OBSERVING FREEZE-THAW TRANSITIONS OVER LAND USING CYGNSS MEASUREMENTS

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ABSTRACT

Measuring freeze-thaw (F/T) changes over land plays a crucial role in various climate, ecological and hydrological processes. Active and passive microwave measurements of land surface have shown a potential to monitor land surface F/T conditions. Especially at L-band, the measurements have previously been shown to be effective in estimating soil freeze-thaw. In this work we plan to look at the GNSS-R reflections over land, captured by the CYGNSS observatories, for this purpose. Though CYGNSS constellation was initially developed for ocean surface roughness measurements, it has shown sensitivity to changes in soil moisture over land, thereby making it a potential candidate for observing freeze-thaw transitions as well. We plan to look for changes in signal SNR during Freeze-thaw transitions due to the changes in the dielectric property of the surface during those events and develop machine learning based empirical regression models to understand the relationship between F/T events and GNSS-R reflections.

Index Terms— CYGNSS, Freeze-thaw, GNSS-R, machine learning

1. INTRODUCTION

About 20% of the Earth's land surface has permafrost or seasonal frost [1]. This has a significant impact on many climate, ecological and hydrological processes [2-4]. Hence, observing F/T events play a pivotal role in better modelling and prediction of the Earth's climate [5-6]. F/T events are highly heterogenous in space and time and detecting and quantifying these rapidly changing processes at large scales requires the help of remote sensing platforms. Microwave remote sensing using radiometers and radars, has shown capabilities over the past several decades of providing information about various land properties such as soil moisture, heat fluxes, F/T states etc. [7-10]. However, these measurements are heavily constrained by very coarse spatial and temporal resolutions.

The relatively recent era of spaceborne Global Navigation Satellite System Reflectometry (GNSS-R) systems operating at L-band have shown an encouraging potential in measuring land surface properties [11-15]. Combining the benefits of all day-all weather capability of GPS L-band signals with rapid revisit capacity of LEO small satellite constellations will form an ideal concoction for F/T measurements.

The Cyclone Global Navigation Satellite System (CYGNSS) is NASA's Global Navigation Satellite System reflectometry (GNSS-R) constellation mission. CYGNSS has a good temporal frequency for studying fast evolving phenomena such as hurricanes by utilizing 8 micro satellites that are equally spaced around a 520 km circular orbit inclined at 35 degrees. This sampling capability is useful to study land processes as well, such as soil moisture measurements, flood/drought monitoring etc. The spacecrafts carry radar receivers tuned to measure Global Positioning System (GPS) L1 signals at 1.575 GHz scattered from the Earth's surface in the forward (specular) direction. The reflected GPS signals captured by the radar receivers onboard the satellites are mapped onto the Delay-Doppler space and are called the Delay-Doppler Maps (DDMs)[16]. These DDMs have shown to be sensitive to changes in surface roughness and dielectric properties [17-18].

The main objective of this paper is to develop a F/T detection algorithm for GNSS-R measurements by CYGNSS with the help of machine learning techniques. This paper is organized as follows: Section 2 describes the datasets used for this analysis; Section 3 briefly discusses the planned strategy for developing F/T detection algorithms for CYGNSS measurements and finally the paper concludes with a summary and next step in this direction.

2. DATA DESCRIPTION

In this analysis we will be using the CYGNSS science quality v3.1 land data for the year 2019. This dataset contains global measurements from all 8 CYGNSS observatories for 365 days. However, for the purposes of F/T transitions we will be focusing on select regions in the United States within 38 deg latitude. The CYGNSS Level 1 data contains the received signal power DDMs. In general, land surfaces exhibit a diverse distribution of reflecting surfaces and therefore the choice between assuming coherent or incoherent processing of this DDM depends on ancillary information about the surface (topography, inland water bodies etc.). For an incoherent scattering surface, we will use the Normalised Bistatic Radar Cross Section (NBRCS) and for a coherent scattering surface we shall be using the surface reflectivity as

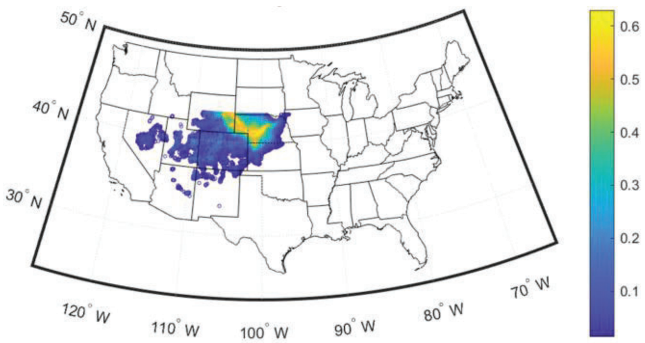

Fig. 1. Sample reference map of F/T events detected on 14th April 2019. Colorbar indicates the strength of the F/T event.

the measurement parameters. The CYGNSS data are filtered for stringent quality measures and only those data with high antenna gain (> 5dB) will be used for this application.

