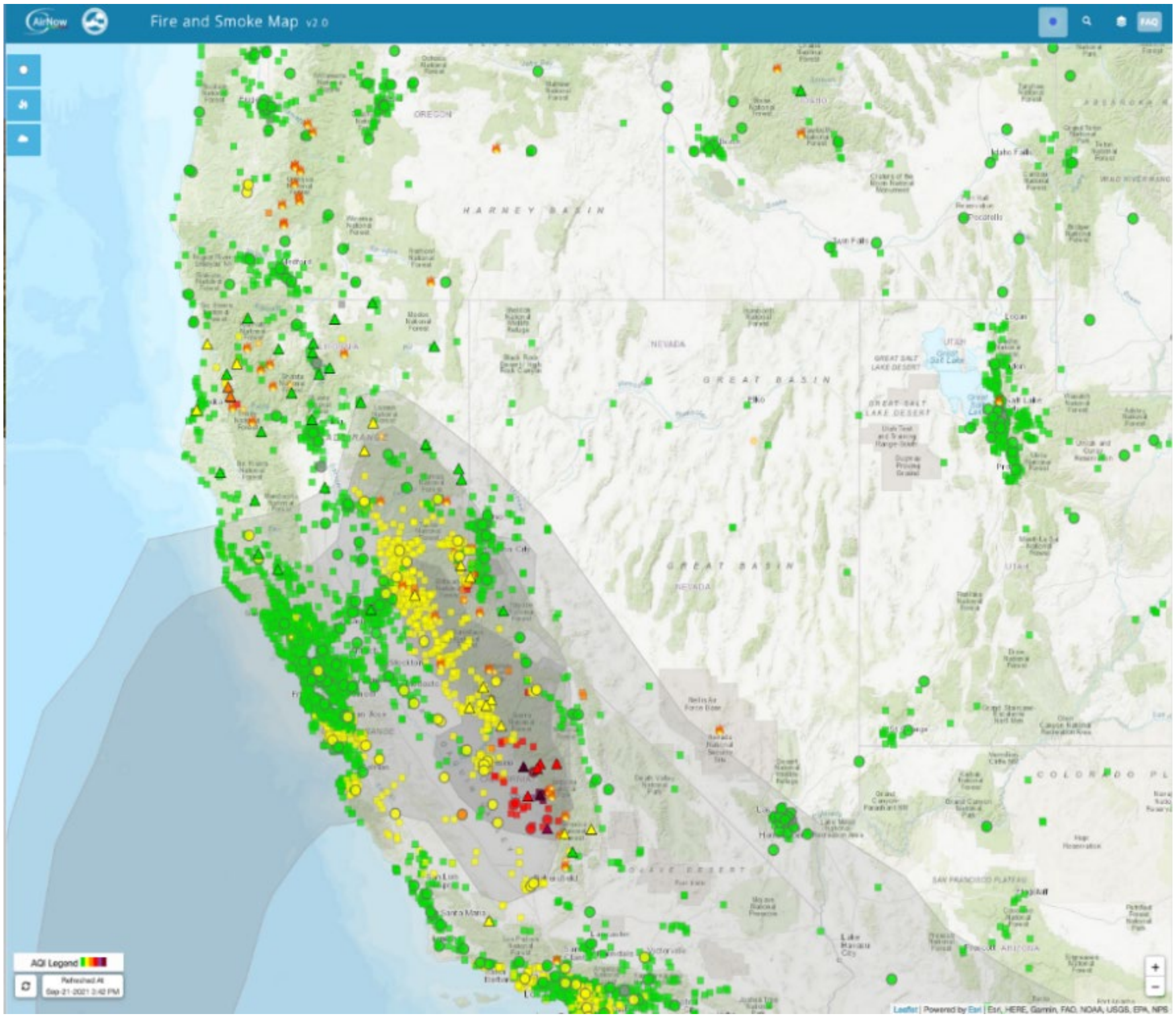

Figure 12. EPA's Air Now Fire and Smoke Map, September 21, 2021 [*EPA 2021A*]

GOES-R improvements allowed HMS to include the higher-resolution 2 km shortwave fire channel, provide more frequent scans due to the improved R-series scan rates, and more accurate pixel geolocation than was possible from GOES-N, -O, -P. These yields improved estimates of spot sizes, temperatures, and trends. In addition, the Geostationary Lightning Mapper (GLM) takes continuous lightning measurements, enabling wildland fire managers to identify potential fire ignitions in fire-risk areas and decreasing response times to new fires. Image sequences can be made into satellite loop videos.

Following a fire detection notification, the NRL's Fire Locating and Modeling of Burning Emissions (FLAMBE) program is used to determine how large the detected fires are, estimate their temperature, and determine how much fuel is available—all in an effort to predict the amount of smoke that will result. FLAMBE uses satellite data from multiple types of satellites.

> "Lightning-initiated wildfires account for 56% of the total acreage burned in CONUS. Nearly half of lightning-induced fires are not observed until one or more days after the event. Lightning-induced fires can smolder for some time before becoming a noticeable wildfire. Also, large fires can produce large plumes of heat and smoke that can generate lightning which triggers more fires. GLM can provide important information critical to the diagnosis of the intensity of updrafts and downdrafts. Safety of wildland firefighters is paramount and with GLM able to detect the full

extent of cloud-to-cloud lightning, this helps to better anticipate cloud to ground lightning strikes which could endanger fire-fighting personnel. GLM data are also useful in the forensics analysis after the fire. Fire investigations help to confirm whether lightning caused power outages, injuries in remote areas, or prove the existence of convection. Detection of continuing current is important and GLM can supplement data from ground-based lightning networks, which may be needed to trigger insurance company damage payments [Balch 2017]"

4.3 Inputs from TPIO-Derived from NOSIA II Data

The Fire Weather MSA, with products associated with the fire weather national service program, had a GOES-R contribution to models of 1.2% and a GOES-R contribution to non-model products of 12.82%. These resulted in a total GOES-R contribution to fire weather products of 14.02%.

4.4 Benefit Assessment

We focused on the potential avoided costs of early detection of wildfires. We obtained estimates on the average annual total socioeconomic impacts of wildfire from Thomas et al. 2017 [*Thomas et al. 2017*]. As noted in Thomas et al. [*Ibid, p. i*], "The economic burden represents the impact wildfire has on the U.S. economy. Tracking the economic burden of wildfire could be used to assess return-on-investment into wildfire interventions. The economic burden is decomposed into: 1. intervention costs; 2. prevention/ preparedness, mitigation, suppression, and crosscutting; 3. and into direct and indirect wildfire related (net) losses" [*Ibid, p. i*]. Thomas et al. [*Ibid*] provide lower- and upper-bound estimates of the total economic burden of wildfires (see Table 7) [*Ibid, p.* i]. We provide the estimates in 2016$ ranging from $71B to $347.8B. This was adjusted to 2020$ using the CPI. To derive an average impact per fire, we obtained information from Hoover and Hanson [*Hoover and Hanson 2021, p.1*] indicating that "From 2011 to 2020, there were an average of 62,805 wildfires annually" [*Ibid*] We divided the total economic impact by the number of fires to derive lower- and upper-bound estimates of the average cost per fire ranging from $1.2M to $6.0M. Again, using the average number of fires per year, we assumed that 1% of these may be detected using weather observations and mitigated before incurring significant impacts. This would represent almost 630 fires per year detected and prevented using weather information. Of these, we attributed 14.02% (or 88.03 fires a year) to GOES-R observing capabilities based on TPIO data of the percent of wildfire forecasts and products attributable to GOES-R (see Table 7).

We then multiplied this by the average costs per fire to derive lower- and upper-bound estimates of the benefit from GOES-R in reducing the potential impacts of wildfires. These baseline estimates range from $107,462,406 to $525,674,048 (in 2020$), as shown in Table 7.

Table 7. Economic Impacts of Wildfires—Number of Fire, Inflation Adjustment, and Value of Fires Prevented

Analysis Factors	Lower Bound	Upper Bound
Total annual economic impacts of wildfire [*Thomas et al. 2017*] ($2016))	71,100,000,000	347,800,000,000
CPI 2016 (240.01)	n/a	n/a
CPI 2020 (258.81)	1.078	1.078
	76,670,522,526	375,049,335,228
Average number of wildfires (CRS. 2021)	62,805	62,805
Average cost per fire (2020$)	1,220,771	5,971,648
Number of fires	62,805	62,805
Percent of fires prevented with weather information	1.00%	1.00%
GOES-R % of weather info (TPIO Input)	14.02%	14.02%
Number of fires prevented	88.03	88.03
Value of fires prevented (2020$)	107,462,406	525,674,048

As with other benefit areas, we assumed changes in weather variability would exacerbate wildfire impacts and factored this in as an annual increase in costs of 1.5%. We further assumed population growth would increase impacts by 0.572% annually and per capita income growth would compound the value of benefits by 1.469%.

We derived lower- and upper-bound present value benefit estimates using the five applicable rates of discount and taking the average of the lower and upper bounds as shown in Table 8 in billions of 2020$. The baseline GOES-R present value contribution to early wildfire detection is **$9.68B**.

Table 8. Present Value Estimates of GOES-R Contribution to Early Wildfire Detection

Discount Rate	0.0%	0.300%	1.185%	3.000%	7.000%
Billions (2020$)	10.96	10.62	9.68	8.11	5.82

4.5 Discussion—Key Uncertainties and Recommended Future Efforts

Characterizing the socioeconomic factors associated with an earlier identification (by satellite) of remote wildfires and the resultant changes in suppression, evacuation, or other response costs are difficult to gauge. Our approach assumed that a small percentage (e.g., 1%) of wildfires were "mitigated" due to early detection. Our assumption, on the percent of the average number of fires per year that may be detected and mitigated, could be further investigated and the value refined. This would then alter the number of fires per year detected and "prevented" or perhaps otherwise reduce or increase and affect the results accordingly.

We also note that we have taken a simple average of the upper- and lower-bound estimates [*Thomas et al. 2017*]. These bounds represent a range of uncertainty of plus or minus 33.9%. If one considered only the uncertainty in the Thomas et al. [*Thomas et al. 2017*] work, it would suggest our benefit estimates have that much uncertainty as well.

We note as well that we have not evaluated several other potential wildfire-related benefits from GOES-R such as decreased response time for active fires, improved decisionmaking for firefighting flight operations related to identifying smoke plumes, improved commercial airport operations, identification of burn scars for post-fire rehabilitation and flash flood prediction, and potential reductions in morbidity and mortality related to improved air quality warnings.

In addition to benefits from GOES-R imagery, the contribution of the GLM should be specifically considered and evaluated. Forecaster use of GLM data is significant and growing monthly. The increase in jump rate detected by GLM in a severe weather event provides clues that may lead to detecting lightning-induced wildfires. The viewpoint of cloud-to-cloud lightning from the GOES-R position above the cloud tops brings new insights to the lightning phenomenon.

5. Winter Storms

5.1 Summary Result

To estimate benefits of GOES-R related to impacts of winter storms, we calculated the potential reduction in winter-storm-related damages and mortality due to weather information. Building on existing information resources, we implemented the following steps to derive an annual benefit estimate:

- Damages:
  - The extant literature on winter weather impacts indicated annual average damages over 37 years ($1.186B/yr)
  - Assumed 10% of impacts are or could be mitigated. **(Note we feel this is a key uncertain parameter.)**
  - Applied the factor of 11.19% as attributable to GOES-R **(TPIO number)** ($28.9M derived annual baseline benefit)
- Fatalities:
  - Took average number of fatalities from NOAA Billion-Dollar Disaster Events database for winter and cold fatalities (34.0 lives)
  - Assumed 10% of fatalities could be or are mitigated (3.4 lives). **(Note we feel this is a key uncertain parameter.)**
  - Assumed that 11.19% of that is attributable to GOES-R **(TPIO number)**
  - Applied USDOT 2020 base year VSL ($11.6M)
  - Derived benefits in reduced winter weather fatalities ($4.4M)
- Added these two together to give an approximate annual 2018 baseline benefit of $33.3M (2020$).

We then aggregated these over the lifetime of the project, accounting for increases in wealth and population. For winter storms, we did not include a weather variability growth factor, assuming that there is even potentially a decrease in cold weather variability.[16] The baseline estimate is an aggregated present value benefit of **$0.84B** (in 2020$).

5.2 Introduction to Application Area

> The cryosphere includes snow, sea ice, lake and river ice, icebergs, glaciers, and ice caps, ice sheets, and ice shelves, permafrost and seasonally frozen ground, and solid precipitation. … Changes in the cryosphere have major impacts on water supply, agriculture, transportation, freshwater ecosystems, hydropower production, health, and

[16] We make a subjective assumption that winter severity will decrease with global warming. This is open to further analysis or support from the extant literature especially to the extent that to which the variability in winter weather may change.

recreation. - hazards include floods, droughts, avalanches, and sea-level rise” [*Key at al. 2020*].

Winter weather causes delays to day-to-day air and land transportation commerce due to snow, ice, or winter storms and impacts maritime transportation on the Great Lakes, commercial aviation departure delays to deicing the aircraft prior to takeoff, and recreational access to mountain resorts. Coverage and movement of ice in aquatic regimes and ice thickness provides important information.

Lake-effect snow can significantly impact weather downwind of the Great Lakes. A Cleveland WFO graphic, from GOES-16 imagery on January 7, 2022, is shown in Figure 13.

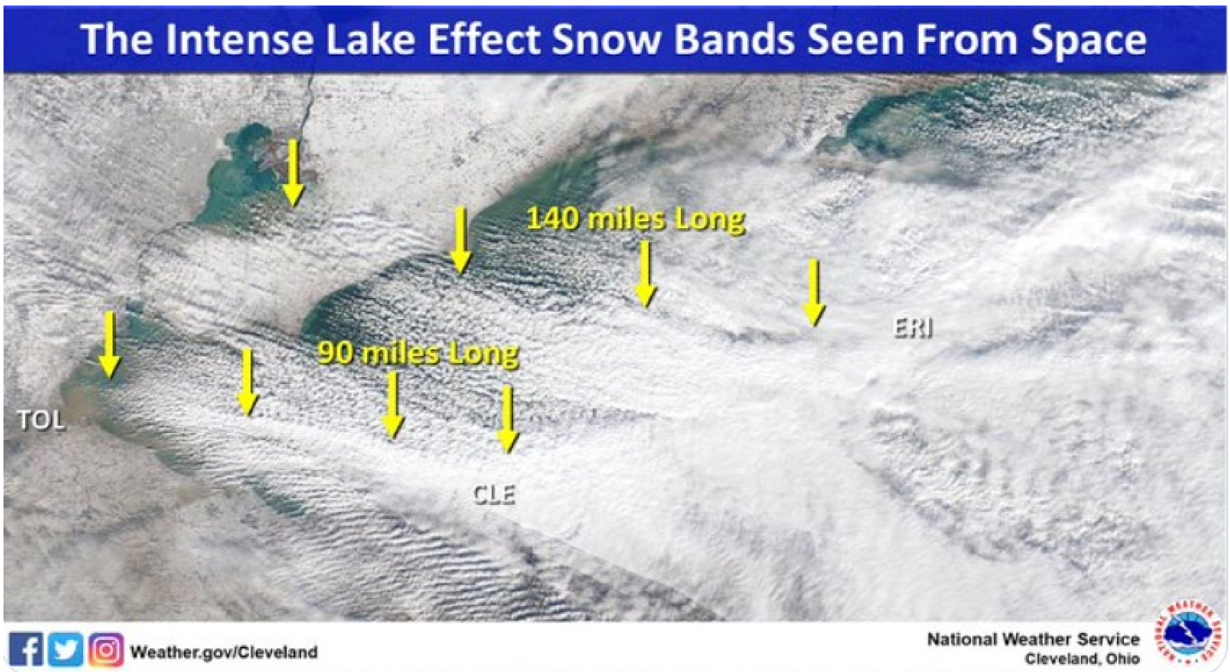

Figure 13. Lake-effect snow bands, derived from satellite imagery [*NWS 2022A*].

For most Americans, snow means difficult travel on roadways, potential isolation at home due to snow amount or drifting, and accompanying cold temperatures that, with the snow load on trees, team up with downed power lines to foster potential frozen water pipes in unheated homes. The advance planning made possible by an accurate forecast does allow for some mitigation of this problem.

Most GOES-R Series contributions to winter weather products are derived from visible or IR imagery. Excellent examples of impacts may be found in two recent meteorological events. First, a major winter storm for the Northeast and coastal Mid-Atlantic states over the weekend of January 28 and 29, 2022, prompted winter storm watches for more than 45 million people all along the mid- and upper eastern seaboard (Figure 14, NWS public service graphic for January 28–30, 2022).

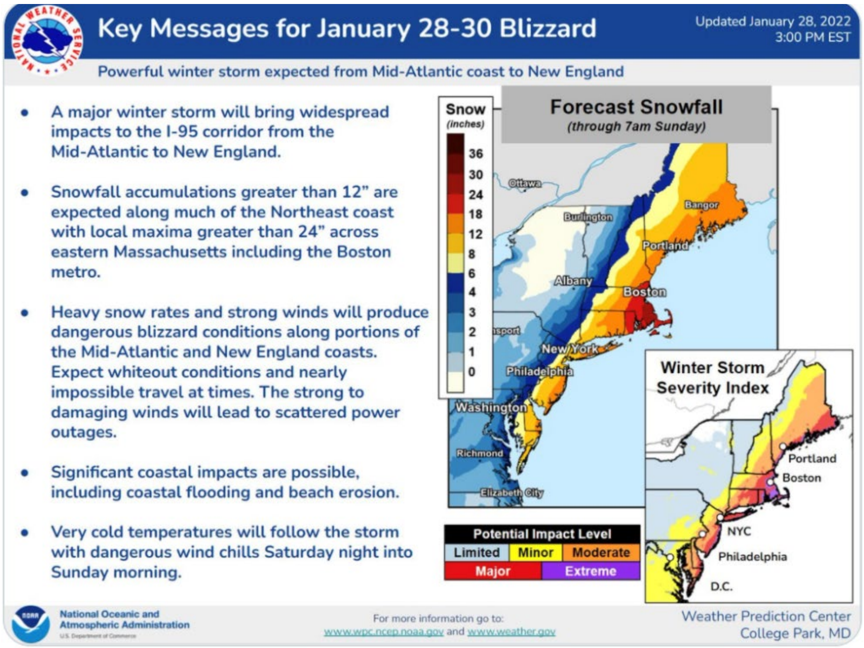

Figure 14. NWS Weather Prediction Center blizzard public service message and graphic (NWS).

Another major winter storm impacted a large swath of the nation on February 1–4, 2022, leading to winter storm watches and ice warnings from states ranging from New Mexico to Maine (Figure 15).

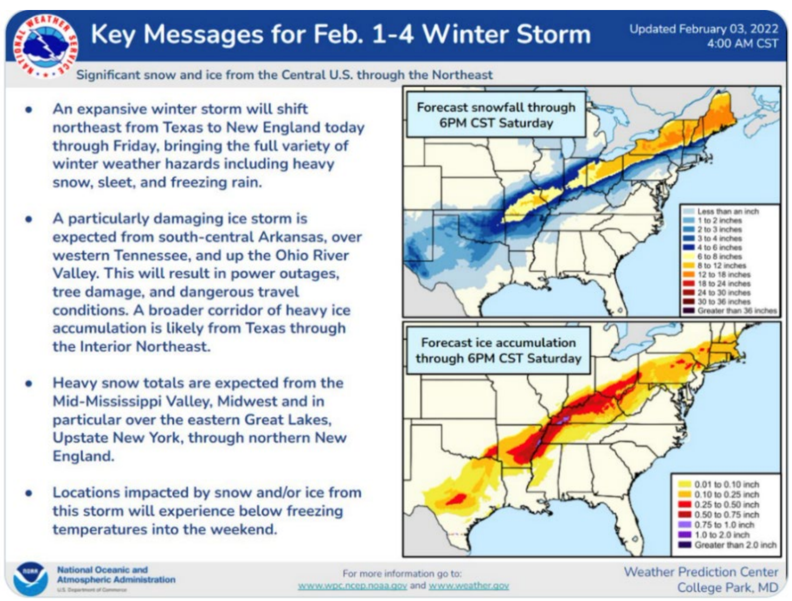

Figure 15. February 1–4, 2022, winter storm watches and ice warnings (NWS).

GOES-R imagery contributed to products associated with both winter storms. Figure 16 shows GOES-16 mid-level water vapor imagery (left panel) showing the precipitation that produced a mid-altitude cyclone, which rapidly intensified off the northeast U.S. coast on January 29, 2022. The right panel shows GOES-16 water vapor images January 29, 2022, with hourly plots of wind barbs and gusts showing the highest wind gusts occurred near the New England coast.

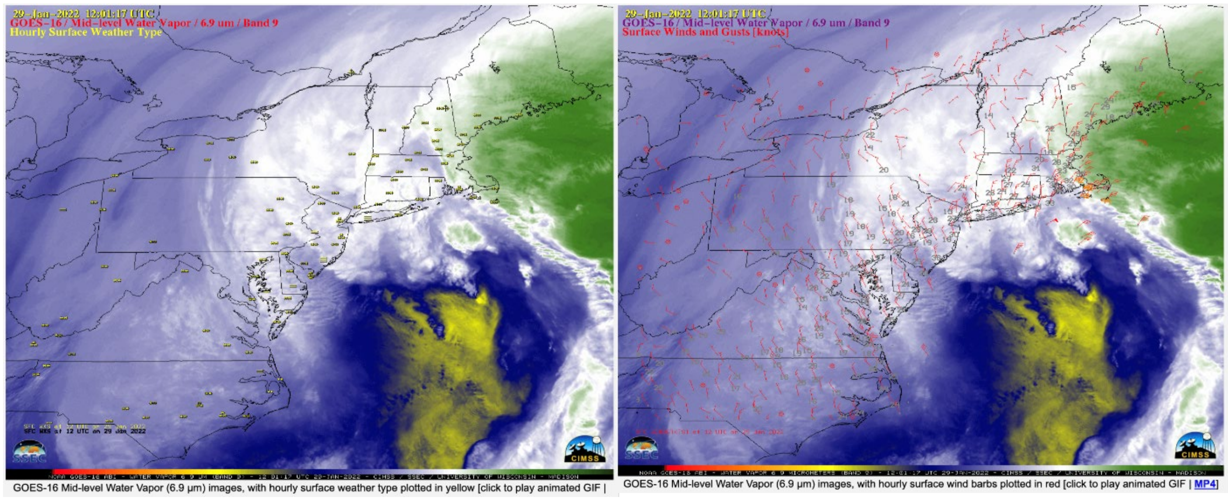

Figure 16. GOES-16 water vapor images January 29, 2022. Source: CIMSS Satellite Blog (NOAA/CIMSS).

Figure 17 shows large winter weather systems affecting much of central United States from New Mexico to New England on February 2, 2022 (NOAA satellites). GOES-R imagery has a key role in forecaster decisions and the development of warning and forecast products in advance of these storms.

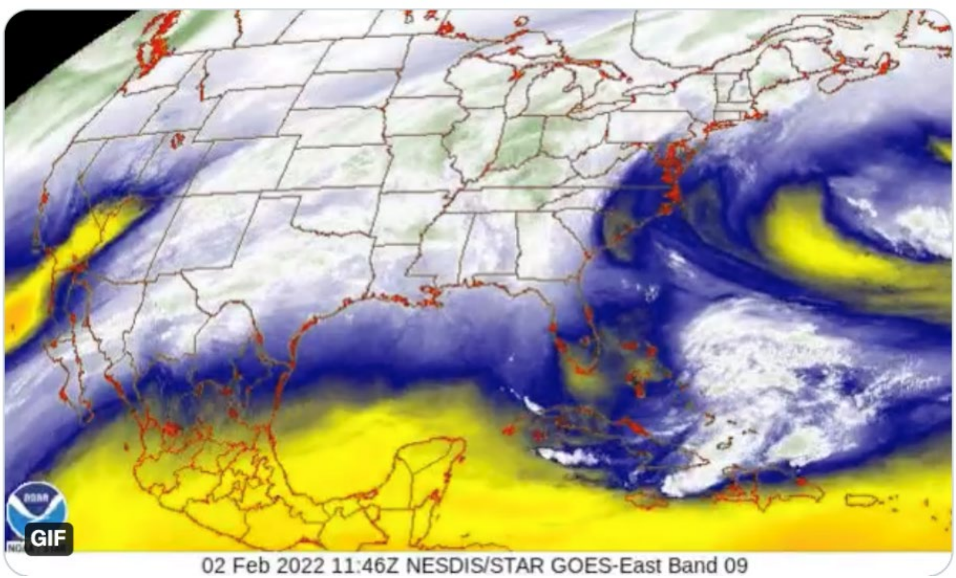

Figure 17. Water vapor from GOES-16, February 2, 2022 (NOAA Satellites).

5.3 Input from TPIO-Derived from NOSIA II Data

The Winter Weather products had a GOES-R contribution to models of 1.01% and a GOES-R contribution to non-model products of 10.17%. This resulted in a total GOES-R contribution to winter weather products of 11.19%.

5.4 Benefit Estimate

To derive estimates of the benefit of GOES-R in reducing winter weather impacts, we examined both reductions in damages or economic impacts and reductions in fatalities associated with winter or cold weather. We obtained damage information from NOAA's Billion-Dollar Weather and Climate Disasters database for the years 1980 through 2021, using CPI-adjusted data. We combined data on winter storm and freeze impacts. We feel it is likely that annual impacts are significantly larger as most individual winter storm impacts do not reach the billion-dollar threshold, and the cumulative annual costs of small storms is likely much more than that of billion-dollar events. Similarly using these data, Lazo et al. [*Lazo et al. 2020*] and Hosterman et al. [*Hosterman et al. 2019*] studied two winter storms in the New York area in 2010 and 2016, comparing the impacts of each of the storms—one after the implementation of the NWS's Impact-based Decision Support Services (IDSS) and one before. That study examined the Northeast Snowfall Impact Scale (NESIS) to characterize and rank the snowstorms as a function of "the area affected by the snowstorm, the amount of snow, and the number of people living in the path of the storm" [*Ibid*]. The study gathered data about the impacts of extreme winter storms, as it looked at emergency management, aviation, ground transportation, and energy areas.

Lazo et al. [*Lazo et al. 2020*] examined the benefits of IDSS using case studies of winter storms impacting New York City. This work is also discussed in Hosterman et al. [*Hosterman et al. 2019*], focusing on the emergency management aspects of IDSS that are critical to value creation. In the literature reviewed for this work, Lazo et al. 2020 [*Ibid*] state:

> "Between 1980 and 2017, fourteen different "billion-dollar" winter storms inflicted a total of $43.9 billion in damages on the United States and caused 1,013 deaths, based on summary data from the National Oceanic and Atmospheric Administration's (NOAA's) Billion-Dollar Weather and Climate Disasters database (https://www.ncdc.noaa.gov/billions/summary-stats). Untold further damage, disruption, injury, and death likely can be attributed to the vast majority of winter storms that did not reach the billion-dollar impact level. During the same time period, the EM-DAT database identifies 355 winter weather disasters accounting for over 19,000 fatalities globally. The EM-DAT database uses a specific classification to include events as disasters (see https://www.emdat.be/). We searched EM-DAT globally for "cold waves" and "severe winter conditions" [*Ibid, p. E626*].)

Table 9 shows our calculation of benefits attributable to GOES-R from NOAA's Billion-Dollar Weather and Climate Disasters database [*NCEI 2022*], we used the annual average damage of $2.7B in 2021$. We assumed that 5% of these damages are already avoided by use of weather information and that 5% more could be avoided with improved use of weather information—thus assuming a total of 10% of the winter weather impact is or could be mitigated. (Note that this is a key unknown parameter in this analysis and subject to further research.) Of this, we attribute 11.19% to GOES-R based on data from TPIO. We then adjusted this estimate back to 2020$ from the 2021$ that the CPI-adjusted damages were reported in in the NOAA database.

Table 9. Calculation of Winter Storm Damages Reductions Attributable to GOES-R

Analysis Factors	Factor	Value
Average Annual Damages—NOAA (1980–2021 CPI Adjusted) [NCEI 2022](B$)	n/a	2.7
Assume 10% could be or are mitigated (B$)	10.0%	0.270
Percent attributable to GOES-R (TPIO) (B$)	11.19%	0.030
Benefits attributable to GOES-R ($)	n/a	30,206,464
CPI adjustment	n/a	n/a
2021	270.97	n/a
2020	258.71	n/a
CPI factor and adjusted value (2020$)	0.96	28,851,035

Using 79 years of data, we regressed fatalities each year to see that winter-weather-related fatalities have been falling significantly for a prolonged period, although it has been highly variable. Using only the winter weather data, we employed the regression to project fatalities to 2040 as well.[17] See Figure 18 for a plot of these regression data. Note that this analysis was used to support our assumptions but not specifically to model reduced fatalities for the benefits assessment. That calculation is described next.

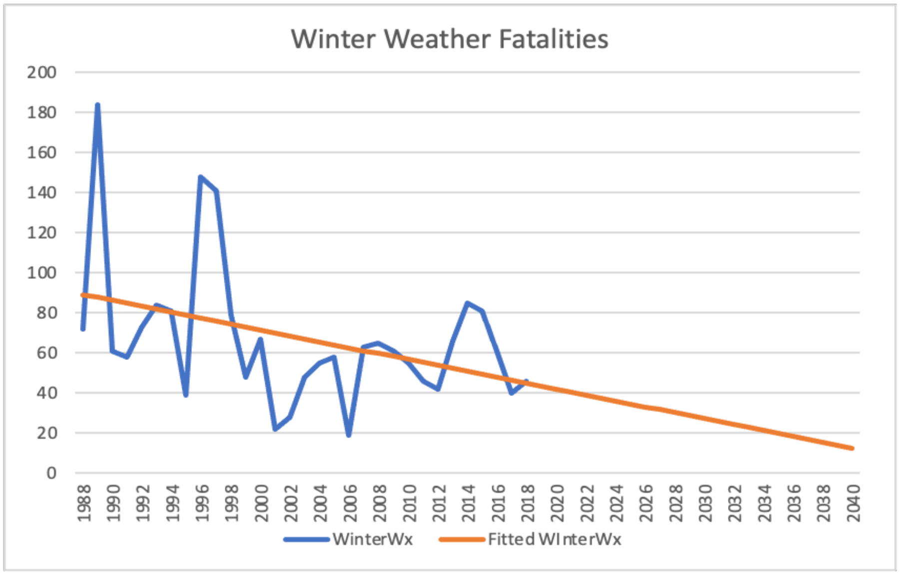

Figure 18. Historical and projected (fitted) winter weather fatalities (not including freeze data) (Lazo/Aerospace).

To maintain consistency with the damage estimation, we took the average number of fatalities per year from winter storms and freeze as reported in NOAA's Billion-Dollar Weather and Climate Disasters database for the years 1980 through 2021 [*NCEI 2022*]. This average of 34 deaths per year likely significantly understates the total due to cold weather as most events do not reach the billion-dollar threshold. For instance, according to an EPA document, "Between 1979 and 2016, the death rate as a direct result of exposure to cold (underlying cause of death) generally ranged from 1 to 2.5 deaths per million people, with year-to-year fluctuations. Overall, a total of more than 19,000 Americans died from cold-related causes since 1979, according to death certificates" [*EPA 2022*]. This translates to over 500 cold-related fatalities a year rather than the 34 derived from the NOAA Billion-Dollar Weather and Climate Disasters database.

As in the damage analysis, we assume that 5% of fatalities are already avoided by use of weather information and that 5% more could be avoided with use of weather information—thus assuming 10% of the winter weather fatalities impact is or could be mitigated. Of this we attributed 11.19% to GOES-R based on data from TPIO's NOSIA II analysis. As shown in Table 10, this represents a reduction in 0.38 annual fatalities. We then applied the VSL estimate of $11.6M per statistical life, which are already in 2020$. The baseline estimate of the GOES-R attributable benefits associated with reductions in winter weather fatalities is $4.4M annually as shown in Table 10.

[17] This is a simple linear model that obviously cannot hold indefinitely as it would eventually project negative fatalities.

Table 10. Calculation of Winter Storm Fatality Reductions Attributable to GOES-R

Analysis Factors	Factor	Value
NOAA Billion-Dollar Disaster - Winter Storm and Freeze Average Annual Fatalities [*NCEI 2022*]	34.00	n/a
Assume 10% could be or is mitigated	3.4	n/a
11.19% of forecasts information attributable to GOES-R (TPIO)	0.38	n/a
VSL - USDOT 2020 base year VSL	n/a	$11,600,000
GOES-R annual reduced fatality benefits (2020$)	n/a	$4,412,381.28

We then summed damage benefits and reduced fatalities benefits for total winter storms benefits. Differently from other benefit areas, we did not assume changes in weather variability would exacerbate winter weather and cold weather impacts as there is some indication this has decreased recently and may continue to decrease over time. In econometric analysis of winter weather impacts on U.S. economic activity, Bloesch and Gourio [*Bloesch and Gourio 2015*] looked for a statistical signal related to increasing temperatures due to climate change. Noting that annual variations likely overshadowed the climate trend, they did find that "… in some cases it is possible to observe a positive trend starting in 1980, which is consistent with the evidence on climate change on the United States" [*Ibid*].

We continued to assume population growth would increase impacts by 0.572% annually and per capita income growth would compound the value of benefits by 1.469%. We derived present value benefit estimates using the five applicable rates of discount as our baseline estimates, as shown in Table 11 in billions of 2020$. The baseline contribution by GOES-R to winter storm forecasting is **$0.84B** in 2020$.

Table 11. Present Value Estimates of GOES-R Contribution to Winter Storm Forecasting

Discount Rate	0.0%	0.300%	1.185%	3.000%	7.000%
Billions (2020$)	0.96	0.93	0.84	0.69	0.48

5.5 Discussion—Key Uncertainties and Recommended Future Efforts

With respect to economic impacts, the current analysis only looks at "damages" as defined in the NOAA Billion-Dollar Weather and Climate Disasters database [*NCEI 2022*]. It seems likely that cumulative daily economic impacts are significantly larger than the billion-dollar threshold. For instance, in detailed econometric analysis of economic data, Bloesch and Gourio [*Bloesch and Gourio 2015*] results indicate "…overall support the view that weather has a significant, but short-lived, effect on economic activity. Except for a few industries, which are affected importantly (such as utilities, construction, hospitality, and, to a lesser extent, retail), the effect is not very large…" [*Ibid, pp.17-18*]. This suggests that there are significant sub-billion-dollar impacts on a broad range of economic activity related to winter weather that do or may see benefits from improved weather information.

The key uncertainties in this analysis are the factors for the percent of damages or fatalities prevented by using weather information. We applied 10% factors for the current analysis but suggest further research to refine this value. We note that the NOAA Billion-Dollar Weather and Climate Disasters database does also present confidence intervals on the damage costs and that information could be used to consider confidence intervals on the current analysis. For instance, the 95% upper and lower bound 1980–2017 CPI-adjusted winter storm cost confidence interval is $40.9B to $60.1B [*EPA 2022*]. This suggests a roughly 20% plus-or-minus probability interval on the current estimates just from the NOAA damage data. The uncertainty in the percent of impacts avoided is likely equal to or greater than this and, for this reason, we have not calculated a confidence interval at this time.

These assumptions, along with the following EPA perspective, suggest we are being very conservative in assessing the number of cold/winter fatalities.

> "While increases in deaths are generally associated with colder temperatures, some winter deaths are due to factors other than exposure to cold conditions. For example, winter is typically flu season. In other cases, even if cold exposure contributes to a death, it may not be reported as 'cold-related' on a death certificate. These limitations, as well as year-to-year variability in the data and a change in classification codes in the late 1990s, make it difficult to determine whether the United States has experienced a meaningful increase or decrease in deaths classified as 'cold-related' over time" [EPA 2022].[18]

We note further that many winter storm fatalities are likely related to vehicle crashes, which also would not be counted in the billion-dollar disaster date. As indicated by the USDOT:

> "The U.S. Department of Transportation (DOT) said more than 5.8 million vehicle crashes occur each year based on statistics from 2007 to 2016. About 21 percent of those, or just over 1.2 million, involved hazardous weather. Those U.S. weather-related automobile crashes have killed an average of 5,376 people annually, accounting for about 16 percent of all vehicular deaths, the DOT said. More than 418,000 others were injured each year during that same period" [The Weather Channel 2022].

It is possible that benefits associated with reductions in winter storm impacts derived here overlap to some degree with the value calculated in the aviation benefits area. Calculating such overlaps is beyond the resources of the current study and is one more reason all the socioeconomic results of this study cannot simply be summed to arrive at a total socioeconomic value for the GOES-R system.

[18] https://www.epa.gov/climate-indicators/climate-change-indicators-cold-related-deaths. Accessed April 26, 2022

6. Flash Flood Warnings—Fatalities

6.1 Summary Results

To estimate benefits of GOES-R related to impacts of flash floods, we calculated the reduction in flash flood fatalities. Note that section 7 examines potential reductions in property damage. Building on existing information resources, we implemented the following steps to derive an annual benefit estimate:

- Fatalities:
  - We obtained annual flood related fatality data from NOAA:
    - Took 30-year average from NOAA flood fatalities 1959–1988 (138.4)
    - Took 30-year average from NOAA flood fatalities 1989–2018 (86.7)
    - Took difference in these averages as reduction in fatalities (51.8)
- We assumed 30% of this reduction is attributable to weather information (15.53 lives saved). **(Note we feel this is a key uncertain parameter.)**
- We then applied a 10.24% factor as contribution of GOES-R (1.59 lives saved) **(TPIO number)**,
- We applied $11.6M VSL to calculate annual benefits in reduced fatalities ($18.4m/yr baseline).

This derivation provided us with baseline year annual benefits from GOES-R of $18.4m/year. We then aggregated these over the lifetime of the GOES-R series, accounting for increases in wealth, population, and weather variability (using a baseline discount rate of 1.185%). The baseline estimate is an aggregated present value benefit of **$0.55B** for flash flood warnings (in 2020$).

6.2 Introduction to Application Area

> "Flooding is an overflowing of water onto land that is normally dry. Floods can happen during heavy rains, when ocean waves come on shore, when snow melts quickly, or when dams or levees break. Damaging flooding may happen with only a few inches of water, or it may cover a house to the rooftop. Floods can occur within minutes or over a long period (of time), and may last days, weeks, or longer. Floods are the most common and widespread of all weather-related disasters. … Flooding occurs in every U.S. state and territory, and is a threat experienced anywhere in the world that receives rain. In the U.S., floods kill more people each year than tornadoes, hurricanes, or lightning combined" [*NOAA NSSL 2021*].
>
> The top eight common causes of flooding:
>
> 1. Heavy rains: the simplest explanation for flooding is heavy rains, which is why rainfall amount and rate are useful information
> 2. Overflowing rivers
> 3. Broken (or failed) dams
> 4. Urban drainage basins being overrun or eliminated

5. Storm surges and tsunamis
6. (Overflowing) channels with steep sides
7. A lack of vegetation (allowing water to flow unimpeded)
8. Melting snow and ice [*NOAA NSSL 2021*]

Related to wildfire impacts and to the use of GOES-R to monitor burn areas, a contributing factor to flooding is the presence of burn scars from land previously subjected to major wildfires now denuded of vegetation. Without the vegetation that was present prior to the wildfire, water and mud flow unimpeded across the burned area.

6.2.1 GOES-R and Rainfall

Data regarding rainfall is essential for the generation of warnings and the management of water resources. Satellites with IR or visible (VIS) sounder and/or imager instruments contribute to the determination of rainfall information. Satellite measurements are able to fill the gaps worldwide not otherwise covered by in situ sensors. Sensors based on microwave techniques or active sensors intended for precipitation measurements may not have some of the limitations that an IR/VIS sensor will have, but most of these types of systems are in non-geostationary orbit, with different coverage properties.

Radiance values from five IR channels, and the differences between those specific channels, are used to retrieve rain rates. Cloud properties can be determined from these measurements, including the water or ice content within the cloud.

GOES-R imagery also provides important contributions to situational awareness for forecasters and has important uses in development of precipitation and flood products.

6.3 Inputs from TPIO-Derived from NOSIA II Data

According to TPIO's NOSIA II data analysis, GOES-R, in the area of integrated water products, made a contribution to models of 2.36% and a contribution to non-model products of 7.88%. These resulted in a total GOES-R contribution to flooding and integrated water products of 10.24%.

6.4 Benefit Assessment for Flood Warning and Hydrology

For this benefit area, we focus on the potential reduction in loss of life primarily related to flash flooding. There is a well-founded research analysis of the causes and situations surrounding loss of life in flash floods. While some fatalities are likely unavoidable due to circumstances, many are avoidable given sufficient warning and prior understanding of appropriate response as well as communicating appropriate responses are part of the warning process [*Lazrus et al. 2016*][*Morss et al. 2016*] [*Morss et al. 2015*]. The majority of flood-related fatalities are in flash floods (as opposed to riverine floods, which are temporally slower to evolve) [*Ashley and Ashley 2008*]. General findings on vulnerable populations and circumstances of flash flood fatalities on a case-by-case base suggest that prior preparation and education, timely warnings, and informed decisionmaking had and could reduce fatalities [*Parker et al. 2005*] [*Špitalara et al. 2014*] [*Terti et al. 2017*].

To assess potential GOES-R-related benefits, we obtained historical fatality data from NOAA [*NOAA Weather.gov 2022*] focusing on the "Flood Fatalities" statistics from 1959 through 2018. Regression analysis indicates there has been a small downward trend in flood fatalities as per regression from 1959 to

2018, as shown in Figure 19. Note that this analysis was used to support our assumptions but not specifically to model reduced fatalities for the benefits assessment. That calculation is described next.

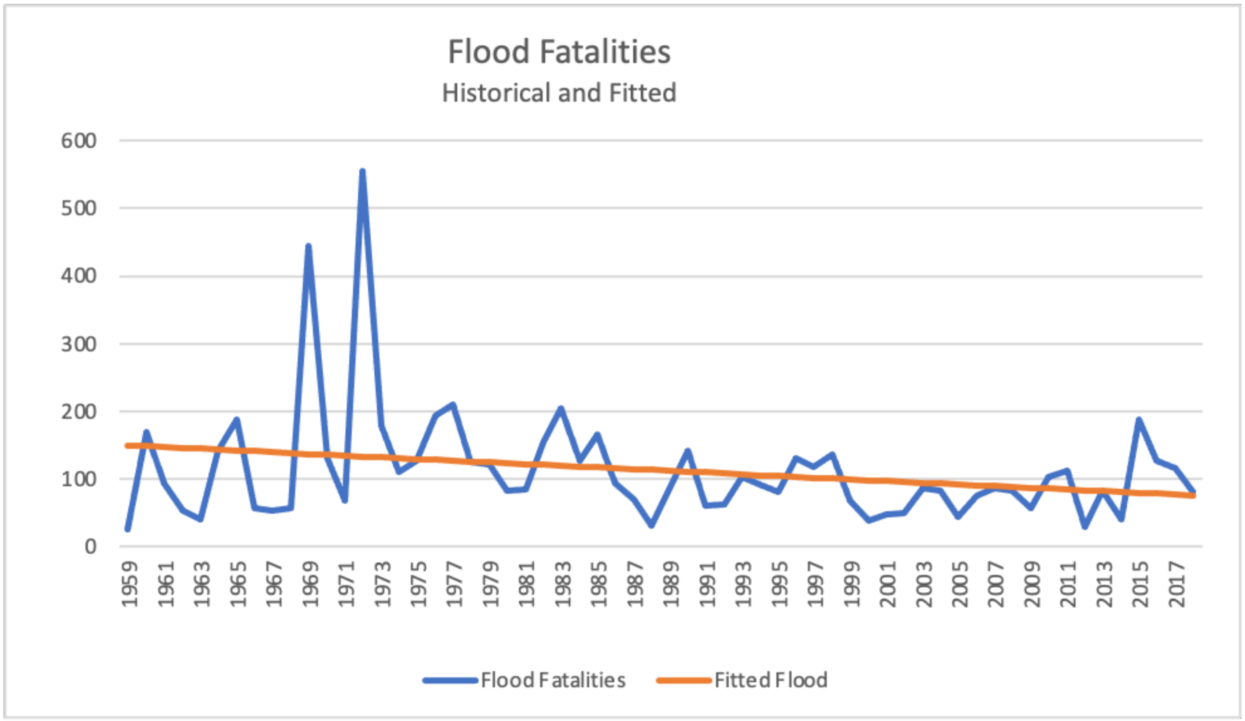

Figure 19. Historical and fitted flood fatalities from 1959 through 2018 [*NOAA Weather.gov 2022*].

