INTEGRATION OF GNSS-R DERIVED SOIL MOISTURE INTO THE USGS WILDLAND FIRE POTENTIAL INDEX

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***Abstract*—Observations of soil moisture have been found to improve predictions of fire danger as soil moisture impacts both fuel load and fuel moisture. A relative soil moisture process was developed and integrated into the USGS Wildland Fire Potential Index data products. The process uses soil moisture estimates from the CYGNSS GNSS-R constellation and compares current to historical values which then modifies the fuel moisture term in the WFPI equations. Comparisons of WFPI with the soil moisture enhanced version over known large fire events indicate a potential improvement in predicting large fire probability. The goal of this process is to identify areas prone to large fire activity that can be used to target additional CYGNSS observations to assist with wildfire monitoring.**

Keywords—fire danger, GNSS-R, CYGNSS, soil moisture, fuel moisture

I. INTRODUCTION

Fire danger is defined by the U.S. National Wildfire Coordinating Group as the sum of constant and variable danger factors affecting the inception, spread, and resistance to control of, and subsequent damage by a wildland fire [1]. Predicting fire danger has become increasingly important for strategic planning of wildfire mitigation actions and preparation of tactical wildfire response resources based on the level of risk occurring in a given time and place. Several local and national level indices and tools are available to predict fire danger over shorter to longer terms, all with their own strengths and limitations. The U.S National Fire Danger Rating System is calculated daily at specific point locations to represent conditions within a fire danger rating area [2,3]. The U.S. National Interagency Predictive Services group provides daily 7-day outlooks and monthly outlooks for the next 4 months describing significant fire potential for predefined areas across the U.S [4]. Yu et al. [5] reviews four fire danger indices and compares the relationship between them and observed wildfire data, along with sensitivity to various weather and fuel variables. As newer remote sensing data sources become available, and additional data processing capabilities evolve, there are opportunities to enhance current fire danger prediction algorithms to improve the ability to forecast potential wildfire activity.

The Distributed Spacecraft with Heuristic Intelligence to Enable Logistical Decisions (D-SHIELD) project has developed a framework for determining optimal data observation and delivery from a satellite constellation with sufficient responsiveness to meet specific scientific objectives [6]. This framework is being adapted to utilize the CYGNSS mission constellation for providing Global Navigation Satellite System Reflectometry (GNSS-R) data that can be used for wildfire monitoring. Multiple products are being developed for this project, including maps of burned area, joint retrieval of soil moisture and vegetation water content, and live fuel moisture. An additional component of this project is the integration of GNSS-R derived soil moisture with a fire danger forecast algorithm.

II. BACKGROUND

The U.S. Geological Survey provides daily 7-day forecasts of the potential for large wildfire occurrence across the conterminous United States. These forecasts are based on the Wildland Fire Potential Index (WFPI) which combines estimates of vegetation greenness, fuel moisture, and predicted weather conditions [7]. WFPI is essentially a combined ratio of “deadness” or what proportion of vegetation is live or dead and “dryness” or how flammable is the vegetation, with adjustments made for the effects of predicted weather

