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ESTIMATING LIVE FUEL MOISTURE IN SOUTHERN CALIFORNIA USING REMOTE SENSING VEGETATION WATER CONTENT PROXIES

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ABSTRACT

Wildfires are a major ecological disturbance in Southern California and often lead to great destruction along the Wildland-Urban Interface. Live fuel moisture has been used as an important indicator of wildfire risk in measurements of vegetation water content. However, the limited field measurements of live fuel moisture in both time and space have affected the accuracy of wildfire risk estimations. Traditional estimation of live fuel moisture using remote sensing data was based on vegetation indices, indirect proxies of vegetation water content and subject to influence from weather conditions. In this study, we investigated the feasibility of estimating live fuel moisture using vegetation indices, Soil Moisture Active Passive L-band soil moisture data and the modeled vegetation water content using a non-linear model based on VIs and the stem factor associated with remote sensing moisture data products. The stem factor describes the peak amount of water residing in stems of plants and varies by land cover. We also compared the outcomes from regression models and recurrent neural network using the same independent variables. We found the modeled vegetation water content outperformed vegetation indices and the L-band soil moisture observations, suggesting a non-linear relationship between live fuel moisture and the remotely sensed vegetation signatures. We discuss our results which will improve the predictability of live fuel moisture.

Index Terms— Wildfire, live fuel moisture, SMAP, soil moisture, vegetation water content, remote sensing, recurrent neural network, Southern California

1. INTRODUCTION

The wildfire phenomenon is a prominent disturbance to the Mediterranean ecosystems and a major natural disaster along the Wildland-Urban Interface (WUI) in Southwestern U.S. and particularly in Southern California, one of the largest metropolitan areas in the U.S. Recent and on-going changes in the fire regime indicate a possible increase of wildfire size and intensity, contributing to the wildfire risk [1]. Monitoring and prediction of the wildfire risk attracts great attention from policy makers in local communities since it can assist urban planning for wildfire management and local disaster response practices. The potential of wildfire occurrences can be quantified as different meteorological and ecological factors. Foliage water content has been proved to be a direct measurement of the moisture in the fuels and successfully indicated the possibility of the wildfire. Live fuel moisture (LFM) is a long-term measured factor in the field as an in-situ observation of foliage water content. Defined as a percentage ratio of the difference between wet and dry weight over the dry weight of a vegetation sample. Currently, manual sampling of LFM at remote sites is labor intensive; hence, LFM data are seriously limited spatially (58 sites only across Southern California) and temporally (weekly or bi-weekly, 23 sites with >10-year long records).

Satellite observations provide extensive and spatially continuous coverage of surface conditions across vast areas on near-daily basis, and have the potential to significantly improve LFM monitoring to overcome limitations in current manual sampling methods. Vegetation Indices (VIs) were designed to address the spectral response to the change of water in the foliage in different bands (visible, NIR, and SWIR) and provided proxies of foliage water content and indicator of fire risk [2, 3]. VIs are also the most commonly used remote sensing observations to estimate the LFM [4, 5]. In addition, by making use of annual extremes and adding the land-cover specified stem factor to address peak amount of water residing in the stems, VIs can be converted to vegetation water content (VWC) by a non-linear model as a more direct measurement of LFM [6, 7].

The L-band radiometer soil moisture product provided another way to estimate the LFM from space that are not subject to the influence from weather conditions. Available at a coarser resolution (9 km) than most products from MODIS, SMOS from ESA (since 2010) and NASA SMAP programs (since 2015) both provide continuous observation of soil moisture. A higher resolution (3-km) soil moisture data was available from SMAP active radar for three months, with a recent release of the SMAP-Sentinel assimilated products at 3 km to serve as a continuing higher resolution soil moisture. As an indicator of above ground vegetation water content, vegetation optical depth (VOD) was usually derived together with soil moisture with a multi-temporal duel channel algorithm (MT-DCAT) [8]. Currently, very limited investigations have been made to utilize these VWC related products in LFM estimation and other wildfire risk evaluations. In this study, we will conduct the estimation of LFM using satellite products in Southern California to address the limitations of LFM estimation and produce a temporally and spatially continuous LFM product. We also compared the estimated LFM with the wildfire history data of the 2017 fire season to evaluate its significance as an alarming signal of wildfire risk.