We took the 30-year average of flood fatalities from 1959 through 1988 and compared these to the 30-year average from 1989 through 2018. Furthermore, we took the difference in these averages as reduction in fatalities and assumed that 30% of this reduction is attributable to weather information. We then used TPIO's estimate of 10.24% of the contribution of GOES-R to hydrology and water resources products. This yielded an estimated 1.59 lives saved per year attributable to GOES-R information as shown in Table 12. Multiplying the lives saved per year by the USDOT VSL (2020$), we derived benefits in reduced flood-related fatalities of $18.4M for the 2018 base year.

Table 12. GOES-R Attributable Benefits from Reducing Flash Flooding Fatalities

Analysis Factors	Factor	Value
Difference in 30-year average annual fatalities (1959–1988 vs. 1989–2018)	n/a	51.77
Reduction in fatalities attributable to weather information	30%	15.53
Percent of this reduction attributable to GOES-R	n/a	10.24%
Lives saved attributable to GOES-R, per year	n/a	1.59
VSL—USDOT 2020 base year VSL	n/a	$11,600,000
Reduced fatalities benefit (2018)	n/a	$18,443,183

As with other benefit areas, we assumed changes in weather variability would exacerbate flooding impacts and factored this in as an annual increase in costs of 1.5%. We further assumed population growth would increase impacts by 0.572% annually and per capita income growth would compound the value of benefits by 1.469%. We derived present value benefit estimates using the five applicable rates of discount as shown in Table 13 in billions of 2020$. Our calculations yielded the baseline present value estimate of GOES-R contribution to flash flood warnings of **$0.55B**.

Table 13. Present Value Estimates of GOES-R Contribution to Flash Flood Warnings

Discount Rate	0.0%	0.300%	1.185%	3.000%	7.000%
Billions (2020$)	0.64	0.62	0.55	0.45	0.30

6.5 Discussion—Key Uncertainties and Recommended Future Efforts

Although GOES-R-derived NOAA/NESDIS products report rainfall rates, we do not believe these data are fully incorporated into forecast end products at this time. Therefore, we feel that future research and effort are likely to yield additional socioeconomic value once these data are more fully utilized in such end products.

A key uncertainty in this analysis is the factor for the percent of reduction in fatalities attributable to weather information. We applied a 30% factor for the current analysis but suggest further research is needed to refine this value.

7. Flash Flood Warnings—Damages

7.1 Summary

To estimate benefits of GOES-R related to physical damages from flash flooding, we calculate potential reductions in socioeconomic impacts with appropriate information and response actions related to building structures and building contents. Building on existing information resources, we implemented the following steps to derive an annual benefit estimate:

- Obtained data on damage losses from flood (1990–2015) (this includes riverine flooding)
- Calculated the average annual losses (replacing 2017 with the average from the other years as it appears to be a significant outlier)[19]
- Assumed of this flooding 50% is flash flood and 50% riverine to derive the portion that is flash flood damages. **(Note we feel this is a key unknown parameter.)**
- From a study recently published in BAMS [*Kreibich et al.*] based on analysis in Germany, we took the percent of damages that can be mitigated with warnings and preventive actions. **(Note we feel this is a key unknown parameter.)**
- We apportioned this to structural damage (two thirds) and contents damages (one third), based on insurance data
- Based on Kreibich et al. [*Ibid*], we applied 2% of structure and 4% of contents damage can be mitigated in flash floods with warnings and appropriate response
- This gives us the avoided damages ($37.27M)
- We then used TPIO estimate of contribution of GOES-R to hydro products (10.24%) to derive an estimate of annual GOES-R benefits ($3.82M)

This provided us with a baseline year annual benefit from GOES-R of $3.82M. We then aggregated these over the lifetime of the project, accounting for increases in wealth, population, and weather variability (using a baseline discount rate of 1.185%). The baseline estimate is a present value benefit of **$0.11B** (in 2020$).

7.2 Inputs from TPIO-Derived from NOSIA II Data

According to TPIO's NOSIA II data analysis, GOES-R, in the area of integrated water products, made a contribution to models of 2.36% and a contribution to non-model products of 7.88%. These resulted in a total GOES-R contribution to flooding and integrated water products of 10.24%.

7.3 Introduction to Application Area

These GOES-R information inputs and applications in this benefit area are essentially the same as those described in section 6.2 for flash flood warnings fatalities.

[19] Note that not replacing this outlier would increase our overall benefit estimates, so we took a conservative approach.

7.4 Benefit Assessment

We focus on the potential avoided damage costs from flash floods with flash flood warnings and appropriate preventative actions. We obtained estimates on the annual economic damages from floods and flash floods from the statista website [*Fernández 2022*]. The website statista.com provides data on "Economic damage caused by floods and flash floods in the U.S. from 1995 to 2020." The source of this information is not available without a subscription, but we note that this data appears to be based on the NOAA Billion Dollar Disaster Events database information. The statista data indicates that this information is for floods and flash floods (e.g., does not separate flash floods from riverine floods). Therefore, we assume that 50% is riverine and 50% flash flood damages.

Figure 20 shows the annual damages in millions of from 1995 to 2019 (21 years). As 2017 damages appear to be significantly larger damages than indicated in any other year, we dropped the 2017 value and took the average of the other 20 years. This conservative approach may thus understate the actual average annual damages. The average annual damages of $2.795B compares reasonably with the recently reported 1980–2021 annual average flood damages of $4.0B (in 2022$) based on the NOAA NCEI "U.S. Billion-dollar Weather and Climate Disasters" presentation [*NCEI 2022B*]. We further note that we did not undertake a CPI adjustment as currently it was unclear if the damage data was in real or nominal terms. By assuming it was real in real terms, and not undertaking the CPI adjustment, we are being conservative by not adjusting annual damages upward.

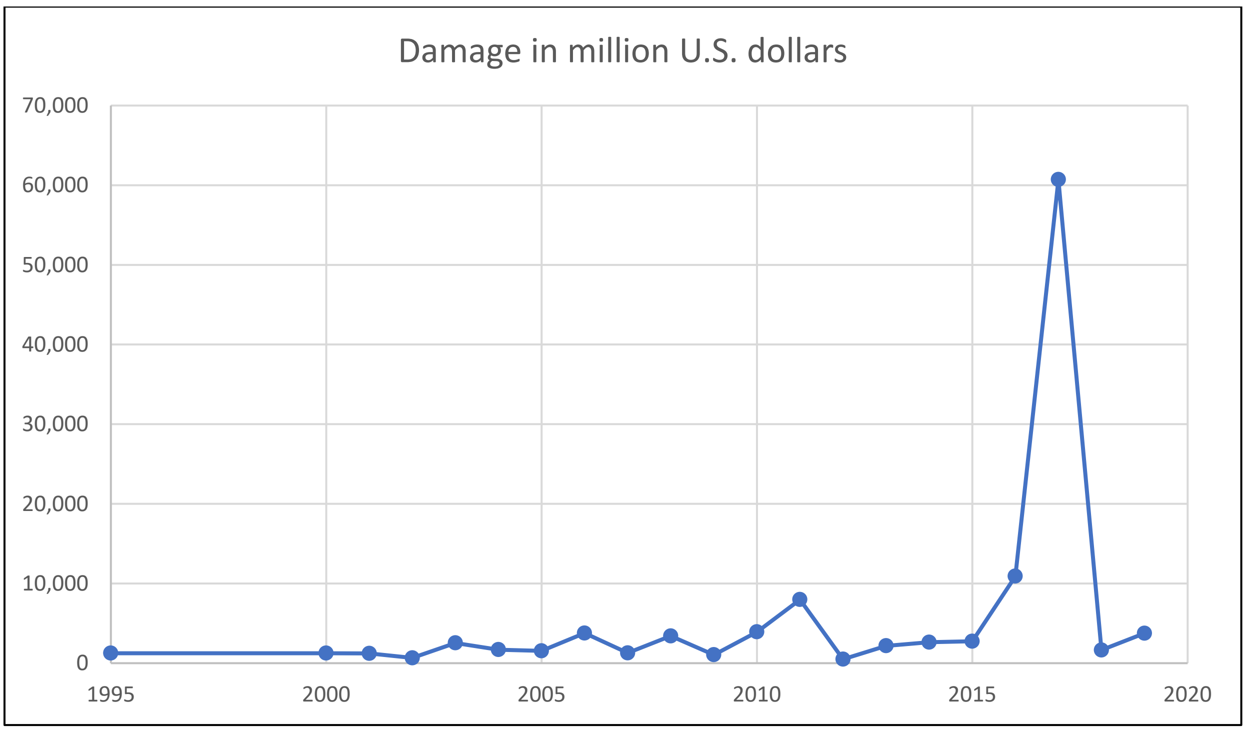

Figure 20. Annual U.S. flood damages [*NCEI 2022B*].

From the Insurance Information Institute (III) website, we obtained information that for property contents, "the coverage is generally 50 to 70 percent of the insurance you have on the structure of the house" [III 2022]. We thus assumed that from total damages, two thirds is structure and one third is contents. This becomes relevant as Kreibich et al. [*Kreibich et al. 2021*] estimated different loss reductions rates for structure than for contents.

Kreibich et al. [*Kreibich et al. 2021*] found that "The average reduction of the household contents loss ratio is 4 percentage points (averaged across all matching methods), a reduction of 3,800 EUR for the average treatment recipient (Fig. 1, averaged across all matching methods). This is substantial in comparison with the mean (median) contents loss ratio of 21% (10%) and absolute contents loss of 17,000 (7,700) EUR. For the building loss ratio, the average reduction is 2 percentage points (averaged across all matching methods), a loss reduction of 10,000 EUR (Fig. 1, averaged across all matching methods)" [*Ibid, p. E1456*]. Thus Kreibich et al. [*Ibid*] find that with flash flood warnings and appropriate prior preparation, structural losses can be reduced by 2% and content losses by 4%. We apply these factors the estimated U.S. structure and content losses as shown in Table 14. As shown in Table 14, we thus estimated that flash flood warnings can reduce U.S. losses by $37.27M. We then apply the TPIO estimate of contribution of GOES-R to hydro products (10.24%) to derive an estimate of annual GOES-R benefits ($3.82M).

Table 14. Reduced Flash Flood Damages

Analysis Factors	Factor	Value
Average annual flash flood damages (millions)	n/a	$2,795.24
Assume 50% is flash floods	50%	$1,397.62
Structure	66.70%	$931.75
Loss reduction—structure	2%	18.63
Contents	33.30%	$465.87
Loss reduction—contents	4%	$18.63
Total damage reduction	n/a	$37.27
Percent of this reduction attributable to GOES-R	n/a	10.24%
Damage reduction attributable to GOES-R	n/a	$3,815,610

As with other benefit areas, we assumed changes in weather variability would exacerbate impacts and factored this in as an annual increase in costs of 1.5%. We further assumed population growth would increase impacts by 0.572% annually and per capita income growth would compound the value of benefits by 1.469%.

We derived lower- and upper-bound present value benefit estimates using the five applicable rates of discount as shown in Table 15 in billions of 2020$. Our baseline benefit estimate for GOES-R attributable reduction in property damage from flash floods is **$0.11B** (2020$).

Table 15. GOES-R Contribution to Reduced Flash Flood Damages

Discount Rate	0.0%	0.300%	1.185%	3.000%	7.000%
Billions (2020$)	0.13	0.13	0.11	0.09	0.06

7.5 Discussion—Key Uncertainties and Recommended Future Efforts

We note that a primary uncertainty in this approach is the allocation of 50% flood damages to riverine flooding and 50% to flash flooding. We assume that with additional research this allocation could be better characterized.

The key study relating warning information to damage reduction is the Kreibich et al. [*Kreibich et al. 2021*] work, which is an empirical analysis conducted in Germany. A key finding of that study is that warnings are associated with reduced structural and building content losses but generally only where there has been prior education and preparatory actions. Similar future work is needed to support Kreibich et al.'s [*Ibid*] findings in the United States.

Finally, we used the TPIO estimate of the contribution of GOES-R to hydro products as our estimate of the contribution of GOES-R in flash flood damage reduction. This could be examined further to determine the relationship between hydro products and flash flood products and services to assess if this is the best estimate of GOES-R contribution.

8. Severe Thunderstorms and Tornadoes

8.1 Summary Result

To estimate benefits of GOES-R related to impacts of severe thunderstorms and tornadoes, we calculated reductions in fatalities due to severe weather (primarily lightning and tornadoes). Building on existing information resources, we implemented the following steps to derive an annual benefit estimate:

- We obtained annual fatality data (for lightning and tornadoes) from the NOAA Weather Related Fatality and Injury Statistics [*NOAA weather.gov 2021*]
- We assumed that, without improved weather information and other actions, fatalities would have remained at the 1940–1979 average (314.1)
- We further assumed that, with improved weather information and other actions, fatalities have been reduced to the 1980–2018 average (114.6)
- We calculated the reduction in lives lost as the difference between these averages (199.5). **(Note we feel this is a key uncertain parameter.)**
- We assumed that 20% of this is attributable to improved weather information (39.89 lives saved). **(Note we feel this is a key uncertain parameter.)**
- We then applied a 13.96% factor as the contribution attributable to GOES-R (5.57 lives saved) **(TPIO number)**
- We applied USDOT 2020 base year VSL ($11.6M) ($64.6M/year attributable to GOES-R).

This provided us with a baseline year annual benefit from GOES-R of $11.6M (2020$). We then aggregated these over the lifetime of the project, accounting for increases in wealth, population, and weather variability (using a baseline discount rate of 1.185%). The baseline estimate is an aggregated present value benefit of **$1.94B** (in 2020$).

8.2 Introduction to Application Area

Meteorological products for severe storm watches, tornado watches, lightning, and outlooks for convective weather and fire are issued by NOAA's Storm Prediction Center (Figure 21). Other warnings and related products are issued by the local WFOs. Specific products include:

- Current weather watches (severe thunderstorm or tornado) over the continental United States
- Current mesoscale discussions (MD)
- Convective outlooks (severe thunderstorms) for Day 1, Day 2, Day 3, and Day 4 through 8
- Thunderstorm outlooks (in 4-to 8-hour time periods)

- Fire weather outlooks (Day 1, Day 2, and Day 3 through 8).[20]

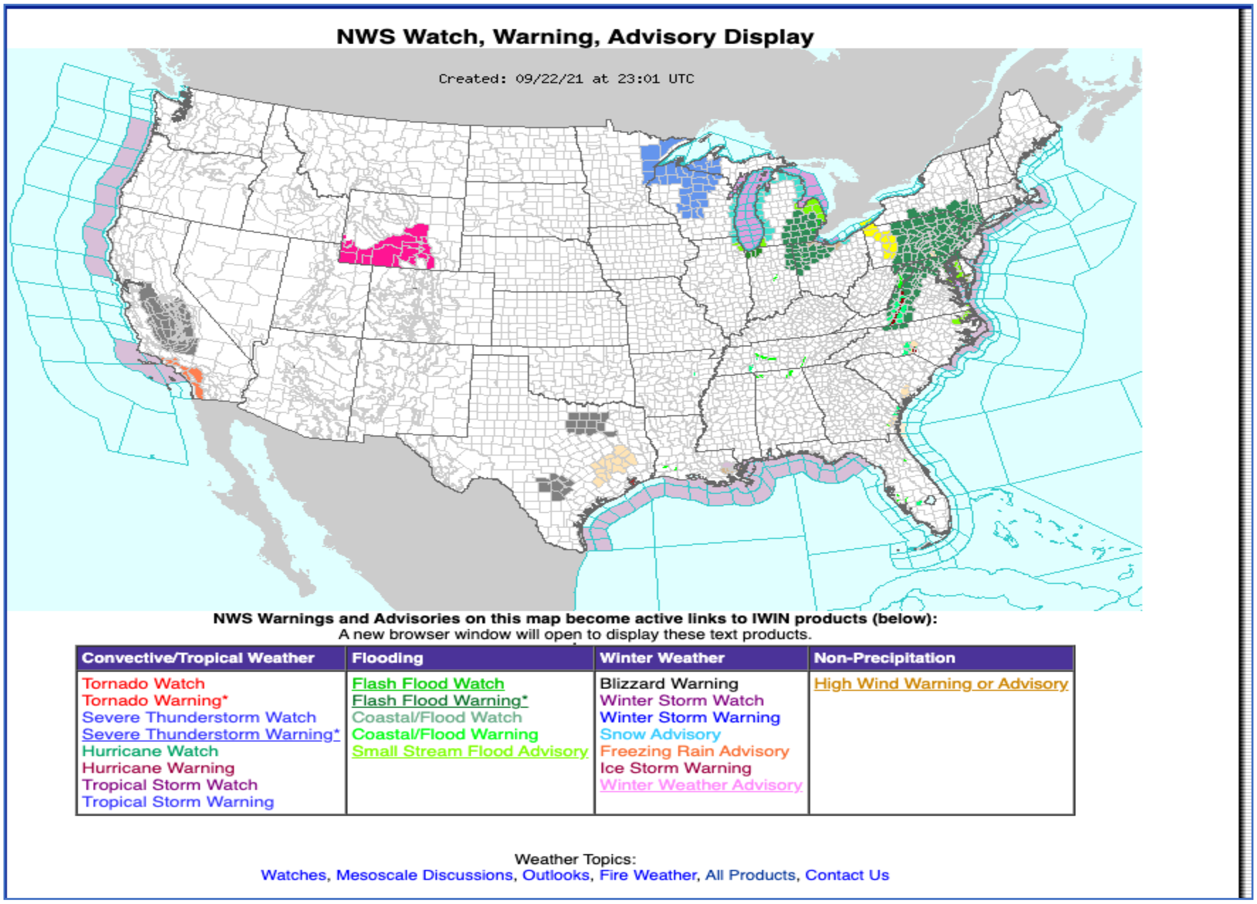

Figure 21. Example text products from the Storm Prediction Center (NOAA/SPC).

The NDFD is a suite of products generated by the NWS using regional WFO data and model-outputs from the National Centers for Environmental Prediction (NCEP) [*NOAA NCEI NDFD 2022*]. NDFD is used to make text, graphic, and digital products for emergency managers and the public. NDFD also provides data for commercial weather companies to generate their own products based on NWS forecasts. This information is available via the NCEI. GOES satellite data are available via the GOES Image Viewer. The NDFD uses GOES-R data as one of its many sources of input (see: https://www.ncei.noaa.gov/products/satellite/goes-r-series).

We have included information on how the GOES-R GLM data are used in support of thunderstorm warnings in Appendix F.

[20] This is obviously a cross-over area with our "Wildfires" benefit area, which illustrates the complexity and potential for possibly double-counting benefits. We note though that this benefit area focused on fatalities and our wildfire benefit assessment focused on reduced costs and thus there is likely little if any overlap between the two.

8.3 Inputs from TPIO-Derived NOSIA II Data

The severe weather products had a GOES-R contribution to models of 0.8% and a GOES-R contribution to non-model products of 13.16%. These resulted in a total GOES-R contribution to severe weather products of 13.96%

8.4 Benefit Assessment

To derive benefit estimates related to severe thunderstorms, we focused on actual and potential reductions in fatalities. We obtained annual fatality information from NOAA "Weather Related Fatality and Injury Statistics" [*NOAA weather.gov 2021*]. We combined lightning and tornado fatalities for analysis as severe weather for this benefit area.

As shown in Figure 22, there has been a downward trend in average annual fatalities over the last eight decades with a possible increase in the last decade.

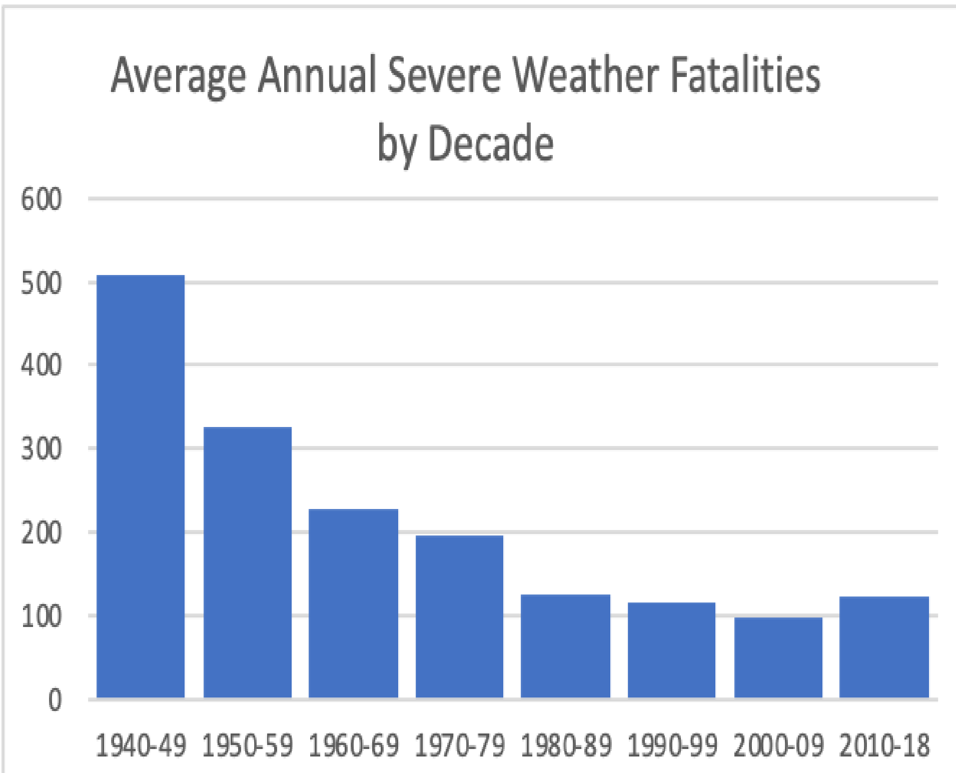

Figure 22. Average annual severe weather (lightning and tornadoes) fatalities by decade (NOAA).

For the current analysis, we assumed that without weather information (and other actions mitigating weather impacts), fatalities would have remained at the 1940–1979 average annual value of 314.05. We further assumed that, because of weather information (and other actions mitigating weather impacts), fatalities have been reduced to the 1980–2018 average of 114.59, representing a fatality reduction of 199.46. This approach may underestimate fatality reductions as population increases would have increased the average fatalities without mitigation. We then assumed that 20% of this is attributable to improved weather information. This is a key uncertainty parameter. Further, we assumed that 13.96% of this is attributable to GOES-R as per input from TPIO. We applied the statistical life (VSL) value estimate of $11.6M to the 5.57 fewer fatalities attributable to GOES-R. As show in Table 16, this yielded an annual benefit estimate (2020$) of $64.6M, which we used as our baseline benefit estimate.

Table 16. Derivation of GOES-R Contribution to Reduced Severe Thunderstorm Fatalities

Analysis Factors	Factor	Value
Average fatalities 1940-1979	n/a	314.05
Average fatalities 1980-2018	n/a	114.59
Reduction in fatalities	n/a	199.46
Attributable to improved weather information	20%	39.89
Attributable to GOES-R (TPIO)	13.96%	5.57
USDOT 2020 base-year VSL	n/a	$11,600,000
Benefit from GOES-R (2020$)	n/a	$64,601,400.53

As with other benefit areas, we assumed changes in weather variability would exacerbate severe thunderstorm impacts and factored this in as an annual increase in costs of 1.5%. We further assumed population growth would increase impacts by 0.572% annually and per capita income growth would compound the value of benefits by 1.469%. We derived a range of present value benefit estimates using the five applicable rates of discount as shown in Table 17 in billions of 2020$. Our baseline annual benefit estimate is $**1.94B** (2020$).

Table 17. GOES-R Contribution to Reduced Severe Thunderstorm Fatalities

Discount Rate	0.0%	0.300%	1.185%	3.000%	7.000%
Billions (2020$)	2.24	2.16	1.94	1.58	1.06

8.5 Discussion—Key Uncertainties and Recommended Future Efforts

Although weather radars play a vital role in the prediction, detection, and monitoring of severe thunderstorms (including tornadoes), GOES-R is also an important contributor to severe thunderstorm and tornado watches, warnings, and other products.

The uncertainties in this analysis are (1) the estimated difference in lives lost, which we used as a measure of the impact of improved weather information, and (2) the degree to which avoidance of such loss is attributable to improved weather information or better situational awareness for forecasters or other factors such as better sheltering [*Simmons and Sutter 2011*]. We applied a 20% factor but recommend further research to better refine this value.

We note that Rowley, Riley, and Reed [*Rowley et al. 2018*] provide a bibliography of studies on the economic impact of tornado warnings and how people behave with advanced warning, organized into four topic areas potentially directly mappable to the value chain process: (1) economic impact, risk, and mitigation; (2) public perception and behavior; (3) tornado identification and technology; and (4) warning process, development, and delivery. Also specific to this area is work by Kevin Simmons and Dan Sutter on the economics of tornadoes, including their 2015 book [*Simmons and Sutter 2011*]. These resources could be examined in more detail to see if they can better inform the current analysis.

We also note that, although the majority of our analysis herein centered on benefits from the ABI sensor and several of the UPS capabilities, we also considered the benefits from the GLM in severe weather monitoring, tracking, and forecasting. Unfortunately, we ran out of the resources and economic data necessary to properly assess even a few of the related GOES-R contributing products. Matthias Steiner, Senior Scientist and Section Head at the UCAR Research Applications Lab (RAL), and colleagues from the National Center for Atmospheric Research, Boulder CO; AvMet Applications, Inc., Reston, VA; and the Federal Aviation Administration (FAA), Washington, D.C., have published several related articles [*Steiner et al. (2013*), *(2014)*, *(2015)*, and *(2016)*].

9. Drought

9.1 Summary

To estimate benefits of GOES-R related to impacts of drought, we calculated potential reductions in socioeconomic impacts from drought with appropriate information and response actions. Building on existing information resources, we implemented the following steps to derive an annual benefit estimate:

- Obtained data on drought disasters from 1980 through 2022 (2020$) ($249B)
- Calculated the average annual drought damages ($5.93B)
- Assumed 10% of these losses are or could be mitigated with drought information, warnings, and decision-support tools ($592.9M). **(Note we feel this is a key unknown parameter.)**
- Assumed 10.24% of this information is attributable to GOES-R ($60.7M) (TPIO number for hydrology)

This provided us with a baseline year annual benefit from GOES-R of $60.7M. We then aggregated these over the lifetime of the project, accounting for increases in wealth, population, and weather variability (using a baseline discount rate of 1.185%). The baseline estimate is a present value benefit of **$1.82B** (in 2020$).

9.2 Introduction to Application Area

Drought forecasting systems use models fed by climatic and atmospheric data (historical/seasonal weather patterns, real-time meteorological monitoring, and weather forecasts) to predict the probability of a drought occurring in a region or area of interest in the future (up to approximately three months). Drought forecasting systems are an important part of early warning systems, as they provide lead-time to planners for threat responses, which helps minimize drought impact risk. Drought forecasting has great impact on agricultural activity and water availability and is therefore particularly important for ensuring food and water security. Effective forecasting systems can give enough lead time to adequately plan for water storage, identify alternative sources of freshwater, implement new (water-saving) agricultural practices, and import food and water, if necessary [*UN CTC-N 2018*].

Scientists can predict the likelihood of a drought by careful monitoring of rainfall, river flow, and soil moisture.

9.2.1 Drought Types

Drought has traditionally been categorized as one of four types—meteorological, hydrological, agricultural, and socioeconomic:

- Meteorological drought: Refers to a deficit in precipitation over some period of time while taking into account differences in local climatology.
- Hydrological drought: If deficits in net water supply at the surface become large, hydrological drought can develop as reflected by groundwater, river, or reservoir levels dropping below normal.

- Agricultural drought: When plant water requirements are not met during the growing season, especially during certain periods critical for yield development, agricultural drought can result.

- Socioeconomic drought considers the impact of drought conditions on the supply and demand of economic goods and services" episodic [*Wilhite and Glantz 1985*].

- Ecological drought: More recently, this fifth drought type has been proposed, referring to "an episodic deficit in water availability that drives ecosystems beyond thresholds of vulnerability, affects ecosystem services, and triggers feedback between natural and human systems" [*Crausbay et al. 2017*].

It should be noted that more than one drought type can occur at the same time at a given location and that droughts can transition from one type to another as conditions and impacts evolve with time [*Otkin et.al. 2018*].

Even more recently, the "flash drought" type has been identified. It refers to the drought that develops and intensifies over a short period of time.

A number of tools available for drought prediction and monitoring are [*USDA National Agricultural Library 2022*]:

- Weather and Drought Monitor (U.S. Department of Agriculture [USDA], Office of the Chief Economist):

  - Meteorologists in USDA's World Agricultural Outlook Board (WAOB) provide weather assessments and realtime yield intelligence for global crop conditions in support of the monthly World Agricultural Supply and Demands Estimates (WASDE) report. WAOB's meteorologists are also responsible for the publication of the Weekly Weather and Crop Bulletin and are contributing authors to the U.S. Drought Monitor.

- National Integrated Drought Information System (NIDIS) (Department of Commerce [DOC]). National Oceanic and Atmospheric Administration [NOAA]):

  - Ensures "collaboration between different government agencies on drought-related issues" and gives information on current drought conditions, forecasting, impacts, and more.

- Drought Monitor (University of Nebraska – Lincoln):

  - "A synthesis of multiple indices, outlooks and news accounts, representing a consensus of federal and academic scientists" from USDA, DOC, the Department of the Interior [DOI] and the National Drought Mitigation Center (NDMC).

- Evaporative Stress Index (ESI) (USDA, Agricultural Research Service):

  - The ESI describes temporal anomalies in evapotranspiration (ET), highlighting areas with anomalously high or low rates of water use across the land surface.

- Evaporative Demand Drought Index (EDDI) (Earth System Research Laboratory, NOAA):

- “The Evaporative Demand Drought Index (EDDI) is an experimental drought monitoring and early warning guidance tool. It examines how anomalous the atmospheric evaporative demand (E0; also known as ‘the thirst of the atmosphere’) is for a given location and across a time period of interest.”

- Advanced Hydrologic Prediction Service (AHPS)[21] (DOC/NOAA/NWS):
  - “Provides new forecast products (including visual displays) depicting the magnitude and uncertainty of occurrence for hydrologic events from hours to days to weeks.”

- Paleoclimatology Data (DOC/NOAA/NESDIS):
  - Paleoclimatology data are derived from natural sources such as tree rings, ice cores, corals, and ocean and lake sediments. These proxy climate data extend the archive of weather and climate information hundreds to millions of years. The data include geophysical or biological measurement time series and some reconstructed climate variables such as temperature and precipitation.

- Water Watch (DOI/United States Geological Survey [USGS]):
  - A compilation of “maps and graphs of current water resources conditions” including daily streamflow condition maps. Daily streamflow condition maps depict streamflow conditions as measured at United States Geological Survey (USGS) gaging stations. Please note that “the real-time data used to produce the maps are provisional and have not been reviewed or edited. The data may be subject to significant change.”

- Weekly Weather and Crop Bulletin (USDA/Joint Agricultural Weather Facility):
  - Contains “weekly national agricultural weather summaries, including the weather’s effect on crops; summaries and farm progress for 44 states and the New England area. This report includes any corrections to the Crop Progress data released the previous day.”

- Handbook of Drought Indicators and Indices (World Meteorological Organization [WMO], Global Water Partnership):
  - “This Handbook of Drought Indicators and is based on available literature and draws findings from relevant works wherever possible. The handbook addresses the needs of practitioners and policymakers and is considered as a resource guide/material for practitioners and not an academic paper. This publication is a ‘living document’ and will be updated based on the experiences of its readers.”

We provide examples of NWS’s Climate Prediction Center (CPC) drought information products in Figure 23:

[21] AHPS uses GOES DCS Gage data. See the background data at: https://water.weather.gov/ahps/about/about.php

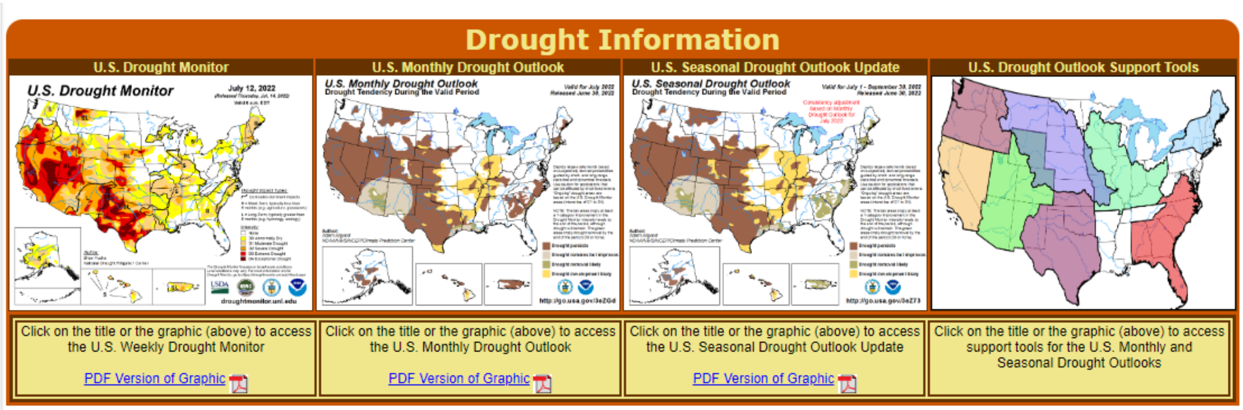

Figure 23. Examples of NWS CPC drought information products [*NWS CPC*].

Another valuable U.S. government drought product is the USDA's National Agricultural Statistics Service (NASS) "U.S. Crops and Livestock in Drought" graphics and accompanying statistics, an example of which we provide in Figure 24. Obviously, crops and livestock are a huge and vital area of the U.S. economy that are very sensitive to drought conditions.

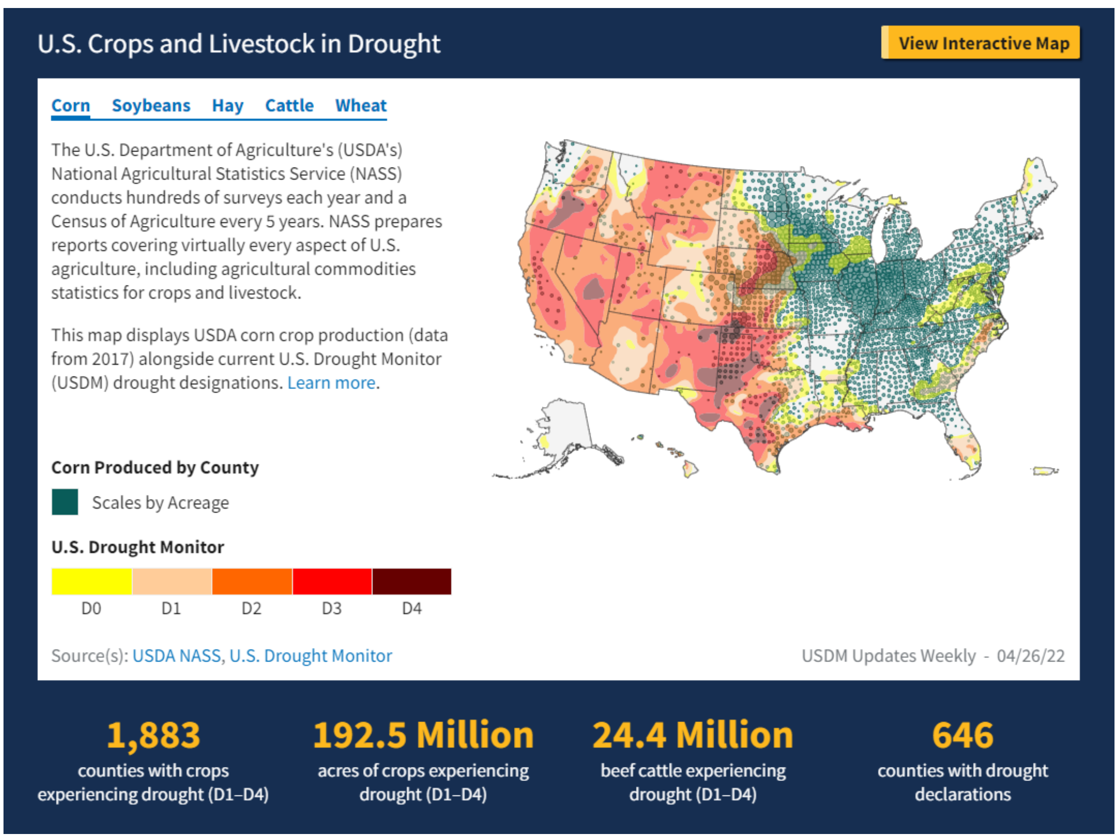

Figure 24. U.S. crops and livestock in drought (USDA NASS).

9.2.2 GOES-R and Drought

Many of the tools for drought prediction and monitoring mentioned previously in section 9.2 rely, at least in part, on inputs from environmental satellites. The GOES-R series satellites are one of those contributing sources.

Most people think of drought in the long-term sense (taking place over a period of months to years), although these obviously exist more in the realm of climatology. GOES-R data certainly contribute to the systems that monitor drought and models that try to predict such outlooks, but there is also a short-term drought type, called "flash drought," that develops and intensifies over a short period of time. GOES-R data is also an important contributor to monitoring and forecasting flash droughts.

> Satellites, like GOES-R, measure energy intensities (radiances) at several wavelengths of the electromagnetic spectrum. This information is useful because everything — the ground, the oceans, the atmosphere, clouds, rain, vegetation, cities, people, etc. — absorbs energy at certain wavelengths and emits energy at other wavelengths.[22]

Due to the depletion of soil moisture caused by drought, a major indicator of drought is vegetative conditions. The GOES-R series ABI is the first GOES to include a "Vegetation/Veggie" band at 0.86 µm. Data from this ABI "Veggie" band is a substantial contributor to the Vegetation Drought Response Index (VegDRI), produced in collaboration between the NDMC, USGS National Center for Earth Resources Observation and Science (EROS), and High Plains Regional Climate Center (HPRCC). "The VegDRI calculations integrate satellite-based observations of vegetation conditions, climate data, and other biophysical information such as land cover/land use type, soil characteristics, and ecological setting. The VegDRI maps that are produced deliver continuous geographic coverage over large areas and have inherently finer spatial detail (1-km2 resolution) than other commonly available drought indicators such as the U.S. Drought Monitor" [*NOAA NIDIS 2022*]. We provide an example VegDRI map product in Figure 25.

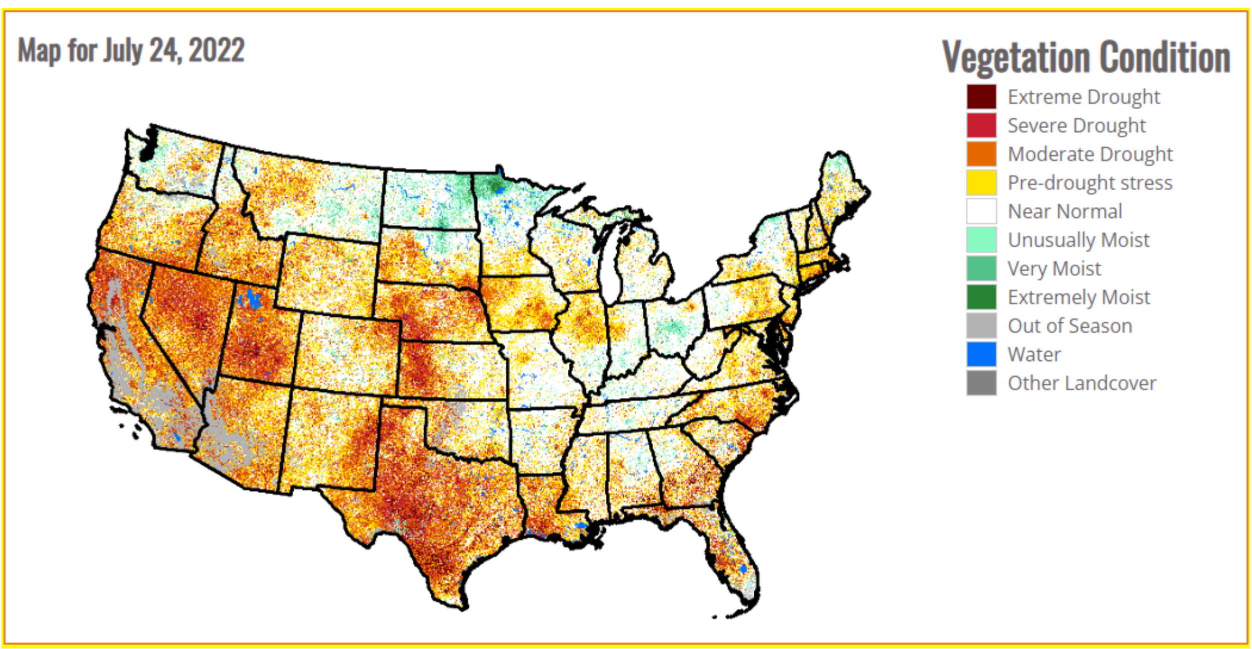

Figure 25. VegDRI map for July 24, 2022 [*NOAA NIDIS 2022*].

The ABI vegetative data can also contribute to the production of a Normalized Difference Vegetation Index (NDVI), which "…quantifies vegetation by measuring the difference between near-infrared (which vegetation strongly reflects) and red light (which vegetation absorbs)" [*GISGeography 2022*].

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[22] Paraphrased from "Satellite-Based Drought Indicators" on the NCEI website accessed on 28 July 2022 at: https://www.ncei.noaa.gov/access/monitoring/dyk/satellite-drought

Although the NDVI is most often produced from polar-orbiting satellite data (i.e., NOAA AVHRR and SNPP and JPSS VIIRS), using data from "GOES-R would allow for shorter time averaging and hence show faster impacts" [*Schmit, T. 2022*]. Figure 26 is a global NDVI map product. "Very low values of NDVI (0.1 and below) correspond to barren areas of rock, sand, or snow. Moderate values represent shrub and grassland (0.2 to 0.3), while high values indicate temperate and tropical rainforests (0.6 to 0.8)" [*NASA EO 2022*].[23]

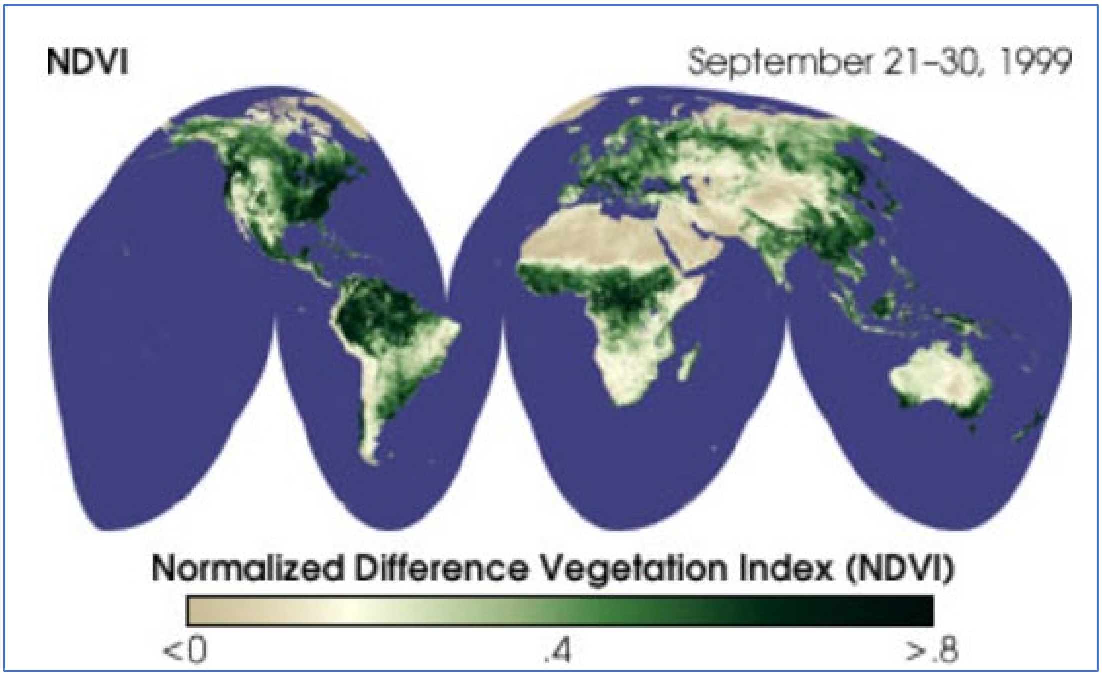

Figure 26. NDVI graphic product [*NASA EO 2022*].

