SMAP Science and Application Results

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***Abstract*—Science and application results appearing in peer-reviewed journal papers in 2021 are highlighted in this paper. With over six years of science data acquisition, science data products of the NASA Soil Moisture Active Passive (SMAP) satellite project are now being applied in diverse subdisciplines in Earth System science. In 2021, there were close to two-hundred papers appearing in peer-reviewed disciplinary journals. In this paper we highlight a few of the research and applications findings that were reported in the calendar year.**

***Index Terms*—Soil Moisture Active Passive, SMAP, Earth Remote Sensing**

I. Hydrology, Hydrologic Processes and the Global Water Cycle

Hitherto unavailable monitoring of landscape soil moisture at global scale, the state-variable of surface water balance, has hindered constraining models used for science and applications. SMAP-based estimates have improved water balance closure [1], [2] and allowed mapping of evaporation [3], [4], drainage [5] and streamflow [6], [7]. Beyond the surface soil moisture, SMAP measurements provide constraints on the estimation of deeper root-zone soil moisture [8], [9] and depth of shallow groundwater [10], [11]. The statistical memory of soil moisture is also applicable to short-term hydrologic predictions [12], [13].

II. Global Ecology: The Microwave Vegetation Optical Depth (VOD) as a New Observation

During 2021, the baseline SMAP surface soil moisture retrieval algorithm switched from the Single-Channel-V-Pol to the Dual-Channel Algorithm (DCA) that estimates the surface soil moisture and microwave optical depth simultaneously (see Fig. 1) [14]. Developments and refinements of DCA has been an active area of research and the use of both H- and V-pol SMAP brightness temperatures adds more constraint to the inversion [15]–[17]. Global ecology and the research into the role of water-limitation on vegetation and the carbon cycle are increasingly adding VOD to their suite of ecological observables. VOD across frequencies is an emerging area of investigation and may both extend the coverage as well as information content on water movement in the soil-vegetation-atmosphere continuum [18]–[21]. A key question is the detection of rehydration versus growth which has implications for land carbon source/sink [22], [23].

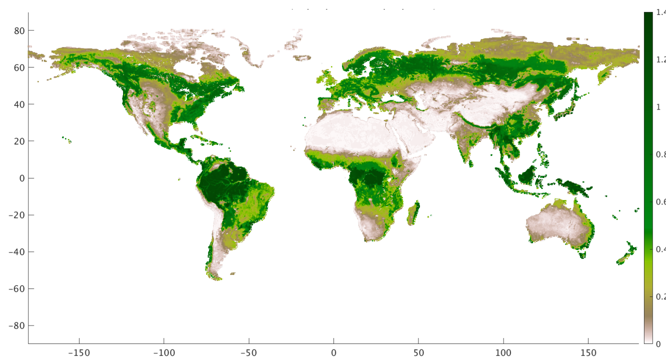

Fig. 1. The climatological map (April 1, 2015 to March 31, 2020) of the SMAP microwave Vegetation Optical Depth (VOD). This variable represents the extinction of surface emission at the SMAP 40 degrees look-angle and it is related to the integrated water content in the path. It represents the water content of the vegetation or crop canopy. Graphic courtesy of M. J. Chaubell at JPL/CalTech .

III. Ocean Sciences: Sea Surface Salinity and Surface Winds

SMAP polarimetric brightness temperature measurements over the oceans have proven to have the precision to allow Sea Surface Salinity (SSS) mapping [24], The SMAP-derived dynamic SSS fields have led to detection of cross-shore river plumes and regions of strong upwelling [25]. The importance of river freshwater runoff into the oceans is now evident with SMAP brightness temperature information [26]–[28]. Regional dynamics of ocean currents are discernable: Gulf of Maine currents in [29], mesoscale eddies and transport in circumpolar currents [30], [31], vertical mixing in response to tropical cyclones [32], and ENSO salinity signatures in [33].