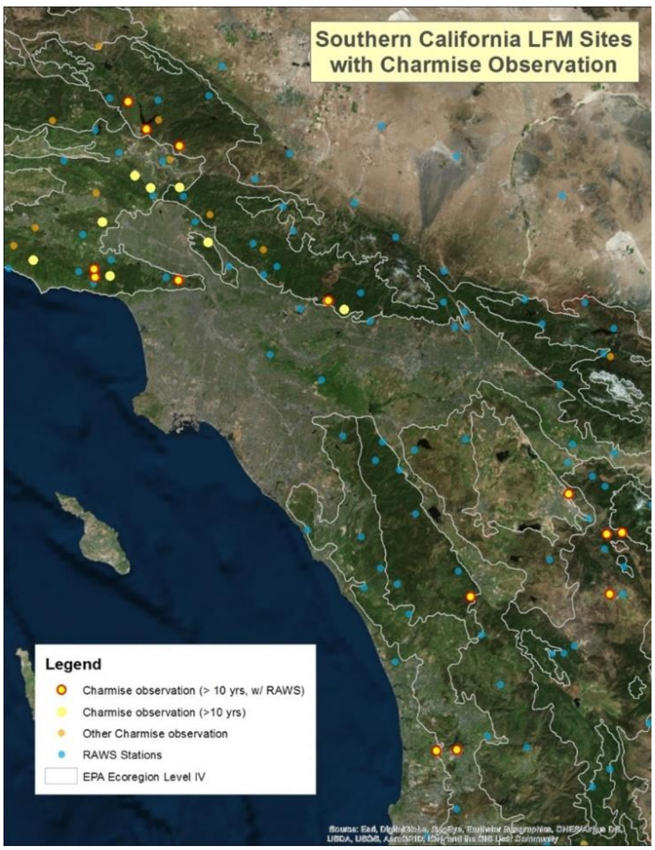

Figure 1. LFM sites in Southern California. LFM sites with long-term observations and a RAWS meteorological station were highlighted in yellow with red circle.

2. LFM ESTIMATION WITH REGRESSION MODEL AND FOLIAGE WATER CONTENT PROXIES

We first calculated a linear regression model between the observed LFM and the soil moisture/VOD at each site, then conducted a pooled model including all the available sites in Southern California (Figure 1). We introduced two fixed effects variables (site and season) to the linear regression model to evaluate if the soil moisture/VOD can address the spatial variability and seasonality. VOD derived from SMAP data were obtained from Konings et al. (2016) [8]. We also calculated the yearly summary statistics (mean, median, max, min, and range) and added to the previous single variable model to address the inter-annual difference and the extremes of VIs and soil moisture/VOD. The generality of the model was assessed using cross-validated adjusted R^2 through leave-one-out cross validation. We applied the same method on a series of VIs derived using MODIS C6 nadir BRDF-adjusted reflectance product as a comparison to the reflectance-based VIs, including Enhanced Vegetation Index (EVI), Normalized Difference Water Index (NDWI), Normalized Difference Vegetation Index (NDVI), and Visible Atmospherically Resistant Index (VARI).

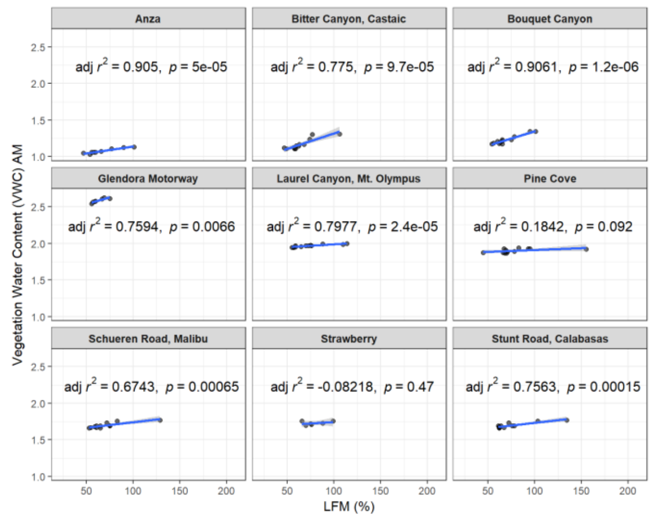

Figure 2. LFM estimation using a linear regression model and VWC at selected sites with long-term chamise LFM observation.