9.3 Inputs from TPIO-Derived from NOSIA II Data

The hydrology and water resources models, forecasting, products, and services saw a total GOES-R contribution of 10.24%.

9.4 Benefit Assessment

9.4.1 Drought Impacts

With respect to the economic magnitude of droughts, Otkin et al. [*Otkin et al.* 2015] note that "The total cost associated with these events has been high, with the 2012 drought alone costing more than $35 billion, making it one of the most expensive natural disasters in U.S. history" [Ibid, p.1073].

Ding et al. [*Ding et al. 2010*] undertook a literature review of the economic impacts of drought, including impacts in agricultural and non-agricultural sectors. Impacted non-agricultural sectors include tourism and recreation, public utilities (e.g., domestic water supply), landscaping services, navigation, construction, and any other activity having significant water consumption or reliance on water. They note that there are direct impacts (e.g., reduced agricultural output) as well as secondary impacts (e.g., reduction in food processing). They further note that while quantifiable market losses can be significant, "…non-market

[23] Accessed from the NASA Earth Observatory website on July 28. 2022 at: https://earthobservatory.nasa.gov/features/MeasuringVegetation

losses could be considerable, quantification of such losses are rarely included into drought impact assessment or other disaster loss calculation" [*Ibid, p.10*]. Ding et al. [*Ibid*] found that drought is a global issue and studies have shown that drought can have a significant impact on even developed nations' economies, noting one study showing "The results indicated that the 2002-2003 droughts caused an overall reduction of Australian GDP by 1.6%, of which 1% was directly related to agricultural sector, and the remaining 0.6% was due to multiplier effects" [*Ibid, p.17*]. Ding et al. [*Ibid*] note that "drought is the most common natural disaster in the United States (14% of the country experiences severe or extreme drought at any one time)" [*Ibid, p.17*].

In a case study of the impacts of drought on a region in north-east Spain, Gil et al. [*Gil et al. 2013*] model secondary and "down-stream" impacts of droughts finding significant local impacts. While Gil et al. [*Ibid*] found direct impacts often 50% or greater in a specific community, they note that "… while indirect impacts can be compensated in the macro level by market fluctuations or trends, they are far greater than the direct effects in absolute terms" [*Ibid, p.2692*].

Zhou et al. [*Zhou et al. 2018*] examined over 50,000 U.S. drought records, finding an average of almost 2,500 drought events/year are recorded, causing average annual losses of $1.684M. Although they did not identify an upward trend in the magnitude of drought damages, they note this could be due to the high regional variability of drought even while noting that "Spatially, vulnerability to droughts has decreased in most of the country" [*Ibid*].

Kuwayama et al. [*Kuwayama et al. 2018*] found direct drought impacts on farm income generally in the 0.1% to 1.2% but ranging up to 8% per week of drought in some counties.

9.4.2 Drought Information

Several studies indicate the accuracy of drought forecasts. For instance, Steinemann [*Steinemann 2006*] noted that "Evaluations of CPC seasonal forecasts issued during 1995–2000 demonstrated positive skill for drought seasons in the Southeast. In addition, using evaluation criteria of water managers, 88% of forecasts for drought seasons would have appropriately prompted drought responses" [*Ibid, p.1353*].

Several studies have demonstrated the actual or potential value of drought warnings, forecasts, indicators, or decision support tools. In a survey-based study of household responses to drought in Indonesia, Kuswanto et al. [*Kuswanto et al. 2019*] found that even though respondents felt drought forecasts had little accuracy, "Households that changed their agricultural practice experienced significantly different losses [i.e., lower] than households that did not do anything differently to their crops." (p.1). Sharda and Srivastava [*Sharda and Srivastava 2016*] examined the use of ENSO forecasts in a tool for municipal water management. Nolan et al. [*Nolan et al. 2016*] evaluated the potential benefits of early-warning drought indicators for both freshwater availability management and understanding impacts on ecological resources. Steinemann et al. [*Steinemann et al. 2015*] develop a drought indicator finding that "Stakeholders report that the framework provides an easily understood and beneficial way to assess and communicate drought conditions, validly compare multiple indicators across different locations and time scales, quantify risks relative to historic droughts, and determine indicators that would be valuable for decision-making" [*Ibid, p.1793*]. Otkin et al. [*Otkin et al. 2015*] stated that "Because droughts impact more people than any other type of natural disaster, robust drought early warning systems that effectively characterize and disseminate information to vulnerable stakeholders are necessary to assist drought mitigation and climate adaptation efforts" [*Ibid, p.1073*].

9.5 Inputs from TPIO-Derived from NOSIA II Data

The hydrology and water resources models, forecasting, products, and services saw a total GOES-R contribution of 10.24%.

9.6 Benefit Analysis

For this benefit analysis, we use summary data from drought.gov on the average annual impacts of drought in the last 42 years. "Since 1980, the U.S. has sustained 258 weather and climate disasters where the overall damage costs reached or exceeded $1 billion (including adjustments based on the Consumer Price Index, as of January 2020). Among these, 26 droughts cost the nation at least $249 billion, with an average cost of more than $9.6 billion incurred during each event" [*NOAA NIDIS 2022A*]. This translates to an average annual impact of droughts of $5.9B.[24]

Next, we assume that 10% of drought impacts are, or could be, mitigated with drought information, warnings, and decision support tools for a benefit of drought information of $592.8M. We then apply the TPIO factor for hydrology of 10.24% to determine the portion attributable to GOES-R. The annual GOES-R benefit in 2018 (measured in 2020$) is taken then as $60.7M as shown in Table 18.

Table 18. Drought Related Economic Benefits of GOES-R

Analysis Factors	Factor	Value
Total losses from droughts in billion-dollar disasters (2020$)	n/a	$249,000,000,000
Number of years (1980–2022)	42	n/a
Average losses per year	n/a	$5,928,571,429
Avoidable with information	10.00%	n/a
Benefit of information	n/a	$592,857,143
Attributable to GOES-R (TPIO)	10.24%	n/a
Annual benefits attributable to GOES-R (2020$)	n/a	$60,695,500

As with other benefit areas, we assumed changes in weather variability would exacerbate impacts and factored this in as an annual increase in costs of 1.5%. We further assumed population growth would increase impacts by 0.572% annually and per capita income growth would compound the value of benefits by 1.469%. We derived present value benefit estimates using the five applicable rates of discount as shown in Table 19 in billions of 2020$. Our baseline benefit estimate is **$1.82B** (2020$).

Table 19. Present Value Estimates of GOES-R Contribution to Drought

Discount Rate	0.0%	0.300%	1.185%	3.000%	7.000%
Billions (2020$)	2.10	2.03	1.82	1.48	1.00

[24] "Since 1980, the U.S. has sustained 258 weather and climate disasters where the overall damage costs reached or exceeded $1 billion (including adjustments based on the Consumer Price Index, as of January 2020). Among these, 26 droughts cost the nation at least $249 billion, with an average cost of more than $9.6 billion incurred during each event. Only hurricanes were more costly. The cumulative cost for all 258 events exceeds $1.75 trillion" [*NOAA NIDIS 2022A*]. Accessed May 10, 2022.

9.7 Discussion—Key Uncertainties and Recommended Future Efforts

We assumed 10% of these average annual drought losses are or could be mitigated with drought information, warnings, and decision-support tools ($592.9M). While there is literature indicating that drought information has value, from the limited literature we reviewed, there is no clear indication of what the level of this benefit is.

We assumed 10.24% of the value of drought information is attributable to GOES-R based on the TPIO-provided factor for hydrology and related products. As with other TPIO provided numbers, we feel it would be useful to better support this attribution with other studies, empirical analysis, or input from verification analysis.

We note that several of these studies reviewed indicated that while there is a physical impact of drought (i.e., a decrease in crop production), there may be a counter-intuitive accompanying increase in farm revenue. From an economic point of view, this is the result of a decrease (shift) of the supply curve interacting with an inelastic demand curve to result in an increase in commodity pricing that offsets the decreased production. While an increase in farm revenues may seem beneficial, the overall societal outcome can be negative as the increase in farm revenue accompanies an even larger loss of consumer welfare (a shift in consumer surplus to producer surplus with an overall negative change in total surplus). See Appendix D for a discussion of shifts in producer and consumer surplus).

10. General Public Forecasts and Warnings

10.1 Summary Result

To estimate benefits of GOES-R related to general public forecasts and warnings, we calculated benefits based on U.S. household (HH) WTP studies/surveys for current forecast quality. Building on existing information resources, we implemented the following steps to derive an annual benefit estimate:

- Used existing literature to determine per HH WTP for "current" services in 2006 (2006$) ($286/HH/year)
- Obtained U.S. total population estimates for 2018 from U.S. Census projections (326.7M)
- Adjusted for 3.62% survey respondents indicating that they do not use forecasts (326.7M − 11.8M = 314.9M)
- Used HH size from Phase 1 analysis (from U.S. Census) (2.53/HH) to calculate number of households in 2018 (124.5M)
- Multiplied $286 by the number of households for total value of current forecasts ($35.6B)
- Assumed that 30% of value of forecasts comes from observations based on prior research. **(Note we feel this is a key uncertain parameter.)**
- Applied 6.38% as attributable to GOES-R **(TPIO number)**
- Used CPI to adjust to 2020$ for baseline a benefit of $875.3M/year

This provided us with a baseline year annual benefit from GOES-R of $875.3M/year (2020$). We then aggregated these over the lifetime of the project, accounting for increases in wealth, population, and weather variability (using a baseline discount rate of 1.185%). The baseline estimate is an aggregated present value benefit of **$26.24B** (in 2020$).

10.2 Introduction to Application Area

Media headlines and statistics often focus upon extreme weather events—tropical cyclones, severe thunderstorms, and the tornadoes that such convective events spawn, as well as wildfires, atmospheric rivers, and the like. However, each day the American public and industry decisionmakers consult routine weather information as a basis for many types of decisions. Routine weather and forecasts, such as rain and temperature fluctuations, fair or cloudy, snow, and wind information, are consulted at least daily by millions of people. Many people consult multi-day forecasts on either broadcasts or via apps on smartphones or the internet.

The 2019–2022 Strategic Plan of the National Weather Service stated a goal to "improve the accuracy of weather and climate forecasts to day-3 for extreme weather events; establishing 10-day forecasts as accurate as [then] current 7-day weather forecasts; and providing seamless week 3-4 temperature and precipitation forecasts to link information at weather and sub-seasonal timescales" [*NOAA NWS 2022*].

A typical day of routine weather across the CONUS is depicted in Figure 27 for February 6, 2022, with a variety of non-severe weather types of events from the GOES-East (16) ABI. GOES-R data contributes in some measure to forecasting and tracking all such weather events. And every day, television broadcast and other news media use GOES-R imagery to represent the state of the weather via thousands of venues for audiences in the hundreds of millions.

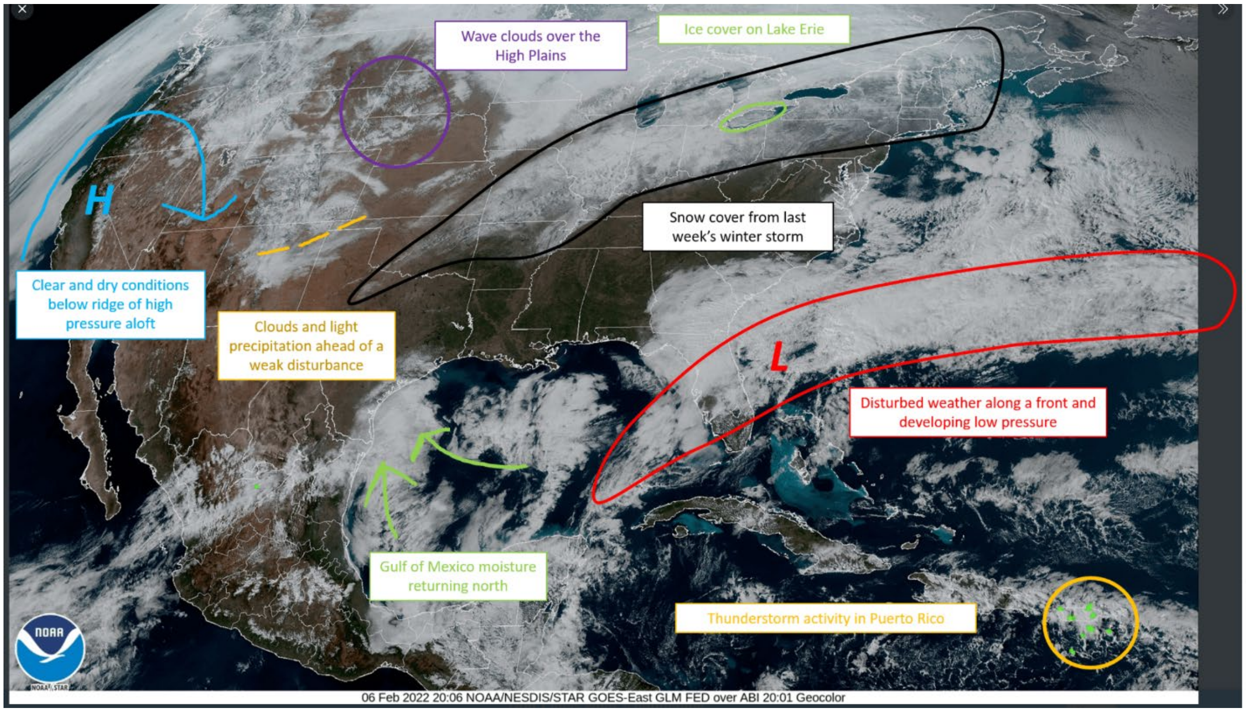

Figure 27. Typical day of non-severe weather across the CONUS on February 6, 2022 [*Twitter NWSWPC 2022*].

The U.S. NWS provides a broad range of products and services to the general public on daily weather information. As discussed in Lazo et al [*Lazo et al. 2009*] "…the average U.S. adult obtains forecasts 115 times per month, which totals to more than 300 billion forecasts per year by the U.S. public." While severe weather information is critical to the mission of the NWS, Lazo et al. found in their survey of the general public that "nearly three-quarters stated that they usually or always use forecasts simply to know what the weather will be like" [*Ibid*]. This includes information obtained directly from the NWS (such as Figure 28) as well as the various other communication channels providing NWS-based weather information.

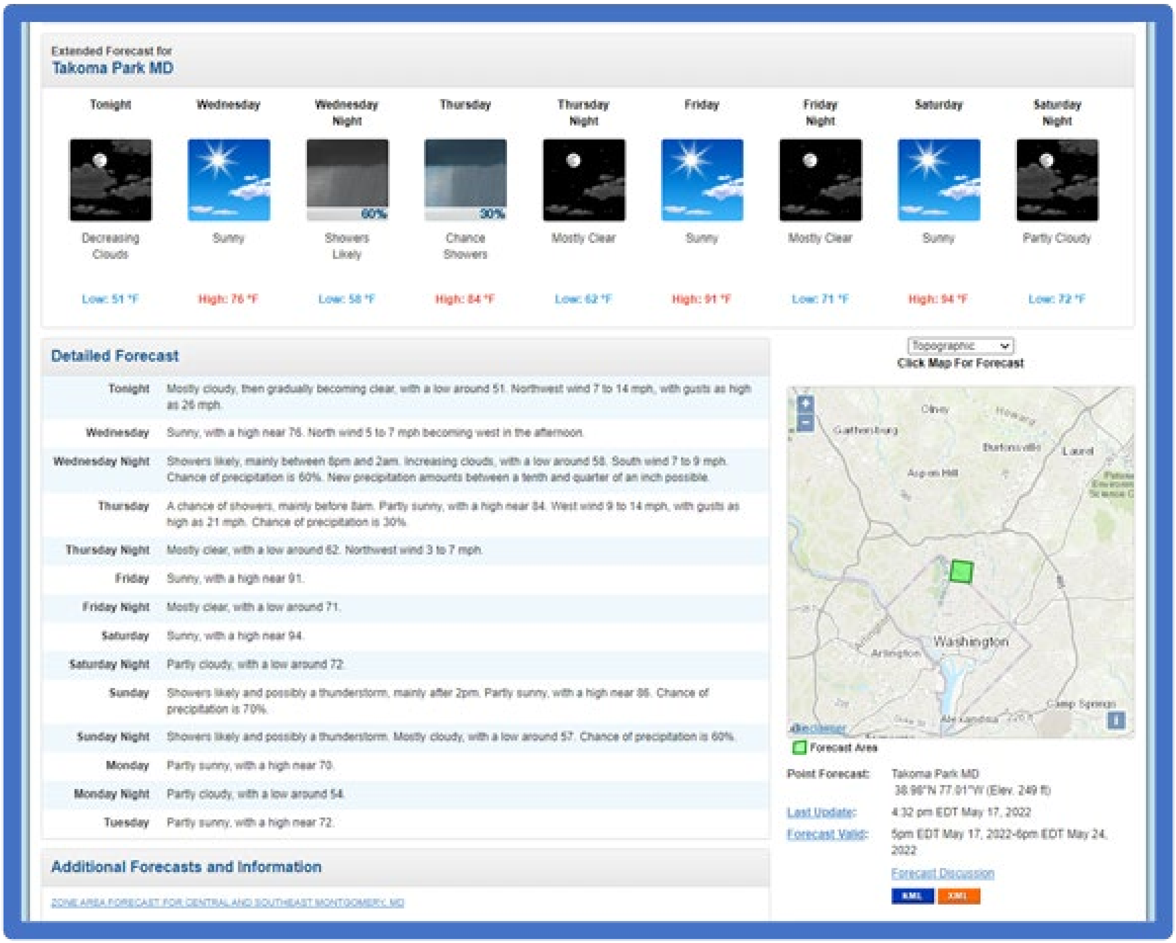

Figure 28. NWS 7-day forecast graphic for May 17, 2022 [*NWS 2022C*].

10.3 Inputs from TPIO-Derived from NOSIA II Data

The general public forecast products had a GOES-R contribution to models of 1.14% and a GOES-R contribution to non-model products of 5.25%. These resulted in a total GOES-R contribution to general public forecasts and warnings of 6.38%.

10.4 Benefit Assessment

To evaluate the benefits from GOES-R in terms of "public" or routine daily weather forecasts, we used value estimates from Lazo et al. [*Lazo et al. 2009*]. In this study, Lazo et al. elicited the value of current weather information to U.S. households as shown in Figure 29 [*Ibid, p.794*] by surveying over 1,400 household members. The caption in this figure explains the derivation of a $286 per household value for weather information in 2006$ (when the survey was implemented). We used this estimate as our baseline value of per-household benefits from general (i.e., "public") weather forecasts.

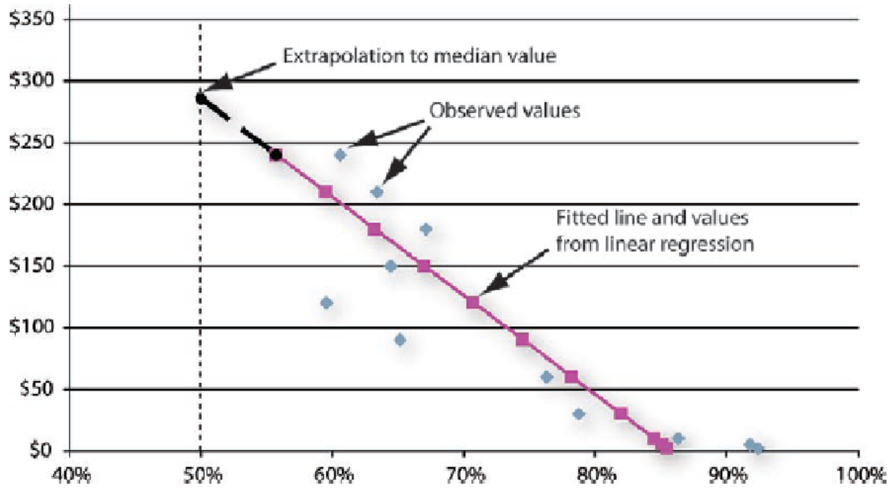

FIG. 7. Assessment of value of all weather forecasting and information services to households (*n* = 1,465). For each of the 11 "offer" prices (vertical axis) we plot the percent (horizontal axis) indicating worth "more than" or "exactly" that amount. Blue diamonds (♦) show actual responses; solid pink line (— —) shows fitted line from linear regression; dashed black line (—) shows extrapolation to median value of $286 per household per year. Following the convention for graphing demand curves in economics, price (the independent variable) is depicted on the y axis, and the quantity, in this case the percentage of people willing to pay (the dependent variable), is depicted on the x axis. The survey question asked "Do you feel that the services you receive from the activities of the NWS are worth more than, exactly, or less than $N a year to your household?"

Figure 29. Derivation of per-household value of current weather information [*Lazo et al. 2009*].

We obtained U.S. total population estimates for 2017 through 2040 from U.S. Census projections [*Census Bureau 2022B*] and used information on household size from our Phase 1 analysis to calculate the number of U.S. households in 2018. We next multiplied this number by the $286/household value for a total value of current forecasts to U.S. households. We assumed that 30% of the value of forecasts comes from observations. This value is based loosely on research by Lazo, Rice, and Hagenstad [*Lazo et al. 2010*], which used expert elicitation to derive an estimate of the contribution of observations to weather forecast improvements. This is a key unknown variable that would benefit from future research. We then applied the percent of public forecast information attributable to GOES-R (6.38%), as provided by TPIO, to derive a total annual benefit from GOES-R of $681M in (2006$). We adjusted this from 2006$ to 2020$ using CPI data (to $875.3M/year [2020$]). Table 20 shows this derivation.

Table 20. Derivation of Benefits of GOES-R in Public Weather Forecasts

Analysis Factors	Factor	Value
Value of current weather information per household [*Lazo et al. 2009*]($2006)	n/a	$286.00
Total population (2018)	n/a	326,687.50
Portion not using forecasts	3.62%	11,826,088
Population using forecasts	n/a	314,861,413
Average Household (HH) size from Phase 1 work	n/a	2.53
Number of households	n/a	124,451,152
Total benefit 2018 (in 2006$)	n/a	$35,593,029,348
Percent attributable to weather observations	30.00%	n/a
Percent attributable to GOES-R (TPIO)	6.38%	n/a
Benefit Attributable to GOES-R	n/a	$681,783,924
Inflation Adjustment to 2020$	n/a	n/a
CPI – 2006	201.6	n/a
CPI – 2020	258.811	n/a
Adjustment ratio	1.284	n/a
Value of public forecasts (2020$) attributable to GOES-R ($)	n/a	$875,263,785.75

We then aggregated the annual benefit estimate of $875.3M using adjustment parameters, including 1.5% for increasing weather variability, 0.572% for population growth (assuming constant household sizes), and 1.469% per capita GDP growth as per our Phase 1 analysis.

As shown in Table 21, this yields an aggregated present value benefit estimate of **$26.24B** at the baseline discount rate. This is a significantly larger benefit estimate than some other benefit areas because of (1) the ubiquitous use of weather forecasts and information daily by virtually all segments of the U.S. population and (2) the large number of forecast users (nearly the entire U.S. population).[25]

Table 21. Present Value Estimates of GOES-R Contribution to Public Weather Forecasts

Discount Rate	0.0%	0.300%	1.185%	3.000%	7.000%
Billions (2020$)	30.31	29.20	26.24	21.34	14.36

10.5 Discussion—Key Uncertainties and Recommended Future Efforts

The key uncertainty in this benefit area analysis is the percent attributable to weather observations. We applied a 30% factor for the current analysis but suggest further research to refine this value.

[25] Lazo et al. (2009) estimated that "Assuming that our respondents are representative of the U.S. population and accounting for the 3.62% of respondents who do not use forecasts, this means an estimated *300 billion forecasts are obtained by U.S. adults each year*." (Italics in the original) [*Lazo et al. 2009, pp. 788-789*]

We note that, in Lazo et al. [*Lazo et al. 2009*], the per-household value estimate may be a lower bound as the maximum offered values for forecasts in the survey was less than the median and thus, the assessment did not obtain a good distribution of value estimates at the higher values of the distribution. The benefit estimates Lazo et al. [*Ibid*] derived there may also have included value for non-routine weather and thus, there may be some overlap (double counting) between this estimate and values in other benefit areas (e.g., for severe weather information and/or air quality information) as evaluated in other benefit areas.

As of this writing, Lazo et al. are re-implementing virtually the exact same survey as the 2006 survey to compare and update results. The current (2022) effort involves making a minor adjustment to the valuation question by adding additional offer values to attempt to better frame the median or mean value. It is indeterminate whether the 2022 results will yield a similar value to that of the Lazo et al. [*Ibid*] analysis relevant to our GOES-R benefit assessment as we have adjusted for the 2009 $286/HH/year value to account for inflation from 2006 to 2020 in the current analysis.

11. Aviation Weather

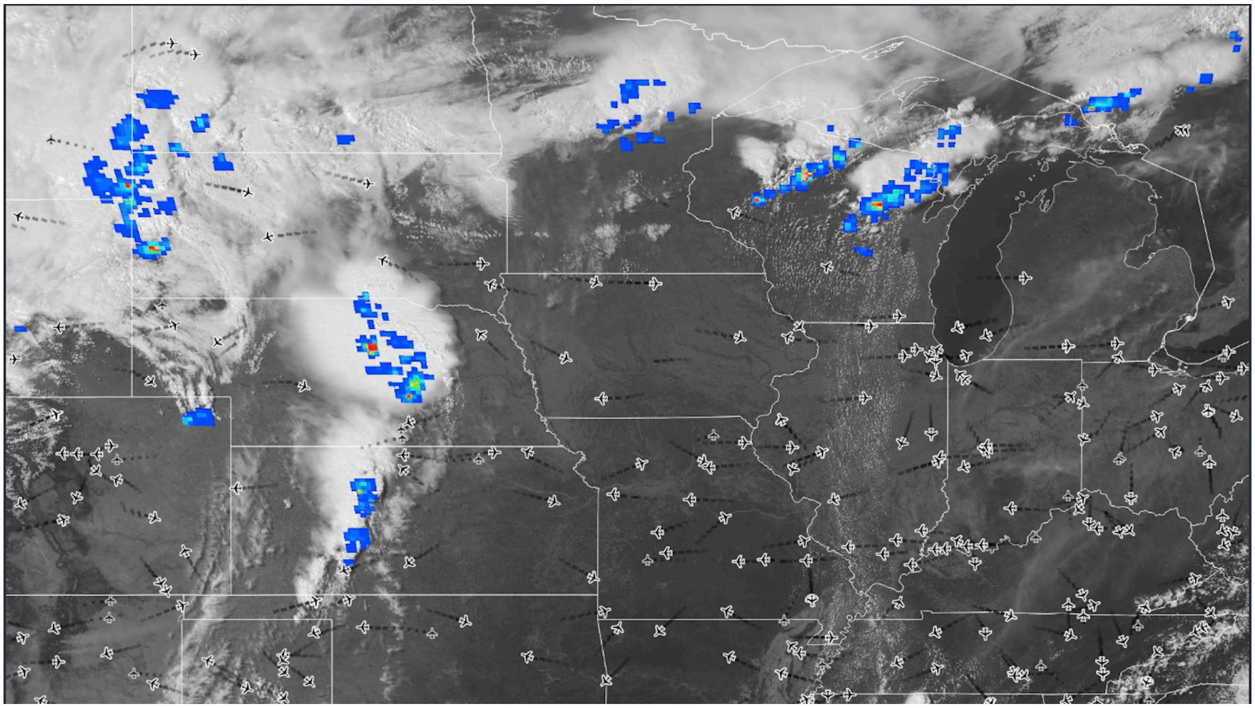

Figure 30. Still shot of NOAA product loop with aviation flights, GOES GLM and ABI imagery combined to show flight routing as severe weather affects flight paths [*Lindsey, D.T. and J. Patten 2022*].

11.1 Summary Result

To estimate benefits of GOES-R contributions related to aviation weather, we calculated the reduction in costs to airlines, passengers, and related industries due to the use of forecasts to avoid and manage around weather delays. Building on existing information resources, we implemented the following steps to derive an annual benefit estimate:

- We obtained average annual estimates on costs of delays across all users from [*FAA APO-100*] for 2016 through 2019 ($23.8B) adjusted to $28.73B (2020$)
- We then obtained Bureau of Transportation Statistics (BTS) data on 17-year average percent of delays attributable to weather (40.0%) and multiplied delay costs by percent attributable to weather to derive weather delay costs ($11.49B)
- Next, we assumed 20% of weather-related costs could be or are avoided with information ($2.3B). **(Note we feel this is a key uncertain parameter.)**
- We further employed 20.47% of supporting weather information as attributable to GOES-R **(TPIO number)**
- We derived an annual benefit estimate of reduction in aviation delays due to the contribution of GOES-R information ($470M) (2020$)

This provided us with a baseline year annual benefit from GOES-R of $470M (2020$). We then aggregated these over the lifetime of the project, accounting for increases in wealth and weather variability (using a baseline discount rate of 1.185%). We used a projected increase in passenger traffic through 2040 to account for increasing demand, rather than the rate of population increase, to account for increased air travel. The program baseline estimate is an aggregated present value benefit of **$19.67B** (in 2020$).

11.2 Introduction to Application Area

Aviation is a highly weather-dependent transportation and economic sector. Weather creates near-constant operational and safety issues and risks within the National Airspace System. "Pilots need to avoid weather that will negatively impact the safety of a flight and understand how it will impact the performance of the aircraft. Air traffic controllers need to understand how the environmental temperatures will affect the takeoff and landing distances. Passengers need to know if an upcoming weather event will cancel future flights. Airlines want to reduce the number of delayed and cancelled flights and need to take into consideration weather specific to each airport and region" [*Goodman et.al. 2019. p.479*]. The three types of weather information that may be needed to conduct aircraft operations are observations, analyses, and forecasts. The GOES-R series provides a substantial portion of this essential observational information for the aviation sector.

Aviation provides a significant contribution to our economy and to our society. Aviation provides the only truly worldwide transportation network, supporting global business and tourism [*ATAG 2005*]. Airlines transported over 4.5 billion passengers in 2019 and facilitates trade by transporting about 6.5 trillion U.S. dollars of goods, which represents about 1% of all international trade [*Ibid*]. Although all mainline and smaller carriers were impacted by the COVID-19 pandemic, many carriers have emerged from this downturn with smaller staffs and reduced schedules. Weather disruptions can have a dramatic impact on these reduced-capacity carriers (Figure 31), making advance forecasts and warnings an even more vital planning resource.

Figure 31. Flight delays for commercial airlines (flyjetoptions.com).

In 2019, flight delays cost U.S. airlines, passengers, and others an estimated $33B, according to the FAA. Weather continues to be the primary cause of flight delays, accounting for as much as 70 percent of all delays [*Daily 2021*]. Our analysis used a 40% weather attribution factor based on BLS data as noted below. The 2021 FAA forecast calls for U.S. carrier domestic passenger growth over the next 20 years to average 4.9 percent per year. (This average, however, includes three double-digit growth years during the recovery from a very low base in 2021 [*FAA 2021*].)

> "All three major forms of aviation (general, commercial, cargo) are weather-sensitive industries. The portion of delay due to weather represented nearly 10 million minutes in 2013. Delays translate into real costs for aircraft operators and passengers. Currently, the cost to the air carrier operators for an hour of delay ranges from about $1,400 to $4,500, depending upon the class of aircraft and if the delay is on the ground or in the air. If the value of passenger time is included, the delay cost increases by another $35 per hour for personal travel or $63 per hour for business travel for every person onboard" [*FAA 2022*].

Important parameters related to aviation meteorology are wind and turbulence, fog, visibility, aerosol/ash loading, ceiling, rain and snow amounts and rates, icing, ice microphysical parameters, convection and precipitation intensity, microbursts, hail, and lightning. Weather conditions that cause or contribute to aviation accidents include wind, visibility/ceiling, high density altitude, turbulence, carburetor icing, updrafts/downdrafts, precipitation, icing, thunderstorms, wind shear, thermal lift, temperature extremes, and lightning [*Gultepe et.al. 2019*].

Severe weather can impact aviation operations on the ground or in-flight (Figure 32). Lightning in the vicinity of a terminal aerodrome can cease operations as ground personnel take shelter. Snow, icing, severe thunderstorms, and tornadoes can all affect ground operations.

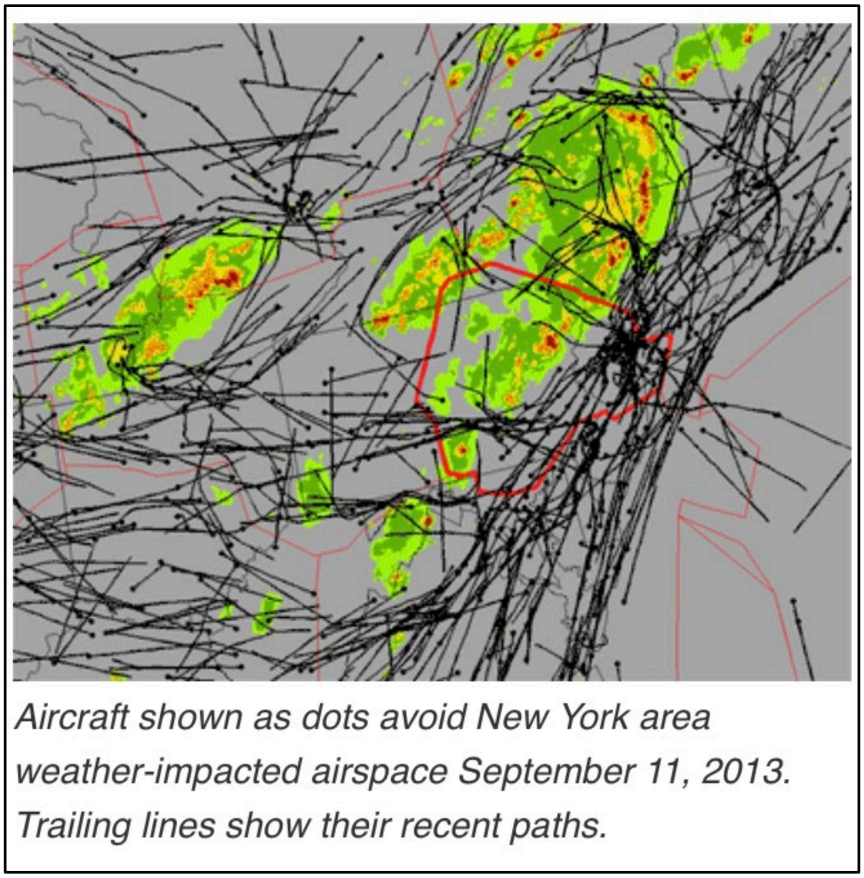

Figure 32. Flight routing around weather-impacted airspace [*FAA 2022*].

Aircraft planning requires as-accurate-as-possible forecasts. However, aviation operations also require nowcasting and short-term forecasts provided two hours in advance and over two hours for airport ground (terminal aerodrome) forecasts. With these short-term horizons, geostationary satellites provide a valuable tool for observations, nowcasting, situational awareness, and assimilation into numerical weather prediction models.

11.2.1 GOES-R Applicability to Aviation Meteorology

Due to the large amount of excellent background information regarding the applicability of GOES-R data to aviation meteorology, we have moved this text to section F.2.

11.3 Inputs from TPIO-Derived from NOSIA II Data

The Aviation Weather MSA, which includes aviation products and volcanic ash products, has a GOES-R contribution to models of 0.88% and a GOES-R contribution to non-model products of 19.59%, according to TPIO analyses of NOSIA II data. These resulted in a total GOES-R contribution to aviation of 20.47%.

11.4 Benefit Assessment

We focused on the potential benefits of reducing weather-related aviation delays across all affected parties (airlines, passengers, and related industries). We obtained estimates on the costs of delays across all users from [*FAA APO-100*] for 2016 through 2019 (see Table 22). This resource provided cost estimates in 2019$ for four years across impacts to airlines, passengers, lost demand, and indirect losses.

We averaged the losses across four years for an average annual cost of delays in billions 2019$ ($28.38B).

Table 22. Cost of Delay Estimates and Weather-Related Share
(FAA APO-100—Cost of Delay Estimates 2019 Dollars – Billions)

	2016	2017	2018	2019	4-Year Average	Weather Related (40% - see Table 23)
Airlines	5.60	6.40	7.70	8.30	7.00	2.80
Passengers	13.30	14.80	16.40	18.10	15.65	6.26
Lost demand	1.80	2.00	2.20	2.40	2.10	0.84
Indirect	3.00	3.40	3.90	4.20	3.63	1.45
Total (2019$B)	23.70	26.60	30.20	33.00	28.38	11.35

Source: https://www.faa.gov/data_research/aviation_data_statistics/media/cost_delay_estimates.pdf. Accessed January 18, 2022.

We obtained BTS data on percent of delays attributable to weather (see Table 23). These provided an estimate of the average percent of total delays attributable to weather over the 17-year period from 2003 to 2019.

Table 23. Weather's Share of Delay as Percent of Total Delay-Minutes, by Year [*BTS 2022*]

Year	% Weather	Fitted % Weather[26]
2003	49.9	48.1
2004	49.7	47.0
2005	47.1	46.0
2006	44.2	45.0
2007	43.6	44.0
2008	45.5	43.0
2009	44.4	42.0
2010	38.1	41.0
2011	38.7	40.0
2012	33.7	39.0
2013	36.5	38.0
2014	32.6	37.0
2015	32.8	36.0
2016	32.9	35.0
2017	33.2	34.0
2018	38.4	33.0
2019	38.7	31.9
Average	40.0%	

Source: https://www.bts.gov/topics/airlines-and-airports/understanding-reporting-causes-flight-delays-and-cancellations#q7. Accessed January 18, 2022

[26] "Fitted" means using the results of the regression analysis to recalculate or project the value as a fixed point (i.e., with no error) on the regression line.

We then regressed the delay percent on years to evaluate if this had changed over time, thus revealing a significant reduction in the percent of delays attributable to weather. This likely is a result of improved forecasting as well as more preventive actions on the part of airlines and passengers. Figure 33 shows the historical and fitted data from our regression analysis.[27]

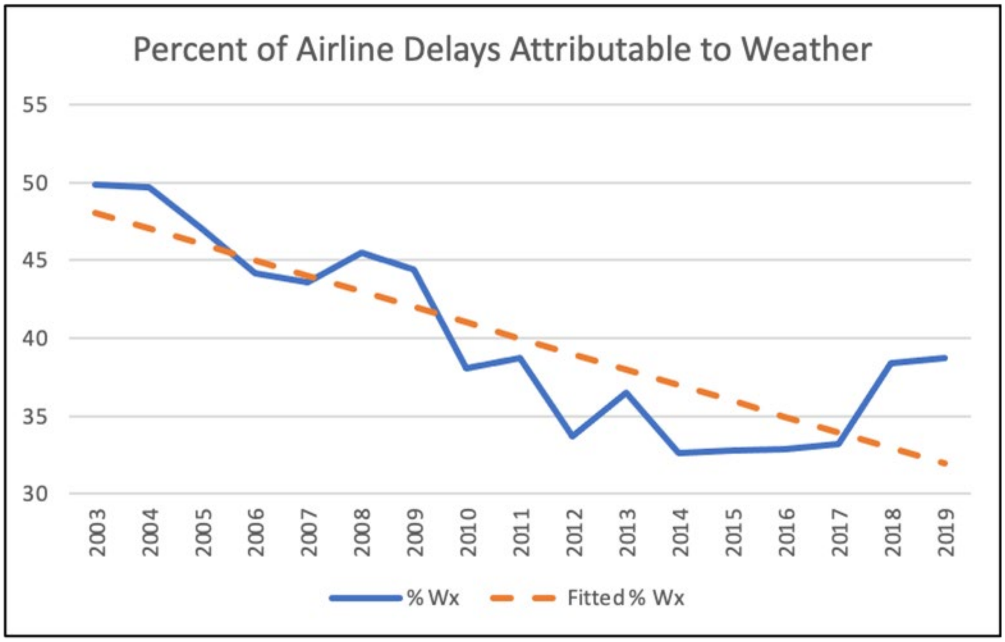

Figure 33. Percent of airline delays attributable to weather—actual and fitted values (source: Lazo/Aerospace).

These delay data indicated an average of 40.0% of delays are attributable to weather (Table 24). We applied this percent to the total delay costs to estimate the delay costs attributable to weather (last column of Table 24). We adjusted this estimate ($11.35B) from 2019$ to 2020$ using CPI data yielding an estimate of $11.49B in weather-related delay costs in 2020$.

Next, we assumed that 20% of weather-related costs could be or are avoided with weather information (i.e., the “value of weather information”) ($2.3B). Based on data from TPIO, we then applied the factor of 20.47% as the portion of weather information attributable to GOES-R. This yielded a baseline estimate of the value of GOES-R information in reducing aviation delays of $470,339,130 in the year 2018 in 2020$. Table 24 shows the calculations and derivation of this $0.47B annual benefit estimate.

Table 24a. Economic Impacts of Aviation Delays and Derivation of GOES-R Benefits — Cost of Delay Estimates (Dollars – Billions $2019) [FAA APO-100]

	2016	2017	2018	2019	4-Year Average
Airlines	5.6	6.4	7.7	8.3	7
Passengers	13.3	14.8	16.4	18.1	15.65
Lost Demand	1.8	2	2.2	2.4	2.1
Indirect	3	3.4	3.9	4.2	3.63
Total (2019$B)	23.7	26.6	30.2	33	28.38

[27] Note that we used an ordinary least squares regression. More sophisticated analysis could account for the time series aspect of this data as well as test for non-linearity.

	2016	2017	2018	2019	4-Year Average
Adjust to 2020$	CPI2019	255.66	n/a	n/a	n/a
n/a	CPI2020	258.81	n/a	n/a	n/a
CPI adjustment factor	n/a	n/a	1.0123	n/a	28.73

Table 24b. Economic Impacts of Aviation Delays and Derivation of GOES-R Benefits Analysis—Factors and Values

Anlaysis Factors	Factor	Value
Percent due to weather	40.00%	n/a
Total costs of weather delay ($B)	n/a	$11.49
Percent avoidable with weather information	20.00%	n/a
Total avoidable costs ($B)	n/a	$2.30
Percent attributable to GOES-R (TPIO)	20.47%	n/a
Value of GOES-R (202$B)	n/a	$0.47

To aggregate these estimates over the lifetime of GOES-R, we obtained estimates of the increases in passenger traffic. A report by the Niagara Frontier Transportation Authority (NFTA) [*NFTA 2022*] indicated that "Over the forecast period from 2012 through 2040, passenger traffic is forecast to grow by a compound annual growth rate ("CAGR") of 4.9%" [*Ibid*]. Alternatively, the FAA Aerospace Forecast Fiscal Years 2019–2039 indicates "The 2019 FAA forecast calls for U.S. carrier domestic passenger growth over the next 20 years to average 1.8 percent per year" [*FAA 2019*]. We applied an average of these two estimates of 3.35% growth in aviation activities.