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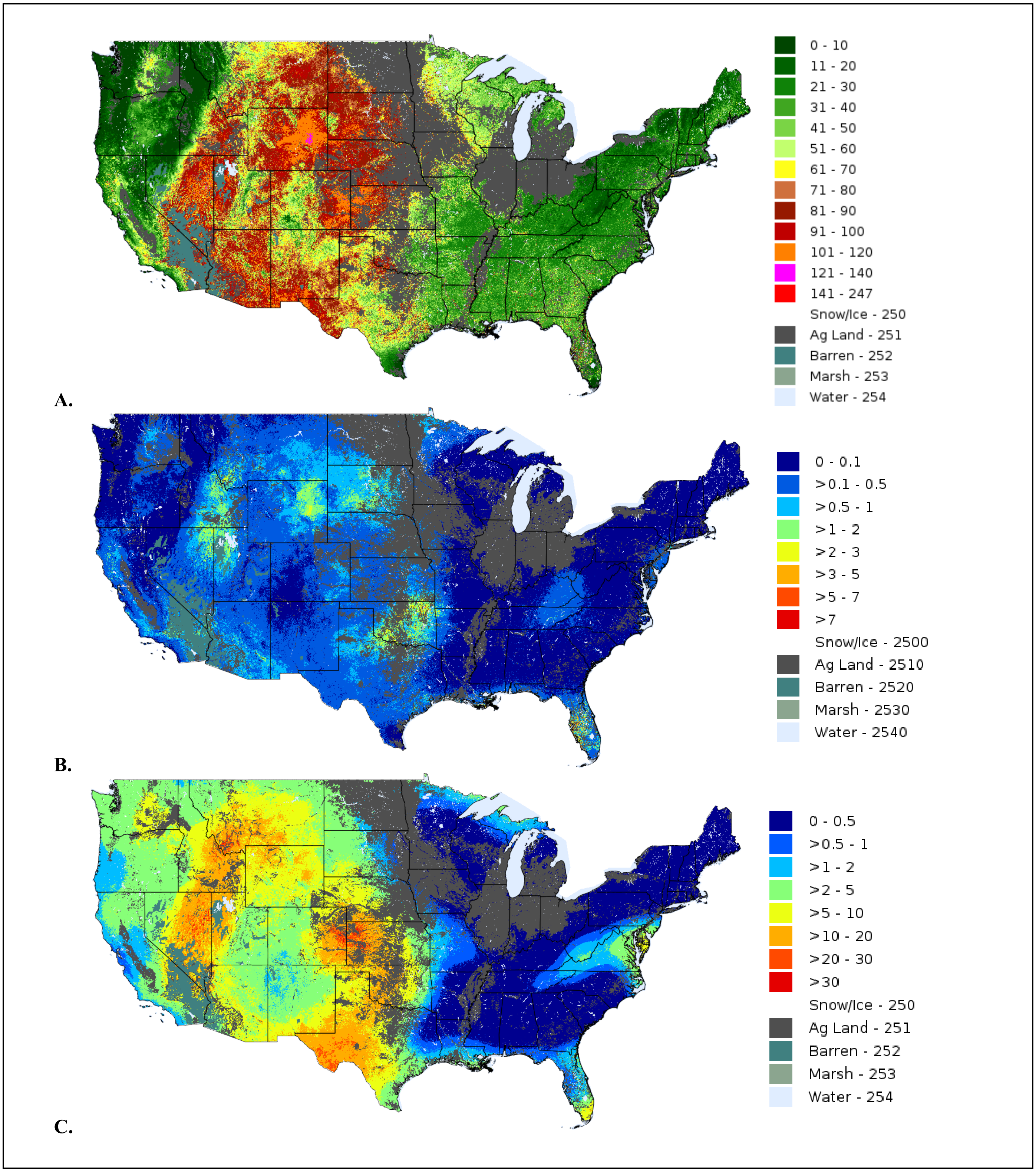

Figure 1- Example Fire Danger Forecast products for October 16, 2024: A. WFPI; B. WLFP; and C. WFSP

conditions. As WFPI values increase, the occurrence of large wildfires, defined as those greater than 202 ha (500 ac), is projected to also increase. This relationship has been demonstrated against historical fire occurrence data [7,8] and WFPI products are used operationally by land management agencies and infrastructure companies to assist with planning wildfire prevention, mitigation, and response activities. Two additional products are derived from the WFPI, the WFPI-based Large Fire Potential (WLFP) and WFPI-based Fire Spread Potential (WFSP). The WLFP estimates the probability that a large fire will occur in a specific location at a specific time and incorporates historical fire activity patterns that are statistically modified by forecasted WFPI values. The WFSP is the probability that an existing fire ignition will escape initial attack and become a large fire and is based on statistical relationships between historical ignitions data and WFPI. All three products are available online with archived data back to 2001 [7,9]; an example of each product is show in Fig. 1.

Previous studies have demonstrated linkages between soil moisture and both live and dead fuel moisture. As soil moisture decreases, so does the available moisture for vegetation affecting fuel load, fuel moisture, and ultimately fire danger [10,11]. Currently, operational WFPI products do not consider soil moisture, rather they incorporate vegetation greenness estimated from VIIRS imagery and 10-hr dead fuel moisture calculated from weather observations. With the availability of soil moisture data from newer sources, including CYGNSS, these data can be integrated into operational fire danger mapping algorithms.

III. METHODS

To integrate soil moisture into the WFPI process, a new term was defined representing the *relative soil moisture (RSM)*, or how current soil moisture relates to a historical range of soil moisture values for each location and time. Soil moisture data were acquired from both CYGNSS and Soil Moisture Active Passive (SMAP) missions for the time period spanning 2015 – 2024 over the conterminous United States below 35 degrees latitude, corresponding to the geographic availability of CYGNSS data. For each day of year, the mean soil moisture value across this period was calculated for each 1-km pixel, matching the spatial resolution of the WFPI products. The RSM term was then calculated for each pixel, for each day of year using:

$$RSM = (SM - SM_{avg}) / SM_{avg} * 100$$

where SM is the currently observed soil moisture from CYGNSS and SM_{avg} is the historical average for the corresponding day of year and location.

The RSM is then used as a modifier to the fuel moisture term in the WFPI calculations. This is consistent with how other terms are integrated in the WFPI calculations which includes fuel moisture modifiers for temperature and precipitation and similar to how the relative vegetation greenness is calculated [12]. The RSM term is incorporated using:

$$FM_{10} = FM_{10} + (\arctan(RSM) * (2 / pi) * FM_{ext})$$

where FM_{10} is the 10-hour timelag class dead fuel moisture, and FM_{ext} is the moisture of extinction for the fuel model defined in the corresponding pixel. The effect of this modifier is to increase fuel moisture up to the moisture of extinction as RSM reaches 100% and reduces fuel moisture to a 2% minimum value as RSM approaches -100%. The enhanced WFPI, termed WFPI-x, is then used in subsequent calculations to produce WLFP-x and WFSP-x.

