DEMONSTRATING A NEW FLOOD OBSERVING STRATEGY ON THE NOS TESTBED

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ABSTRACT

A new observing strategy for floods was demonstrated and evaluated in a testbed environment. The strategy coordinates several observing platforms, including in situ and space based, to observe a flood from multiple vantage points and dynamically target predicted flood events with high-resolution observations. The coordinated observations were assimilated back into the model to continuously improve forecasts and future observation selection. The demonstration shows the potential for coordinated, model-driven observing strategies and the feasibility of the NOS Testbed for demonstrating and evaluating new observing strategies.

Index Terms— NOS, Floods, Distributed Observations

1. INTRODUCTION

New Observing Strategies (NOS) is a thrust area of the NASA Advanced Information Systems Technology (AIST) program within the Earth Science Technology Office [1]. It is developing technologies which will enable coordinated and dynamically targeted observations from multiple vantage points—including in-situ sensors, science satellites, and commercial smallsats—to acquire a more complete and in-depth picture of Earth system processes. The NOS testbed is an environment for developing, evaluating, and demonstrating NOS observing concepts and technologies.

The first demonstration on the NOS Testbed is an observing strategy that coordinates several platforms to observe a flood from multiple vantage points. A flood model triggers high-resolution observations from taskable commercial satellites and priority downlink processing of flood products from science satellites. The model and triggers are further informed by in situ stream gage and soil moisture sensors. All the observations are assimilated back into the model to improve its forecast for the next observing cycle.

The observing strategy was demonstrated on the NOS testbed in two modes. The first was a faster-than-real-time execution using historical data from the Midwest flood of March 2019, near Omaha, Nebraska, to simulate observations. The faster-than-real-time testbed environment facilitates demonstration and experimentation, and the historical scenario provides ground truth as a basis for evaluation. The second was in real time using interfaces to real observing platforms, which shows feasibility of that strategy in a more realistic scenario.

2. OBSERVING STRATEGY AND SCENARIO

The observing strategy coordinates in situ sensors, science satellites, commercial smallsats and a flood forecast modeling environment to improve forecasts and acquire more detailed observations of flood events. Figure 1 shows the information flow. A flood forecast model predicts where and when floods are likely to occur. An automated planner schedules taskable commercial small satellites to acquire high-resolution close-up images of the forecasted event and derives surface water extent through a machine learning algorithm. Flood forecasts confirmed by stream gauges trigger priority downlink and processing of Visible Infrared Imaging Radiometer Suite (VIIRS) flood products. The flood model assimilates the new observations—surface water extent, flood product, soil moisture, and stream gauges—and generates a new improved forecast. The observing strategy then repeats with the improved forecast. This observing strategy improves forecast skill by assimilating coordinated observations from multiple vantage points and provides high resolution estimates of peak flows.

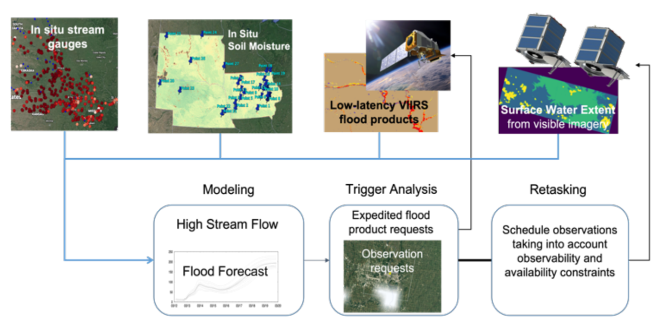

Figure 1: New observing strategy for the flood scenario

3. NOS TESTBED IMPLEMENTATION

The observing strategy was implemented in the NOS Testbed [2], which is a software environment for developing, demonstrating, and evaluating new observing strategies and technologies. The observing strategy was implemented first on the testbed in the "fast" mode for development and evaluation, and then in the real-time "slow" mode.

3.1 Testbed architecture

The testbed consists of two types of coordinating software "nodes": technology nodes implement the observing strategy, and observation nodes that are proxies for platforms, which can be a simulated or interface to real observing data.

The technology nodes for the flood observing strategy include the flood forecast model, a federated scheduler for dynamically tasking satellite observations, a ground station as a service capability that schedules and processes priority VIIRS products, upscaling of in situ soil moisture sensors, and trigger processing of stream gauge data.

Observing nodes are how the testbed interfaces to the observing platforms. For the flood scenario, these are the in-situ soil moisture sensors, in-situ stream gauges, the VIIRS products, and commercial smallsats. For the historical demonstration, the observing nodes returned archived observations. For the real-time experiment, the observing nodes interfaced with actual data sources.

The nodes communicate with each other over the NOS testbed message broker to implement the observing strategy. The architecture also provides management capabilities such as starting and stopping execution runs and setting the clock speed.