As with other benefit areas, we assumed changes in weather variability would exacerbate delay impacts and factored these in as an annual increase in delay costs. We did not, though, factor in population growth as we assumed this is factored into the estimates of increases in aviation activity from the FAA and NFTA. We did factor in wealth growth as this will relate to the value of time and thusthe socioeconomic costs of delays. We aggregated these over the relevant GOES-R lifetime using the five previously established discount rates and applicable adjustment factors. We estimated the baseline present value benefit, at the 1.185% discount rate, to be **$19.67B** in 2020$ as shown in Table 25.

Table 25. Present Value Estimates of GOES-R Contribution to Reduced Aviation Delays

Discount Rate	0.0%	0.300%	1.185%	3.000%	7.000%
Billions (2020$)	23.02	22.11	19.67	15.68	10.09

11.5 Discussion—Key Uncertainties and Recommended Future Efforts

The key uncertainty in this analysis is the factor for the percent of weather-related costs that could be or are avoided with weather information. We applied a 20% factor for the current analysis but suggest further research to refine this value.

We note also that compared to other benefit areas with roughly similar baseline annual benefits, the aviation benefits aggregate to a significantly larger present value. This is driven largely by the projected growth in airline traffic of 3.35% applied over the GOES-R lifetime. For other benefit areas, the relevant growth rate in population was 0.572%. This difference also highlights the impact of individual parameters on the results and suggests the need for further sensitivity analysis.

We note that there are several areas in aviation that have not been evaluated here, including potentially reduced accidents (likely more in civil aviation [*Long 2022*][*Fultz and Ashley 2016*]), reductions in inflight costs, and flight impacts related to volcanic ash.

As we noted earlier at the end of section 8.5, although the majority of our analysis herein centered on benefits from the ABI sensor and several of the UPS capabilities, we also considered the benefits from the GLM in severe weather monitoring, tracking, and forecasting but also in aviation delays at airfields due to lightning. Unfortunately, we ran out of the resources and economic data necessary to properly assess even a few of the related GOES-R contributing products. Matthias Steiner, Senior Scientist Section Head at the UCAR RAL and colleagues from the National Center for Atmospheric Research, Boulder CO; AvMet Applications, Inc., Reston, VA; and the FAA, Washington, D.C., have published several related articles [*Steiner et al. (2013)*, *(2014)*, *(2014A)*, *(2015)*, and *(2016)*] .

12. Air Quality

12.1 Summary Result

To estimate benefits of GOES-R related to air quality, we calculated the reduction in mortality in the over-65 population in the United States due to air quality warnings. Building on existing information resources, we implemented the following steps to derive an annual benefit estimate:

- From extant literature [*Buonocore et al 2021*] , we derived the reduction in mortality risks from air quality warning information on ozone and $PM_{2.5}$ (0.6817 per million population over 65)
- As Buonocore et al. [*Ibid*] provide analysis across three cities, we assumed the average reduction in mortality for these three cities is applicable nationwide. **(Note we feel this is a key unknown parameter.)**
- We obtained the total U.S. population in 2020 from the U.S. Census (326,687,501) and percent over 65 (15.8%) to determine total U.S. population over 65 (51,616,625)
- We applied an average mortality rate reduction to determine reduction in mortality (35.18 people/year) attributable to air quality warnings
- We applied the percent of warnings information attributable to GOES-R (8.16%) to derive lives saved attributable to GOES-R (2.25) **(TPIO number)**
- We used VSL from USDOT of $11.6M to determine the GOES-R benefit value for 2020 in 2020$ ($26.1M/year)

This provided us with a baseline year annual benefit from GOES-R of $26.1M (2020$). We then aggregated these over the lifetime of the project, accounting for increases in wealth, population, and weather variability (using a baseline discount rate of 1.185%). The baseline estimate is an aggregated present value benefit of **$1.00B** (in 2020$).

12.2 Introduction to Application Area

12.2.1 Air Quality

> "Aerosols are solid and semisolid particles suspended in the air that have harmful impacts on human health and the environment. Particles that are smaller than 2.5 μm in aerodynamic diameter are the most harmful as they can penetrate deep into the lungs and pass into the bloodstream, causing and exacerbating respiratory and cardiovascular diseases. … They [aerosols] have many natural and anthropogenic sources, including urban/industrial pollution, fires (natural and prescribed), dust/sandstorms, and biogenic emissions" [*Kondragunta at al. 2020*].

Large wildfires and other extreme air-pollution-contributing events can produce "a mixture of air pollutants of which particulate matter is the principal public health threat. … Wildfire smoke produced from combustion of natural biomass contains thousands of individual compounds, including particulate matter, carbon dioxide, water vapor, carbon monoxide, hydrocarbons and other organic chemicals, nitrogen oxides, and trace minerals. Wildfires can move into the wildland urban interface, burning homes and structures and thereby consuming man-made materials in addition to natural fuels" [*Ibid*]

12.2.2 Impacts

> "Aerosols are a key component of urban/industrial photochemical smog that leads to deteriorated air quality. They are also the primary pollutant in natural environmental disasters such as volcanic eruptions, dust outbreaks, biomass burning associated with agricultural land clearing, and forest fires. High concentrations of aerosols, when inhaled, lead to upper respiratory diseases including asthma. They decrease visibility which leads to unsafe conditions for transportation. The American Lung Association estimates that more than 133.9 million people in the United States live in areas of poor air quality" [*GOES-R 2022*].

Poor air quality is responsible for an estimated more than 100,000 premature deaths in the United States each year. Costs from air-pollution-related illnesses are estimated at $150B per year [*NWS 2022B*]. A recent *Washington Post* article cited a report that found air pollution is responsible for one in six deaths worldwide over the past five years [*Patel, 2022*].

12.2.3 Air Quality Warnings

NOAA's National Air Quality Forecast Capability (NAQFC) develops and implements operational air quality forecast guidance for the United States. NOAA and the EPA partner in developing a national air quality forecast. Operational products include ozone, smoke dust, and fine particulate matter ($PM_{2.5}$) at the surface in the air we breathe [*NWS 2022*].

> "Under the Clean Air Act, the U.S. Environmental Protection Agency (EPA) is required to develop a national air quality monitoring system and uniform air quality index (AQI). EPA regulations state that metropolitan statistical areas with a population of more than 350,000 must report their AQI daily to the general public; areas with consistently low pollution levels may be exempted from this requirement" [*Buonocore et al. 2020*].

Those measurements, as required by the EPA, are monitored with a network of ground-based sensors, and those networks are located mainly in urban and suburban regions. Additionally, those ground-based sensors may not make measurements every day, resulting in spatial and temporal gaps in the nationwide monitoring of $PM_{2.5}$.

Smoke from wildfires, pollutants, dust storms, and ash from volcanic eruptions all may contribute to air quality. For a visual example, see the Aerosol Watch website, from NOAA's NESDIS STAR organization at https://www.star.nesdis.noaa.gov/smcd/spb/aq/AerosolWatch/.

Air quality warnings instruct people to reduce exposure by limiting outdoor activity or by staying indoors. Some populations have increased sensitivity to high AQI levels and may heed those warnings more so than other segments of the population. As indicated in a 2020 study that evaluated three urban areas, "[an] individual's decisions to stay indoors likely depend upon the value of the health benefits compared with the value of foregone work and leisure activities" [*Ibid*]. Not everyone may be aware of the AQI warning, or they may not fully understand or misinterpret the warning per the study.

12.2.4 GOES-R Air Quality Information

GOES-R provides aerosol optical depth (AOD), smoke and dust mask aerosol detection, and other imagery to assist forecasters. These high temporal and spatial resolution space-based measurements provide a way to fill the surface gaps for $PM_{2.5}$ measurements taken by ground sensors. These products support both air quality monitoring and forecasting.

The GOES-R ABI sensor, and its high temporal resolution (every 5 minutes) with spatial resolution of about 2 km for the CONUS, makes a significant contribution to the forecaster's ability to warn of air quality from $PM_{2.5}$. Additionally, the aerosol detection of smoke and dust help forecasters to understand that environmental area of concern.

Note that AOD from GOES-R also benefits visibility and aviation forecasts and provides data valuable for climate models. Those values are not factored into this air quality topic. A technical paper, presented at the 2021 American Geophysical Union (AGU) Annual Meeting, discusses how GOES-R data can be used to fill in the gaps between the terrestrial monitoring stations [*Kondragunta and Zhang 2021*].

GOES-R contributes to the air quality products by monitoring aerosols.

> Aerosols are solid and semi-solid particles suspended in the air that have harmful effects on human health and environment.
>
> - Aerosol Optical Depth (AOD) is a qualitative measure of the solid and/or liquid particles suspended in the air including dust, sand, volcanic ash, smoke and urban/industrial aerosols. AOD measures the amount of light lost due to the presence of aerosols on a vertical path through the atmosphere.
>
> - Aerosol Detection Product (ADP) is a qualitative product that indicates the presence of aerosol (dust and/or smoke) for each pixel in the satellite image area. This can be used to quickly identify the locations of dust and smoke plumes [*GOES-R 2022*].

Aerosol Watch, a NESDIS STAR-hosted web page, uses satellite imagery from both GOES-R satellite's ABI instrument and from VIIRS sensors on the JPSS and SNPP polar orbiters to show layers of $PM_{2.5}$ particles. GOES-R satellite-sensed layers include the Fire RGB, Aerosol Optical Depth, AOD Composite, Smoke Dust Mask and Fire as exemplified in Figure 34.

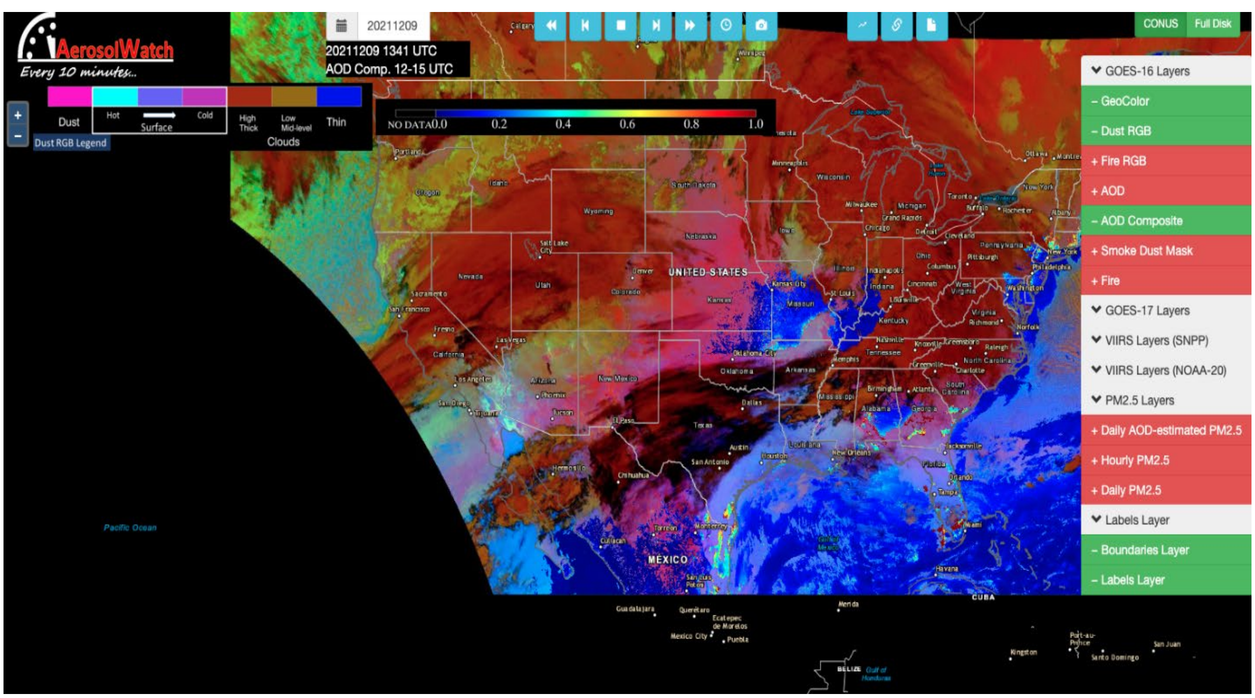

Figure 34. GOES-16 AOD composite, December 12, 2021 [*NESDIS STAR 2022*].

> "When present in high concentrations, aerosols are easily visible in satellite imagery. For routine detection and quantitative retrieval of aerosol amounts, the challenge is to separate the aerosols from clouds and bright surfaces. This can be done by comparing values from multiple wavelengths in the visible light and thermal infrared portion of the electromagnetic spectrum.
>
> "GOES-R aerosol products will be more accurate than current GOES (e.g., GOES-N, -O, -P series) products (GOES-R ABI accuracy is ~ 10% compared to current GOES-N, -O, -P AOD at ~20%). Additionally, the availability of these products at 5-minute intervals will be beneficial to the user as the products can be tailored to the 15-minute or 30-minute composites to fill the data gaps associated with clouds. The use of the near real-time fire and smoke aerosol emissions in operational numerical air quality prediction models will greatly enhance the accuracy of forecast guidance. The combination of numerical forecast guidance and near real-time satellite aerosol imagery will benefit field forecasters in their air quality warnings and alerts" [*GOES-R AWG 2022*].

GOES-R imagery has shown the movement of wildfire smoke across broad portions of the CONUS. The impact of wildfire smoke is not limited to the immediate area or even the immediate state where the fire occurs.

12.3 Inputs from TPIO-Derived from NOSIA II Data

The air quality products had a GOES-R contribution to models of 1.22% and a GOES-R contribution to non-model products of 6.94%. This resulted in a total GOES-R contribution to air quality of 8.16%.

12.4 Benefit Assessment

The analysis presented here focuses on potential reductions in mortality for over-65 U.S. populations nationwide in response to air quality warnings. There is little existing research on responses to air quality warnings and related health impacts. For this analysis, we took estimates from Buonocore et al. [*Buonocore et al. 2021*] of reduction in mortality risks from warning information based on historical data. Using historical pollution data in three U.S. cities, Buonocore et al. [*Ibid*] estimated potential benefits of air quality warnings focusing on mortality risks among the population above 65 years of age. Under strong assumptions of no infiltration of pollutants into the house, no indoor pollution sources, and compliance with warnings, Buonocore et al. [*Ibid*] estimated the benefits associated with avoiding ambient ozone and fine particle exposure to be generally less than $14 per person for 1 additional hour spent indoors on days when air quality thresholds are exceeded. While we do not directly use their benefit estimates, they also calculated changes in mortality per million 65-and-older people per year, which we do apply in our analysis.

We took an average from Buonocore et al.'s [*Ibid*] analysis across three cities for ozone and $PM_{2.5}$ per million population as shown in Table 26. To be conservative, we used the mean values of mortality risk change rather than the maximum. This suggests that there is a reduction in mortality per million population over 65 of average of 0.6817 due to air quality warnings.

Table 26. Mortality Risk Reduction with Air Quality Warnings
(Table VII Buonocore et al. [*Ibid*] Mortality Risk Change 10^{-6})

Location	Pollutant	Annual Concentration-Response Function (CRF)
Denver	Ozone	0.0000
Denver	PM2.5	0.0000
Los Angeles	Ozone	1.6000
Los Angeles	PM2.5	1.8000
Pittsburgh	Ozone	0.5200
Pittsburgh	PM2.5	0.1700
Average	n/a	0.6817

We then assumed this average reduction in mortality for these three cities is applicable nationwide and obtained the total U.S. population of 326,687,501 in 2018 from the U.S. Census. We also determined that 15.8% of the total U.S. population was 65 years or older in 2018[28] yielding a 65+ population of 51,616,625 [*Census Bureau 2022A*]. Applying the Buonocore et al. [*Buonocore et al. 2021*] average reduction in mortality risks indicated a reduction in annual mortality in 2018 of 35.2 individuals due to air quality warnings.

We then used information from TPIO with respect to the percent of warnings attributable to GOES-R of 8.16%, indicating a 2.87-person reduction in mortality attributable to GOES-R. We applied the VSL estimate from USDOT of $11.6M to determine GOES-R benefit for 2020 in 2020$ of $33,294,763. We show these calculations in Table 27.

Table 27. Air Quality Warnings Benefit Calculations

Analysis Factors	Factor	Value
Total U.S. population 2020	n/a	326,687,501
Percent of population over 65	15.80%	n/a
Population over 65	n/a	51,616,625
Average mortality reduction per million	0.6817	n/a
Mortality reduction over 65	n/a	35.19
Air quality warnings attributable to GOES-R (TPIO)	8.16%	n/a
Lives saved attributable to GOES-R	2.87	n/a
USDOT 2020 base-year VSL	n/a	$11,600,000
Annual benefit (2020$) attributable to GOES-R ($)	n/a	$33,294,763

[28] Source: https://www.census.gov/data/tables/2018/demo/age-and-sex/2018-older-population.html. Accessed January 25, 2022. Percent for both sexes.

As with other benefit areas, we assumed changes in weather variability would exacerbate air quality impacts and factored this in as an annual increase in impacts of 1.5%. We further assumed population growth would increase impacts by 0.572% annually and per capita income growth would compound the value of benefits by 1.469%. It may be reasonable to also account for an increase percent of the population being 65 years or older, but we have not attempted that adjustment here. The baseline aggregated benefit estimate for air quality warnings attributable to GOES-R is **$1.00B** (2020$) as shown in Table 28.

Table 28. Present Value Estimates of GOES-R Contribution to Air Quality Warnings

Discount Rate	0.0%	0.300%	1.185%	3.000%	7.000%
Billions (2020$)	1.15	1.11	1.00	0.81	0.55

12.5 Discussion—Key Uncertainties and Recommended Future Efforts

The key uncertainties in this analysis are (1) how much mortality decreases as a result of air pollution warnings (i.e., the value from Buonocore et al., [*Buonocore et al. 2021*]) and (2) how much GOES-R contributes to air quality warnings.

For the first value, as can be seen in Figure 35, the mean mortality risk reduction varies considerably based on location. While further review of the extant literature may provide additional input on these values, there is little research on responses to air quality warnings and the subsequent health impacts. Further, as Buonocore et al. [*Ibid, p.4*] noted, “the benefits of warnings under wildfire conditions are likely to be much larger than found here.” We have not accounted for air quality warning health benefits under conditions of wildfire either here or in the wildfire benefit area analysis and thus this could be an area of future analysis.

For the contribution of GOES-R to air quality warnings, we rely on a point estimate from TPIO. As with all other uses of these values in these analyses, further input on the reliability of these estimates would improve confidence in the benefit analysis.

Omitted from the current analysis is consideration of air quality warning benefits to populations not over 65 years of age. As shown in Figure 35 from the EPA website, research from Neidell [*Neidell 2009*] shows that there is a significant reduction in asthma-related hospitalizations in younger populations when air quality alerts are available. We have not attempted to estimate the GOES-R-related economic benefits of this or similar morbidity reductions but suggest that this issue could be examined in future research.

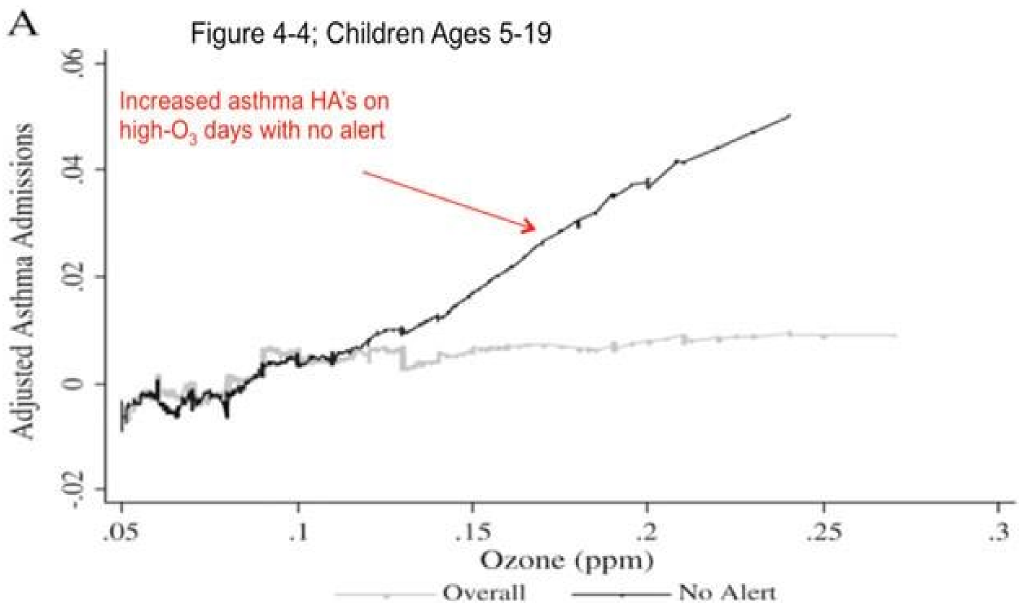

Figure 35. Asthma-related hospital child admissions as a function of ozone levels and alerts. Source: https://www.epa.gov/pmcourse/patient-exposure-and-air-quality-index: Accessed April 26, 2022 [*EPA 2022B*] (source: https://www.mayoclinic.org/diseases-conditions/copd/symptoms-causes/syc-20353679, accessed June 30, 2022).[29]

In addition to the reduction in asthma-related hospitalizations in younger populations when air quality alerts are available, there are other maladies, whose impact may be positively affected by GOES-R-improved air quality warnings as indicated on the Mayo Clinic website:

"• Asthma: Approximately 25 million Americans have asthma. This equals to about 1 in 13 Americans, including 8 percent of adults and 7 percent of children. About 20 million U.S. adults aged 18 and over have asthma. Asthma is more common in adult women than adult men. Asthma is the leading chronic disease in children.

- Chronic Obstructive Pulmonary Disease (COPD): COPD is a chronic inflammatory lung disease that causes obstructed airflow from lungs. Symptoms include breathing difficulty, cough, mucus (sputum) production and wheezing. It's typically caused by long-term exposure to irritating gasses or particulate matter. People with COPD are at increased risk of developing heart disease, lung cancer and a variety of other conditions. Emphysema and chronic bronchitis are the two most common conditions that contribute to COPD" [*Mayo Clinic 2022*].

[29] Caption from EPA website for this Figure "Figure 11. Adjusted asthma hospital admissions (HA) by age on lagged ozone by alert status, ages 5-19. Neidell, M." "Information, Avoidance Behavior, and Health: The Effect of Ozone on Asthma Hospitalizations." Journal of Human Resources 44.2 (2009): 450-478. © 2009 by the Board of Regents of the University of Wisconsin System. Reproduced by the permission of the University of Wisconsin Press. Source: https://www.epa.gov/pmcourse/patient-exposure-and-air-quality-index accessed January 25, 2022.

13. Search and Rescue

13.1 Summary

To estimate benefits of GOES-R related to search and rescue information, we calculate potential reductions in mortality with appropriate information and response actions related to the COSPAS[30]-SARSAT Satellite System for Search and Rescue. Building on existing information resources, we implemented the following steps to derive an annual benefit estimate:

- Obtained the number of people saved from the SARSAT website for 2001 through 2020 [*NOAA SARSAT 2022*]
- Regressed lives on years to identify temporal trend in people saved
- Using regression results, fitted number of rescues out to 2040
- Assumed 5% of non-rescued individuals would have died to estimate number of "lives saved." **(Note we feel this is a key unknown parameter.)**
- Assumed 50% reliance on satellite information. **(Note we feel this is a key unknown parameter.)**
- Assumed 50% reliance on GOES-R to derive projected annual number of lives saved. **(Note we feel this is a key unknown parameter.)**
- Applied VSL to this to derive annual benefits over project lifetime
- Aggregated present value by discounting to 2020$

This provided us with a baseline year annual benefit from GOES-R in 2018 of $177.3M. This increases each year with the number of lives saved and increasing VSL. We then applied the baseline discount rate of 1.185% and aggregated to 2020$. The baseline estimate is an aggregated present value benefit of **$1.30B** (2020$).

13.2 Introduction to application area

Along with the DCS, the SARSAT is yet another UPS provided by the GOES-R Series satellites.

> "As an integral part of the international search and rescue satellite program called COSPAS-SARSAT, NOAA operates the Search and Rescue Satellite-Aided Tracking (SARSAT) system to detect and locate mariners, aviators, and other recreational users in distress almost anywhere in the world at any time and in almost any condition. This system uses a network of satellites to quickly detect and locate distress signals from emergency beacons onboard aircraft, vessels, and from handheld personal locator beacons called PLBs. The SARSAT transponder on board GOES-R Series satellites provides the capability to immediately detect distress signals from emergency beacons and relay them to ground stations - called local user terminals. In turn, this signal is routed to a SARSAT mission control center and then sent to a rescue coordination center which

[30] COSPAS" is acronym for the Russian expression "Cosmicheskaya Sistyema Poiska Avariynich Sudov," which means "Space System for the Search of Vessels in Distress."

dispatches a search and rescue team to the location of the distress" [*GOES-R Program Office, 2022*].

Figure 36 provides a graphic overview of the overall COSPAS-SARSAT system.

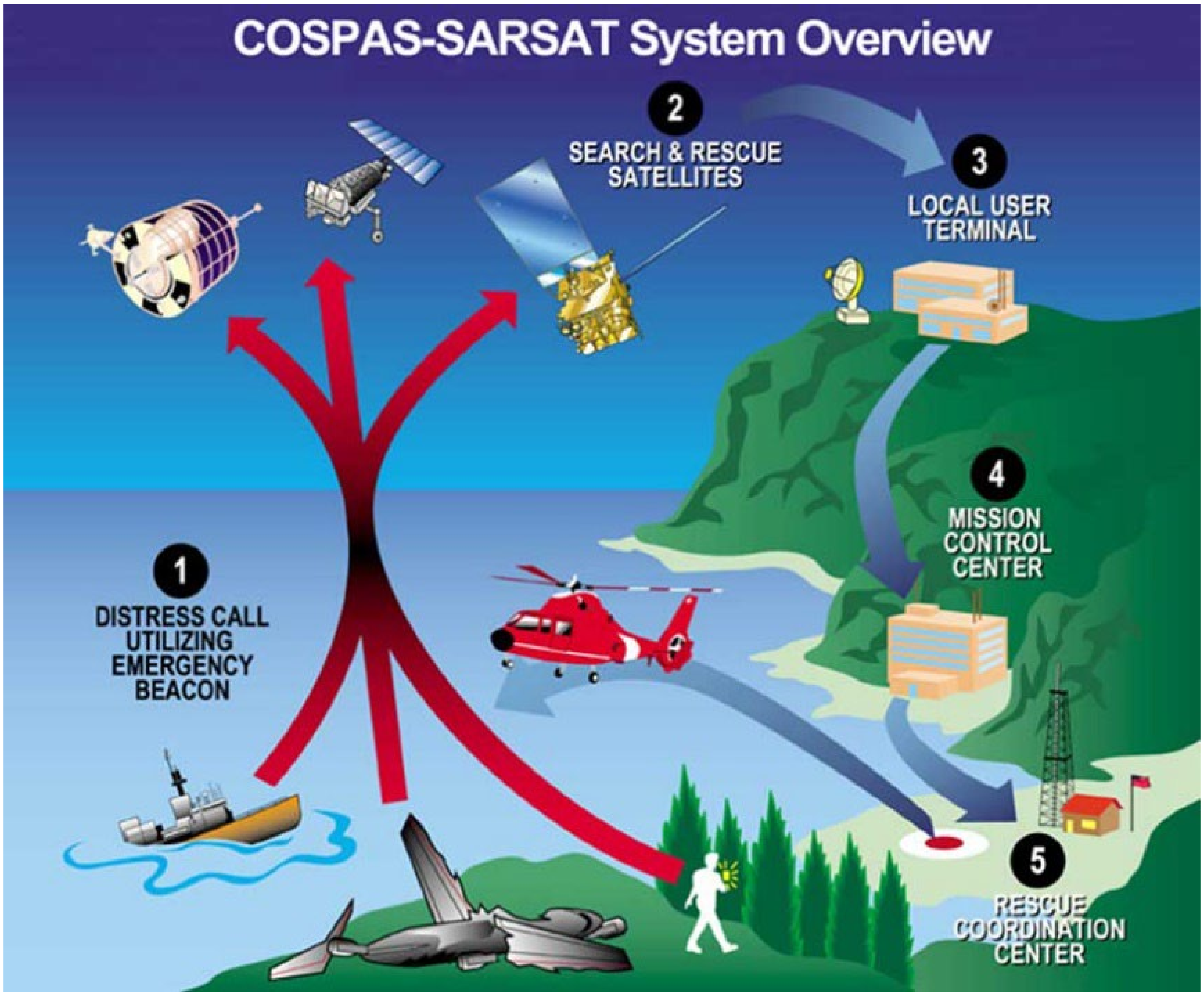

Figure 36. Overview of the international COSPAS-SARSAT system [*Ibid*].
Inputs from TPIO-Derived from NOSIA II Data

There are no data available from the NOSIA II study/database related to this benefit area.

13.3 Benefit Assessment

As discussed in an article in the spring 2013 *Proceedings of The Radio Club of America, Inc.* [*King 2013*] on "COSPAS-SARSAT: An Overview of the Satellite System that has Saved More than 33,000 Lives Worldwide," as of 2013, "COSPAS-SARSAT, which started as an experiment by four countries in the 1970s, soon became an international satellite system for search and rescue. The system is now operated by more than 40 countries around the world and has been credited with saving over 33,000 lives worldwide since it began operating in 1982" [*Ibid*].

The primary contribution of GOES-R in this process is to facilitate rapid communication of emergency beacon information from individuals in distress. "The SARSAT transponder on board GOES-R Series satellites provides the capability to immediately detect distress signals from emergency beacons and relay them to ground stations - called local user terminals" [*GOES-R Program Office, 2022*]. SARSAT is part of the GOES-R UPS suite.

SARSAT provides rescue services on land and on the water (ocean, lakes, and rivers) and internationally as well in cooperation with a large number of countries. We focused on the potential benefit domestically and thus may have underestimated benefits.

The potential loss of life in backcountry situations is documented in part by the National Park Service (NPS) through their Mortality Dashboard [*NPS 2022*]. The NPS Key Statistics CY2014 - CY2016 reports that "A total of 990 deaths were reported in national parks from 2014 to 2016 which equals to an average of 330 deaths per year or 6 deaths a week" [*Ibid*]. Assuming a portion of these are related to lost individuals suggested the potential value of improved search and rescue processes, including communications.

To estimate the number of impacted individuals, we used the annual data on the "Number of People Rescued" from the SARSAT website [*NOAA SARSAT 2022*]. This website provides "Recent Calendar Year Totals in the United States" for the years 2001 through 2020 (20 observations). We undertook an ordinary least squares (OLS) regression on these data with U.S. rescues (the number of individuals rescued) as the dependent variable and "year" as the only independent variable. The regression model yielded:

$$\begin{array}{llcl} \text{U.S. Rescues} = & -12982.737^{***} & + & 6.589\ \text{Year}^{***} \\ & (3888.482)^{\dagger} & & (1.934)^{\dagger} \end{array}$$

*** Significant at <1.0%   † Standard error of the estimate

Adjusted R square 0.358 (n=20)

For a more-detailed explanation of this regression model and its results, see Appendix D.

We then used the regression model to project the number of people rescued through the life of the GOES-R (to 2040) as shown in Figure 37.

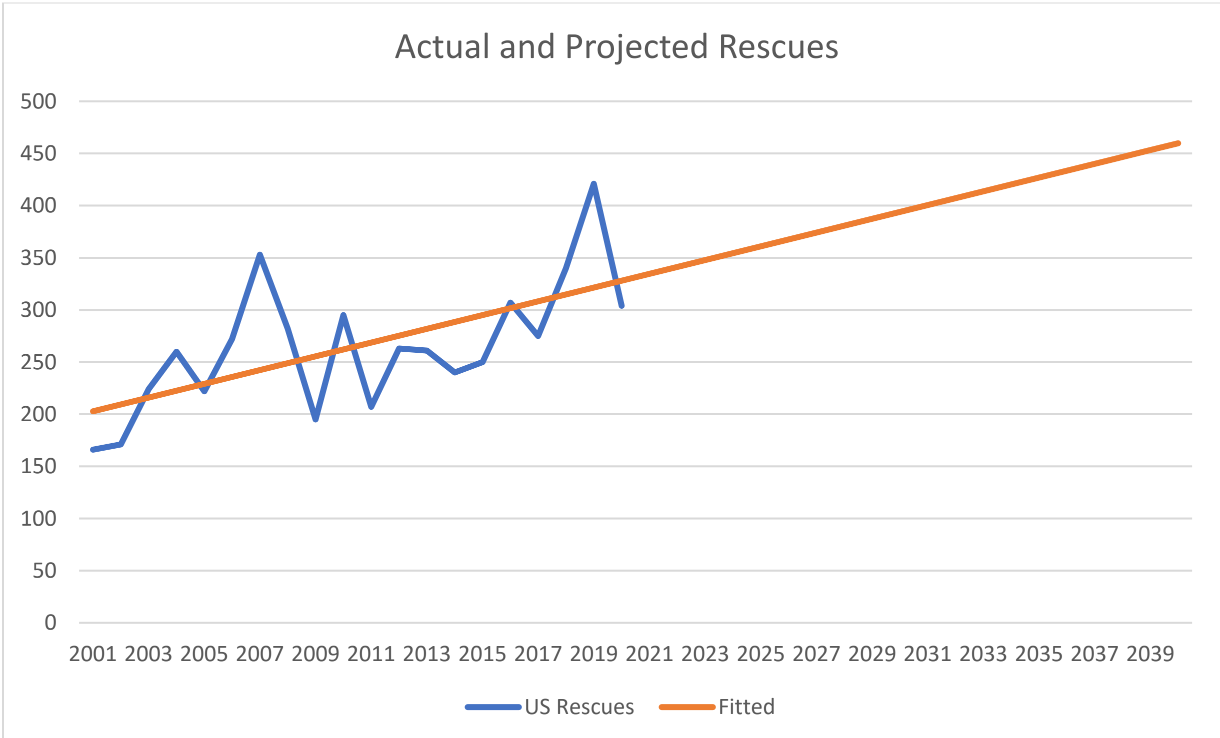

Figure 37. People saved with SARSAT and projections to 2040 from regression analysis (source: Lazo/Aerospace).

We note that the existing information on SARSAT often refers to all individuals rescued as "lives saved." Without further information, we assumed that most of those individuals may have survived (albeit after some delay and potential suffering) and thus conservatively adjusted the "number saved" to 5% who would not have otherwise survived (i.e., would have died). We used the number of "fitted rescues" and then used initial ("heuristic") estimates to adjust for the portion of these whom would not have survived if not rescued (5%) and what portion of the SARSAT information is attributable to satellites (50%) and the portion of that attributable to GOES-R (50%). We then multiplied these results for each year by the VSL value adjusted using the factor for increased wealth (1.469%) over time. Table 29 shows this information over the 2018–2040 analysis period.

Table 29. Annual Benefit of Fitted Lives Saved 2018–2040

Year	Fitted Rescues	Lives Saved (5%)	Attributable to Satellites (50%)	Attributable to GOES-R (50%)	VSL (2020 Base)	Benefit
2018	314.82	15.74	7.87	3.94	$11,266,557	$44,336,868
2019	321.41	16.07	8.04	4.02	$11,432,063	$45,929,817
2020	328.00	16.40	8.20	4.10	$11,600,000	$47,560,000
2021	334.59	16.73	8.36	4.18	$11,770,404	$49,228,166
2022	341.18	17.06	8.53	4.26	$11,943,311	$50,935,079
2023	347.77	17.39	8.69	4.35	$12,118,758	$52,681,519
2024	354.36	17.72	8.86	4.43	$12,296,783	$54,468,277
2025	360.95	18.05	9.02	4.51	$12,477,423	$56,296,161
2026	367.54	18.38	9.19	4.59	$12,660,716	$58,165,995
2027	374.13	18.71	9.35	4.68	$12,846,702	$60,078,616

Year	Fitted Rescues	Lives Saved (5%)	Attributable to Satellites (50%)	Attributable to GOES-R (50%)	VSL (2020 Base)	Benefit
2028	380.72	19.04	9.52	4.76	$13,035,420	$62,034,878
2029	387.31	19.37	9.68	4.84	$13,226,910	$64,035,650
2030	393.89	19.69	9.85	4.92	$13,421,214	$66,081,818
2031	400.48	20.02	10.01	5.01	$13,618,371	$68,174,284
2032	407.07	20.35	10.18	5.09	$13,818,425	$70,313,966
2033	413.66	20.68	10.34	5.17	$14,021,418	$72,501,800
2034	420.25	21.01	10.51	5.25	$14,227,393	$74,738,739
2035	426.84	21.34	10.67	5.34	$14,436,393	$77,025,754
2036	433.43	21.67	10.84	5.42	$14,648,464	$79,363,834
2037	440.02	22.00	11.00	5.50	$14,863,649	$81,753,984
2038	446.61	22.33	11.17	5.58	$15,081,996	$84,197,230
2039	453.20	22.66	11.33	5.67	$15,303,551	$86,694,616
2040	459.79	22.99	11.49	5.75	$15,528,360	$89,247,207

As we had developed a time series estimate of the number of lives saved, we did not factor in increases in weather variability as the benefits are not necessarily "climate dependent" (i.e., this is not a weather impact benefit but benefit from the communication systems) nor did we factor in population growth. We did factor in per capita income growth would compound the value of benefits by 1.469% (i.e., compounded the VSL value).

We derived present value benefit estimates using the five applicable rates of discount as shown in Table 30 in billions of 2020$. Our baseline benefit estimate is **$1.30B** (2020$) as shown in Table 30.

Table 30. Present Value Estimates of GOES-R Search and Rescue Benefits

Discount Rate	0.0%	0.300%	1.185%	3.000%	7.000%
Billions (2020$)	1.50	1.44	1.30	1.06	0.72

13.4 Discussion—Key Uncertainties and Recommended Future Efforts

The key uncertainties in the current analysis are the factors for number of non-rescued individuals who would have died and how much the SAR process relied on satellite information and what portion of that is attributable to GOES-R versus other satellite information. These factors are:

- 5% of non-rescued individuals would have died to estimate number of "lives saved"
- 50% reliance on satellite information
- 50% reliance on GOES-R to derive projected annual number of lives saved

Further research is warranted to evaluate each of these initial factor values.

In addition, more robust regression analysis may be examined for estimating and projecting the time trends of number of individuals rescued. It is likely there are non-linear processes involved and we may be under- or over-estimating these trends. It would also be reasonably straightforward to develop confidence intervals from the regression analysis of the number of people saved each year. The bounds on this are likely much smaller than the uncertainty in the three factors noted above so we have not calculated those confidence intervals at this time.

It may also be worthwhile to explore projected increases in outdoor recreation as there likely have been structural changes in the use of the back country for personal recreation with the onset of COVID-19. This may have been captured in the regression analysis but could be further explored.

14. DCS: Riverine Flood Warnings and Marine Transportation

14.1 Summary Results

To estimate benefits of GOES-R related to impacts of riverine flooding and hydrogeological information in marine settings, we calculated (1) the reduction in riverine flood damages from warnings and forecasts and (2) the reduction in riverine flooding, damages to marine shipping and port property, and fatal accidents, both due to DCS data channels. Note that there are multiple benefit assessments in this area related to the unique communications capability (aka., UPS) of GOES-R in supporting the GOES DCS.

This assessment did not attempt a comprehensive valuation of the information carried by the GOES DCS. We felt that determining the total value of the service was beyond our scope of work, and that GOES-R contribution is for the communication services and their hemispherical coverage that make the other services possible. No one should conclude that the values contained herein reflect the total value of the various services that are relayed via the DCS UPS.

Building on existing information resources, we implemented the following steps to derive an annual benefit estimate:

- Riverine flood information through DCS:
  - We obtained 2020 flood damage reduction by U.S. Army Corp of Engineers (USACE) [*USACE 2022*] ($257B)
  - We obtained the reduction by USACE-supported emergency operations (EO) ($1.34M)
  - We calculated the percent attributable to USACE EO (0.0000052%)
  - We then obtained the 10-year average annual riverine flood damage reduction ($161B)
  - We multiplied the 10-year average by the percent reduction to derive an average annual benefit ($843K)
  - We applied a USACE-indicated percent dependent on GOES-R DCS (50%). **(Note we feel this is a key unknown parameter.)**
  - We calculated the annual flood reduction benefits attributable to GOES-R ($421K)
- National Ocean Service's DCS-related PORTS:
  - We obtained literature comparing impacts between ports with and without PORTS over 10 years [*Wolfe and MacFarland 2013*]:
    - Reduction in ship damages (average annual $7.3M)
    - Reduction in average annual accidental loss of life (1.9 lives)
    - Applied USDOT VSL of $11.6M ($22.0M)
  - We summed the reduction in property and fatalities ($29.3M)

- We applied a 90% factor for reliance on PORTS data ($26.4M). **(Note we feel this is a key unknown parameter.)**
- We then applied 10.24% (TPIO number) contribution from GOES-R to derive annual ship damages and accidental loss-of-life reduction benefits attributable to GOES-R ($2.64M).

These provided us with baseline year annual benefits from GOES-R ($421K and $2.64M). We then aggregated these over the lifetime of the GOES-R series accounting for increases in wealth, population, and weather variability (using a baseline discount rate of 1.185%). The baseline estimate is an aggregated present value benefit of **$0.09B** for benefits from DCS (in 2020$).

14.2 Introduction to Application Area

In situ measurements of water levels provide an important contribution to hydrology and flood forecasting and support safe navigation of inland waterways and ports in the United States and Canada. Although those measurements are not performed by the GOES-R satellite, the reporting of such data are only possible in near-realtime by using a unique communications capability of the GOES-R satellite that provides hemispheric coverage of the uplink signal in the ultra-high frequency (UHF) band.

The DCS consists of platforms collecting environmental information primarily in remote areas within the footprint of the GOES-R satellites, where the GOES satellites serve as the communications link between the remote platform and processing facility.[31] Users include U.S. and international agencies responsible for monitoring environmental and Earth resources, including U.S. NWS flood warning and forecasting. We focus here on (1) potential benefits from riverine flood information made feasible by DCS and GOES-R and (2) benefits from the National Ocean Service's (NOS's) PORTS system in reducing ship damages and accidental loss of life. The DCS also serves multiple international agencies, as well as other domestic agencies including the USGS for earthquake monitoring and U.S. Forest Service (USFS) forest wildfire operations. We have not attempted to quantify benefits from these services, but these likely provide significant additional socioeconomic benefits from GOES-R.[32]

The GOES DCS relays the original telemetry data from river, stream, tide, and coastal gages, located throughout the hemisphere. Over 30,000 geographically diverse data collection platforms (DCPs) are located throughout the western hemisphere that uplink at UHF via the GOES-R UPS for transmission to federal and non-federal ground stations (Figure 38). The gages are owned by private, non-federal, and federal agencies, and the information is used to manage critical infrastructure, measure levels on the nation's inland waterways, and provide hydrologic data that detects—and is used to warn of—flood conditions. Gage data are input into numerical weather prediction models as a verification of precipitation levels.

Sensors on the DCPs include river, stream, tide, and coastal gages for the management of reservoirs, locks, and dams. Sensors installed in the nation's seaports aid pilots entering and departing the ports, thus enhancing maritime safety.