Table 1. Single site LFM modeling using multiple VIs.

Site	NDVI	NDWI	EVI	VARI
Anza	0.4550	0.5645	0.4442	0.4101
Bitter Canyon	0.6957	0.6901	0.688	0.7258
Bouquet Canyon	0.7050	0.7014	0.7146	0.6277
Glendora Motorway	0.4948	0.5204	0.5014	0.5274
Laurel Canyon	0.6542	0.6497	0.6858	0.722
Pine Cove	-0.0648	-0.0536	-0.0639	-0.014
Schueren Road	0.7152	0.7111	0.7186	0.7524
Strawberry	0.3729	0.3235	0.3531	0.3409
Stunt Road	0.7263	0.7153	0.7473	0.7611

The outcome of single variable model showed that the VWC significantly improved the estimation of LFM. Figure 2 showed a comparison between the outcome of VI-based models and the soil moisture product based models at nine sites with the longest and the most continuous observation of LFM in chamise (*Adenostoma fasciculatum*). The adjusted R^2 across different sites were generally higher than the outcomes from MODIS-based VIs (Table 1), including two sites with an adjusted R^2 above 0.9. Some sites had consistently poor performance because of the poor continuity of LFM observations (Pine Cove and Strawberry).

There was no significant improvement in the pooled model comparing to the VI-based estimation. We compared VWC predicted LFM with predictions using NDWI, which was the best-performed VI among the four investigated VIs (Figure 3). However, VWC estimated LFM had a less prominent saturation issue in spring than the NDWI model, while the VOD did not show any improvement in this issue. Similar as previous studies, LFM estimation using remotely sensed dataset had the best performance during the driest season (summer and fall). The seasonal difference between the LFM estimation needs a more in-depth investigation.

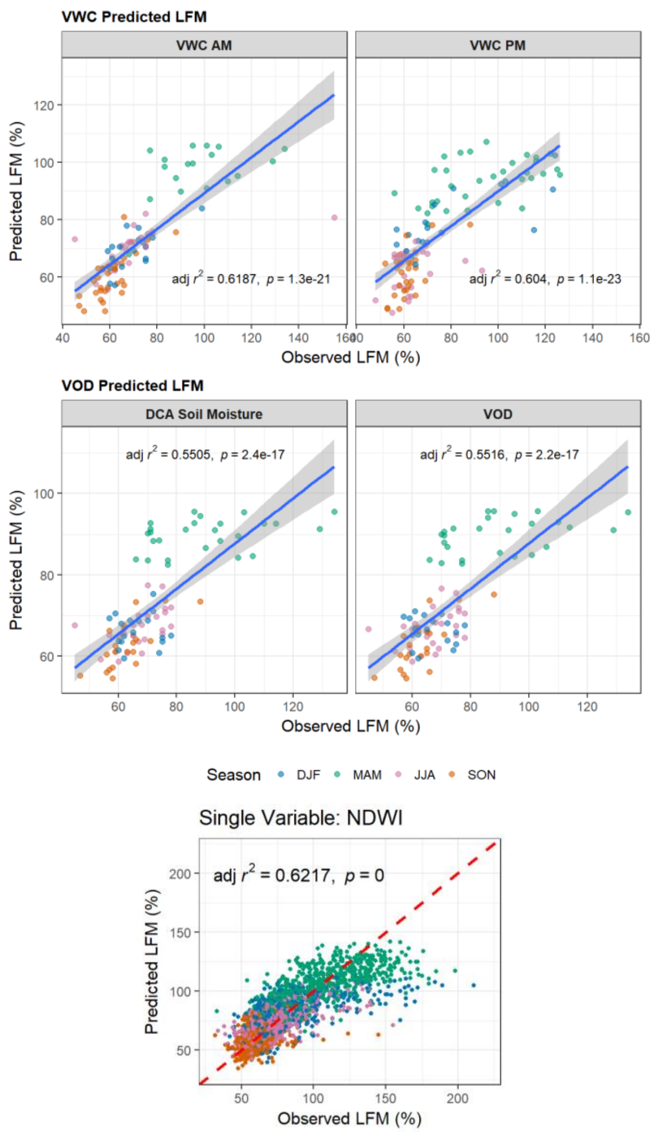

Figure 3. Pooled model using VWC, VOD, and NDWI. Results were colored by seasons. Spring (MAM) has the highest LFM and fall (JJA) has the lowest LFM.