IV. Cryospheric Applications

The expanse and remoteness of land cryosphere limits the availability of in situ monitoring networks. SMAP land and ice freeze and melt estimates are used to enhance this coverage and in fact allow dynamic mapping. The timing and spatial extent of unusual melting episodes in the Greenland ice sheets have been detected [34]. In the critical and sensitive Third Pole region in the high plateaus of Asia [35] and elsewhere [36], SMAP land freeze/thaw classifications allow tracking of year-to-year changes.

V. Multi-Source Data Fusion and Downscaling to Finer Resolution Products

The baseline SMAP surface soil moisture product has been shown to outperform reanalysis estimates and open loop models as well as other satellite products, when compared to over 800 in situ sensors world-wide [37]. There is nevertheless the need to identify smaller scale landscape features than is possible with L-band radiometery alone. The topic of spatial disaggregation to finer resolutions (km and sub-km) remains an active area of research and development. Machine Learning techniques are increasingly used to merge SMAP brightness temperature and standard geophysical products with other sources of higher-resolution information. A key finding is that surface micrometeorological data and static landscape characteristics (e.g., terrain, slopes, aspect, vegetation, soil texture) are valuable sources of information on how soil moisture fields vary around the near-mean value captured by L-band radiometry [38]–[43]. Examples on the merger of SMAP and higher resolution satellite information in order to produce km and sub-km surface soil moisture include the use of thermal inertia [44], [45], visible and incident shortwave radiation [46], and land surface temperature [47]–[51]. The land surface temperature-vegetation index, the so-called Triangle Method for surface soil moisture and evaporation water stress, has a long history due to the early availability of high-resolution optical and infrared remote sensing measurements. Application of the Triangle Method and its comparison with various microwave-based products show that the SMAP estimates are linked most closely [52].

Soil texture classifications based on ground samples are known to be a major source of error in hydrologic modeling and forecasting. Weighted averages of point-samples of soil hydraulic properties do not necessarily scale to represent the effective properties when applied to large areas represented by pixel units within hydrologic and climate models. Effective soil texture information has been deduced from SMAP measurements by model calibration and show to improve the predictive skill of land surface models [53].

The SMAP active-passive product for higher resolution soil moisture currently uses the Copernicus Program Sentinel-1 series of global C-band radar measurements. Other sources of C-band radar information, such as RISAT-I [54] and RADARSAT-2 [55], are now being explored for development of high-resolution active-passive surface moisture products. The NASA-ISRO NISAR L-band SAR mission is scheduled to be launched in early 2023 and it is expected to enhance the coverage and accuracy of active-passive products to regions with greater vegetation density.

VI. Applications and Applied Sciences

Mapped information on surface soil moisture is expected to have an impact on applications with societal benefit that currently rely on modeled estimates of soil moisture. These include drought monitoring and flood prediction which, for decades, have been operational but rely on soil moisture estimates from water balance accounting (precipitation inputs and parameterized evaporation and drainage extractions). The transition of data products from research projects such as SMAP to the operational domain is challenging because: 1) the impact of the data on the models is largely unknown, and 2) the continuity of the data stream in the long-term is not guaranteed. Nevertheless the SMAP Project and the user community are actively working on removing the obstacles. Research demonstrations of application value and applied science uses of the science data products are key steps that need to be taken. For example, the combination of SMAP and Landsat remote sensing measurements are used to map flood inundation, especially in areas without ground sampling [56]. The high-resolution SMAP-Sentinel-1 active-passive product is used to detect irrigation areas at 1 km resolution [57]. The larger irrigation areas are detectable using the radiometer-only SMAP products [58], [59].

Other application areas where the assimilation of SMAP products have been used to support and improve natural hazards include: lower-atmosphere ozone concentration (human and crop health hazards) predictions [60], crop water stress [61]–[63], heat stress and flash droughts [64], wildfire fuel assessments [65]–[67], and landslides [68], [69].

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