[31] Paraphrased largely from https://www.noaasis.noaa.gov/GOES/GOES_DCS/goes_dcs.html Accessed February 8, 2022.
[32] NESDIS provides several examples and anecdotes of the value and use of DCS information services that could potentially be quantified as well. https://www.noaasis.noaa.gov/GOES/GOES_DCS/dcs_in_action.html

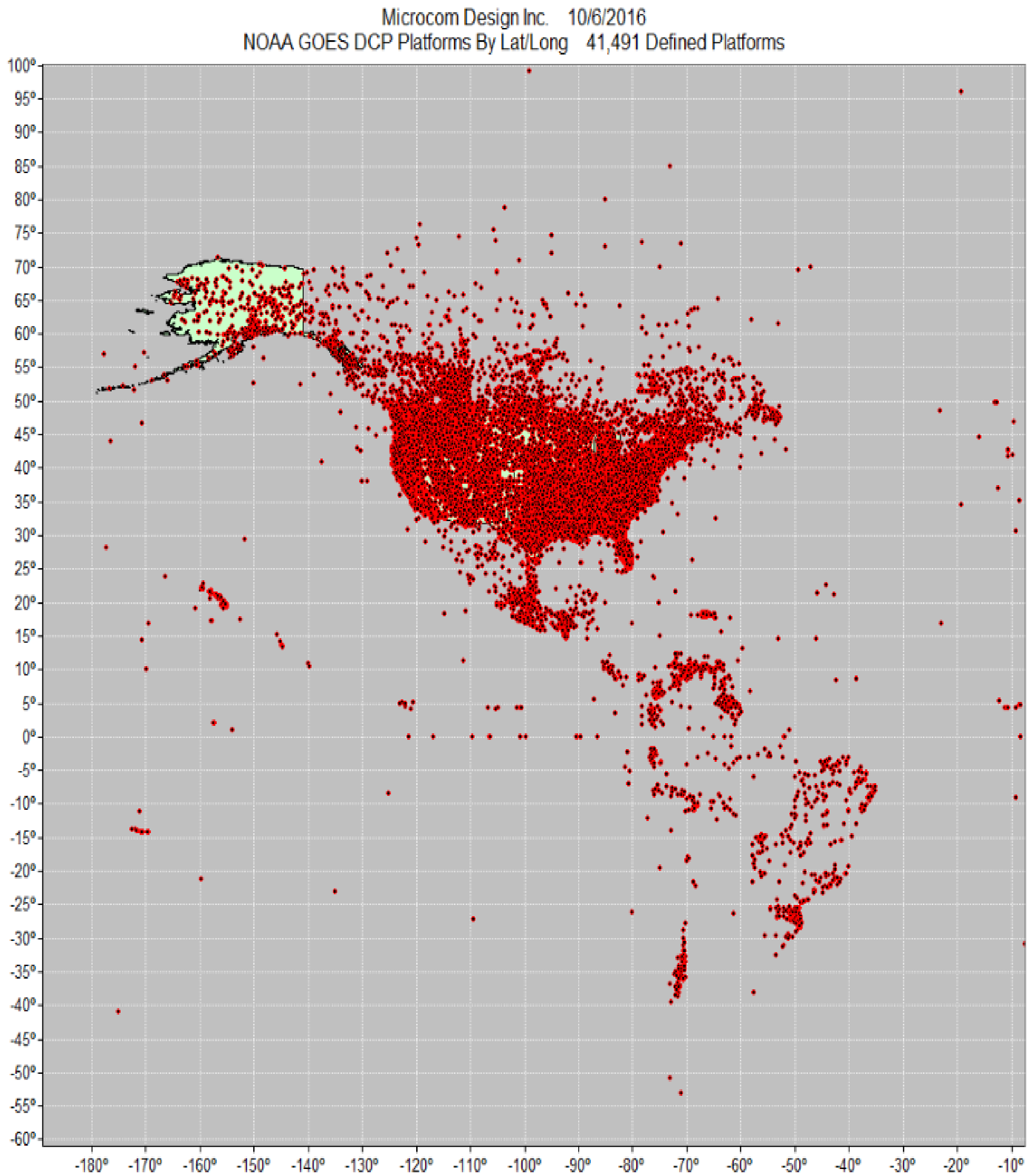

Figure 38. DCPs transmitting to GOES-R (source: NOAA/Microcom Design).

The frequency coverage to receive these data collection platform uplink signals is located in a radio spectrum that is generally reserved for meteorological or environmental use. There is no commercial service that could receive the uplink signals from DCPs in the frequency range allocated for the wide coverage area (much of the visible hemisphere) associated with GOES DCS (Figure 39).

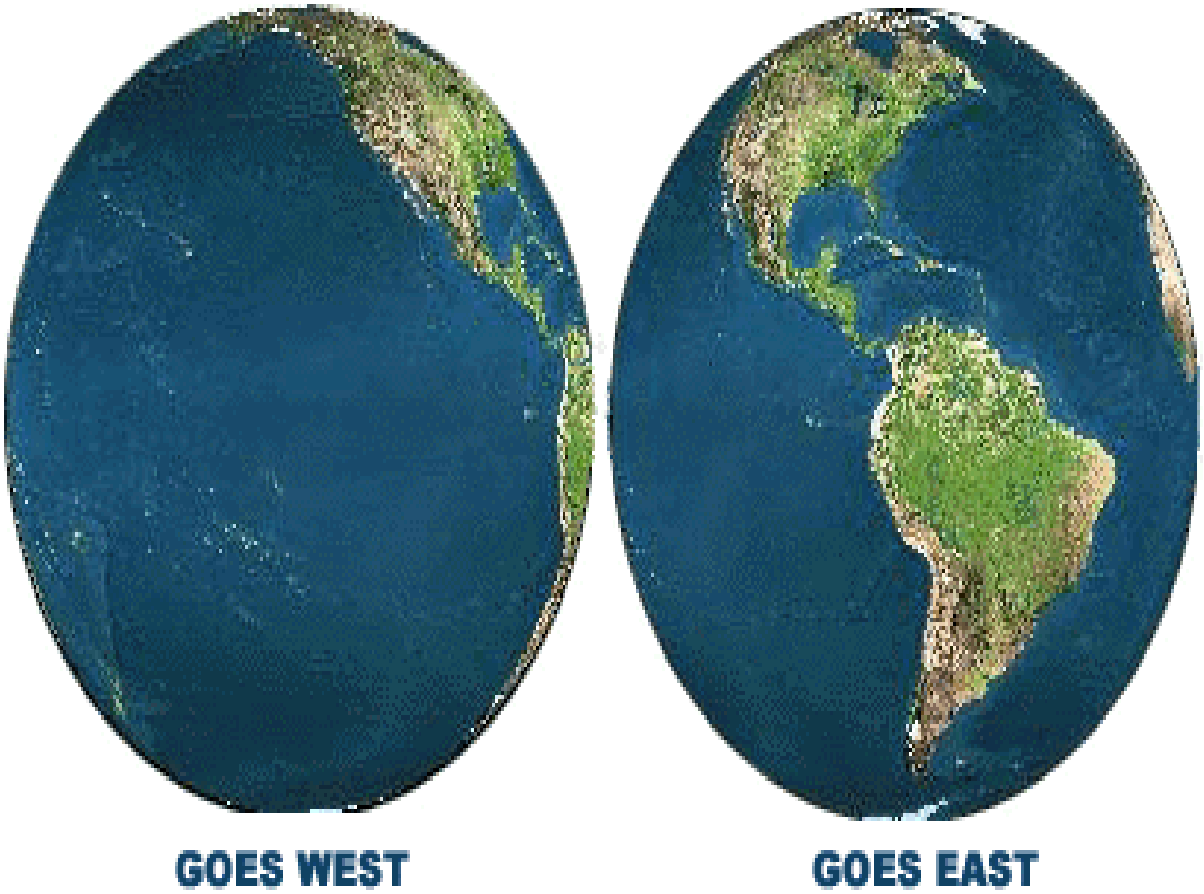

Figure 39. Approximate coverage area for GOES-DCS at UHF frequencies (NOAA).

14.2.1 NOAA's PORTS

This assessment examines the value from flood avoidance at the USACE and maritime safety at the nation's ports from NOAA's NOS. From these data, we have determined the portion of the socioeconomic contribution from DCPs related to the unique DCS uplink communications coverage of GOES-R.

Figure 40 indicates the usage of PORTS sensors at U.S. seaports as of 2014. As of January 2022, there are 36 existing PORTS at 80 of the nation's top 175 seaports. Those 80 seaports presently host about 88% of the total tonnage and about 91% of the total value of cargo from the top 175 seaports. Figure 40 may not reflect that updated information.

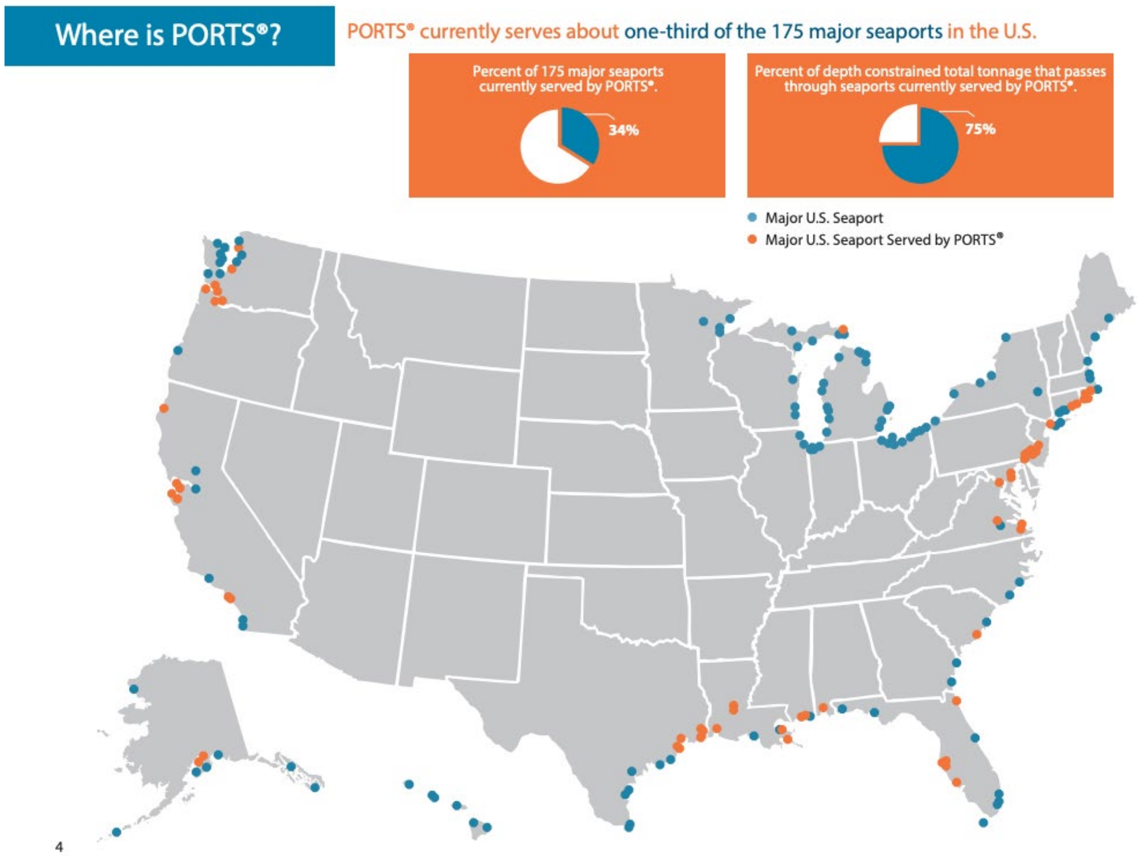

Figure 40. PORTS installations in U.S. seaports (NOAA NOS).

14.3 Inputs from TPIO-Derived from NOSIA II Data

According to TPIO's NOSIA II data analysis, GOES-R, in the area of integrated water products, made a contribution to models of 2.36% and a contribution to non-model products of 7.88%. These resulted in a total GOES-R contribution to flooding and integrated water products of 10.24%.

14.4 Benefit Assessments

14.4.1 Riverine Flood Warnings: DCS Flood Benefit Calculations

For riverine flooding, we obtained prevented-flood-damage information from the USACE Annual Flood Damage Reduction Report, including the document "Appendix G: Annual Flood Damage Reduction Report," provided by CECW-CE (Hydrology & Hydraulics Community of Practice).[33]

We used the 2020 document and data as provided to us by the USACE [*USACE 2020*]. Table 1 (2020 document) reported the "Average Damage Reduction FY2011-2020" of $161,834,232 attributable to USACE flood control operations [*Ibid*]. We show the annual and average prevented damages as reported by USACE in Figure 41, copied from Appendix G of that report [*Ibid*]. As can be seen, there is a significant year-to-year variation in the benefits of USACE flood control activities, but the last five years

[33] The 2020 version is available at https://water.usace.army.mil/a2w/r/cwms_crrel/files/static/v16/APPN-G-2018_FINAL.PDF. Accessed February 8, 2022. Table 1 of Appendix G reports on "Flood Damage Reduction by State (Thousands of Dollars) During Fiscal Year 2019."

have all been above average. This may suggest an upward trend in benefits partly in relation to increasing weather variability.

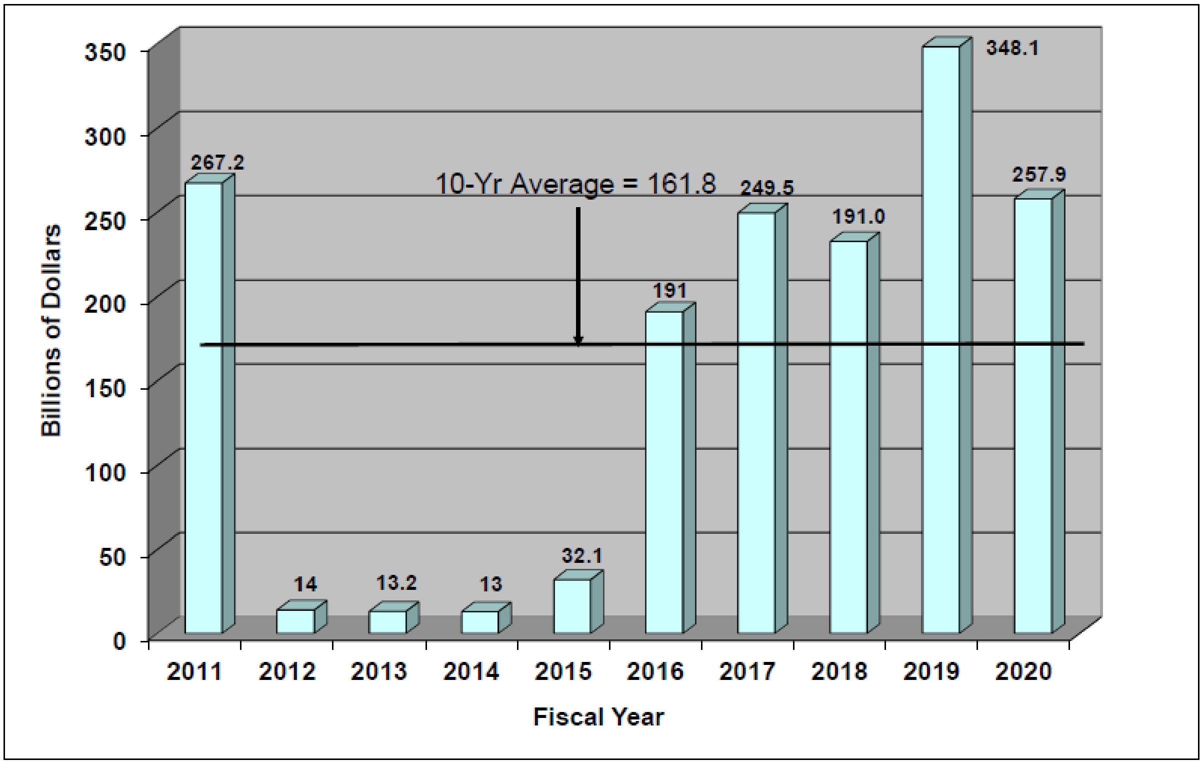

Figure 41. Flood damage reduction attributable to USACE flood control operations [*USACE 2022*].

For the year 2020, the Appendix G table reports "Reduction by Corps Supported Emergency Operations" of $1.344M out of $257.9B or 0.00052% of total avoided damages attributable to emergency operations [*Ibid*]. We focused on the reductions attributable to emergency operations because of the high dependency on temporally sensitive data for these operations. Lysanias Broyles (Department of Defense [DOD] USACE) stated in an email communication (January 26, 2022) that applying a factor for GOES-R of "50 – 67% of flood damages prevented would be appropriate [as] the vast majority of our flood control projects use GOES as a method of telemetry." We used the lower value of 50% for our analysis. Table 31 shows the derivation of the baseline benefits from reductions in riverine flooding.

Table 31. Reduction in Riverine Flood Damages Attributable to GOES-R DCS Systems

Analysis Factors	Factor	Value
Average damage reductions 2010–2019 ($)	n/a	$161,834,232
Reduction by Corps-supported emergency operations (FY2020)	n/a	$1,344,000
Total flood damage reduction by the Corps of Engineers (FY2020)	n/a	$257,913,371,000
Percent attributable to emergency operations	0.00052%	n/a
Benefit of emergency operations	n/a	$843,327
Percent dependent on GOES-R DCS (email from USACE)	50.00%	n/a
Annual benefits attributable to GOES-R (2020$)	n/a	$421,663

14.4.2 PORTS Benefit Calculations

The maritime transportation-related benefit use of GOES-R DCS systems is the PORTS program aiding maritime navigation. NOAA's PORTS program is a decision support tool to improve the safety and efficiency of maritime commerce and coastal resource management through the collection and dissemination of observations of water levels, currents, salinity, bridge air gap and meteorological parameters for navigational safely and to improve the efficiency of U.S. ports and harbors and ensure the protection of coastal marine resources [*NOAA 2022B*]. The overall PORTS system is pictorially represented in Figure 42, which also indicates the critical role of GOES-R DCS in communicating information in a time-sensitive manner.

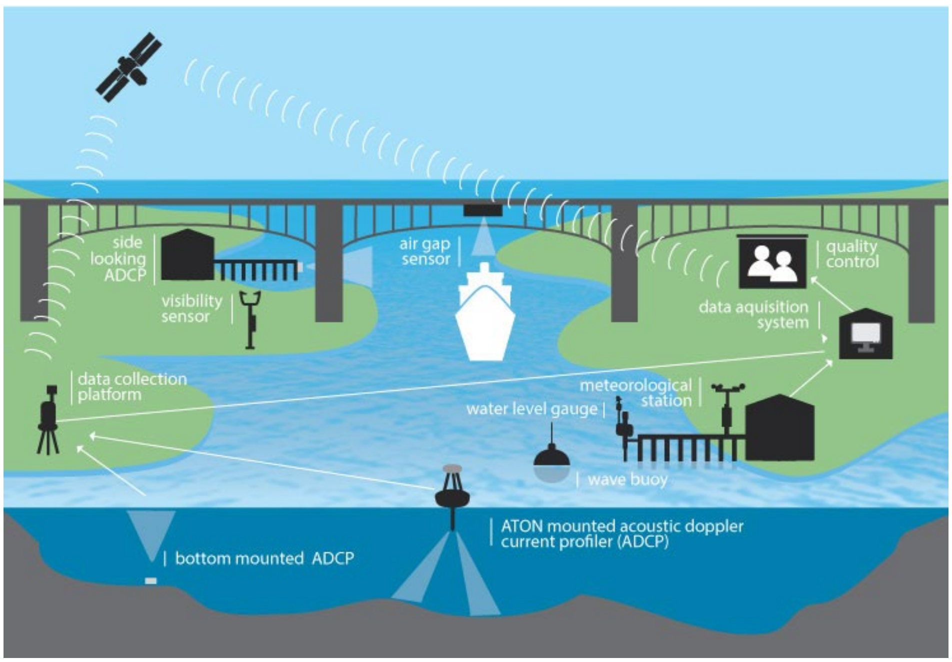

Figure 42. Operation and functioning of the PORTS system indicating the DCS function [*Ibid*].

As indicated by Nathan Holcomb (NOAA - NOS) [*Holcomb 2022*] on January 31, 2022[34]:

> "… over 90% of PORTS® stations depend on GOES as their primary telemetry with cellular communications as a backup. The 36 existing PORTS® (as of Jan 2022) support safe and efficient marine navigation at 80 of the Nation's top 175 seaports. Those 80 seaports presently host ~88 percent of the total tonnage and ~91 percent of the total value of cargo from the top 175 seaports."

In 2017, NOAA published an internal economic analysis that looked in more depth at the incidence of accidents (allisions[35], collisions, and groundings [ACGs]) during the period 2005 to 2016, based on

[34] These data appear to have been published in Wolfe and MacFarland [*Wolfe and MacFarland 2016*]. At this time, we have not cross-checked the two sources for consistency, but a brief review suggests that estimates provided by Holcomb are reasonably close to those in Wolfe and MacFarland possibly with some adjustments made in the published article.

[35] An allision is "the running of one ship upon another ship that is stationary —distinguished from collision" (source https://www.merriam-webster.com/dictionary/allision#:~:text=Definition%20of%20allision,is%20stationary%20%E2%80%94distinguished%20from%20collision accessed June 30, 2022)

locations with and without PORTS [*Wolfe and Mitchell 2018*]. Some of the most significant impacts of PORTS included:

> "Over 10 years, seaports with access to real-time PORTS® information were estimated to have realized about $183 million, or two-thirds of total savings, from ACG reduction alone. There were 19 fewer lives lost (value of $102 million), 41 fewer injuries (value of $8 million), lower property losses (value of $73 million), and reduced oil pollution remediation costs (value about $1 million)" [*Ibid, p.1*].

We used the sum of reduced property losses and remediation costs ($73M) over 10 years to derive an annual PORTS benefit estimate of $7.3M. For reduced fatalities, we took the annual average (1.9 lives per year) and applied the $11.6M VSL for an annual PORTS benefit of $29.3M. Note that we do not use the VSL estimate from the NOAA report but use the DOT VSL estimate to maintain consistency with the other benefit analysis in this report. We also do not use the injury information as in general, while important, reduced morbidity is a significantly smaller benefit than reduced mortality and we do not have clear information from the content reviewed of the nature and degree of reduced morbidity to incorporate it into our computations.

We summed the two benefit areas (property and reduced loss of life) and applied the "90% of PORTS stations depend on GOES as their primary telemetry" factor [Holcomb 2022] and further assumed that 10% of the reduction in losses is attributable to the information use.[36] This generated a baseline GOES-R DCS benefit annual estimate of $2,640,600.

Using these data, we calculated an annual baseline benefit attributable to the GOES-R DCS system of $3.06M. This is likely a conservative estimate of the benefits of GOES-R DCS as we (1) have not included any attribution to potentially flood-related reduced loss of life (this may be captured within the flash flooding benefit area); (2) have not included benefits from the non-emergency flood prevention benefits, which are much more than 99% of the total benefits of DCS; and (3) have not included other non-flood/non-PORTS benefit areas from GOES-R DCS systems. In Table 32 we show our calculation of the total reduction in marine damages attributable to the GOES-R DCS systems and PORTS.

Table 32. Reduction in Marine Damages Attributable to GOES-R DCS Systems and PORTS

Analysis Factors	Factor	Value
Lowered property losses and reduced oil pollution remediation costs	n/a	$73,000,000
Annual average	n/a	$7,300,000
Lives	n/a	n/a
19 fewer lives lost	19.0	n/a
Annual average	1.9	n/a
VSL	n/a	$11,600,000
Reduced fatality benefits	n/a	$22,040,000
Total PORTS Benefit	n/a	$29,340,000
Reliance on GOES-R data	90%	n/a
Changes attributable to GOES-R	10%	n/a
PORTS Benefit Attributable to GOES-R ($)	n/a	$2,640,600
Total Riverine Flooding (Table 33) and PORTS Benefits (2020$)	n/a	$3,062,263

[36] This is a key parameter that should be further evaluated for the appropriate level and application of this adjustment.

14.4.3 Aggregation of Benefits: DCS: Riverine Flood Warnings and Marine Transportation

As with other benefit areas, we assumed changes in weather variability would exacerbate flooding impacts and factored this in as an annual increase in costs of 1.5%. We further assumed population growth would increase impacts by 0.572% annually and per capita income growth would compound the value of benefits by 1.469%. We derived the aggregated present value benefit estimates using the five applicable rates of discount as shown in Table 33 in billions of 2020$. Our baseline estimate of GOES-R benefits in DCS is **$0.09B** (2020$).

Table 33. Benefit Estimates of GOES-R DCS Reduced Riverine Flooding and PORTS Benefits (Billions [2020$])

Discount Rate	0.0%	0.300%	1.185%	3.000%	7.000%
Riverine Floods	0.01	0.01	0.01	0.01	0.01
PORTS	0.09	0.09	0.08	0.06	0.04
Total DCS Benefits	0.11	0.10	0.09	0.07	0.05

Note: This assessment did not attempt a comprehensive valuation of the information carried by the GOES DCS. We felt that determining the total value of the service was beyond our scope of work and that the GOES-R contribution is for the communication services and their hemispherical coverage that make the other services possible.

No one should conclude that the values contained herein reflect the total value of the various services that are relayed via the DCS UPS.

14.5 Discussion—Key Uncertainties and Recommended Future Efforts

The key uncertainties in this analysis are (1) the factor for the percent of "percent dependent on GOES-R DCS" (we applied a 50% factor for the current analysis based on input from USACE but suggest further research to refine this value) and (2) the "changes attributable to GOES-R" for PORTS (we applied a 10% factor for the current analysis based on input from USACE but suggest further research to refine this value).

While much of the analyses here are subjective, we note in particular that the research team is less familiar with this benefit area; thus, the use of PORTS information in this benefit area is less clear. Therefore, we feel the logic model of attribution of the PORTS benefits should be explored further and validated with appropriate subject matter experts.

For the contributions by the GOES-DCS and the UPS on the GOES-R satellites, although GOES-R is providing a relay of near-realtime data, the geographic diversity throughout the hemisphere and the unique frequency range that is restricted to meteorological and hydrological use by frequency management regulations define a service that is not available commercially. The need for reception from the installed base of data collection platforms and the benefits throughout the hemisphere were not computed for all countries that benefit from the GOES-DCS system.

The nation's seaports support the marine transportation system that transports the products that American businesses and residents use every day. As reported in the press, as a result of COVID-19-related supply chain issues, there is a considerable backlog of ships awaiting to unload that are anchored offshore. Further due diligence may reveal additional contributions of the GOES-DCS-enabled PORTS in the management of marine traffic as seaport managers work off this backlog of awaiting ships. Examination of data statistics from the DOT Maritime Administration [*USDOT 2022*] may be warranted in future work.

As noted in the benefit analysis section, this assessment has not included other non-flood, non-PORTS usage of the GOES-DCS system, which are also supported via the GOES-R UPS communications relay. Some of those other uses are monitoring of fire weather conditions from remote platforms, protecting the lives of wildland firefighters, and enabling management of the firefighting strategies. Although this is not a flooding and hydrology topic, further work in this area could contribute to other benefit areas of this study.

15. Climate Policy

15.1 Summary

To estimate benefits of GOES-R related to climate policy, we assumed that information from GOES-R contributes to the understanding of climate change and thus supports decisionmaking with respect to mitigating and adapting to those changes. Building on existing information resources, we implemented the following steps to derive an annual benefit estimate:

- We assumed the potential value of GOES-R is in informing policy actions to mitigate and adapt to climate change
- Obtained 2018 GDP [*BEA 2022B*] ($20,527.2B) and converted to 2020$
- Applied information from Tol [*Tol 2019*] on climate economics, including impacts and policy, indicating on average a 1.3% decrease in income with a 2.5-degree global temperature increase
- Assumed that 10% of climate impacts can be mitigated with policy. **(Note we feel this is a key unknown parameter.)**
- Assumed 1% of climate policy information comes from GOES-R. **(Note we feel this is a key unknown parameter.)**

This provided us with a baseline year annual benefit from GOES-R in 2018 of $2.7M in informing climate policy. We then aggregated these over the lifetime of the project, accounting for increases in wealth, population, and weather variability (using a baseline discount rate of 1.185%). The baseline estimate is a present value benefit of **$8.10B** (in 2020$).

15.2 Introduction to Application Area

Numerical forecasting of weather is commonly discussed by meteorologists, and numerical weather prediction (NWP) is an essential tool for operational weather forecasters. Weather forecasting for up to approximately fourteen days can often be determined after using the NWP model outputs, with data from many types of meteorological or environmental satellites and other (non-satellite) observational data used for model initial conditions. Any forecast beyond two weeks may be considered a climate prediction.

However, climate modeling and forecasting differ as follows:

> "Climate modeling, in one sense of the word, is simply an extension of weather forecasting, but over a very long-time scale. A climate model would predict how average conditions will change in a region over the coming decades" [*Harper 2018*].

Climate models serve a very different purpose than those for short-term weather forecasting. Climate also falls into a separate group of MSAs from the WRN MSAs (as shown in Figure 43) and we treat it separately in this report.

NOAA Mission Service Areas (MSAs)			GOES-R Socioeconomic Benefits Study Area
Applicable NOAA Org.	**Applicable MSA Category**	**Applicable Mission Service Area**	
NOS	Resilient Coasts	Resilience to Coastal Hazards & Climate Change (RC-RCC)	**Climate Policy**
OAR	Climate	Assessments of Climate Changes & Its Impacts (CLI-ACC)	
OAR	Climate	Climate Mitigation & Adaptation Strategies (CLI-CMA)	
OAR	Climate	Climate Science & Improved Understanding (CLI-SIU)	
OAR	Climate	Climate Prediction and Projections (CLI-CPP)	
(Derived from: "NOAA's Approach to Observing System Requirements Management," Martin Yapur; Prepared for U.S. IOOS Advisory Committee, February 11, 2020.)			

Figure 43. NOAA MSAs related to climate and climate benefit area
(Note: OAR = NOAA Office of Oceanic and Atmospheric Research).

According to the MIT Joint Program on the Science and Policy of Global Change, "Today's climate challenge requires policies designed to reduce greenhouse gas emissions and air pollution, and to prepare populations and infrastructure for the impacts of climate change through adaptation" [*MIT 2022*]. Furthermore, the independent, nonprofit research institution, Resources for the Future (RFF), states: "Federal climate policy is the set of actions taken by the US federal government to address and mitigate the effects of climate change. Climate policy includes policies to mitigate climate change (reducing greenhouse gas emissions and removing greenhouse gases from the atmosphere, so that the climate does not change as much or as quickly); and to adapt to climate change (helping communities and businesses to build resilience and avoid the worst effects of warmer temperatures, extreme weather, and other impacts)" [*RFF 2022*].

Climate policy is part of the larger environmental policy. "Environmental policy in the United States involves governmental actions at the federal, state, and local level to protect the environment and conserve natural resources. Environmental protection is balanced with other public policy concerns, such as economic growth, affordable energy, and the rights of businesses and individuals. Debates over state and federal environmental policies often involve discussions of the trade-offs associated with environmental laws. Environmental policy can include laws and policies addressing water and air pollution, chemical and oil spills, smog, drinking water quality, land conservation and management, and wildlife protection, such as the protection of endangered species" [*Ballotpedia 2022*].

The climatic data records (CDRs) collected from the GOES-R series (and other environmental satellite systems) play a vital role in helping provide a basis for climate policy, and not just in the U.S., but also in other countries around the world.

15.3 Inputs from TPIO-Derived from NOSIA II Data

None. There are no such data available from the NOSIA II study/database.

15.4 Benefit Assessment

Climate change is considered by many to be the largest environmental, social, and economic threat to humanity. As Kumar et al. [*Kumar et al 2021*] stated "Climate change has given rise to many existential threats, including a rise in global temperatures, melting of glaciers and polar ice caps, increment in sea level, loss of biodiversity, extreme weather events, and an outbreak of uncountable diseases" [*Ibid, p.1*][37] Having a long-term set of climate data is key to understating climate and potential climate change and to informing policy to mitigate and adapt to climate impacts. As noted in the NRC report, *Options to Ensure the Climate Record from the NPOESS and GOES-R Spacecraft*, "The value of sounding from GEO, however, goes beyond maintenance of a long-term record. The ability to sense water vapor in the atmosphere is crucial for monitoring and predicting hazardous weather conditions"[*NRC 2008, p.35*] Further, as noted by Hsiang et al., "Estimates of climate change damage are central to the design of climate policies" [*Hsiang et al. 2017, p.1*].

To evaluate the potential contribution of data from GOES-R in informing climate policy, we provide subjective estimates of the contribution of GOES-R to the climate record and then of how the climate record contributes to climate policy. An underlying assumption is that better climate data can reduce potential uncertainty in forming climate policy and reduce the costs of climate impacts. We use information from a literature review by Tol [*Tol 2019*] in which he conducts an analysis of climate economics, including impacts and policy. Tol's review of 27 published studies of the economic impacts of climate change indicates on average a 1.3% decrease in income with a 2.5-degree (centigrade) increase in global temperature. We applied this 1.3% impact to GDP projections for the United States as climate impacts through 2040, noting that the more negative impacts may be further in the future.

We obtained 2018 GDP of $20,527.2B [*BEA 2022*]. We then adjusted this value to 2020$ of 20,780.4B. Based on Tol [*Tol 2019*], we assumed that the impact of climate change is a reduction in GDP of 1.30% or $270.15B. Assuming that the potential value of GOES-R is in informing policy actions to mitigate and adapt to climate change, we first assumed that 10% of climate impacts could be mitigated with policy based on climate information. Of this, we then assumed that 1% of climate policy information comes from GOES-R. This generated a baseline benefit estimate of $270.15M (2020$). We show these calculations in Table 34.

Table 34. Economic Benefits of GOES-R Contribution to Climate Policy

Analysis Factors	Factor	Value
U.S. GDP 2018	n/a	$20,527,200,000,000
CPI 2018	255.66	n/a
CPI 2020	258.81	n/a
2018 GDP adjusted to 2020$	1.012336842	$20,780,440,821,882
Climate impact—reduction in GDP	1.30%	$270,145,730,684
Avoidable with policy	10.00%	$27,014,573,068
Annual Benefit of Policy information from GOES-R (2020$)	1.00%	$270,145,731

As with other benefit areas, we assumed changes in weather variability would exacerbate impacts and factored this in as an annual increase in costs of 1.5%. We further assumed population growth would increase impacts by 0.572% annually and per capita income growth would compound the value of benefits by 1.469%. We derived aggregated present value benefit estimates using the five applicable rates

[37] See also https://climate.mit.edu/ask-mit/why-do-some-people-call-climate-change-existential-threat. Accessed June 15, 2022.

of discount as shown in Table 35 in billions of 2020$. Our aggregated baseline benefit estimate is **$8.10B** (2020$).

Table 35. Present Value Estimates of GOES-R Contribution to Climate Policy

Discount Rate	0.0%	0.300%	1.185%	3.000%	7.000%
Billions (2020$)	9.36	9.01	8.10	6.59	4.43

15.5 Discussion—Key Uncertainties and Recommended Future Efforts

Two key uncertainties in this analysis are:

1. The assumption that 10% of climate impacts can be mitigated with policy
2. The assumption that 1% of climate policy information comes from GOES-R

It is likely there are existing benefit estimates related to the first assumption based on models of policy responses. The second assumption is less understood and is a worthwhile point of analysis and discussion. In essence, these assumptions are placeholder responses to questions aboutthe role more accurate climate information plays in climate policy and how much of that comes from GOES-R (or any other specific source).

Our analysis could build further on the literature on the benefits of climate policy, including alternative valuations approaches such as survey-based willingness-to-pay studies that potentially better capture the full socioeconomic benefits of reducing climate impacts. For instance, Kotchen et al. [*Kotchen et al. 2013*] found that “Based on a survey of 2034 American adults, we find that households are, on average, willing to pay between $79 and $89 per year in support of reducing domestic greenhouse-gas (GHG) emissions 17% by 2020. Even very conservative estimates yield an average WTP at or above $60 per year” [*Ibid, p.617*]. If aggregated across the entire U.S. population of more than 100 million households, this represents significant economic benefits from climate policy implementation.

16. Benchmarking

16.1 Summary Result

To estimate benefits of GOES-R related to the entire U.S. economy, we applied a top-down method developed by World Bank for assessing the total national value of investment in hydro-met services. Benchmarking is not an additional benefit area, but a "top-down" calculation that could be compared to the order-of-magnitude results in our benefit areas. Rough correlation should improve confidence in the values shown in the benefit areas in our study. Building on existing information resources, we implemented the following steps to derive an annual benefit estimate:

- We obtained data on total and sectoral U.S. GDP for 2018 ($20,580.2B)[38] [*BEA 2022C*]
- We obtained estimate of the variability in U.S. GDP attributable to weather (1.4%) from published empirical literature
- We multiplied the GDP by 1.4% to derive overall annual variability in U.S. GDP due to weather ($288B)
- We assumed 5% of this impact can be mitigated, or benefits increased, by 5% for a total benefit of weather information of 10% ($28.8B). **(Note we feel this is a key uncertain parameter.)**
- We applied a factor of 6.38% as portion of this benefit attributable to GOES-R ($1.84B) **(TPIO number)**
- We adjusted dollars from 2018$ to 2020$ using the CPI ($1.87B)

This provided us with a baseline year annual benefit from GOES-R. We then aggregated these over the lifetime of the project, accounting for increases in wealth, population, and weather variability (using a baseline discount rate of 1.185%). The aggregated baseline estimate is a present value benefit of **$45.66B** (in 2020$).

16.2 Introduction to Application Area

WMO [*WMO 2015*] describes the benchmarking approach as a method for top-down assessment of the benefits of National Hydrological and Meteorological Services (NHMS). Benchmarking is not a detailed assessment but is useful for "providing order-of-magnitude valuations that help NMHSs justify increasing public funds to support their services" [*WMO 2015*]

As explained on the Bureau of Economic Analysis (BEA) website of the U.S. Department of Commerce (the same federal department in which NOAA and the NWS reside), GDP is "a comprehensive measure of U.S. economic activity. GDP measures the value of the final goods and services produced in the United States (without double counting the intermediate goods and services used up to produce them). Changes in GDP are the most popular indicator of the nation's overall economic health" [*BEA 2022B*]. GDP is thus a measure of the total economic output of the United States across all sectors and states. Total economic output is taken as a measure of the total welfare of the population and thus changes in GDP reflect changes in welfare. Variability in GDP due to weather variability are measures of the socioeconomic

[38] We note that some of the GDP values for the same year may vary slightly depending on when the data was extracted from the relevant sources and potential differences in methods or conversions between various sources. Any differences in initial GDP estimates are well within any reasonable margin of error in this analysis.

impact of weather. Reductions in this variability due to the use of weather information reflect potential benefits of this weather information. As explicated in Lazo et al. [*Lazo et al 2011*], changes in GDP from the use of weather information are reflected in the changes in societal welfare on the "production side." According to Lazo et al. [*Ibid*] (as copied to Appendix D), this provides a conceptual model of these impacts. The benchmarking approach is a subjective order-of-magnitude approach to estimating the benefits from using weather information to reduce GDP variability.

16.3 Benefit Assessment

> "The World Bank conducted a series of studies to assess the avoided costs associated with large-scale modernization of NMHS services in 11 countries in Europe and Central Asia. These studies rely on simplified approaches, specifically sector-specific and benchmarking approaches, developed by the Bank to compare order-of-magnitude benefits of reducing damages from weather-related events to the costs associated with improving met/hydro services" [*WMO 2015, p. 71*].

The method, as implemented by WMO, is similar to an expert elicitation but, in general, used a single expert from the relevant National Meteorological Hydrological Service (NMHS) to provide an impact estimate. As stated in the WMO/World Bank/USAID volume describing economic approaches to evaluating the value of NMHSs, "The sector-specific method values the economic benefits that would accrue in weather-dependent sectors from modernization of NMHS agencies. This method relies on available country data and surveys of national experts from NMHS agencies and weather-dependent sectors to (a) estimate current sectoral losses from weather events, and (b) determine the potential reduction in losses that modernization would achieve" [*Ibid, p. 72*].

The most basic benchmarking approach involves a two-staged tactic. The first stage defines the average values of two key parameters. One then applies these to the GDP of the country as an estimate of the potential value of improved hydro-meteorological information. The two key parameters are:

1. **The level of annual direct economic losses** caused by hydrometeorological hazards as a share of GDP
2. **The level of annual prevented losses** (i.e., losses that are potentially avoided due to the use of improved weather forecasts and warnings) expressed as a percentage of the total losses [*Tsirkunov et al. 2007*]

Building on this approach in projects for the World Bank, Lazo and colleagues [*Lazo 2015*][*Lazo 2018*][*Lazo 2017*][*Lazo and Quiroga 2018*] further developed and implemented the benchmarking approach. These developments included using a larger number of experts than implemented in prior World Bank studies and including experts from specific sectors under study.

For the current analysis, we undertook a preliminary benchmarking approach using U.S. economic data on sector-specific GDP as shown in Table 36 [*BEA 2022C*]. This shows the value added by each sector as defined by the North American Industry Classification System (NAICS). By definition, this totals to U.S. GDP, which is a measure of all economic activity in the country and a primary measure of economic wellbeing in the country.

Table 36. Implementation of the Benchmarking Approach in the United States—2018 GDP by Sector

Value Added by Industry [Billions of dollars] Bureau of Economic Analysis Release Date: October 29,2019	2018 ($B)	Percent Annual Impacts	Annual Impacts ($B)	Improved Forecasts Reduction or Increase	Benefits of Forecasts ($B)	GOES-R Attribution	GOES-R Benefits
Agriculture, forestry, fishing, and hunting	166.5	1.40%	2.331	10.00%	0.233	6.38%	0.015
Mining	346.6	1.40%	4.852	10.00%	0.485	6.38%	0.031
Utilities	325.9	1.40%	4.563	10.00%	0.456	6.38%	0.029
Construction	839.1	1.40%	11.747	10.00%	1.175	6.38%	0.075
Manufacturing	2,321.2	1.40%	32.497	10.00%	3.250	6.38%	0.207
Wholesale trade	1,212.2	1.40%	16.971	10.00%	1.697	6.38%	0.108
Retail trade	1,126.9	1.40%	15.777	10.00%	1.578	6.38%	0.101
Transportation and warehousing	658.1	1.40%	9.213	10.00%	0.921	6.38%	0.059
Information	1,067.7	1.40%	14.948	10.00%	1.495	6.38%	0.095
Finance, insurance, real estate, rental, and leasing	4,301.6	1.40%	60.222	10.00%	6.022	6.38%	0.385
Professional and business services	2,579.4	1.40%	36.112	10.00%	3.611	6.38%	0.231
Educational services, health care, and social assistance	1,792.5	1.40%	25.095	10.00%	2.510	6.38%	0.160
Arts, entertainment, recreation, accommodation, and food services	860.6	1.40%	12.048	10.00%	1.205	6.38%	0.077
Other services, except government	437.2	1.40%	6.121	10.00%	0.612	6.38%	0.039
Government—Federal, State, and Local	2,544.6	1.40%	35.624	10.00%	3.562	6.38%	0.227
Gross domestic product	**20,580.2**	**n/a**	**288.121**	**n/a**	**28.812**	**n/a**	**1.840**

From Lazo et al. [*Lazo et al 2011*], we use twice the coefficient of variation (CoV), or 1.4%, as the variation in GDP related to variation in weather (see Figure 44). This represents both negative impacts (decreases in GDP below average) and benefits (increases in GDP above average) without specifying the underlying causality. Lazo et al. represents a statistical analysis of the relationship at a high level of aggregation. Using twice the CoV from the study means that, for roughly 95% of years, GDP will fall within that range that represents impacts from weather on the economy. Figure 44 shows various measures from Lazo et al. of the impact of weather variability on the economy. We feel that the coefficient of variation represents the most conservative measure of weather impacts (i.e., rather than the "percent range" of 3.36%, which is dependent on the range of years included in the analysis and not a statistical measure of variability as the CoV is).

Overall U.S. weather sensitivity (48 contiguous states).	
Measure	**National GSP (billion U.S. year 2000 dollars)**
Average	7,692.38
Standard deviation	54.71
Coefficient of variation	0.0071
Maximum (1969)	7,813.38
Minimum (1939)	7,554.63
Absolute range	258.75
Percent range	3.36%
2008 GDP (billions 2008 US dollars)	14,441.4
3.36% of 2008 GDP (billions 2008 US dollars)	485.23

Figure 44. Calculation of coefficient of variation from [*Ibid*].

We multiplied the sector GDP by the 1.4% to derive overall impacts of weather variability in each sector to derive the "annual impacts" in each sector. Note that, for the current analysis, we applied the same factor to each sector. Future work (possibly based on Lazo et al. [*Ibid*]) could use different factors for different sectors.