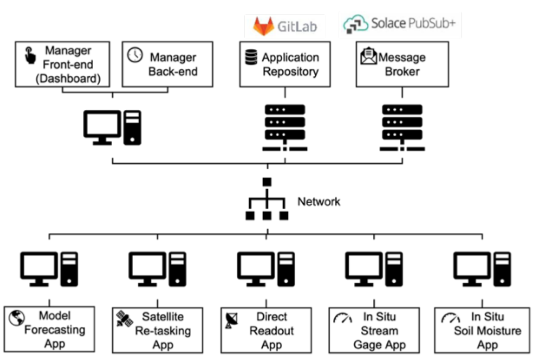

Figure 2: NOS Testbed Architecture

3.2 Flood forecast model

The forecast model node generates forecasts of where flooding is expected over the next several days. Locations where flooding is expected to be particularly high are called *triggers*. These are locations and times where the forecast exceeds the seasonally expected baseline by a pre-specified threshold with high confidence. The model sends these triggers to the planning node to schedule high resolution close-up observations of those locations and times. Surface water extent is derived from the high-resolution images and assimilated back into the model, along with other satellite and in situ observations. The model then generates an improved forecast for the next set of observations.

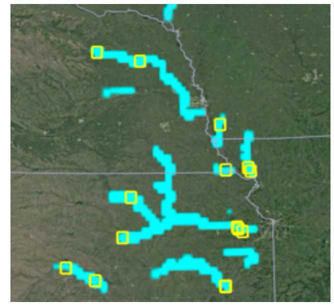

Figure 3: Planned observations (yellow) are selected from the forecasted triggers (teal) to maximize utility while meeting constraints and considering contention.

The implementation is enabled by the NASA Land Information System (LIS) [3]. Within LIS, the Noah-MP land surface model and the HyMAP river routing model [4] are driven by observation-informed surface meteorology to generate ensemble flood forecasts.

The forecasts are converted to triggers. The forecasted water extent and depth in each grid cell is compared to the expected distribution as derived from a climatology baseline. Values above the 90% threshold are flagged as triggers. Triggers can be augmented with a confidence value based on the number of forecast ensemble member that agree the forecast will be above the threshold.

3.3 Federated planner for dynamic satellite tasking

The planning node schedules taskable commercial smallsats to acquire high-resolution close-up images of the forecasted flood peaks. The node builds on prior work on directing satellite measurements based on alerts to track flooding [5] and volcanic activity [6]. The triggers indicate the expected times and locations of flood peaks and the estimated utility of acquiring that observation. The utility is the severity, as estimated by how far it exceeds the expected threshold. There are typically more triggers than can be observed. This may be due to factors such as the satellite not being in position, committed to another customer, and cost constraints. The planner considers several satellites and schedules a set of observations that maximizes the utility while meeting the constraints as shown in Figure 3.

Satellites may not always fulfill an observation request. It may get 'bumped' in favor of a higher priority observation, or there may be operational conflicts (clouds, faults, etc.). The federated planner reasons about this possibility [7]. It models the probability that a request will be satisfied based on expected contention for a given observation. It weights the requests accordingly to maximize utility (e.g., prefer higher utility observations that are most likely to be satisfied).

For the demonstration scenario, the taskable smallsats were simulated Planet Skysat satellites. These acquire optical panchromatic images at 0.86 m resolution and can be pointed off nadir [8]. Historical SkySat images were not available for the period of the flood event, so the observations were simulated with lower resolution Dove imagery but using SkySat pointing and overflight specifications. Surface water extent is derived from the images as shown in Figure 4 and sent to the model for assimilation.

3.4 Upscaled in situ soil moisture measurements

The soil moisture node monitors in situ sensors and upscales them to a gridded product so it can be assimilated into the land surface model of the NASA Land Information System (LIS). Antecedent soil moisture is an important factor for flood forecasts (intuitively, water soaks into dry soils but runs off saturated soils).

The in situ soil moisture data are obtained from hourly U.S. Climate Reference Network (USCRN) [9] sensors located throughout the Mississippi Basin. In situ sensors provide very high temporal and spatial resolution data with sparse coverage that complement remote sensing products that are coarser and less frequent but have wider extent.

The node upscales the in situ point data to a 100m gridded product. A Random Forest regression algorithm combines the point data with ancillary data such as texture, topography, precipitation, and temperature to estimate the maximum likelihood values for each grid cell [10]. The node sends daily upscaled products to the modeling node for assimilation.

This approach shows how in situ sensing data can inform forecast models as part of a coordinated observing strategy. A similar approach could be used for other in situ sensors.

3.5 In Situ stream gauge alerts

This node monitors USGS National Water Information System (NWIS) stream gauges [11] and sends trigger alerts when it detects flows above a climatology baseline. USGS has a dense network of in situ sensors across the US river network that provides data in real time. The node monitors this feed at 15-minute intervals looking for gauges that are above the statistically expected values. The threshold is a configurable parameter and is set by default to trigger on values above the 75% confidence interval. The triggers are sent to the ground station node to trigger priority flood product downlink and processing.