The CYGNSS measurements will be gridded and matched to certain key variables for detecting F/T events in the ERA5-Land reanalysis dataset. The ERA5-Land is a reanalysis dataset providing a consistent view of the evolution of land variables over several decades at an enhanced resolution [19]. The horizontal resolution is 0.1 x 0.1 deg, and the temporal resolution is hourly. We plan to use 5 land variables - temperature of air 2m above the land surface, skin temperature of the Earth and soil temperature at 3 different levels (0-7 cms, 7-28 cms, 28-100 cms).

3. PROPOSED METHODOLOGY

The location of CYGNSS measurements on the surface is dependent on the location of the GPS satellite and the CYGNSS observatory. Therefore, the measurements are randomly distributed on the surface. As the first step in data processing, we grid the CYGNSS data into regular grid cells using an appropriate interpolation algorithm. The grids will be finer than the horizontal grid resolution of ERA5- Land dataset, to utilize the information from the random sampling by CYGNSS. This gridded CYGNSS land measurement dataset will then be matched to the ERA5-Land variables. Next, to train the machine learning algorithms, we develop reference maps for F/T transitions by defining the freeze and thaw events as a function of time and temperature of the surface. These reference maps are F/T transition scores with a dynamic range from -1 to 1. The score definitions are given below.

FS= fraction of last 72 hr when surface temperature < -3^o C)
TS = fraction of next 72 hr when surface temperature > $+3^o$ C)
FT = (FS – 0.5) + (TS – 0.5) (1)

Here, FS, the freeze score, is the fraction of time during the 72 hr period prior to the time of interest when the surface temperature is less than -3^o C and TS, the thaw score, is the fraction of time during the 72 hr period after the time of interest when the surface temperature is greater than $+3^o$ C. FT, the freeze-thaw transition score, combines both FS and TS to produce a measure of the likelihood of occurrence of a F/T transition event. When FT is > 0, an F/T event is said to have occurred and not otherwise. The positive magnitude of the FT score defines the likelihood of an F/T event. Such a smooth varying score will help train the machine learning algorithms to better capture the F/T events unlike the commonly used binary classification methods. Fig. 1 gives an example of this FT score map on one day of the winter to spring transition period in the western plains of the US.

FS is measured for a 72 hr window in the past and TS is measured for a 72 hr window in the future, relative to the time of interest. If the temperature during the previous 72 hr is less than -3^o C for more than half of the time and the temperature during the following 72 hr is greater than 3^o C for more than half of the time, then the FT score will be greater than 0. For the limiting case when previous temperatures are always less than -3^o C and following temperatures are always greater than 3^o C, the FT score will be at its maximum value of 1.

As the final step in developing the detection algorithm, we plan to train and assess the performance of different machine learning techniques over this dataset to identify the best choice for this application. We plan to use several figures of merit such a Root Mean Squared Difference (RMSD), probability of detection, false alarm rates etc. to evaluate its performance. We also plan to compare the results with other satellite observations like SMAP to assess the detection ability.

4. SUMMARY

In this work we have discussed a plan to attempt at developing a machine learning based regression model for F/T estimation from GNSS-R measurements made by the CYGNSS mission. Firstly, we plan to interpolate the CYGNSS measurements to a uniform grid and match it to 5 essential F/T parameters from the ERA5-Land reanalysis dataset; namely, temperature of air at 2m above the land surface, skin temperature of the Earth, and temperature of soil at 3 different levels (0-7 cm, 7-28 cm, 28-100 cm). Next, we will develop “ground truths” for F/T transitions by setting the definition of freeze and thaw as a function of soil temperature and time. Next, we will train different machine learning algorithms over this dataset to understand the dependence of GNSS-R signals on the various parameters listed above, to detect a F/T event. Finally, we will characterize the algorithm performance and error characterization based on different figures of merit such as RMSD, probability of detection, false alarm rates etc. As the future steps in this direction, we are also interested in classifying F/T states for different soil types.

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