Of the annual impacts, we the assumed that 5% of the negative impact can be mitigated, or benefits increased, by 5% for total benefit of weather information of 10%. For the current analysis, these two factors (the 1.4% applied to sector value-added and the 5% × 2 applied to the sector impact) are the key uncertain parameters. Combining these two adjustments provided a "benefits of forecasts" value. We then multiplied this by the percent of forecasts contributed to by GOES-R for public forecasts (6.38%), as estimated by TPIO analysis. We felt that public forecasts provided the broadest measure of GOES-R contributions across all activity that may be applicable for the entire U.S. economy. We summed these "GOES-R benefits" across all sectors to derive our baseline value of the benefits of GOES-R across the entire U.S. economy in 2018$ based on 2018 GDP [*BEA 2022*]. We then adjusted these for inflation to 2020$ (i.e., impacts in the year 2018 measured in 2020$).

Table 37 summarizes these benchmarking calculations more succinctly as we used a single factor for the "Percent Annual Impacts" (1.4%). If these were varied sector by sector, we would have to use something similar to Table 36 to show sector-level calculations. As shown in Table 37, our baseline annual benefit from GOES-R, based on this approach across the entire U.S. economy, is a little over **$1.87B**.

Table 37. Benchmarking Calculations

Analysis Factors	Factor	Value
Gross domestic product (2018$B)	n/a	20,580.20
Percent annual impacts	1.40%	n/a
Annual impacts (2018$B)	n/a	288.120
Improved forecasts reduction or increase	10%	n/a
Benefits of forecasts (2018$B)	n/a	28.810
GOES-R attribution	6.38%	n/a
GOES-R benefits (2018$B)	n/a	1.840
2018 CPI	251.107	n/a
2020 CPI	255.657	n/a
CPI adjustment factor	1.018	n/a
GOES-R attributable benefits in 2020$	n/a	1,872,987,740

As with other benefit areas, we assumed changes in weather variability would exacerbate economic impacts and factored this in as an annual increase of 1.5%. We further assumed population growth would increase by 0.572% annually and per capita income growth would compound the value of benefits by 1.469% annually. We derived aggregated present value benefit estimates using the five applicable rates of discount as shown in Table 38 with our aggregated baseline estimate of **$45.66B** (2020$).

Table 38. Benchmarking Estimates of GOES-R Contribution to GDP

Discount Rate	0.0%	0.300%	1.185%	3.000%	7.000%
Billions (2020$)	64.87	56.14	45.66	45.66	30.73

16.4 Discussion—Key Uncertainties and Recommended Future Efforts

As we noted previously, the key uncertainties in this analysis are the factor for the "percent annual impacts," and how much improved forecasts reduce or increase these impacts. We applied factors of 1.4% and 10%, respectively, to these for the current analysis but suggest further research to refine these values.

The results of our benchmarking analysis are the same order of magnitude as those values for public forecasting. We feel that further analysis is required to utilize the benchmarking technique to its full potential. As the parameters used in the analysis are preliminary, this represents an order-of-magnitude assessment for which we recommend further work (e.g., an expert elicitation of the appropriate experts) to better implement this method.

17. Summary, Discussion, Key Uncertainties, Lessons Learned, and Recommended Future Efforts

17.1 Summary

Our phase 2 work focused on multiple different potential benefit areas in the value chain. Figure 45 repeats the hurricane value chain model from the phase 1 study. Similar value chains could be developed for each benefit area to better characterize the value creation process; identify key actors, decisions, and information pathways; explicate and assess the logic model of our analysis; and highlight key uncertainties and assumptions in each benefit assessment.

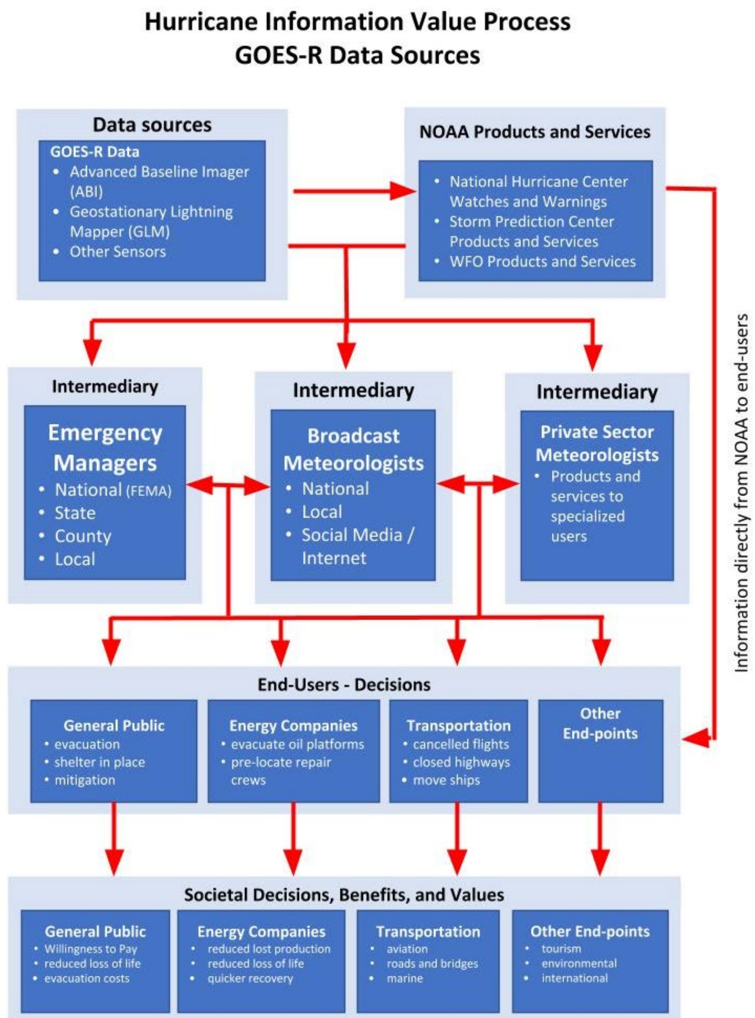

Figure 45. GOES-R hurricane information value chain model [*Lubar et al. 2021*].

Table 39 shows all the benefit areas, including the phase 1 hurricane analysis, the impact evaluated in terms of how impacts were monetized, the baseline annual benefit estimates in 2020$, and the aggregated present value of benefits (also in 2020$ using the 1.185% rate of discount).

We note again that we cannot simply sum all the evaluated benefit areas to derive a total value of GOES-R. Some of the benefit areas may overlap with other areas (e.g., air quality and general public forecasts may overlap as may winter weather and aviation). In addition, some evaluation approaches are specifically designed to encompass some or all the other areas—specifically, the benchmarking approach attempts to cover all potential areas economy wide and thus explicitly does include all the other benefit areas.

For extreme weather, though, we feel that the different weather event types and the types of impact evaluated (e.g., WTP versus fatalities versus damage reduction) do allow us to sum across all the extreme weather events as shown.

Table 39. GOES-R Benefit Estimates for Various Benefit Areas (Baseline Parameters with Discount Rate 1.185%)

	Impact Evaluated	**Baseline Annual Benefits Millions 2020$**	**Present Value of Benefits Billions 2020$**
Extreme Weather	n/a	n/a	n/a
Hurricanes (Phase 1)	Willingness to Pay (WTP)	312.16	8.36
Wildfires	Reduced costs with early detection	316.57	9.68
Winter Storms	Reduced "billion-dollar" disasters	33.26	0.84
Flash flooding -- riverine flood warnings	Reduced fatalities	18.44	0.55
Flash flooding -- riverine flood warnings	Reduced damages	3.82	0.11
Severe thunderstorms and tornadoes	Reduced fatalities	64.60	1.94
Drought	Reduced "billion-dollar" disasters	60.70	1.82
n/a	**Total Extreme Weather**	**809.55**	**23.30**
General public forecasts and warnings	WTP	875.26	26.24
Air Quality	Reduced fatalities	33.29	1.00
Aviation Weather	Reduced weather-related delays	470.34	19.67
Unique Payload Services	n/a	n/a	n/a
Search and Rescue (SAR)	Reduced fatalities	44.34	1.30
DCS data communication	n/a	n/a	n/a
Riverine flooding	Reduced flood damages	0.42	0.10
PORTS	Lower property losses and oil pollution remediation costs / reduced fatalities	2.64	0.08
Climate Policy	Reduced climate impacts	270.15	8.10
Benchmarking	Reduced negative / increased positive impacts on GDP	1,872.99	45.66

We feel that the three broadest benefit approaches of "extreme weather," "general public forecasts and warnings," and "benchmarking" provide order-of-magnitude indications of the total value of GOES-R socioeconomic benefits. The total estimates for these aggregated benefit areas of $23.3B, $26.4B, and $45.66B, respectively, suggest a total benefit of GOES-R in the $20B to $50B range. In presenting this aggregate benefit range, we note strongly that (1) the results reported here should be considered "preliminary" in that they would benefit from further review to ascertain their validity and reliability,

(2) these results have significant degrees of uncertainty due to limited information to quantify each step in the "value chain," and (3) some of the benefit areas presented here are "strawmen" intended to suggest potentially important or interesting benefit areas for future analysis.

Table 40 provides the aggregated benefit estimates for each of the five discount rates assessed.

Table 40. Phase 2 Baseline Benefit Area Benefits Estimates (Billions 2020$)

BENEFIT AREAS EVALUATED	Discount Rate 0.000%	Discount Rate 0.300%	Discount Rate 1.185%	Discount Rate 3.000%	Discount Rate 7.000%
EXTREME WEATHER	n/a	n/a	n/a	n/a	n/a
HURRICANES (Phase 1)	9.61	9.27	8.36	6.85	4.68
WIDFIRES	10.96	10.62	9.68	8.11	5.82
WINTER STORMS	0.96	0.93	0.84	0.69	0.48
FLASH FLOODING -- FATALITIES	0.64	0.62	0.55	0.45	0.30
FLASH FLOODING -- DAMAGES	0.13	0.13	0.11	0.09	0.06
SEVERE THUNDERSTORMS & TORNADOES	2.24	2.16	1.94	1.58	1.06
DROUGHT	2.10	2.03	1.82	1.48	1.00
TOTAL EXTREME WEATHER	26.65	25.74	23.30	19.25	13.40
PUBLIC FORECASTS	30.31	29.20	26.24	21.34	14.36
AIR QUALITY	1.15	1.11	1.00	0.81	0.55
AVIATION DELAYS	23.02	22.11	19.67	15.68	10.09
DCS/UPS	n/a	n/a	n/a	n/a	n/a
SEARCH AND RESCUE	1.50	1.44	1.30	1.06	0.72
DCS -- RIVIEINE FLOOD	0.01	0.01	0.01	0.01	0.01
DCS -- PORTS	0.09	0.09	0.08	0.06	0.04
TOTAL DCS	1.60	1.54	1.39	1.13	0.77
CLIMATE PICY	9.36	9.01	8.10	6.59	4.43
BENCHMARKING	64.87	55.14	45.66	45.66	30.73

17.2 Discussion

We felt that in light of our phase 1 hurricane products benefits estimate of $8.4B [*Lubar et al. 2021*] based on the four hurricane products/attributes evaluated there, it was reasonable to predict that the present value of GOES-R economic benefits value for <u>all</u> forecasts and products (e.g., for air quality, severe thunderstorms and tornadoes, winter storms, flooding, wildfires, aviation weather, and even every-day, non-severe weather forecasts) to which the GOES-R series contributes data over its lifetime would be significantly larger. Our phase 2 analysis as shown in Figure 46 supports this.

It is important to note that most of the benefits areas we assessed in this study were in reference to the contributions of the GOES-R ABI to various NWS products and services. What we did not assess were the contributions of the other GOES-R instruments nor the possible synergies between GOES-R instruments. One outstanding example is the powerful capabilities of the ABI and GLM used together to provide a substitute weather radar capability for intermountain locations where the land-based radars are blocked and for oceanic locations that are out of reach of land-based weather radars. Although we did no specific economic valuations on the GLM in this report, we did include general qualitative assessments for the GLM within applicable benefit area chapters.

We note that the Solar Ultraviolet Imager (SUVI), Extreme Ultraviolet and X-Ray Irradiance Sensors (EXIS), Space Environment In-Situ Suite (SEISS), Compact Coronagraph (CCOR)[39] and Magnetometer (MAG) instruments have made or will have contributions that we did not factor into our current efforts.

Also, the UPS are communications transponder payloads on GOES-R series satellites that provide communications relay services in addition to the primary GOES mission data. Although both the SAR section (section 13) included support of the SAR transponder to global search and rescue efforts, and the flooding section (section 14) included support of the GOES DCS of in situ sensors using the Data Collection Platform Report (DCPR), both of which assessed the capabilities of the GOES-R UPS, there are additional contributions that were not included in this phase 2 effort. There are many domestic and international organizations who utilize the broadcasts from the UPS to contribute to their forecasting and warning products and services. We have not considered the socioeconomic value for these uses unless specifically noted. Such an additional payload providing added UPS capabilities is the GRB transmission for which Figure 46 gives just one example.

The January 15, 2022, eruption of Hunga Tonga, a volcano in the Pacific Ocean region near the island nation of Tonga, resulted in a record-setting ash cloud that exceeded the previous record height of the volcanic plume recorded by meteorological satellite observation. This type of event imagery would not have normally been provided to National Weather Forecast offices with the highest resolution possible, because some of this type of data from ocean areas are not usually sent via communication satellites to the Advanced Weather Information Processor (AWIPS) due to bandwidth limitations on the commercial transponder used to broadcast information to all National Weather Service offices. However, the full resolution imagery is available via the UPS's GOES ReBroadcast (GRB) transmission from GOES-R satellites. The staff of the Cooperative Institute for Meteorological Satellite Studies (CIMSS) at the University of Wisconsin/Madison noticed the event and inserted the higher-resolution data as received by this non-Federal receiving site into the AWIPS data stream. The 10-minute GOES-17 Visible and Infrared images during the first 30 minutes (only 20 minutes after eruption onset) were available for meteorological examination and tsunami forecast assessments.

GOES-17 also directed a Mesoscale Domain Sector over the southern Pacific Ocean, to provide imagery of the volcanic event at 1-minute intervals. This GOES-R capability was not evaluated in this study.

[39] CCOR on GOES-U spacecraft only

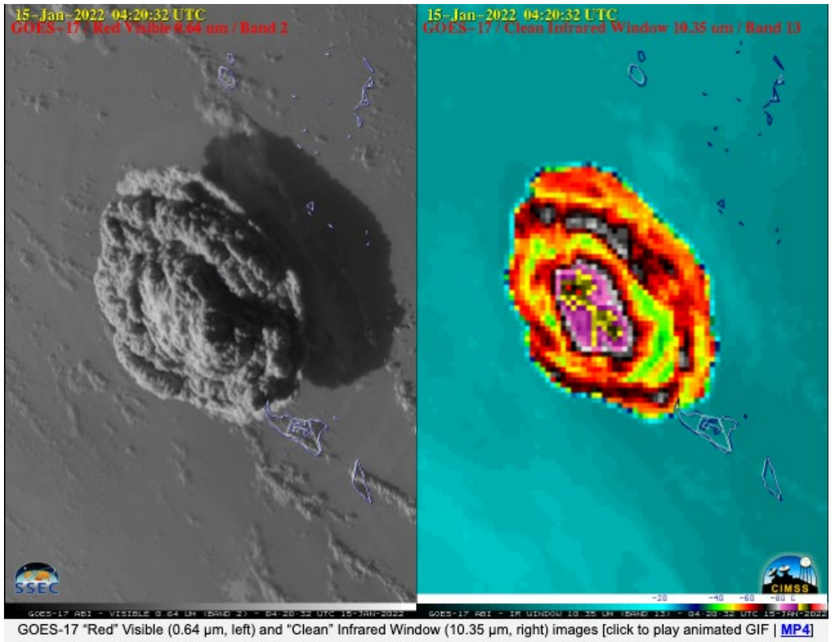

Figure 46. Hunga Tonga Volcano (NOAA/CIMSS).

The January 15, 2022, eruption of Hunga Tonga, a volcano in the Pacific Ocean region near the island nation of Tonga, resulted in a record-setting ash cloud that exceeded the previous record height of the volcanic plume recorded by meteorological satellite observation.
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GOES-17 also directed a Mesoscale Domain Sector over the southern Pacific Ocean, to provide imagery of the volcanic event at 1-minute intervals. This GOES-R capability was not evaluated in this study.

17.3 Strengths and Challenges

It was out of the scope for our study to consider all the possible NOAA MSAs. But much like the NOAA fleet study [*Abt 2018*]that used a small number of marine and oceanic product values to support the whole NOAA fleet of ships, one of our goals was to monetize the socioeconomic benefits of improved GOES-R data sufficiently to suggest that the benefits exceed the overall cost of the GOES-R system over its lifetime.

Strengths of our study:

- In phase 1, we developed a rigorous result using specific and directly applicable WTP cost data from several existent studies coupled with estimates of the GOES-R percentage contributions to the same forecast products elicited from NWS experts.

- In phase 2, we were able to take advantage of all the extensive elicitations of NWS personnel accomplished by the NESDIS TPIO NOSIA II team to assess GOES-R impacts and importance percentages for the various benefit areas.

- In this phase, we implemented the World Bank/WMO benchmarking method to perform a top-down assessment of the total national value of investment in hydro-met services as an order-of-magnitude check on our general public forecasts and warnings assessments. This provided an order-of-magnitude validation of our general public forecasts and warnings assessment results that we had sought.

- Our identification of useful economic methods, concepts, and areas for future studies

Challenges of our study:

- The lack of specific benefit value data from possible previous studies that we could transfer in our calculations for GOES-R benefits monetization

- Lacking such extant benefit value data, we had to make several initial subjective judgements for key parameters (educated heuristic estimations), which represent the greatest uncertainties (key uncertainty parameters) of several of our Phase 2 benefit areas, such as:

  - Percent of event impacts avoided because of weather observation, modeling, and forecasting early detection,

  - Percent of storm impacts (e.g., damages and/or fatalities) that are or could be mitigated,

  - Percent of various impact reductions attributable to weather information,

  - Percent reduction in lives lost which is attributable to improved weather information,

  - Percent value of forecasts from observations based on prior research,

  - Specifically for the Benchmarking approach, assumed a percent of overall annual variability in U.S. GDP due to weather impact that can be mitigated, or benefits increased, by another estimated percent, for a total benefit of weather information of twice these to percentages.

Each of these “challenges” suggest areas where ongoing or future research could improve, refine, change, or validate our (often subjective) estimates.

17.4 Further and/or Follow-On Analysis/Studies

We hope that our study assists in informing future environmental satellite benefits studies and analyses. For example, ongoing NOAA value studies for the GeoXO program have made the value connection of user information to potential benefit areas in society-developing values chains as depicted in Figure 47.

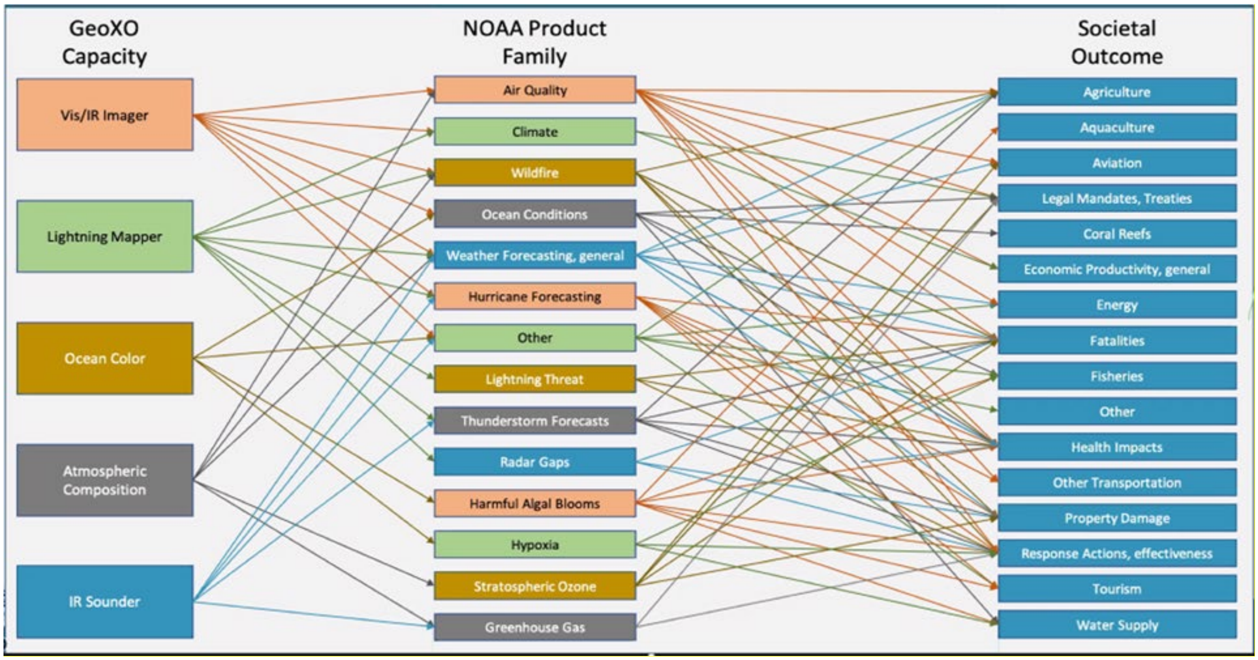

Figure 47. GeoXO connections to NOAA products to potential benefit areas [*Lindsey et al. 2022*].

It is promising that similar study efforts can use, and are using, similar value-chain and societal-benefits techniques as we employed in our study. We believe these kinds of efforts, when undertaken with appropriate resources and time, will produce more valid and reliable economic value assessments, especially when concentrated in particular individual benefits areas.

17.5 Lessons Learned

Finally, we address our "lessons learned" from both Phase 1 and Phase 2 as guidance to ongoing and future work:

- We found the value chain concept to be very useful to (1) improve and integrate communication across research disciplines, (2) inform research subjects about the topic and relevance of different participants in the project, and (3) ensure the validity and reliability of the economic assessment by demonstrating the connection of GOES-R observations to outcomes and economic values held by members of the general public.

- The combination of team members (a meteorologist, an engineer, and an economist) allowed us to better characterize the information process throughout the value chain. Any benefit assessment requires the requisite expertise at each step of the value chain to provide and assess the logic model and ensure analysis quality.

    - Asking meteorologists to assign economic values to products does not work, but they can characterize improvements in data and information for forecasting.

    - Asking economists to assign information improvement percentages to weather forecasts does not work but they can characterize the value of improvements in forecast information.

- Our approach required both identifying where GOES-R makes the greatest contributions, identifying available end-user economic benefit information, and filling in the process between these as there were neither the time nor resources to gather extensive primary data.

- A lack of readily available or identified primary economic studies in certain areas of interest to use for benefits transfer limited the implementation of our Phase 2 approach, thus indicating the need for well-chosen primary and focused studies to support future benefits assessments.

- The methods implemented in the Phase 1 Pathfinder—a combination of the value chain approach, modified expert elicitation, and benefits transfer—can be judiciously applied to focus on additional information processes to develop order-of-magnitude estimates of other benefit areas.

17.6 Future Considerations and Efforts

Based upon our experiences with executing this study, we submit the following ideas for future considerations and efforts:

- Any effort to assess all GOES-R-related product values would be a considerably larger task (in time, manpower and funding), than the effort and resources available for this study. As with any economic analysis, the resources to be applied to the analysis should be commensurate with the needs for economic analysis.

- It is critical that NOAA not reinvent the wheel with every new socioeconomic benefits study. We hope this effort increases the socioeconomic literacy of the participants on the GOES-R technical side and the understanding of the GOES-R program and products on the economics side that can better support future studies.

  - As noted by a reviewer of our Phase 1 report [*Lubar et al. 2021*]:

    "Practically speaking, there may never be a need to attempt a full assessment of GOES-R benefits. Once the lower-bound estimates for several benefit classes exceeds the cost by a sufficient margin, the economic case for this investment will be solid. Except, of course, that this analysis looks at investments in GOES-R in isolation from alternative investments that could generate additional net benefits (e.g., other satellite investments that could achieve similar levels of performance or even investments in risk communication, which could potentially have a greater effect on societal outcomes than improved forecasting)."

  - We agree that the appropriate use of benefit analysis should evaluate all alternatives and the choice made between all viable options.

- We feel it is worth pursuing a broader critique and evaluation of the study and consider submitting its results to peer review. This would permit the project sponsors to obtain external input on the reliability and validity of the study process—the methods and results. It would also put this information "in the literature" which can provide a stronger foundation for any forthcoming studies of the socioeconomic benefits of observational systems.

- We note that as of this writing (December 2022) a manuscript is under peer review at The Bulletin of the American Meteorological Society (BAMS). We will continue to develop, evaluate, and improve this Phase 2 work as guided by the GOES-R Program Office. We will also consider developing a manuscript on the Phase 2 work or some portion thereof for future submission to a peer review journal.

- We hope that our study will better inform the future GeoXO efforts on the benefits and values of capabilities potentially contributing to the NWS WRN MSAs covered herein. In fact, the work associated with the GOES-R ABI is directly relevant to GeoXO, not accounting for the increased resolution of the GeoXO-era instrument.

18. Acronyms

ABI	Advanced Baseline Imager
ACG	allision, collision, and grounding
ADP	Aerosol Detection Product
AGU	American Geophysical Union
AHPS	Advanced Hydrologic Prediction Service
AMS	American Meteorological Society
AOD	Aerosol Optical Depth
APO	FAA Office of Aviation Policy and Plans
AQI	air quality index
ASPB	Advanced Satellite Products Branch
ATAG	Air Transport Action Group
ATS	Applications Technology Satellite
AVHRR	Advanced Very High Resolution Radiometer
AWC	Aviation Weather Center
AWIPS	Advanced Weather Information Processor
B	billion
BAMS	Bulletin of the American Meteorological Society
BEA	Bureau of Economic Analysis
BLS	Bureau of Labor Statistics
BTS	Bureau of Transportation Statistics
CAGR	compound annual growth rate
CAT	Clear air turbulence
CCOR	Compact Coronagraph (GOES-R Instrument on GOES-U only)
CDO	Convective Diagnostic Oceanic
CDR	Climatic Data Record
CRS	Congressional Research Service
CECW-CE	U.S. Army Corps of Engineers Chief of Engineering and Construction Division, Civil Works Directorate
CI	confidence interval
CIMSS	Cooperative Institute for Meteorological Satellite Studies
CLI	Climate Policy
CONUS	Continental United States
COPD	Chronic Obstructive Pulmonary Disease

COSPAS	Cosmicheskaya Sistyema Poiska Avariynich Sudov
COVID-19	Coronavirus Disease 2019
CoV	Coefficient of variation
CPC	NWS Climate Prediction Center
CPI	Consumer Price Index
CRS	Congressional Research Service
CSG	(Aerospace) Civil Systems Group
DCP	data collection platform
DCPR	Data Collection Platform Report
DCS	Data Collection System
DOC	Department of Commerce
DOD	Department of Defense
DOI	Department of the Interior
DOT	Department of Transportation
DR	Discount Rate
EDDI	Evaporative Demand Drought Index
EM-DAT	Center for Reseach on the Epidemiology of Disasters International Disaster Database
EMWIN	Emergency Managers Weather Information Network
ENSO	El Niño-Southern Oscillation
EO	emergency operations
EO	NASA Earth Observatory
EPA	Environmental Protection Agency
EROS	Earth Resources Observation and Science
ESI	Evaporative Stress Index
ET	evapotranspiration
EXIS	X-Ray Irradiance Sensors (GOES-R Instruments)
EUR	Euro
FAA	Federal Aviation Administration
FDC	Fire Detection / Hot Spot Characterization
FLAMBE	Fire Locating and Modeling of Burning Emissions
GDP	Gross Domestic Product
GEO	Geostationary (or Geostationary orbit)
GeoXO	Geostationary Extended Observations program
GHG	Green House Gas

GIS	Geographic Information System
GLM	Geostationary Lightning Mapper
GOES N-O-P	Geostationary Operational Environmental Satellite – N, O, and P Series
GOES-R	Geostationary Operational Environmental Satellite – R Series
GOES-East (16)	Geostationary Operational Environmental Satellite – 16 (aka., GOES-East and GOES-R)
GRB	GOES ReBroadcast
GSP	Generalized System of Preferences
HA	Hyaluronan
HH	household
HMS	Hazard Mapping System
HPRCC	High Plains Regional Climate Center
HRIT	High-Rate information Transmission
IDSS	Impact-based Decision Support Services
IFR	Instrument Flight Rules
III	Insurance Information Institute
IR	infrared
JPSS	Joint Polar Satellite System
K	Kelvin
K	Given Cost for Capital
km	kilometer
LEO	low Earth orbit
LWIR	long-wave infrared
M	million
MAG	Magnetometer (GOES-R Instrument)
MD	Mesoscale Discussion
MEO	medium Earth orbit
MIR	mid-wave infrared
MIT	Massachusetts Institute of Technology
MSA	Mission Service Area
NAICS	North American Industry Classification System
NAQFC	National Air Quality Forecast Capability
NASS	National Agricultural Statistics Service
NCEI	National Centers for Environmental Information
NCEP	National Centers for Environmental Prediction

NDFD	National Digital Forecast Database
NDGD	National Digital Guidance Database
NDMC	National Drought Mitigation Center
NDVI	Normalized Difference Vegetation Index
NESDIS	National Environmental Satellite Data and Information Services
NESIS	Northeast Snowfall Impact Scale
NFTA	Niagara Frontier Transportation Authority
NHMS	National Hydrological and Meteorological Services
NIDIS	National Integrated Drought Information System
NGSO	Non-geostationary satellite systems
NLSC	National Lightning Safety Council
NMHS	National Meteorological Hydrological Service
NOAA	National Oceanic and Atmospheric Administration
NOS	National Ocean Service
NOSIA	NOAA Observation Systems Integrated Analysis
NPOESS	National Polar Orbiting Environmental Satellite System
NPS	National Park Service
NRC	National Research Council
NWP	numerical weather prediction
NWS	National Weather Service
OAR	NOAA Office of Oceanic and Atmospheric Research
OLS	ordinary least squares
OMB	White House Office of Management and Budget
OPPA	NESDIS Office of Projects, Planning, and Analysis
$PM_{2.5}$	Particulate Matter that is 2.5 microns or less in width
PLB	Personal Locator Beacon
PM	particulate matter
PORTS®	Physical Oceanographic Real-Time System®
RAL	UCAR Research Applications Lab
RC-MTS	Resilient Coasts - Marine Transportation
RFF	Resources for the Future
RGB	Red Green Blue
RTMA	Real-Time Mesoscale Analysis
SARSAT	Search and Rescue Satellite-Aided Tracking

SAS	Statistical Analysis System
SatMOC	Satellite Meteorology, Oceanography and Climate
SFO	San Francisco International Airport
SIGMET	NWS Significant Meteorological Advisory
SIGWX	NWS Significant Weather Advisory
SEISS	Space Environment In-Situ Suite (GOES-R Instrument)
SSEC	Space Science and Engineering Center (Univ. of Wisconsin-Madison)
SMS	Synchronous Meteorological Satellite
SMS	Short Message Service
SNPP	Suomi National Polar-orbiting Partnership
SPC	NWS Storm Prediction Center
STAR	NESDIS Center for Satellite Applications & Research
SUVI	Solar Ultraviolet Imager (GOES-R Instrument)
TAF	Terminal Aerodrome Forecast
TOWR-S	Total Operational Weather Readiness - Satellites
TPIO	Technology, Planning and Integration for Observation office
TTX	tabletop exercise
UCAR	University Corporation for Atmospherice Research
UHF	Ultra-High Frequency
UPS	Unique Payload Services
U.S.	United States
USACE	U.S. Army Corp of Engineers
USAID	United States Agency for International Development
USDA	United States Department of Agriculture
USDOT	U.S. Department of Transportation
USFS	U.S. Forest Service
USGS	United States Geological Survey
VegDRI	Vegetation Drought Response Index
VIIRS	Visible Infrared Imaging Radiometer Suite
vis/VIS	visible
VSL	Value of Statistical Life
WAOB	World Agricultural Outlook Board
WASDE	World Agricultural Supply and Demands Estimates
WF-ABBA	Wildfire Automated Biomass Burning Algorithm

WFO	Weather Forecast Office
WMO	World Meteorological Organization
WRN	Weather Ready Nation
WTP	Willingness to pay

19. References

[1] Abt Associates; Corona Environmental Consulting; United States National Oceanic and Atmospheric Administration. Office of Marine and Aviation Operations. 2018. NOAA Fleet Societal Benefit Study. https://repository.library.noaa.gov/view/noaa/20723. Accessed July 1, 2022.

[2] Abt, Karen L.; Jeffrey P. Prestemon and Krista M. Gebert. 2009. "Wildfire Suppression Cost Forecasts from the Us Forest Service." Journal of Forestry, 107, 173-78.

[3] Adams, R. M., L. L. Houston, and R. F. Weiher. 2004: The value of snow and snow information services. NOAA National Operational Hydrological Remote Sensing Center Rep., 49 pp.

[4] Air Transport Action Group (ATAG), "The economic and social benefits of air transport," September 2005. https://www.icao.int/meetings/wrdss2011/documents/jointworkshop2005/atag_socialbenefitsairtransport.pdf. Accessed April 13, 2022.

[5] Ashley, S. T., and Ashley, W. S. 2008. Flood Fatalities in the United States, Journal of Applied Meteorology and Climatology, 47(3):805-818. Source: https://journals.ametsoc.org/view/journals/apme/47/3/2007jamc1611.1.xml. Accessed January 31, 2022.

[6] Ashley, S. T., and Ashley, W. S. 2008. Flood Fatalities in the United States, Journal of Applied Meteorology and Climatology, 47(3):805-818. Source: https://journals.ametsoc.org/view/journals/apme/47/3/2007jamc1611.1.xml. Accessed January 31, 2022.

[7] Balch, J.K, Bethany A. Bradley, John T. Abatzoglou, R. Chelsea Nagy, Emily J. Fusco, and Adam L. Mahood. "Human-started wildfires expand the fire niche across the United States," PNAS, February 27, 2017, 114 (11) 2946-2951, https://www.pnas.org/doi/full/10.1073/pnas.1617394114.

[8] Ballotpedia "Environmental policy in the United States" Web Page: https://ballotpedia.org/Environmental_policy_in_the_United_States. Accessed on May 24, 2022.

[9] BEA 2022. Bureau of Economic Analysis "National Data – National Income and Products Accounts" Web Page: https://apps.bea.gov/iTable/iTable.cfm?reqid=19&step=2#reqid=19&step=2&isuri=1&1921=survey. Accessed June 16, 2022.

[10] BEA 2022B. Bureau of Economic Analysis "Gross Domestic Product" Web Page: https://www.bea.gov/data/gdp/gross-domestic-product. Accessed April 27, 2022.

[11] BEA 2022C. Bureau of Economic Analysis "GDP-by-industry" Web Page: https://apps.bea.gov/iTable/index_industry_gdpIndy.cfm. Accessed January 27, 2022.

[12] Bloesch, J. and F. Gourio. 2015. The Effect of Winter Weather on U.S. Economic Activity. Journal of Economic Perspectives. 39(1). https://www.chicagofed.org/publications/economic-perspectives/2015/1q-bloesch-gourio

[13] Boldin, Michael, and Wright, Jonathan H. "Weather Adjusting Economic Data," Brookings, fall 2015, found at https://www.brookings.edu/bpea-articles/weather-adjusting-economic-data/

[14] Brotzge, J., and S.Erickson, 2010: "Tornadoes without NWS warning." Wea. Forecasting, 25, 159–172, available at: https://doi.org/10.1175/2009WAF2222270.1.

[15] BLS Data 2022, "Databases, Tables & Calculators by Subject," https://data.bls.gov/timeseries/CUUR0000SA0, Series Id: CUUR0000SA0; Series Title: "All items in U.S. city average, all urban consumers, not seasonally adjusted." Accessed September 2022.

[16] BTS 2022. U.S. Dept. of Transportation Bureau of Transportation Statistics "Understanding the Reporting of Causes of Flight Delays and Cancellations" Web Page: https://www.bts.gov/topics/airlines-and-airports/understanding-reporting-causes-flight-delays-and-cancellations#q7. Accessed January 18, 2022.

[17] Buonocore, J.J, Lisa A Robinson, James K Hammitt, Lucy O'Keefe, "Estimating the Potential Health Benefits of Air Quality Warnings," Risk Analysis, Wiley, 2020, https://doi.org/10.1111/risa.13640

[18] Buonocore, J.J., et.al., "Potential Health Benefits of Air Quality Warnings", Harvard T. H. Chan School of Public Health, https://cdn1.sph.harvard.edu/wp-content/uploads/sites/1273/2019/09/Buonocore-Robinson-Hammitt-OKeeffe-2019.pdf

[19] Buonocore, J.J., Robinson, L.A., Hammitt, J.K. and O'Keeffe, L., 2021. Estimating the Potential Health Benefits of Air Quality Warnings. Risk Analysis. 41(645-660) https://doi.org/10.1111/risa.13640.

[20] Calhoun, K. M., 2018: "Feedback and Recommendations for the Geostationary Lightning Mapper (GLM) in Severe and Hazardous Weather Forecasting and Warning Operations." NOAA Report. 15pp. at: https://hwt.nssl.noaa.gov/ewp/projects/GLM-HWT-report_2018.pdf.

[21] Calhoun, K. M., 2019: "Feedback and Recommendations for the Geostationary Lightning Mapper (GLM) in Severe and Hazardous Weather Forecasting and Warning Operations." NSSL Hazardous Weather Testbed — GOES Proving Ground 2019 Experimental Warning Program Report, 31 July 2019, at: https://hwt.nssl.noaa.gov/ewp/projects/GLM-HWT-report-2019.pdf.

[22] Census Bureau 2022. U.S. Census Bureau "International Database - Population estimates and projections for 227 countries and areas," Web Page: https://www.census.gov/data-tools/demo/idb/#/country?COUNTRY_YEAR=2022&COUNTRY_YR_ANIM=2022. Accessed September 29, 2022.

[23] Census Bureau 2022A. U.S. Census Bureau "The Older Population in the United States: 2018," Web Page: https://www.census.gov/data/tables/2018/demo/age-and-sex/2018-older-population.html. Accessed January 25, 2022.

[24] Census Bureau 2022B. U.S. Census Bureau "International Database (IDBB – Demographic Overview," Web Page: https://www.census.gov/data-tools/demo/idb/#/table?COUNTRY_YR_ANIM=2021&COUNTRY_YEAR=2022&menu=tableViz&FIPS=US&TABLE_RANGE=2017,2040&TABLE_YEARS=2017,2018,2019,2020,2021,2022,2023,2024,2025,2026,2027,2028,2029,2030,2031,2032,2033,2034,2035,2036,2037,2038,2039,2

040&TABLE_USE_RANGE=Y&TABLE_USE_YEARS=N&TABLE_STEP=1. Accessed July 1, 2022.

[25] Cousins, K, 2017. The Economic Benefits and Costs of Snow in the Upper Colorado Basin. Earth Economics, Tacoma, WA. found at https://static1.squarespace.com/static/561dcdc6e4b039470e9afc00/t/5eb43b203e3fb45bd2a517c3/1588869929162/EconomicBenefitsandCostsofSnow_EarthEconomics_2017.pdf

[26] Crausbay, S.D., Ramirez, .R., Carter, S.L., Cross, M.S., Hall, K.R., Bathke, D.J., Betancourt, J.L., Colt, S., Cravens, A.E., Dalton, M.S., Dunham, J.B., Hay, L.E., Hayes, M.J., Mcevoy, J., Mcnutt, C.A., Moritz, M.A., Nislow, K.H., Raheem, N. and Sanford, T. “Defining Ecological Drought for the Twenty-First Century,” Bulletin of the American Meteorlogical Sociaety, Vol 98: Issue 12, 1 Dec 2017, DOI: https://doi.org/10.1175/BAMS-D-16-0292.1; Page(s): 2543–2550.

[27] Daily, L. 2021. Article: “With weather delays in the forecast, air travelers should pack their patience and follow these tips”, Washington Post, July 22, 2021. https://www.washingtonpost.com/lifestyle/travel/weather-delays-air-travel-tips/2021/07/22/402007b4-e4d5-11eb-b722-89ea0dde7771_story.html. Accessed April 13, 2022.

[28] Derrick W. Snyder, “Evaluation and economic value of winter weather forecasts, Purdue University, dissertations, AAI1565324, https://docs.lib.purdue.edu/dissertations/AAI1565324/

[29] Dhall, A, et.al, “A survey on systematic approaches in managing forest fires”, Applied Geography 121 (2020) 102266

[30] Diaz, J.M., 2021. Economic Impacts of Wildfire. Southern Fire Exchange, SFE Fact Sheet 2012-7 located at https://fireadaptednetwork.org/wp-content/uploads/2014/03/economic_costs_of_wildfires.pdf Accessed April 26, 2022.

[31] Ding, Ya; Hayes, Michael J.; and Widhalm, Melissa, “Measuring Economic Impacts of Drought: A Review and Discussion” (2010). Papers in Natural Resources. 196. https://digitalcommons.unl.edu/natrespapers/196

[32] Doswell, Charles A., III, 2003, “Societal impacts of severe thunderstorms and tornadoes: Lessons learned and implications for Europe”, Atmospheric Research 67 (2) found at https://www.researchgate.net/publication/228548711_Societal_impacts_of_severe_thunderstorms_and_tornadoes_Lessons_learned_and_implications_for_Europe

[33] Ellrod, G.P., and K. Pryor. 2019. Applications of Geostationary Satellite Data to Aviation. Pure Appl. Geophys. 176:2017–2043 https://doi.org/10.1007/s00024-018-1821-1

[34] EPA 2019. “Wildfire Smoke: A Guide for Public Health Officials,” (Revised 2019), EPA-452/R-21-901, September 2021, found on the Internet at https://www.airnow.gov/sites/default/files/2021-09/wildfire-smoke-guide-forward_0.pdf

[35] EPA. 2021. Climate Change and Social Vulnerability in the United States: A Focus on Six Impacts. U.S. Environmental Protection Agency, EPA 430-R-21-003.

[36] EPA 2021A. EPA “Air Now Fire and Smoke Map,” Web Page: https://fire.airnow.gov. Accessed September 21, 2021.

[37] EPA 2022. Web Page “Climate Change Indicators: Cold-Related Deaths”: https://www.epa.gov/climate-indicators/climate-change-indicators-cold-related-deaths. Accessed January 27, 2022 and April 26, 2022.

[38] EPA 2022B. Web Page “Patient Exposure and the Air Quality Index”: https://www.epa.gov/pmcourse/patient-exposure-and-air-quality-index. Accessed April 26, 2022.

[39] FAA APO-100 Cost of Delay Estimates 2019. https://www.faa.gov/data_research/aviation_data_statistics/media/cost_delay_estimates.pdf. Accessed January 18, 2022.

[40] FAA 2019. Federal Aviation Administration “Aerospace Forecasts, FY2019-39,” Washington, D.C.: FAA. TC19-0002. https://www.faa.gov/data_research/aviation/aerospace_forecasts/media/fy2019-39_faa_aerospace_forecast.pdf. Accessed January 18, 2022.

[41] FAA APO-100. 2019. 2020. Cost of Delay Estimates. 2019. https://www.faa.gov/data_research/aviation_data_statistics/media/cost_delay_estimates.pdf. Accessed January 18, 2022

[42] FAA. 2020. The Economic Impact of Civil Aviation on the US Economy Jan 2020. https://www.faa.gov/about/plans_reports/media/2020_jan_economic_impact_report.pdf. Accessed July 20, 2022.

[43] FAA 2021. FAA Aviation Forecasts - “Aerospace Forecast: Fiscal Years 2021-2041,” p. 2, https://www.faa.gov/data_research/aviation/.