3. LFM ESTIMATION WITH RECURRENT NEURAL NETWORK

Considering the non-linear relationship and the complexity between LFM and remote sensing-based proxies of foliage water content, we tested out recurrent neural network (RNN) with long short-term memory (LSTM) unit, a deep learning system that can take short-term memory of the sequential data (e.g. a time series) to avoid the vanishing gradient problem in other deep learning algorithm[9]. Site Schueren Road at Malibu was chosen to run RNN with LSTM because it has less missing data of LFM observation since 2001 (observations of 2000 was missing). After the pre-processing steps including gap filling and normalization, we trained the model with LFM observation and responding VIs, SMAP soil moisture, and VWC as used in the linear regression models at a learning rate of 0.01. The outcome of training and testing was significantly better than the pooled linear regression models (Table 2 and Figure 4).

Table 2. R^2 and Correlation of linear regression model and RNN with LSTM

	Performance Metrics	Regression	RNN with LSTM
Train	R^2	0.7419	0.8544
	Correlation	0.8585	0.9243
Test	R^2	0.6595	0.8035
	Correlation	0.8374	0.8981

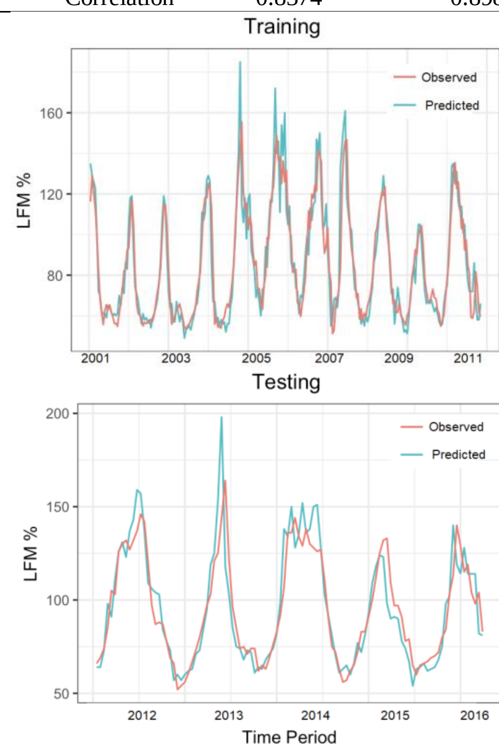

Figure 4. LFM estimation at Schueren Road, Malibu from training (2001 – 2011) and testing (2012-2016) of RNN with LSTM.

4. DISCUSSION AND CONCLUSIONS

The model outcome presented here indicated that VWC calculated based on a non-linear model using the stem factor can provide significant improvement in LFM estimation, especially in single site models. The improvement can be interpreted as a success of addressing the non-linear pattern of the response from foliage water content to the change of moisture conditions, as well as the importance of the stem factor, which describes the maximum amount of water that can be held in the plant. Single VIs and SMAP soil moisture/VOD had a similar modeling performance. Although SMAP soil moisture and related products such as VOD have excluded the errors introduced by atmospheric conditions, they are less correlated with the foliage water content than VWC. In terms of a method to construct the model, RNN with LSTM performed better than traditional regression models and has the capability to test out large number of potential predictors. A future study is needed to evaluate the influence from environmental factors on the performance of VWC and other proxies of foliage water content, especially the measurements of surface moisture conditions (e.g. precipitation and evapotranspiration). Although the predictability is limited as independent variables for LFM estimation, surface moisture conditions determine the amount of water available for plants to take up and store. This study will be valuable to understand the inter-annual difference in model predictability between wet and dry years. Adding more physically meaningful variables and statistics to address the extremes within each water year to the RNN with LSTM can also be useful to utilize the capability of deep learning algorithms, such as greening-up/browning-down speed of plants. Our methodology has wide applications in remote sensing and environmental studies as well as the utilization of data analyses including deep learning algorithms.

5. ACKNOWLEDGEMENT

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