Testing of operational WFPI-x, WLFP-x, and WFSP-x processes is ongoing utilizing CYGNSS Level 3 soil moisture version 3.2 which provides daily soil moisture retrievals gridded to 9-km spatial resolution [13]. The data are resampled to 1-km resolution to match the WFPI products.

IV. RESULTS

Daily WFPI-x was calculated for the period 2018-2022 using CYGNSS soil moisture inputs. The WFPI-x values were then compared against the operational WFPI values from the USGS Fire Danger Forecast data archive. Differences between the two products were summarized over areas with known large fire activity as derived from the Monitoring Trends in Burn Severity (MTBS) program [14] for the date of ignition. The MTBS database contains 1,591 fires, encompassing 2.3 million ha (5.7 million ac) that overlapped with the WFPI-x test data. The differences between WFPI and WFPI-x were separated between wildfires and prescribed fires. Initial comparisons showed a small negative bias across all known fires (Fig. 2). It is often observed, however, that the largest growth periods for many wildfires do not necessarily occur on the date of ignition. Therefore, time series' of WFPI and WFPI-x were extracted for each known large fire encompassing the periods between fire ignition and containment. Summaries of the time series showed a more positive bias in the wildfire data with a slightly negative bias in the prescribed fire data (Fig. 3).

V. DISCUSSION

The comparison results between WFPI and WFPI-x over known large fire locations indicate a generally small shift in fire danger index values when integrating RSM, indicating overall stability in the fire danger model as implemented. The lower average WFPI-x values over known large fires on the date of ignition matches general observations of the largest fire growth days often being later than the date of ignition. The increased average WFPI-x values when incorporating time series data indicate the fire danger is being forecasted to increase over time when large fire growth is occurring. Newly available historical fire progression data from the National Interagency Fire Center may be useful in identifying specific dates of large growth, enabling a more targeted validation of the effect of RSM integration on WFPI forecast values for those time periods.

Conversely, over known large, prescribed fire locations, the lower average WFPI-x values are reasonable because prescribed fires are generally conducted under specific conditions and generally much shorter timeframes that allow low to moderate fire activity to achieve desired fire effects while limiting the risk of escape. Therefore, optimal prescribed

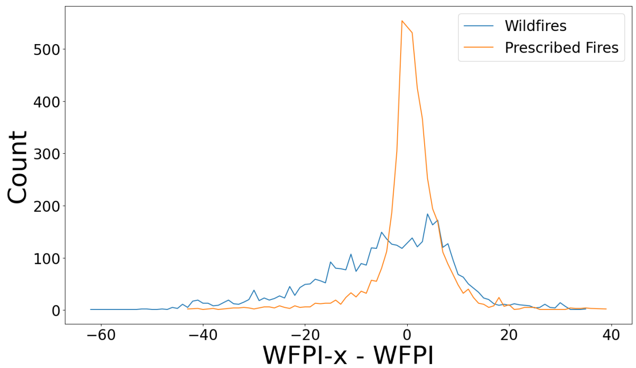

Figure 2- Differences between WFPI-x and WFPI for known large fire locations on date of ignition.

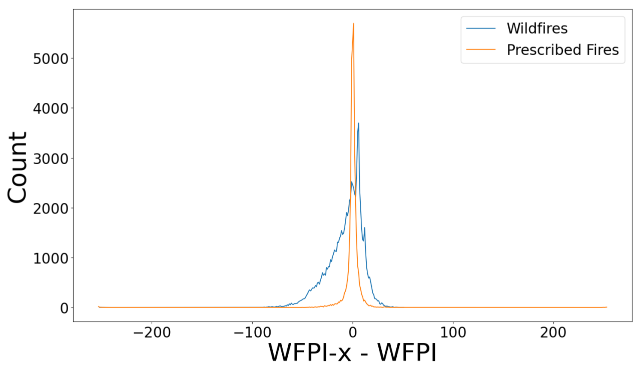

Figure 3- Differences between WFPI-x and WFPI for known large fire locations across all dates of fire activity.

fire conditions would generally not be associated with increased WFPI-x values as higher potential for large fire growth would likely exceed the prescription conditions.

VI. Conclusions

Preliminary results of integrating CYGNSS soil moisture observations into the USGS Fire Danger Forecast products indicate reasonable shifts in the product values that may be useful for operational incorporation to improve predictions of fire danger. Next steps in development of this process are to: further characterize WFPI-x performance using fire progression data; evaluate WLFP-x and WFSP-x against historical fire occurrence and ignition records; and implement a near real-time prototype system for producing these products with operational CYGNSS soil moisture data. The outputs from this prototype system can then be used as inputs back into the D-SHIELD planner to identify areas of high fire danger and large fire probability, increasing the value of observations across the constellation in those areas.

VII. ACKNOWLEDGMENTS

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