[44] FAA 2022. Federal Aviation Administration Next Gen, “FAQ: Weather Delay” https://www.faa.gov/nextgen/programs/weather/faq/. Accessed April 13, 2022.

[45] Fangjun, L., et.al, “A preliminary evaluation of GOES-16 active fire product using Landsat-8 and VIIRS active fire data, and ground-based prescribed fire records.” Remote Sensing of Environment, 237 (2020) 111600

[46] Federal Aviation Administration (FAA). 2019. FAA Aerospace Forecast Fiscal Years 2019-2039. Washington, D.C.: FAA. TC19-0002. https://www.faa.gov/data_research/aviation/aerospace_forecasts/media/FY2019-39_FAA_Aerospace_Forecast.pdf

[47] Folger, Peter, “Severe Thunderstorms and Tornadoes in the United States,” 2013, Congressional Research Service found at https://sgp.fas.org/crs/misc/R40097.pdf

[48] Fultz, A.J. and W.S. Ashley. 2016.: Fatal Weather-Related General Aviation Accidents in the United States. Physical Geography, DOI:10.1080/02723646.2016.1211854.

[49] Gil., M., A. Garrido, and N. Hernández-Mora . 2013. Direct and indirect economic impacts of drought in the agri-food sector in the Ebro River basin (Spain). Nat. Hazards Earth Syst. Sci., 13:2679–2694. www.nat-hazards-earth-syst-sci.net/13/2679/2013/. doi:10.5194/nhess-13-2679-2013.

[50] GISGeography 2022. Geographic Information Systems Geography Web Page: https://gisgeography.com/ndvi-normalized-difference-vegetation-index/, Accessed May 30, 2022.

[51] GOES-R 2022. GOES-R Fact Sheet, "Aerosols/Air Quality Applications," Web Page: https://www.goes-r.gov/education/docs/fs_aerosols.pdf. Accessed September 22, 2022.

[52] GOES-R AWG 2022. GOES-R Algorithm Working Group "Aerosol Detection" Web Page: https://www.star.nesdis.noaa.gov/goesr/product_aero_det.php. Accessed September 22, 2022.

[53] GOES-R Program Office, "Mission - GOES-R Series Unique Payload Services (UPS)" Web Page: https://www.goes-r.gov/mission/ups.html. Accessed April 4, 2022 and June 14, 2022.

[54] Goodman, C.J. and J.D.S. Griswold. 2019. Meteorological Impacts on Commercial Aviation Delays and Cancellations in the Continental United States. JAMC. 58(3):479-494. https://doi.org/10.1175/JAMC-D-17-0277.1.

[55] Goodman, Steven J., 2020, "GOES-R Series Introduction," from 'The GOES-R Series – A New Generation of Geostationary Environmental Satellites', Elsevier, ISBN: 978-0-12-814327-8.

[56] Goss, H. 2020: "Lightning research flashes forward," Eos, 101, Published on 24 April 2020. Available at: https://doi.org/10.1029/2020EO142805.

[57] Grajdura, S., et.al., "Awareness, departure and preparation time in no-notice wildfire evacuations," Safety Science 139 (July 2021) 105258 https://doi.org/10.1016/j.ssci.2021.105258

[58] Gultepe, I., et.al., "A Review of High Impact Weather for Aviation Meteorology," J. Pure Appl Geophys., 2019, https://doi.org/10.1007/s00024-019-02168-6. Accessed April 13, 2022.

[59] Harper, L. "What Are Climate Models and How Accurate Are They?", Columbia Climate School, May 18, 2018. https://news.climate.columbia.edu/2018/05/18/climate-models-accuracy/#:~:text=Essentially%2C%20climate%20models%20are%20an,region%20over%20the%20coming%20decades.

[60] Holcomb, N. 2022. Email correspondence with Nathan Holcomb, NOAA NOS, January 31, 2022.

[61] Hollandsworth, S., 2017, "The Day the Fire Came," Texas Monthly, July 2017, at: https://features.texasmonthly.com/editorial/the-day-the-fire-came/.

[62] Hoover, K. and L.A. Hanson. 2021. In Focus: Wildfire Statistics. Congressional Research Service Updated October 4, 2021. https://crsreports.congress.gov/product/pdf/IF/IF10244. Accessed January 19, 2022.

[63] Hosterman, H.R., J.K. Lazo, J.M. Sprague-Hilderbrand, and J.E. Adkins. 2019. Using the National Weather Service's Impact-Based Decision Support Services to Prepare for Extreme Winter Storms. Journal of Emergency Management. 17(6):455-467. DOI:10.5055/jem.2019.0439

[64] Hsiang, S., R. Kopp, A. Jina, J. Rising, M. Delgado, S. Mohan, D. J. Rasmussen, R. Muir-Wood, P. Wilson, M. Oppenheimer, K. Larsen, and T. Houser. 2017. Estimating economic damage from climate change in the United States. Science. 356(6345). DOI: 10.1126/science.aal4369

[65] Hunt, A.; Julia J. Ferguson; Michela M. Baccini; Paul P. Watkiss and Vladimir V. Kendrovski. 2017. "Climate and Weather Service Provision: Economic Appraisal of Adaptation to Health Impacts." Climate Services, 7, 78-86.

[66] III 2022. Insurance Information Institute Web Page "What is covered by standard homeowner's insurance?" at: https://www.iii.org/article/what-covered-standard-homeowners-policy. Accessed April 28, 2022.

[67] International Airport Review. 2005. "How to avoid bad weather delays" https://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=&ved=2ahUKEwj_8arzs5ryAhUM6J4KHT9HAO84WhAWegQIBhAD&url=https%3A%2F%2Fwww.internationalairportreview.com%2Farticle%2F1834%2Fhow-to-avoid-bad-weather-delays%2F&usg=AOvVaw0pMnSNB6i0zZ4Ibs1dr2bj

[68] Jensenius, J. S., 2020: "A Detailed Analysis of Lightning Deaths in the United States from 2006 through 2019," available at https://www.weather.gov/media/safety/Analysis06-19.pdf

[69] Key, J. Y, Liu, X. Wang, A. Letterly and T. Painter. 2020. Snow and Ice Products from ABI on the GOES-R Series. 10.1016/B978-0-12-814327-8.00014-7.

[70] King, James V. Spring 2013 Proceedings of The Radio Club of America, Inc. (Vol. 85 (1)), Item 2013.01.05, "COSPAS-SARSAT: An Overview of the Satellite System that has Saved More than 33,000 Lives Worldwide," https://www.radioclubofamerica.org/content.aspx?page_id=86&club_id=500767&item_id=115071.

[71] Koltunov, A., et.al, "The development and first validation of the GOES Early Fire Detection (GOES_EDF) algorithm," Remote Sensing of Environment, 184 (October 2016), pp 436-453 https://doi.org/10.1016/j.rse.2016.07.021

[72] Koltunov, A., et.al., "On timeliness and accuracy of wildfire detection by GOES WF-ABBA algorithm over California during the 2006 fire season," Remote Sensing of Environment, 127 (December 2012) pp 194-209 https://doi.org/10.1016/j.rse.2012.09.001

[73] Kondragunta, S., I. Laszlo, H. Zhang, P. Ciren and A. Huff. 2020. "Chapter 17 - Air Quality Applications of Abi Aerosol Products from the Goes-R Series," S. J. Goodman, T. J. Schmit, J. Daniels and R. J. Redmon, The Goes-R Series. Elsevier, 203-217.

[74] Kondragunta, S., H. and Zhang. 2021. "Estimates of Surface PM2.5 using Merged GOES-16/17 ABI Aerosol Optical Depths for 2020 California Fires," presented Tuesday Dec 14, 2021, American Geophysical Union Annual Meeting, New Orleans, LA.

[75] Kotchen, M.J., K.J. Boyle, and A.A. Leiserowitz. 2013. "Willingness-to-pay and policy-instrument choice for climate-change policy in the United States," Energy Policy, Elsevier, vol. 55(C), pages 617-625.

[76] Kreibich, H., P. Hudson, and B. Merz. 2021. Knowing What to Do Substantially Improves the Effectiveness of Flood Early Warning, Bulletin of the American Meteorological Society, 102(7), E1450-E1463. https://journals.ametsoc.org/view/journals/bams/102/7/BAMS-D-20-0262.1.xml. Accessed Apr 28, 2022.

[77] Kulesa, Gloria, “Weather and Aviation: How Does Weather Affect the Safety and Operations of Airports and Aviation, and How Does FAA Work to Manage Weather-related Effects?”, US DOT https://www.transportation.gov/sites/dot.gov/files/docs/kulesa_Weather_Aviation.pdf

[78] Kumar, A., S. Nagar, and S. Anand. 2021. Climate change and existential threats. Global Climate Change. Eds: S. Singh, P. Singh, S. Rangabhashiyam, and K.K. Srivastava. Elsevier. 2021(1-31). ISBN 9780128229286.

[79] Kuswanto, H., F. Hibatullah, and E.S. Soedjono. 2019. Perception of weather and seasonal drought forecasts and its impact on livelihood in East Nusa Tenggara, Indonesia. Heliyon. 5(8):1-8. ISSN 2405-8440. https://doi.org/10.1016/j.heliyon.2019.e02360.

[80] Kuwayama, Y., Thompson, A., Bernknopf, R., Zaitchik, B. and Vail, P. (2018), Estimating the Impact of Drought on Agriculture Using the U.S. Drought Monitor. American Journal of Agricultural Economics, 101: 193-210. https://doi.org/10.1093/ajae/aay037

[81] Lazo, J. and Mills, B. 2021: “Weather-Water-Climate Value Chain(s): Giving VOICE to the Characterization of the Economic Benefits of Hydro-Met Services and Products.” An AMS Policy Program Study. The American Meteorological Society, Washington, D.C. at: https://www.ametsoc.org/ams/assets/File/policy/WWC_Value_Chain_Economic_Benefits.pdf

[82] Lazo, J.K, Hosterman, H.R., Sprague-Hilderbrand, J. M., and Adkins, J.E., “Impact-Based Decision Support Services and the Socioeconomic Impacts of Winter Storms,” Bulletin of Am. Met. Soc., 101 (5), 2020, pgs. E626-E639, https://doi.org/10.1175/BAMS-D-18-0153.1

[83] Lazo, J.K. 2018. Survey of Bangladeshi Public: Socio-Economic Value of Weather, Water and Climate Information. Draft Final Report to the World Bank. August 27, 2018.

[84] Lazo, J.K. and S. Quiroga, 2018. Economic Analysis of Potential Improvements in Hydrological, Meteorological, and Climate Products and Services in Nicaragua. Final report to NCAR under contract to The World Bank. Draft final report: February 6, 2018.

[85] Lazo, J.K., 2015. Survey of Mozambique Public on Weather, Water, and Climate Information. NCAR Technical Note NCAR/TN-521+STR, 236 pp, DOI: 10.5065/D6B56GS4.

[86] Lazo, J.K., 2017. Economic Analysis of Potential Improvements in Hydrological, Meteorological, and Climate Products and Services in Honduras. Final report to NCAR under contract to The World Bank. Draft final report: November 21, 2017

[87] Lazo, J.K., H.R. Hosterman, J.M. Sprague-Hilderbrand, and J.E. Adkins, 2020: Impact-Based Decision Support Services and the Socioeconomic Impacts of Winter Storms. Bull. Amer. Meteor. Soc., 101, E626–E639, https://doi.org/10.1175/BAMS-D-18-0153.1

[88] Lazo, J.K., M. Lawson, P.H. Larsen, and D.M. Waldman. June 2011 “United States Economic Sensitivity to Weather Variability.” Bulletin of the American Meteorological Society. 92: 709-720. DOI:10.1175/2011BAMS2928.1

[89] Lazo, J. K., Rice, J. S., and Hagenstad, M. L. 2010: “Benefits of investing in weather forecasting research: An application to supercomputing.” Yuejiang Academic Journal. 2, 18-39, October 26, 2010. http://n2t.net/ark:/85065/d79s1rgm.

[90] Lazo, J.K., Morss, R. E. and Demuth, J.L.. 2009: [Lazo et al. 2009] "300 Billion Served." Bulletin of the American Meteorological Society. 90: 785–798. DOI: https://doi.org/10.1175/2008BAMS2604.1.

[91] Lazrus, H., Morss, R.E., J.L., Demuth, J.K. Lazo, and A. Bostrom. 2016. Know what to do if you encounter a flash flood: Mental models analysis for improving flash flood risk communication and public decision making. Risk Analysis. 36(2):411–427. DOI: 10.1111/risa.12480.

[92] Lindley, T.T, Douglas A. Speheger, Matthew A. Day, Gregory P. Murdoch, Bradley R. Smith, Nicholas J. Nauslar, Drew C. Daily, "Megafires on the Southern Great Plains," J. Operational Meteor. 7 (12), 164-179 https://doi.org/10.15191/nwajom.2019.0712

[93] Lindley, T.T., Aaron R Anderson, Vivek N. Mahale, and Thomas S. Curl, William E. Line, Scott S. Lindstrom, A. Scott Bachmeier, "Wildfire Detection Notifications for Impact-based Decision Support Services in Oklahoma Using Geostationary Super Rapid Scan Satellite Imagery." J. Operational Meteor., 4(14):182-191 http://dx.doi.org/10.15191/nwajom.2016.0414

[94] Lindsey, D., A. Heidinger, and R.I. Lana. 2022. "GeoXO User Engagement Efforts and Value Studies – Leveraging NOAA Pathfinder to Demonstrate Value of Mission Information," AMS 2022 Annual Meeting, 18th Operational Environmental Satellite Systems Symposium presentation. V.M. Escobar, NOAA/NESDIS/GeoXO. January 24, 2022.

[95] Lindsey, D.T. and J. Patten 2022. "GOES-18 First Public-Release Images," Presentation, AMS 25th Satellite Meteorology, Oceanography and Climatology/Joint 2022 NOAA Satellite Conferences, Madison WI, August 10, 2022.

[96] Long, T. 2022. Analysis of Weather-Related Accident and Incident Data Associated with Section 14 CFR. Part 91 Operations. Collegiate Aviation Review International. 40(1):25-39.

[97] Lubar, D.G., M.L. Jamilkowski, and J.K. Lazo. 2021. GOES-R Socioeconomic Benefits Study: Phase 1 - Hurricane Products. Final Report. Submitted to the GOES-R Series Program Office: May 3, 2021. Aerospace Corporation - under contract to the GOES-R Program Office. Aerospace Report No. ATR-2021-00933.

[98] Masters, J. 2021. "World hammered by record 50-billion-dollar weather disasters in 2020", Yale Climate Connections, 2021 found at https://yaleclimateconnections.org/2021/01/world-hammered-by-record-50-billion-dollar-weather-disasters-in-2020/

[99] Mayo Clinic 2022. Mayo Clinic "COPD" Web Page: https://www.mayoclinic.org/diseases-conditions/copd/symptoms-causes/syc-20353679. Accessed June 30, 2022.

[100] McLeod, Jonathan D.; Gigi Owen; Crystal A. Kolden; Daniel B. Ferguson and Timothy J. Brown. 2012. "Wildfire Management and Forecasting Fire Potential: The Roles of Climate Information and Social Networks in the Southwest United States." Weather, Climate, and Society, 4(2), 90-102.

[101] Mecikalski, J.R., et.al, "Aviation Applications for Satellite-Based Observations of Cloud Properties, Convection Initiation, In-Flight Icing, Turbulence, and Volcanic Ash", BAMS, October 2007, pp. 1589-1607. https://doi.org/10.1175/BAMS-88-10-1589.

[102] MIT Joint Program on the Science and Policy of Global Change: https://globalchange.mit.edu/research/focus-areas/climate-policy. Accessed on May 24, 2022.

[103] Miller, T., and Casadevall, T. 2000. "Volcanic ash hazards to aviation: Encyclopedia of volcanoes," at: https://www.researchgate.net/publication/284772630_Volcanic_ash_hazards_to_aviation_encyclopedia_of_volcanoes.

[104] Morss, R. E., J. L. Demuth, A. Bostrom, J. K. Lazo, and H. Lazrus. 2015. Flash flood risks and warning decisions: A mental models study of forecasters, public officials, and media broadcasters in Boulder, Colorado. Risk Analysis. 35(11):2009-28. doi:10.1111/risa.12403.

[105] Morss, R.E., K.J. Mulder, J.K Lazo, and J.L Demuth. 2016. How Do People Perceive, Understand, and Respond to Flash Flood Risks and Warnings? Journal of Hydrology. 541:649–664. http://dx.doi.org/10.1016/j.jhydrol.2015.11.047

[106] NASA EO 2022. NASA Earth Observatory "Normalized Difference Vegetation Index (NDVI)," Accessed on 28 July 2022 at: https://earthobservatory.nasa.gov/features/MeasuringVegetation.

[107] National Academies of Sciences, Engineering and Medicine, "Attribution of Extreme Weather Events in the Context of Climate Change", National Academies Press, 2016. http://www.nap.edu/catalog/21852/attribution-of-extreme-weather-events-in-the-context-of-climate-change.

[108] National Research Council 2008. Options to Ensure the Climate Record from the NPOESS and GOES-R Spacecraft: A Workshop Report. Washington, DC: The National Academies Press. https://doi.org/10.17226/12033.

[109] NCEI - NOAA National Centers for Environmental Information (NCEI) U.S. Billion-Dollar Weather and Climate Disasters. 2022. https://www.ncei.noaa.gov/access/monitoring/billions/. DOI: 10.25921/stkw-7w73

[110] NCEI 2022. NOAA National Centers for Environmental Information (NCEI) "U.S. Billion-Dollar Weather and Climate Disasters, 2022 – Summary Stats," Web Page: https://www.ncei.noaa.gov/access/billions/summary-stats. Accessed April 12, 2022.

[111] NCEI 2022A. NOAA National Centers for Environmental Information (NCEI) "U.S. Billion-Dollar Weather and Climate Disasters – Time Series," Web Page: https://www.ncdc.noaa.gov/billions/time-series. Accessed January 10, 2022 and April 26, 2022.

[112] NCEI 2022B. NOAA National Centers for Environmental Information (NCEI) "U.S. Billion-Dollar Weather and Climate Disasters, 2022." https://www.ncei.noaa.gov/access/monitoring/billions/. DOI: 10.25921/stkw-7w73.

[113] NCEI 2022, NOAA National Centers for Environmental Information (NCEI) "2021 U.S. Billion-dollar Weather and Climate Disasters in Historical Context - Hazard and Socioeconomic Risk Mapping" presentation at the 2022 AMS Washington Forum. https://www.ncei.noaa.gov/monitoring-content/billions/docs/2021-us-billion-dollar-weather-and-climate-disasters-hazard-and-socioeconomic-risk-mapping-ams-washington-forum.pdf. Accessed May 25, 2022.

[114] Neidell, M. 2009. Information, Avoidance Behavior, and Health: The Effect of Ozone on Asthma Hospitalizations. Journal of Human Resources. 44.2: 450-478.

[115] NESDIS STAR 2022. Center for Satellite Applications & Research "Aerosol Watch" Web Page: https://www.star.nesdis.noaa.gov/smcd/spb/aq/AerosolWatch/. Accessed September 22, 2022.Neumann, J.E., J. Willwerth, J. Martinich, J. McFarland, and M. Sarofim. 2020. The University of Chicago Press Journals, Review of Environmental Economics and Policy, "Climate Damage Functions for Estimating the Economic Impacts of Climate Change in the United States." pp. 14, 25–43. https://www.journals.uchicago.edu/doi/10.1093/reep/rez021.

[116] Newell, R.G. 2021. "Federal Climate Policy 101: Reducing Emissions," at: https://www.rff.org/publications/explainers/federal-climate-policy-101/. Accessed on May 24, 2022.

[117] NOAA's National Ocean Service, "The Value of PORTS® to the Nation," August 2014 https://tidesandcurrents.noaa.gov/publications/Value_of_PORTS_to_the_Nation_Aug_2014.pdf Accessed April 27, 2022.

[118] NOAA GEO Flyout 2021. "NOAA Geostationary Satellite Programs Continuity of Weather Observations," Web Page (as of December 2021): https://www.nesdis.noaa.gov/s3/2022-01/GEO-Flyout-December-2021_signed.pdf.

[119] NOAA SARSAT 2022. NOAA "Search And Rescue Satellite-Aided Tracking" Web Page: https://www.sarsat.noaa.gov/sarsat-us-rescues/. Accessed June 14, 2022.

[120] NPS 2022. National Park Service "Mortality Dashboard Key Statistics CY2014 - CY2016," Web Page: https://www.nps.gov/orgs/1336/upload/CY14-CY16-Mortality-Dashboard-Key-Statistics.pdf. Accessed June 14, 2022.

[121] NOAA 2022B, NOAA National Ocean Service Center for Operational Oceanographic Products and Services "Tides & Currents" Web Page: https://tidesandcurrents.noaa.gov/ports_info.html. Accessed February 8, 2022.

[122] NOAA NCEI NDFD 2022, National Digital Forecast Database (NDFD) Web Page: https://www.ncei.noaa.gov/products/weather-climate-models/national-digital-forecast-database. Accessed April 22. 2022.

[123] NOAA NESDIS Web Page 2022, https://www.nesdis.noaa.gov/current-satellite-missions/currently-flying. Accessed May 11, 2022.

[124] NOAA's National Ocean Service, "The Value of PORTS® to the Nation," August 2014, https://tidesandcurrents.noaa.gov/publications/Value_of_PORTS_to_the_Nation_Aug_2014.pdf. Accessed April 27, 2022.

[125] NOAA NSSL 2021, NOAA National Severe Storms Laboratory (NSSL) "Severe Weather 101," https://www.nssl.noaa.gov/education/svrwx101/floods/. Accessed December 1, 2021.

[126] NOAA NIDIS 2022. NOAA National Integrated Drought Information System (NIDIS) "Drought.gov," Web Page: https://www.drought.gov/data-maps-tools/vegetation-drought-response-index-vegdri. Accessed on July 28, 2022.

[127] NOAA NIDIS 2022A. NOAA National Integrated Drought Information System (NIDIS) "The High Cost of Drought,' January 23, 2020. Web Page: https://www.drought.gov/news/high-cost-drought. Accessed April 28, 2022.

[128] NOAA's National Weather Service, "2019-2022 Strategic Plan", Goal 1.7, at: https://www.weather.gov/media/wrn/NWS_Weather-Ready-Nation_Strategic_Plan_2019-2022.pdf.

[129] NOAA Technical Report, NESDIS 147 (DOI: 10.7289/V52V2D1H) "NOAA Observing System Integrated Analysis (NOSIA-II) Methodology Report" (May 2016). https://www.nesdis.noaa.gov/sites/g/files/anmtlf151/files/2021-08/noaa_tech_report_nesdis_147_nosia_ii_methodology_v1_95.pdf. P.10.

[130] NOAA weather.gov 2021. Web Page, "80 Years of Weather-Related Fatality Data," at: https://www.weather.gov/media/hazstat/80years.pdf. Accessed January 31, 2022.

[131] NOAA weather.gov 2022.

[132] Nolan, C.B., Tufford, D.L. and Chalcraft, D.R., 2016. Needs assessment of coastal land managers for drought onset indicators in the southeastern United States. Journal of Coastal Research, 32(5), pp.1016-1024.

[133] NWS 2022. National Weather Service 'weather.gov' "Air Quality Forecast Partnership" Web Page: https://www.weather.gov/safety/airquality-forecast-partnership. Accessed September 22, 2022.

[134] NWS 2022A. National Weather Service 'weather.gov' "Why Air Quality Is Important" Web Page: https://www.weather.gov/cle/, Accessed January 7, 2022.

[135] NWS 2022B. National Weather Service 'weather.gov' "Why Air Quality Is Important" Web Page: https://www.weather.gov/safety/airquality. Accessed September 22, 2022.

[136] NWS 2022C. National Weather Service 'weather.gov' "Baltimore MD Weather Forecast for May 17, 2022" Web Page: https://forecast.weather.gov/MapClick.php?lat=38.98638925988869&lon=-77.00994602284794#.YoQRLujMJjE.

[137] NWS CPC. Climate Prediction Center "Drought Information," Web Page: https://www.cpc.ncep.noaa.gov/products/Drought/. Accessed July 5, 2022.

[138] OMB 2003, Circular A-4, September 17, 2003. https://obamawhitehouse.archives.gov/omb/circulars_a004_a-4/. Accessed March 24, 2022.

[139] OMB 2019, Circular A-94, December 17, 2019, https://www.whitehouse.gov/wp-content/uploads/2019/12/M-20-07.pdf. Accessed March 24, 2022.

[140] Otkin, J.A., Svoboda, M., Hunt, E,D., Ford, T.W., Anderson, M.C., Hain, C., and Basara, J.B., 2018, "Flash Droughts: A Review and Assessment of the Challenges Imposed by Rapid-Onset Droughts in the United States," Bulletin of the American Meteorological Society, Vol. 99: Issue 5, 1 May 2018.

[141] Otkin, J. A., Shafer, M., Svoboda, M., Wardlow, B., Anderson, M. C., Hain, C., & Basara, J. (2015). Facilitating the Use of Drought Early Warning Information through Interactions with Agricultural Stakeholders, Bulletin of the American Meteorological Society, 96(7), 1073-1078. Retrieved Apr 7, 2022, from https://journals.ametsoc.org/view/journals/bams/96/7/bams-d-14-00219.1.xml

[142] Parker, D., S. Tunstall, and T. Wilson. 2005. Socio-Economic Benefits of Flood Forecasting and Warning. International conference on innovation advances and implementation of flood forecasting technology. October 2005, Tromsø, Norway

[143] Parker, D., S. Tunstall, and T. Wilson. 2005. Socio-Economic Benefits of Flood Forecasting and Warning. International conference on innovation advances and implementation of flood forecasting technology. October 2005, Tromsø, Norway

[144] Patel, Kasha. 2022. "Report: pollution responsible for 1 in 6 deaths worldwide over past five years." The Washington Post, May 19, 2022, p. A3

[145] Prestemon, J. P.; D. T. Butry and D. S. Thomas. 2016. "The Net Benefits of Human-Ignited Wildfire Forecasting: The Case of Tribal Land Units in the United States." Int J Wildland Fire, 25(4), 390-402.

[146] Prins, E.M., and W.P. Menzel. 1992. Geostationary satellite detection of biomass burning in South America. Intl J of Remote Sensing, 13(15):2783–99. https://doi.org/10.1080/01431169208904081

[147] Resources for the Future (RFF): https://www.rff.org/publications/explainers/federal-climate-policy-101/. Accessed on May 24, 2022.

[148] Rowley, K., T. Riley, and C. Reed. 2018. Tornado Warnings: Delivery, Economics, & Public Perception: Bibliography. NCRL subject guide 2018-15. 10.7289/V5/SG-NCRL-18-15.

[149] Rudlosky,S., Goodman, S., Calhoun, K., Schultz, C., Back, A., Kuligowski. R., Stevenson, S., and Gravelle, C. 2020. "Geostationary Lightning Mapper Value Assessment," NOAA Technical Report NESDIS 153, https://doi.org/10.25923/2616-3v73; https://repository.library.noaa.gov/view/noaa/27429.

[150] Samet, Jonathan M., "Do air quality alerts benefit public health? New evidence from Canada", The Lancet, 2(January 2018) https://doi.org/10.1016/S2542-5196(17)30184-5

[151] Santek, D., Nebuda, S., and Stettner, D., 2014: Feature-tracked winds from moisture fields derived from AIRS sounding retrievals. International Winds Workshop, 12th, Copenhagen, Denmark, 15-20 June 2014. EUMETSAT, Darmstadt, Germany, 2014

[152] Sarofim, M.C., J. Martinich, J.E. Neumann, J. Willwerth, Z. Kerrich, M. Kolian, C. Fant, and C. Hartin. 2021. A temperature binning approach for multi-sector climate impact analysis. Climatic Change, 165, doi:10.1007/s10584-021-03048-6. Available online at https://link.springer.com/article/10.1007/s10584-021-03048-6

[153] Schmidt, Chris. 2020. "Chapter 13 - Monitoring Fires with the Goes-R Series," S. J. Goodman, T. J. Schmit, J. Daniels and R. J. Redmon, The Goes-R Series. Elsevier, 145-63.

[154] Schmit, T.J. Email 2022, Meteorologist, NESDIS/STAR/CRPD, Advanced Satellite Products Branch (ASPB), University of Wisconsin, Madison WI, Subj: "GOES-R Contributions to Drought Forecasting," 21 July 2022.

[155] Sharda, V. and Srivastava, P., 2016. Value of ENSO-forecasted drought information for the management of water resources of small to mid-size communities. Transactions of the ASABE, 59(6), pp.1733-1744.

[156] Simmons, K., and Sutter, D. 2011. Economic and Societal Impacts of Tornadoes. Publisher: AMS Books / University of Chicago Press. ISBN: 978-1-878220-99-8.

[157] Smith, A. B. and J. L. Matthews 2015. "Quantifying Uncertainty and Variable Sensitivity within the U.S. Billion-dollar Weather and Climate Disaster Cost Estimates," Natural Hazards, 77 (2015), pgs., 1829-1851. See: https://www.ncdc.noaa.gov/monitoring-content/billions/docs/smith-and-matthews-2015.pdf.

[158] Špitalara, M., J.J. Gourley, C. Lutoff, P. Kirstettere, M. Brilly, and N. Carr. 2014. Analysis of flash flood parameters and human impacts in the US from 2006 to 2012. J. of Hydrology. 519A:863-870. https://doi.org/10.1016/j.jhydrol.2014.07.004

[159] Statista, "Economic damage caused by tornadoes in the U.S. from 1995 to 2020" https://www.statista.com/statistics/237409/economic-damage-caused-by-tornadoes-in-us/ Accessed April 27, 2022.

[160] Steinemann, A. C. 2006. Using Climate Forecasts for Drought Management, Journal of Applied Meteorology and Climatology, 45(10), 1353-1361. https://journals.ametsoc.org/view/journals/apme/45/10/jam2401.1.xml?tab_body=pdf

[161] Steinemann, A., Iacobellis, S.F. and Cayan, D.R., 2015. Developing and evaluating drought indicators for decision-making. Journal of Hydrometeorology, 16(4), pp.1793-1803

[162] Steiner, M.; W. Deierling; and R. Bass, Balancing safety and efficiency of airport operations under lightning threats, The Journal of Air Traffic Control, 55(2), 16 – 23, 2013.

[163] Steiner, M., Deierling, W., Ikeda, K., Nelson, E., and Bass R.G. 2014. Airline and Airport Operations under Lightning Threats – Safety Risks, Impacts, Uncertainties, and how to deal with them all. American Institute of Aeronautics and Astronautics.

[164] Steiner, M., Deierling, W., Ikeda, K., and Bass R.G. 2014. [*Steiner et al. 2014A*] "Implications of Lightning Data Uncertainty on Personnel Safety and Operational Efficiency Decisions." 23rd International Lightning Detection Conference and 5th International Lightning Meteorology conference, 18 – 21 March, 2014.

[165] Steiner, M., Deierling, W., Ikeda, K., and Bass R.G. 2015. Ground Delays from Lightning Ramp Closures and Decision Uncertainties. Air Traffic Control Quarterly, 22(3), 223 – 249, 2015.

[166] Steiner, M., Deierling, W., Ikeda, K., Robinson, M., Klein, A., Bewley, J., and Bass R.G. 2016. Air Traffic Impacts Caused by Lightning Safety Procedures, American Institute of Aeronautics and Astronautics.

[167] T.R. Carroll, Donald Cline, C.M. Oldheiser, A.A. Rost, "NOAA's National Snow Analysis," 2005 https://www.researchgate.net/publication/241593178_NOAA's_national_snow_analyses Accessed April 27, 2022.

[168] Terti, G., I. Ruin, S. Anquetin, and J.J. Gourley. 2017. A Situation-Based Analysis of Flash Flood Fatalities in the United States, Bulletin of the American Meteorological Society, 98(2), 333-345. https://journals.ametsoc.org/view/journals/bams/98/2/bams-d-15-00276.1.xml

[169] The Lancet Commission on pollution and health, 2017. https://www.thelancet.com/commissions/pollution-and-health. Accessed Jan 31, 2022

[170] Thomas, D., D. Butry, S, Gilbert, D, Webb, and J. Fung. 2017. The Costs and Losses of Wildfires: A Literature Review. National Institute of Standards and Technology. NIST Special Publication 1215. https://doi.org/10.6028/NIST.SP.1215. Accessed January 19, 2022.

[171] Tol, R.S.J. 2019. Economic Analysis of Climate, Climate Change and Climate Policy. 2nd edition. Edward Elgar. ISBN: 9781786435071. 256 pp.

[172] TPIO 2021. NOAA Observation Systems Sankey Diagram, provided by NESDIS/OSAAP/PPSAD Technology, Planning, and Integration for Observation (TPIO) Division (Hilary Olesen and Alexander Vanplantinga) via email on October 4, 2021.

[173] Tsirkunov, V.S., Ulatov, M., Smetanina, M., and Korshunov, A., 2007. "Customizing Methods of Assessing Economic Benefits of hydrometeorological Services and Modernization Programs: Benchmarking and Sector-Specific Assessment." In Elements for Life. Tudor Rose on behalf of the WMO. Geneva.

[174] Twitter NWSWPC 2022. National Weather Service Weather Prediction Center tweet: https://twitter.com/nwswpc/status/1490457278557863939?s=21.

[175] UN CTC-N 2018, Climate Technology Centre & Network (CTC-N), Water Adaptation Technology Brief: "Drought forecasting systems," March 19, 2018, accessed on July 21, 2022 at: https://www.ctc-n.org/sites/www.ctc-n.org/files/resources/drought_forecasting_systems.pdf.

[176] University of Wisconsin – Madison, SSEC, 1996 "The Spin-Scan Camera Idea", ATS-III Image Collection, Schwerdtfeger Library, University of Wisconsin-Madison found at https://library.ssec.wisc.edu/spinscan/about.php (Excerpt from "Verner E. Suomi, 1916-1995: A man for all seasons", University of Wisconsin-Madison, WI, Space Science and Engineering Center, 1996).

[177] USACE 2020. U.S. Army Corps of Engineers Chief of Engineering and Construction Division, Civil Works Directorate "Annual Flood Damage Reduction Report," at: https://water.usace.army.mil/a2w/r/cwms_crrel/files/static/v16/APPN-G-2018_FINAL.PDF. Accessed February 8, 2022.

[178] USACE 2022. U.S. Army Corps of Engineers' Flood Damage Data at: https://www.iwr.usace.army.mil/missions/flood-risk-management/flood-damage-data-collection/. Also see: USACE Flood Risk Management Program at: https://www.iwr.usace.army.mil/Missions/Flood-Risk-Management/Flood-Risk-Management-Program/ and https://water.usace.army.mil/a2w/r/cwms_crrel/files/static/v16/APPN-G-2018_FINAL.PDF.

[179] USDA National Agricultural Library 2022, "Drought Prediction and Monitoring Tools," at: https://www.nal.usda.gov/legacy/waic/drought-prediction-and-monitoring-tools. Accessed on July 21, 2022.

[180] USDA NASS. National Agricultural Statistics Service 2022, "U.S. Crops and Livestock in Drought," Web Page: https://www.drought.gov/sectors/agriculture#:~:text=Agricultural%20Production%20Losses,through%20government%20disaster%20assistance%20programs. Accessed April 28, 2022.

[181] USDOT 2021, "Departmental Guidance Treatment of the Value of Preventing Fatalities and Injuries in Preparing Economic Analyses March 2021." Available at: https://www.transportation.gov/sites/dot.gov/files/2021-03/DOT%20VSL%20Guidance%20-%202021%20Update.pdf.

[182] USDOT 2022, U.S. Department of Transportation Maritime Administration "Data Statistics" Web Page: https://www.maritime.dot.gov/data-reports/data-statistics/data-statistics. Accessed September 26, 2022.

[183] USDOT VSL 2022, "Departmental Guidance on Valuation of a Statistical Life in Economic Analysis," https://www.transportation.gov/office-policy/transportation-policy/revised-departmental-guidance-on-valuation-of-a-statistical-life-in-economic-analysis. Accessed March 24, 2022.

[184] Wilhite, D. A. and Glantz, M. H., 1985, "Understanding the drought phenomenon: the role of definitions," Water International 10(3), pp. 111-120, at: https://doi.org/10.1080/02508068508686328, https://www.tandfonline.com/doi/abs/10.1080/02508068508686328.

[185] The Weather Channel 2022. "Weather-Related Vehicle Accidents Far More Deadly Than Tornadoes, Hurricanes, Floods." Web Page: https://weather.com/safety/winter/news/weather-fatalities-car-crashes-accidents-united-states. Accessed July 19, 2022.

[186] WMO, WBG, GFDRR & USAID. 2015. Valuing Weather and Climate: Economic Assessment of Meteorological and Hydrological Services. World Meteorological Organization, World Bank Group, Global Facility for Disaster Reduction and Recovery, and United States Agency for International Development, WMO No. 1153, Geneva, Switzerland. https://library.wmo.int/doc_num.php?explnum_id=3314.

[187] Wolfe, E. and K.N. Mitchell. 2018 "Allisions, Collisions and Groundings: Estimating the Impact of the Physical Oceanographic Real Time System (PORTS®) on Accident Reduction," Journal of Ocean and Coastal Economics. 5(1)Article 4. DOI: https://doi.org/10.15351/2373-8456.1091

[188] Wolfe, K.E. and D. MacFarland, 2013. An Assessment of the Value of the Physical Oceanographic Real-Time Systems (PORTS®) to *The Economy*, September 30, 2013 https://tidesandcurrents.noaa.gov/publications/ASSESSMENT_OF_THE_VALUE_OF_PORTS_TO_THE_US_ECONOMY.pdf Accessed Apr 27, 2022.

[189] Wolfe, K.E. and D. MacFarland. 2016. A Valuation Analysis of the Physical Oceanographic Real Time System (PORTS). Journal of Ocean and Coastal Economics. 3(1) Article 12 as found on the Internet at https://cbe.miis.edu/joce/vol3/iss1/12/ https://doi.org/10.1535/2373-8456.1058

[190] Xie, Z., W. Song, R. Ba, X. Li, and L. Xia. 1992. A Spatiotemporal Contextual Model for Forest Fire Detection Using Himawari-8 Satellite Data. Remote Sensing, 10, 1992 (8 Dec 2018) https://doi.org/10.3390/rs10121992

[191] Xu, W, M.J. Wooster, G. Roberts and P. Freeborn. 2010. New GOES imager algorithms for cloud and active fire detection and fire radiative power assessment across North, South and Central America. Remote Sensing of Environment, 114: 9, 15 Sept 2010, pp. 1876-1895 https://doi.org/10.1016/j.rse.2010.03.012

[192] Xua, W., M.J.Wooster, J. He, and T. Zhang. 2021. Improvements in high-temporal resolution active fire detection and FRP retrieval over the Americas using GOES-16 ABI with the geostationary Fire Thermal Anomaly (FTA) algorithm. Science of Remote Sensing, 3 (2021) 100016

[193] Yapur, M., 2020 "NOAA's Approach to Observing System Requirements Management," PowerPoint presentation, prepared for U.S. IOOS Advisory Committee, February 11, 2020. https://cdn.ioos.noaa.gov/media/2020/02/9-NOAAs-Approach-to-Observing-System-Requirements-Management-YAPUR.pdf

[194] Yin, R., W. Han, Z. Gao, and J. Li. 2021. Impact of high temporal resolution FY-4A Geostationary Interferometric Infrared Sounder (GIIRS) radiance measurements on Typhoon forecasts: Maria (2018) case with GRAPES global 4D-Var assimilation system. Geophysical Research Letters, 48, e2021GL093672. https://doi.org/10.1029/2021GL093672

[195] Zhou, Q., Leng, G. and Peng, J., 2018. Recent changes in the occurrences and damages of floods and droughts in the United States. Water, 10(9), p.1109.

Appendix A. Population Projections and Annual Growth Rates

Table 41. Population Projections and Annual Growth Rates (Census Bureau)

Year	Population	Annual Growth Rate %
2017	324,985,539	0.63000
2018	326,687,501	0.52000
2019	328,239,523	0.48000
2020	332,639,102	0.71091
2021	334,998,398	0.70192
2022	337,341,954	0.69169
2023	339,665,118	0.68030
2024	341,963,408	0.66809
2025	344,234,377	0.65621
2026	346,481,182	0.64372
2027	348,695,115	0.62961
2028	350,872,007	0.61463
2029	353,008,224	0.59896
2030	355,100,730	0.58281
2031	357,147,329	0.56643
2032	359,146,709	0.55009
2033	361,098,559	0.53402
2034	363,003,410	0.51840
2035	364,862,145	0.50333
2036	366,676,312	0.48895
2037	368,447,857	0.47529
2038	370,178,704	0.46240
2039	371,871,238	0.45033
2040	373,527,973	0.43913
Average	**n/a**	**0.57249**

Source: https://www.census.gov/data-tools/demo/idb/#/table?COUNTRY_YR_ANIM=2021&COUNTRY_YEAR=2022&menu=tableViz&FIPS=US&TABLE_RANGE=2017,2040&TABLE_YEARS=2017,2018,2019,2020,2021,2022,2023,2024,2025,2026,2027,2028,2029,2030,2031,2032,2033,2034,2035,2036,2037,2038,2039,2040&TABLE_USE_RANGE=Y&TABLE_USE_YEARS=N&TABLE_STEP=1. Accessed January 18, 2022.

Appendix B. Consumer Price Index 1913-2018 (Base Year 1982 to 1984=100)

Table 42. Consumer Price Index 1913-2018 (Base Year 1982 to 1984=100) (BLS)

Year	Annual	Year	Annual	Year	Annual
1913	9.90	1949	23.80	1985	107.60
1914	10.00	1950	24.10	1986	109.60
1915	10.10	1951	26.00	1987	113.60
1916	10.90	1952	26.50	1988	118.30
1917	12.80	1953	26.70	1989	124.00
1918	15.10	1954	26.90	1990	130.70
1919	17.30	1955	26.80	1991	136.20
1920	20.00	1956	27.20	1992	140.30
1921	17.90	1957	28.10	1993	144.50
1922	16.80	1958	28.90	1994	148.20
1923	17.10	1959	29.10	1995	152.40
1924	17.10	1960	29.60	1996	156.90
1925	17.50	1961	29.90	1997	160.50
1926	17.70	1962	30.20	1998	163.00
1927	17.40	1963	30.60	1999	166.60
1928	17.10	1964	31.00	2000	172.20
1929	17.10	1965	31.50	2001	177.10
1930	16.70	1966	32.40	2002	179.90
1931	15.20	1967	33.40	2003	184.00
1932	13.70	1968	34.80	2004	188.90
1933	13.00	1969	36.70	2005	195.30
1934	13.40	1970	38.80	2006	201.60
1935	13.70	1971	40.50	2007	207.34
1936	13.90	1972	41.80	2008	215.30
1937	14.40	1973	44.40	2009	214.54
1938	14.10	1974	49.30	2010	218.06
1939	13.90	1975	53.80	2011	224.94
1940	14.00	1976	56.90	2012	229.59
1941	14.70	1977	60.60	2013	232.96
1942	16.30	1978	65.20	2014	236.74
1943	17.30	1979	72.60	2015	237.02
1944	17.60	1980	82.40	2016	240.01
1945	18.00	1981	90.90	2017	245.12
1946	19.50	1982	96.50	2018	251.11
1947	22.30	1983	99.60	2019	255.66
1948	24.10	1984	103.90	2020	258.81

Source: https://data.bls.gov/timeseries/CUUR0000SA0 Series Id: CUUR0000SA0; Series Title: All items in U.S. city average, all urban consumers, not seasonally adjusted.

Appendix C. Supplementary Note on Regression on Number of SARSAT-Related Rescue

As noted in the text, to estimate the number of impacted individuals, we undertook a regression using data on “Number of People Rescued” because of SARSAT. We had 20 years of data indicating the number of people rescued each year from 2001 through 2020. To estimate (project) the number of individuals who may be rescued during the time frame of the GOES-R analysis (out to 2040), we undertook a~~s~~ regression using past data and used the regression results to project into the future.