3.6 Ground station as a service: low-latency products

Surface water extent products from the VIIRS instrument provide daily data over a 3000 km-wide swath at 375 meter resolution. Latencies can be reduced from 3 hours to 20 minutes by downlinking direct broadcast signals through a commercial ground station and immediately processing the data in the cloud [12]. Lower latencies allow the product to be assimilated sooner into the model so that targeted observations are selected with the most recent information.

The low-latency product generation is triggered only when floods are expected to minimize resource costs. The flood forecast triggers scheduling of a future overpass downlink on an Amazon Web Services (AWS) ground station. If in situ stream gauges confirm flood conditions immediately before the pass, it is executed. Otherwise, it is canceled at no cost. The data is processed in the cloud to generate the standard flood product.

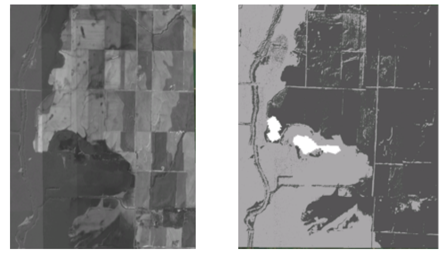

Figure 4: Surface water extent (R, white) is derived from the dynamically targeted high-resolution image (L). Raw image courtesy Planet labs.

Event-triggered priority processing is a capability that could be relevant to other observing strategies where low latency data are important for assimilation and forecasting (e.g., weather), and for targeted observations in rapidly evolving phenomena where the most up to date information is critical to selecting high value observations.

4. HISTORICAL AND REAL-TIME SCENARIOS

The observing strategy was implemented first on the testbed in “fast” mode using historical data to simulate observations and running faster than real time to facilitate development, evaluation and demonstration. The scenario used remote sensing and in situ data from a flood of the US Midwest that occurred in March of 2019. The historical data provided ground truth for evaluation. Using simulated observations simplifies implementation and allows for future platforms.

The strategy was then implemented in “slow” mode: running in real time with interfaces to real platforms. The observation nodes for the in situ sensors interfaced with online data feeds for existing sensor networks. The low-latency node downlinked direct broadcast data from VIIRS through an AWS ground station and processed the data in the cloud. The planning node requested observations from SkySat using their public tasking interface. For demonstration purposes, a focusing element was added to restrict the system to a particular region (a lat/lon box) and limit the number of observations.

The system ran for several weeks in late Fall. The model predicted a flood event near the Texas coast and acquired an image. Though it was too cloudy to extract surface water extent, it did demonstrate the system working. The weather turned dry and cold before we could acquire more images.

5. ANALYSIS OF RESULTS

The observing strategy was evaluated experimentally in the NOS Testbed against the historical flood scenario. The scenario began March 14. Each simulated day the model forecast floods for the next four days and requested new observations. Assimilating those observations improved the accuracy of the next four-day forecast by 30% for a one-day

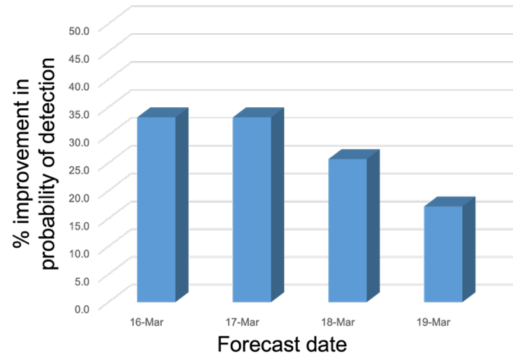

Figure 5: Skill improvement of a four-day forecast, started on March 15, that assimilated NOS observations vs a baseline that omits them. Assimilating NOS observations improved one-day lead skill by 30%.

lead and 15% for a four-day lead (Figure 5). The forecast skill was determined by comparing it to the historical ground truth, which was available to analysts but not to the NOS system. The model skill improvement was determined by comparing the forecast with NOS observations to a baseline forecast run made without those observations.

The NOS Testbed enabled this evaluation approach through its ability to execute different observing strategies (baseline and NOS) under the same conditions, and knowledge of historical ground truth. The same approach could be taken to evaluate other concepts and component technologies and shows feasibility of the NOS Testbed for evaluating observing strategies.

6. CONCLUSIONS

This is a first demonstration of a new observing strategy in the NOS Testbed. The strategy coordinates several observing platforms—science satellites, commercial smallsats, and in situ sensors—to create a more comprehensive picture of a flood event. A forecast model predicts when flood events will occur, which triggers high resolution observations of flood peaks as well as priority downlink processing of flood products. The coordinated observations improve the model forecast skill as well as providing targeted observations from multiple vantage points. This demonstrated feasibility of the NOS testbed for developing, demonstrating, and evaluating new observing strategies and the potential for coordinated, model-driven observing strategies.

7. ACKNOWLEDGEMENTS

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