Regression is a statistical method used to assess the relationship between variables – in this case the number of people rescued and the year in which those rescued occurred. Our goal was to see if there was a statistically significant relationship between these in order to project them out into the future. As noted, we undertook an ordinary least squares (OLS) regression on these data with U.S. Rescues (the number of individuals rescued) as the dependent variable and “Year” as the only independent variable.

In this simple “model” we are using the available data to “fit” a line (e.g., Y = a + b*X):

U.S. Rescues = Constant + (Year Number of Rescues) x (Year)

“U.S. Rescues” is the “dependent variable” in that it depended on the year being examined. The constant is the “intercept” or, in this case, the number of rescues if the year was “0” which is obviously outside our consideration. The parameter named “Year Number of Rescues” is not the number rescued in any given year but the number dependent on the actual number of the year (e.g., 2005 or 2008).

Because the number of rescues varies considerably year by year and is not a strict linear relationship, the model included an error term which we assumed to be zero on average:

U.S. Rescues = Constant + (Year Number of Rescues) x (Year) + error

Ordinary least square (OLS) regression is used to “choose” parameters to “fit” the data to a line while minimizing the squared sum of the errors from the observed data. Since there is uncertainty or variation in the estimation method, the output reports the estimates of the parameter as well as *standard errors of the estimates* (or estimates of how precise the parameter estimates are). These standard errors (SE) are commonly reported in the output in parentheses under the parameter estimates as shown below:

U.S. Rescues =	Constant	+	(Year Number of Rescues) x (Year)
	(SE Constant)		(SE Year Number of Rescues)

The standard errors are used to test the hypothesis that the parameter estimates are equal to zero, which would basically mean that they have no relationship or do nothing to help explain the dependent variable (Number of Rescues). If the parameters are “significant” below some chosen criteria level (quite often 5% or 10%), then it is concluded that there is a relationship between the variables. In this case, finding a statistically significant and positive relationship between *Number of Rescues* and *Year Number of Rescues* means that the number of rescues is increasing each year in a statistically significant manner.

As reported in section 13.3, the regression model yielded:

$$\text{U.S. Rescues} = -12982.737^{***} + 6.589\ \text{Year}^{***}$$

$$(3888.482)^{\dagger} \qquad (1.934)^{\dagger}$$

*** Significant at <1.0% † Standard error of the estimate

Adjusted R Square 0.358 (n=20)

The *** appended to each parameter estimate (the *Constant* and the *Year Number of Rescues*) indicates that these are significant and explanatory in understanding the number of U.S. Rescues. The parameter estimate on Year of 6.589 means that (on average) the number of U.S. Rescues has increased by 6.589 people each year.

The "adjusted R-squared" is an indication of the reliability of the overall model (all ~~of~~ parameters combined). This is also subject to a statistical F-test which indicates overall model significant of 0.3% and which is well below any standard criteria of 10% or 5% for evaluating a model such as this. (We note though, that this is actually a "time-series" model which does generally have a higher level of significance than other non-time-series models and for which we have not evaluated the time series components of the statistical model at this time.)

We then assumed that this linear relationship holds into the future to "predict" how many U.S. Rescues there will be over the lifetime of the analysis (out to the year 2040). We did this by simply inserting the number "Year" into the model for each year of interest. This generated an estimated number of U.S. Rescues for the "observed" years as well as out to the year 2040, as show in Table 43.

We note that this is only the simplest model that could be used to examine the relationship between years and rescues and that there are certainly many other factors influencing the number of rescues over time. For purposes of the current analysis, there are any number of other sources of uncertainty in our analysis and further examination of these using better models (e.g., more complicated) of the number of U.S. Rescues may improve our overall benefit estimates.

Table 43. U.S. Rescues – Actual and Fitted from Regression Analysis

Year	Actual U.S. Rescues	Fitted U.S. Rescues
2001	166	202.8
2002	171	209.4
2003	224	216.0
2004	260	222.6
2005	222	229.2
2006	272	235.7
2007	353	242.3
2008	282	248.9
2009	195	255.5
2010	295	262.1
2011	207	268.7
2012	263	275.3
2013	261	281.9
2014	240	288.5

Table 43. U.S. Rescues – Actual and Fitted from Regression Analysis (cont.)

Year	Actual U.S. Rescues	Fitted U.S. Rescues
2015	250	295.1
2016	307	301.6
2017	275	308.2
2018	340	314.8
2019	421	321.4
2020	304	328.0
2021	n/a	334.6
2022	n/a	341.2
2023	n/a	347.8
2024	n/a	354.4
2025	n/a	360.9
2026	n/a	367.5
2027	n/a	374.1
2028	n/a	380.7
2029	n/a	387.3
2030	n/a	393.9
2031	n/a	400.5
2032	n/a	407.1
2033	n/a	413.7
2034	n/a	420.3
2035	n/a	426.8
2036	n/a	433.4
2037	n/a	440.0
2038	n/a	446.6
2039	n/a	453.2
2040	n/a	459.8

These numbers are then plotted in Figure 48 (same as Figure 61) where the (wiggly) blue line ~~is~~ represents the values actually observed and the straight orange line ~~is~~ represents the number of estimated U.S. rescues derived using the regression model.

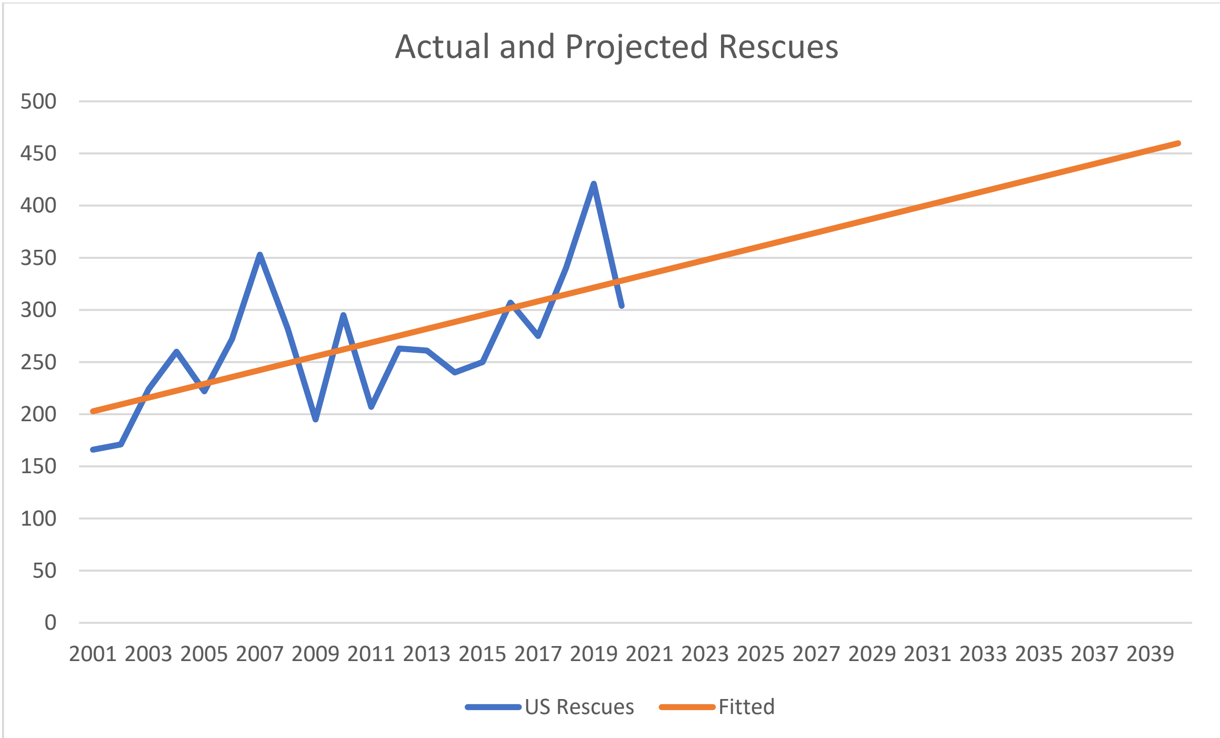

Figure 48. People saved with SARSAT and projections to 2040 from regression analysis.

To further explore this, we also undertook regression analysis in the Statistical Analysis System (SAS) which allowed us to automatically generate fitted values and confidence intervals on those values. Figure 49 shows the same information along with 95% confidence intervals on the regression line (the solid green and yellow lines) and the 95% confidence intervals on the "predictions" (dashed lines). We show this to indicate that there is uncertainty in the projected number of lives saved using the simple regression analysis. At this time, we have only used the projected number of lives saved indicated by the solid black line. Further uncertainty analysis could account for the 95% prediction confidence intervals as shown by the dashed lines as part of a more rigorous sensitivity analysis.

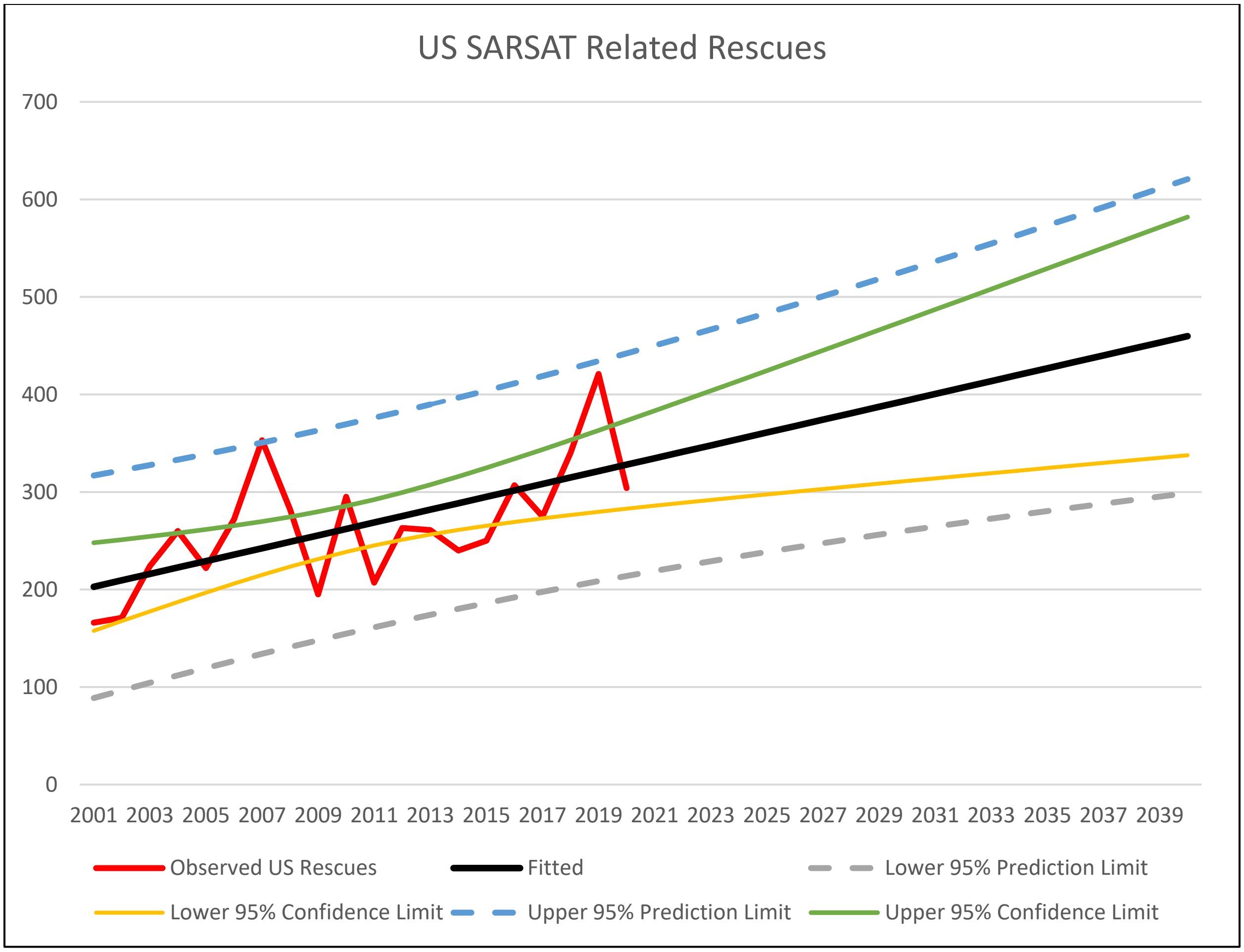

Figure 49. People saved with SARSAT—observed projections to 2040
from SAS-based regression analysis with confidence limits.

Appendix D. Explanation of "How Weather Variability Affects the Economy"

(COPIED IN FULL FROM LAZO ET AL. 2011 [*Lazo et al. 2011*] with figure numbers changed to maintain numerical order within this report)

How weather variability affects economic activities can be conceptualized, modeled, and analyzed from many different perspectives – no one being the single "right" approach but some more amenable to quantitative analysis or policy applications. Therefore, it is important to have a clear definition of weather sensitivity that is both based on generally accepted economic theory and amenable to objective, empirical analysis. We present the following example of skiing in Colorado to develop a working definition of "economic sensitivity to weather variability" consistent with our empirical analysis. Throughout this discussion we assume that the sector, and subsequently the sectors in our analysis, are competitive. For the level of aggregation in our analysis we feel this is a reasonable assumption.

Weather affects the economy by affecting both supply and demand for the products and services of an industry. We note particularly the consumption (i.e., demand) side of this discussion as consideration of weather impacts are usually focused primarily on the production (i.e., supply) side. For this example, consider Colorado's ski industry, a subsector of the services industry. In economics, the quantity demanded of a good—total days of skiing—is the relationship between price (e.g., price of lift tickets for a day of skiing) and quantity demanded (holding everything else constant). Some other things held constant are factors such as tastes, preferences, and income. "Tastes and preferences" means how much people want of a particular of good or service based on how much enjoyment they get from it—if skiing suddenly became the latest fashion buzz or, alternatively, if people decided skiing was passé, these would be considered changes in tastes and preferences. Also, if consumers' income were higher, demand for total skiing days at any given price would be higher because more people could afford to ski.[40] It should be noted that weather forecasting accuracy is one of the many aspects of consumer demand held constant in the demand function.

Demand for skiing also depends on snow conditions and snow levels, which are determined by weather conditions (W). With tastes and preferences and income held constant and snow conditions held constant at some initial level W^0, the demand curve labeled $D(W^0)$ in Figure 50 shows the relationship between price of a day skiing and the number of skiing days demanded. The lower the price of a day skiing, the more total days skiing people will want with the initial snow conditions, W^0, and thus the downward sloping demand curve.

[40] We implicitly assumed stable tastes and preferences and constant income and did not include these in our modeling; we therefore suppress that notation in the figures.

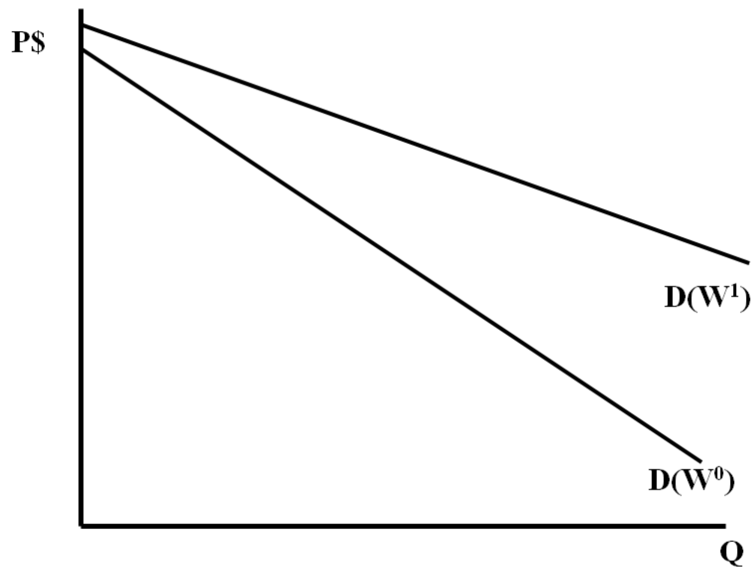

Figure 50. Demand for skiing.

The quantity of skiing demanded at each price with snow level W^0 given tastes and preferences and income held constant. The shift in demand for skiing is shown as the quantity of skiing demanded at each price shifts with weather W^1, i.e., more snow.

The demand curve shows only the relationship between price and quantity, holding all else constant. Changes in price cause movement along the curve. Changing any other relevant factor (such as tastes and preferences or income or snow conditions) would shift the curve. Improvements in snow conditions as a result of changes in weather (from W^0 to W^1) will shift the demand curve—better snow means more total days of skiing will be demanded at any given price level. This shift is shown in Figure 50 to the new demand curve, labeled $D(W^1)$.

Economic theory indicates that the price an individual is willing to pay for an additional unit of a good (e.g., an extra day of skiing) is a measure of the additional (i.e., marginal) benefit he receives from consuming that additional unit of the good. The height of the demand curve thus shows the marginal benefit of consumption at each quantity, so the total area under the curve from zero to *q* is equal to the total benefits of consumption of q.[41]

On the supply side, given current technology (current weather impacts mitigation investments and weather forecasts are an implicit part of technology), economists would model ski areas as using physical capital (K), labor (L), and energy (E) to produce skiing days—the total costs of which also depend on the quantity of snow provided by nature (W).[42] The higher the price, the more total skiing days that profit-maximizing firms will supply. For instance, they might open more ski lifts and more terrain for skiers, and even more ski areas could be opened. This relationship between prices and total days skiing supplied is shown as an upward sloping supply curve in Figure 51. Similar to the demand curve, the quantity supplied (e.g., skiing) is shown as the relationship between price and quantity supplied holding all else

[41] Technically, the total benefit is the integral under the marginal benefit curve (i.e., the demand curve), from q = 0 to the level of consumption q'. Total Benefit = $\int_{q=0}^{q=q'} P_d(q)dq$.

[42] Materials (M) are often considered an input to production along with K, L, and E, but lacking reliable data on materials inputs, we suppress M without further discussion.

constant (e.g., technology, wage rates, interest rates, energy prices). This relationship is shown in Figure 51 by the supply curve labeled $S(K,L,E;W^0)$.[43]

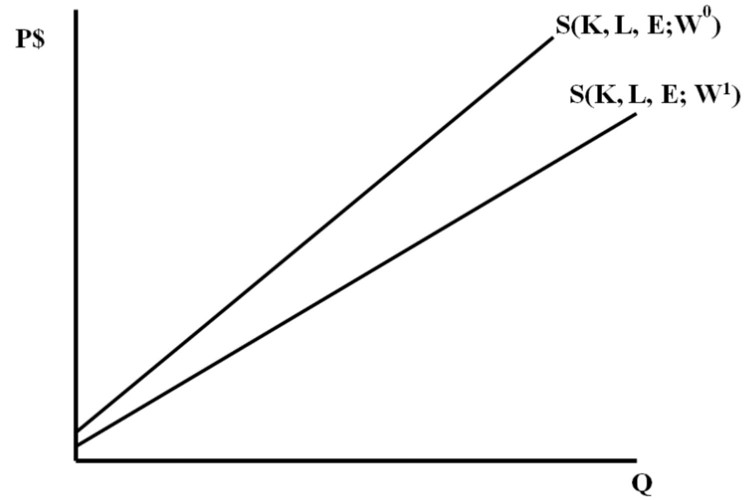

Figure 51. Supply of skiing.

The quantity of skiing supplied at each price with snow level W^0, given costs for capital (K), labor (L), and energy (E), and the state of technology. The shift in supply of skiing with better snow, W^1, lowers production costs and means more skiing supplied at each price than with snow level W^0.

Similar to the relationship of the demand curve to marginal benefits to consumers, the height of the supply curve represents the marginal (variable) costs of production to the producer. The total area under the curve between zero and q is equal to the total variable costs of production for any given level of output, q.[44]

Improvements in snow conditions may lower costs to the ski areas (less capital, energy, and labor spent on snowmaking) and thus shift the supply curve to the right—more skiing supplied at any given price—as shown in Figure 52 by the new supply curve $S(K,L,E;W^1)$.

Returning to the initial level of snow (W^0), supply and demand interact in a competitive market to determine an equilibrium price (P*) and quantity (Q*), as shown in Figure 52. At this equilibrium, the quantity demanded equals the quantity supplied given the consumers' tastes, preferences, and income, given the producers' technology and costs and given the weather conditions (W^0).

[43] Because technology changes over time, and generally will lower costs per unit output, we controlled for this in our statistical analysis. Technological change is not the focus of the current research, and we don't discuss it further here. Future research should examine whether weather sensitivity has increased or decreased over time, which may be closely related to technological change.
[44] Technically, the total variable cost of production is the integral under that marginal cost curve, P_s, i.e., the supply curve, from q = 0 to the level of production q'. Total Variable Cost= $\int_{q=0}^{q=q'} P_s(q)dq$.

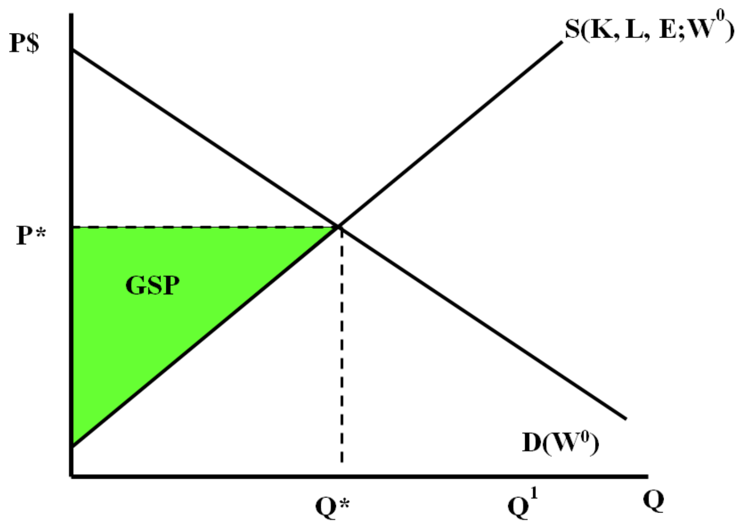

Figure 52. Equilibrium price and quantity (P* and Q*).

The green area in Figure 52 represents gross state product at equilibrium (value added or total revenue minus total costs).

In Figure 53, total revenue (TR) is the price times the quantity (P* × Q*). Total variable cost (TVC) is the area under the supply curve up to the equilibrium quantity. The difference between total revenue and total variable costs (TR – TVC), which we define as gross product, is a measure of the value added by the industry. This is the green area in Figure 53 (labeled GSP for Gross State Product defined further below). With better snow conditions (from W^0 to W^1) shifting the supply and demand curves, a new equilibrium price (P^1) and quantity (Q^1) will be reached. At this new equilibrium, gross product from the ski industry will change (the yellow area in Figure 53).

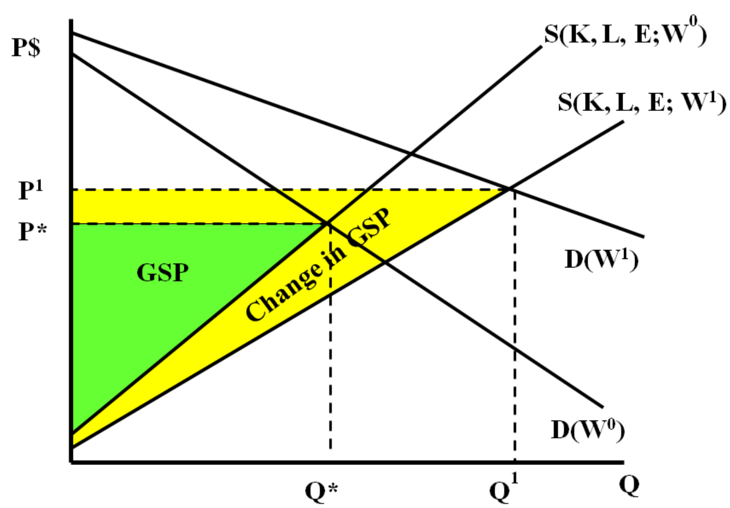

Figure 53. GSP change induced by weather change and supply and demand shifts.

Gross state product (GSP; also called gross domestic product by state) is “a measurement of a state's output; it is the sum of value added from all industries in the state. GDP by state is the state counterpart to the Nation's gross domestic product (GDP)” (Bureau of Economic Analysis 2007). In other words, GSP for a sector is total revenue minus total cost for all firms in that sector across the entire state (e.g., see Figure 53).

The skiing industry is part of the recreation sector of the economy, which in turn is a component of the larger services supersector. Thinking now about moving from the subsector of skiing to the entire services sector, the aggregation of all revenues minus costs for all service industries in Colorado represents the GSP for services in Colorado, and across all states this represents the GSP for services in the United States.

We expect other subsectors and sectors to have similar responses to variation in weather, in that other sectors will be affected by both shifting supply and demand curves. Of course, weather affects supply and demand in very different ways for every sector and subsector and over different spatial and temporal scales. For instance, more Colorado snow may mean more skiing but less construction in Colorado, and more snow and skiing in Colorado may mean fewer trips to the beach in Hawaii. It follows that GSP may go up in one sector in one state and down in another sector in another state in response to a change in weather conditions.

We emphasize that in this discussion and in our analysis reported below, GSP is a monetary measure (price times quantity) and not only a quantity measure of impacts of weather. Thus, while there may be negative or positive quantity impacts from weather related shifts in demand and supply if these are offset by price changes, the impacts from an economic perspective will not be as apparent.

Based on this conceptual model and underlying economic theories of individual and market demand, firm and market supply, market equilibrium, and the concept of gross product as value added, we define and measure weather sensitivity as *the variability in gross product owing to weather variability, accounting for changes in technology and for changes in the level of economic inputs (i.e., capital, labor, and energy)*. Be "accounting for" (also called "controlling for" in economics lingo) we mean we are identifying the variability in GSP associated with variability in weather separate from variability in other inputs such as capital, labor, energy, technology, and current and past investments in weather impact mitigation and weather forecasting.

Appendix E. TPIO NOSIA 2.1 GOES-R Data Analysis for Primary Benefit Areas

This table provides a sampling of the first four to five top GOES-R-contributing products in each of our seven primary benefit areas and Mission Service Areas (MSAs). Most benefit areas/MSAs have many more products that comprise the total percentages we used in Phase 2, but we present these few as examples/samples.

Table 44. Top GOES-R-Contributions Products Seven Primary Benefit Areas and MSAs

Focus	MSA (Mission Service Area)	MSA ID	Product Name	Product ID	Impact of GOES on MSA by Product
Air Quality	Advanced Systems Performances Evaluation tool for NESDIS	WRN_ASPEN	Tropical Cyclone Vitals Analysis Package: NHCHSU	TCVitals21 NHCHSU	0.54%
Air Quality	Advanced Systems Performances Evaluation tool for NESDIS	WRN_ASPEN	Tropical Cyclone Analysis Package Update	HurrUpdt CPHC	0.52%
Air Quality	Advanced Systems Performances Evaluation tool for NESDIS	WRN_ASPEN	Tropical Weather Outlook: CPHC	TrpWxOtlk CPHC	0.31%
Air Quality	Advanced Systems Performances Evaluation tool for NESDIS	WRN_ASPEN	Tropical Cyclone Forecast Package Combination - proxy	HurrPkg NWS	0.30%
Air Quality	Advanced Systems Performances Evaluation tool for NESDIS	WRN_ASPEN	Land Surface Temperature from GOES	LndSfcTempSat SPB	0.29%
Aviation Weather	Aviation Weather and Volcanic Ash National Service Program	WRN_AWX	Terminal Aerodrome Forecast Combination	TAF NWS	6.01%
Aviation Weather	Aviation Weather and Volcanic Ash National Service Program	WRN_AWX	Significant Meteorological Information: Dust and Sand	SIGMETDst AWCDOB	1.77%
Aviation Weather	Aviation Weather and Volcanic Ash National Service Program	WRN_AWX	Significant Meteorological Information (SIGMET)-Volcanic Ash Combination	SIGMETAsh NWS	1.27%

Focus	MSA (Mission Service Area)	MSA ID	Product Name	Product ID	Impact of GOES on MSA by Product
Aviation Weather	Aviation Weather and Volcanic Ash National Service Program	WRN_AWX	Volcanic Ash Advisories: SAB	AshAdv21 SAB	0.92%
Aviation Weather	Aviation Weather and Volcanic Ash National Service Program	WRN_AWX	Significant Meteorological Information (SIGMET)-Turbulence Combination	SIGMETTrbc NWS	0.76%
Fire Weather	Fire Weather National Service Program	WRN_FWX	Incident Meteorological Forecasts Combination	IMETFldSvc21 NWS	1.82%
Fire Weather	Fire Weather National Service Program	WRN_FWX	Red Flag Warning Combination	RdFlgWrng NWS	1.77%
Fire Weather	Fire Weather National Service Program	WRN_FWX	Site Specific Fire Weather Spot Forecast Combination	SptFcst NWS	1.70%
Fire Weather	Fire Weather National Service Program	WRN_FWX	National Fire Danger Rating System Forecast: NIFC - proxy	FireDngrRtgSys_ Forecast NIFC	1.45%
Fire Weather	Fire Weather National Service Program	WRN_FWX	Fire Warning: WFO	FireWrn NWS	1.37%
Integrated Water and Prediction Information	Integrated Water and Prediction Information	WRN_IWPI	Flood Watch: Forecast Points	FldWtch-P WFOMPX	1.58%
Integrated Water and Prediction Information	Integrated Water and Prediction Information	WRN_IWPI	Flood Warning, Areal Combination	FldWrng-A NWS	1.10%
Integrated Water and Prediction Information	Integrated Water and Prediction Information	WRN_IWPI	Flash Flood Warning and Flash Flood Statement Combination	FFWrng NWS	0.86%
Integrated Water and Prediction Information	Integrated Water and Prediction Information	WRN_IWPI	WFO Flash Flood Watches	FFWtch21 NWS	0.81%

Focus	MSA (Mission Service Area)	MSA ID	Product Name	Product ID	Impact of GOES on MSA by Product
Integrated Water and Prediction Information	Integrated Water and Prediction Information	WRN_IWPI	Flood Watch, Areal Combination	FldWtch-A NWS	0.79%
Public Weather	Public Weather	WRN_PWX	National Digital Forecast Database Combination	NDFD NWS	4.27%
Public Weather	Public Weather	WRN_PWX	Excessive Heat Warning	ExcsvHtWrng WFOLWX	0.95%
Public Weather	Public Weather	WRN_PWX	Forecast Verification Guidance	FcstVerfctn MDL	0.89%
Public Weather	Public Weather	WRN_PWX	Heat Index Probability Forecast: Day 3-7	HtIndxFcst WPCFOB	0.22%
Severe Weather	Severe Weather National Service Program	WRN_SEV	Severe Tornado Watch: Storm Prediction Center	SvrTorWtch SPCOB	2.96%
Severe Weather	Severe Weather National Service Program	WRN_SEV	Severe Thunderstorm Watches Combination	SvrTSWtch NWS	2.38%
Severe Weather	Severe Weather National Service Program	WRN_SEV	Severe Thunderstorm Warnings and Severe Weather Statements: Average	SvrTSWrnavg NWS	2.35%
Severe Weather	Severe Weather National Service Program	WRN_SEV	Tornado Warning Combination	TorWrng NWS	1.72%
Severe Weather	Severe Weather National Service Program	WRN_SEV	Mesoscale Discussions: SPC	MesoAnal21 SPCOB	1.23%
Winter Weather	Winter Weather	WRN_WWX	Winter Storm Warning Combination	WntrStrmWrng NWS	2.14%
Winter Weather	Winter Weather	WRN_WWX	Hard Freeze Warning Combination	HrdFzWrng NWS	1.80%
Winter Weather	Winter Weather	WRN_WWX	Blizzard Warning Combination	BlzrdWrng NWS	1.77%

Focus	MSA (Mission Service Area)	MSA ID	Product Name	Product ID	Impact of GOES on MSA by Product
Winter Weather	Winter Weather	WRN_WWX	Ice Storm Warning Combination	IceStrmWrng NWS	1.39%
Winter Weather	Winter Weather	WRN_WWX	Winter Storm Watch Combination	WntrStrmWtch NWS	1.17%

Source: NESDIS TPIO (Hilary Olsen) Email: “Re: Analyses of NOSIA 2.1 GOES-R Data for Primary Benefit Areas,” with attached Excel file, April 19, 2022.

Appendix F. Additional Background Information on Selected Benefit Areas

This appendix provides additional background information for selected GOES-R socioeconomic benefit areas that we considered a bit too lengthy to include in the main body of this report. See the Phase 1 report for more detailed information on GOES-R and its payloads. [*Lubar et al. 2021*]

F.1 The Value of the GOES-R GLM

Although most of our focus in this study was on the GOES-R series ABI, we would be remiss if we did not at least mention the general benefits of the GLM.

When the GOES-R GLM is integrated into the warning process for severe thunderstorms or tornado warnings, those data may facilitate making the decision to warn earlier or to end warnings sooner. The latter reduces unnecessary coverage and false alarms. The rapid update of GLM allows forecasters to visualize the rapid intensification of thunderstorms earlier in their development. GLM updates every 20 seconds nominally, and within NWS operations, every minute, whereas radar average volume scans are available about every 5 minutes [*Calhoun, 2018, 2019*]. *If a r*adar is not functioning, a warning forecaster could use the 1-minute Flash Extent Density from GLM to assess rapid intensification of storms. In January 2020, the Huntsville, Alabama, WFO relied on GLM to reissue a tornado warning [*Goss 2020*]. GLM can have significant impact on warning decisions in regions of poor radar coverage [*Brotzge and Erickson, 2010]*. GLM data are valuable for forecaster's monitoring and warning on storms offshore (but near the coast) where land-based radar has diminished capacity. Since about 30% of the U.S. population lives in coastal counties adjacent to the Atlantic, Gulf, and Pacific coasts, any improvements can positively impact a considerable portion of the U.S. population.

"The value of lightning information has been demonstrated by widespread purchases of lightning detection equipment and data from private vendors." Before the GLM became operational, lightning detection was primarily limited to cloud-to-ground detection over land. Although the National Lightning Detection Network is robust and highly capable in providing realtime lightning data over land, the GLM measurements provide a unique additional resource as viewed from above the cloud tops. The GLM data may be available to a wider audience of local athletic officials, farmers, and members of the general public engaging in outdoor activities or recreation than that of a private network. These users are less likely to have access to paid lightning network data, whereas the GLM data is made freely available. A detailed account of lightning deaths in the United States is maintained by the National Lightning Safety Council (NLSC) and the NWS. [*Jensenius 2020*] describes activities leading to deaths from lightning strikes in males ages 10 to 60, such as fishing, beach and camping recreation, boating, and yard work. Although the GLM data have only been available for about four years, its usage in this arena will only continue to grow. [*Rudlosky 2020*] described a use case where a large outdoor country music concert was underway in Alabama in June 2018. NWS forecasters were able to determine the storm was moving away from the almost 30,000 people gathered by using the GLM Flash Extent Density product, GOES-R ABI imagery and multi-radar, multi-sensor data.

F.2 GOES-R Applicability to Aviation Meteorology

Ellrod and Pryor [*Ellrod and Pryor 2019*] discuss the specific applications of GEO satellite data to aviation. "Observations are needed to discern and monitor meteorological parameters required for safe and efficient aviation operations. These are clearly needed in the terminal area of major airports and at cruise levels along flight routes, but also over wide areas to support a range of operational activities at smaller airfields and other remote locations. Helicopter air ambulance operation in remote areas, for example, represents a particular aviation weather need that creates significant forecasting challenges" [*Gultepe et.al. 2019, Sec. 2*].

Ellrod and Prior [*Ibid*] refer to the following specific applications of GEO data:

- Convective initiation: Thunderstorms can disrupt aircraft by producing enroute hazards such as hail or strong turbulence, forcing flights to reroute. This contributes to late arrivals, ground delays, and airport gridlock.

- Locating hazardous thunderstorms over oceanic areas: Avoidance of embedded convection or tropical weather systems that can cause severe turbulence or icing. SIGWX charts are issued by Area Forecast Centers or SIGMET advisories are issued by Meteorological Watch Offices such as the Aviation Weather Center (AWC). GOES data is combined with other cloud-top data and ground lightning data to create a Convective Diagnostic Oceanic (CDO) product used at the AWC.

- Lightning activity with oceanic convection: Lightning data is used in remote areas to identify thunderstorm activity. Lightning in or near tropical cyclones provides insights into whether the storm is strengthening, weakening, or at a steady state.

- Severe storm identification: Overshooting cloud tops are most often associated with heavy rainfall, as noted in ABI imagery. Rapid increases in total lightning flashes from GLM often precede severe weather activity.

- Convective microbursts: Older generations of GOES used sounder data for the nowcasting of convective storm potential. Vertical temperature and humidity profiles can be generated from the ABI and models.

- Fog and low cloud detection: Improvements in the ABI such as 2 km IR resolution and repeat scans from 1 to 5 minutes yield better detection of valley fog.

- Estimating time of clearing: Certain airports, such as San Francisco, Seattle, and Los Angeles, are prone to weather delays caused by fog. A March 2017 test comparing GOES-16 versus an older generation GOES-West satellite allowed determination that clearing would occur more rapidly with the former than the latter. The reduction in ground stop time at San Francisco International Airport (SFO) yielded a $50K saving to airlines and passengers from the reduced ground stop time.

- Estimating areas of instrument flight rules conditions: Detection of low clouds and fog are improved using GOES-R with emissivity derived from data received in two different channels.

- Upper-level clear air turbulence: “Clear air turbulence (CAT) occurs at high altitudes [6–15 km] in a nearly cloud-free atmosphere and is usually associated with vertical wind shears near the jet stream and upper-level fronts. It is one of the most common causes of accidents involving large commercial jet airliners, resulting in injuries to air crews and passengers” [*Ibid, Sec 4.4.1*] .

- Mountain waves: GOES-R imagery clearly shows mountain waves. “When moderate to strong winds blow across mountain ridges in the presence of a stable layer near the mountain tops, mountain waves occur. When moisture is present near the base of the inversion, wave cloud appearing as washboard-like patterns can be seen in imagery” [*Ibid, Sec 4.4.2*] High-wind episodes and reports of moderate to severe turbulence can occur in Colorado and Wyoming. ABI band 10 is often used to reveal mountain waves.

- <u>Volcanic ash monitoring:</u> GOES-R is well suited to identify the presence of volcanic ash clouds, where Volcanic Ash Advisory Centers issue advisories and SIGMETs to pilots in flight. "It has been estimated that volcanic ash can be present in air routes at altitudes greater than 9 km [30,000 feet] on approximately 20 days per year worldwide [*Miller and Casadevall, 2000*]. GOES-R is effective in detecting volcanic eruptions using multiple band products. For operational, real-time detection of erupting volcanoes and timely notification for aircraft in adjacent airspace, a response time of 5 min or less is desirable" [*Ellrod and Pryor, Ibid, Sec. 4.5*], Remote sensing of sulfur dioxide emitted from volcanoes also can be used to warn aircraft in flight about volcanic activity.

- <u>Aircraft icing:</u> "Aircraft icing is a significant hazard to aircraft leading to loss of performance, especially among smaller general aviation and commuter class aircraft. A GOES-R Flight Icing Threat index was developed, based on a combination of a satellite-derived icing mask, icing probability and intensity" [*Ibid, Sec. 5*].

Although not specifically called out in the Ellrod paper, the movement of smoke from wildfires and airborne ash from volcanic eruptions detected by GOES-R imagery that would impact visibility would be reported in Terminal Aerodrome Forecasts (TAFs). For example, the Denver/Boulder WFO used GOES-R imagery to track the movement of smoke from Colorado's Marshall Fire on December 30, 2021, and issued a TAF for Denver International Airport.

Examples of satellite contributions include GOES-R fog product examples such as instrument flight rules (IFR) probabilities. Figure 54 from GOES-17 on December 10, 2021, provided forecasters and Air Traffic Controllers situational awareness for fog and low stratus clouds. This image highlights regions where IFR conditions are most likely. IFR probabilities for the Pacific U.S. region are available every 5 minutes on the Space Science and Engineering Center (SSEC) RealEarth visualization tool from the University of Wisconsin-Madison.

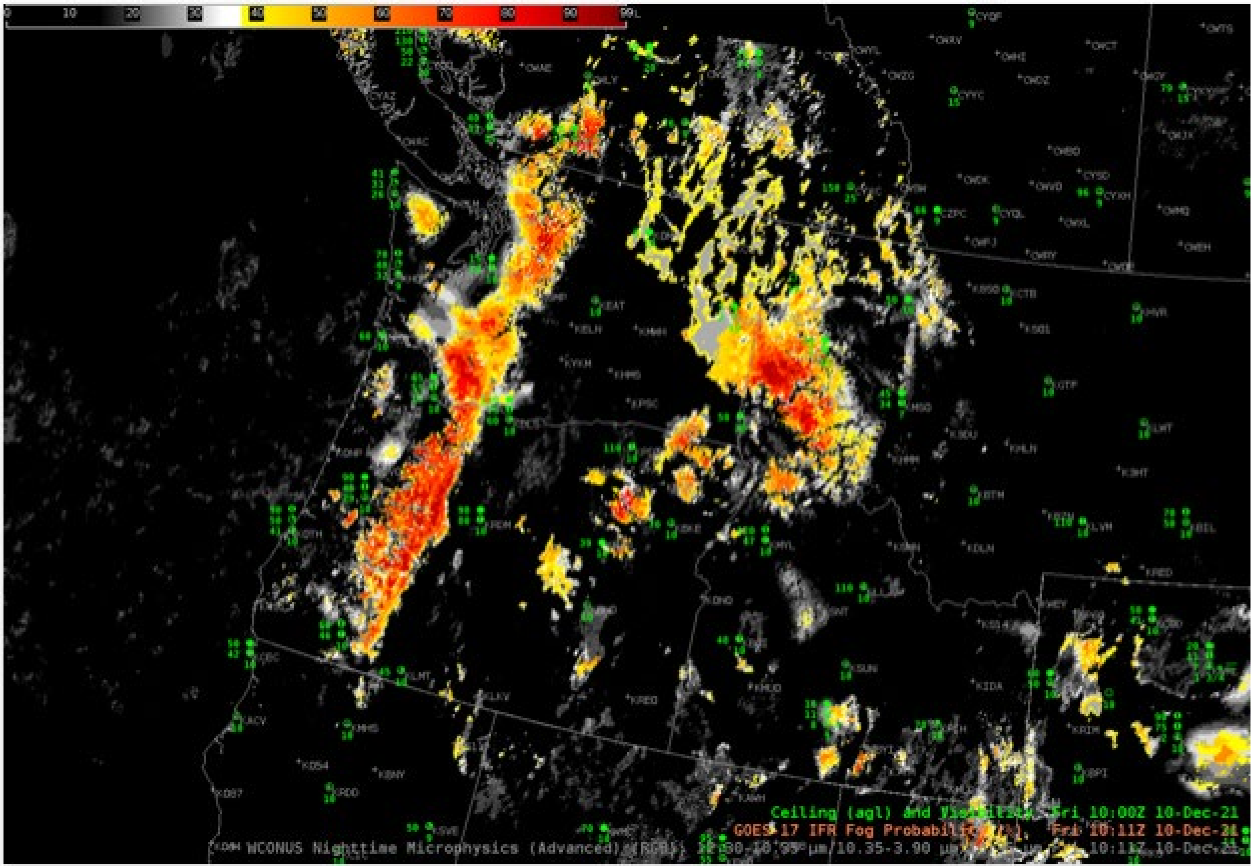

Figure 54. GOES-17 IFR probability over Pacific Northwest, December 10, 2021 (NWS/AWC).

The nighttime microphysics RGB imagery product can be used for qualitative situational awareness. In Figure 54, regions of low clouds are shown in yellow. Furthermore, high clouds to the east of Seattle and Portland are obscuring the view of low clouds in that region. For more information on both of these examples (and further discussion of fog imagery), see the CIMSS website on the internet at https://fusedfog.ssec.wisc.edu