Optical Sensing of Vegetation Water Content: A Synthesis Study

Ying Gao, *Student Member, IEEE*, Jeffrey P. Walker, *Member, IEEE*, Mahdi Allahmoradi, Alessandra Monerris, *Member, IEEE*, Dongryeol Ryu, and Thomas J. Jackson, *Fellow, IEEE*

***Abstract*—Vegetation water content (VWC) plays an important role in parameterizing the vegetation influence on microwave soil moisture retrieval. During the past decade, relationships have been developed between VWC and vegetation indices from satellite optical sensors, in order to create large-scale VWC maps based on these relationships. Among existing vegetation indices, the normalized difference vegetation index (NDVI) and the normalized difference water index (NDWI) have been most frequently used for estimating VWC. This work compiles and inter-compares a number of equations developed for VWC derivation from NDVI and NDWI using satellite data and ground samples collected from field campaigns carried out in the United States, Australia, and China. Four vegetation types are considered: corn, cereal grains, legumes, and grassland. While existing equations are reassessed against the entire compiled data sets, new equations are also developed based on the entire data sets. Comparing with existing equations, results show superiorities for the new equations based on statistical analysis against the entire data set. NDWI_{1640} and NDVI are found to be the preferred indices for VWC estimation based on the availability and the error statistics of the compiled data sets. It is recommended that the new equations can be applied in the future global remote sensing application for VWC map retrieval.**

***Index Terms*—Estimation, normalized difference vegetation index (NDVI), normalized difference water index (NDWI), vegetation water content (VWC).**

I. Introduction

OVER the past three decades, it has been shown that the vegetation water content (VWC) is an important variable in climatic, agricultural, and forestry applications [1]–[4]. In passive microwave remote sensing, a vegetation canopy over the soil absorbs the emission of the soil and adds to the total radiative flux with its own emission. With an estimate of VWC, the vegetation optical depth and transmissivity can be modeled [5]. Thus, VWC plays a particularly important role in soil moisture retrieval by parameterizing the effects of vegetation on the observed land surface emission.

Spatially distributed VWC information over large regions is not readily available. One approach is to use relationships with spectral reflectance measured by optical satellites with an appropriate function in order to map VWC (e.g., [4], [6]–[9]). These functions have been developed using relationships between the remotely sensed indices available from Landsat thematic mapper (TM) and Enhanced TM Plus (ETM+) sensors (with 16 days repeat at 30 m resolution), or the moderate resolution imaging spectroradiometer (MODIS) (with daily repeat at 250 m resolution), together with ground-based spectral and VWC measurements.

The normalized difference vegetation index (NDVI) proposed by Rouse *et al*. [10] for estimating VWC is one of the most widely used indices

$$\mathrm{NDVI} = \frac{\mathrm{NIR}_{860} - \mathrm{RED}_{650}}{\mathrm{NIR}_{860} + \mathrm{RED}_{650}} \tag{1}$$

where NIR is the reflectance in the near infrared channel (centered at 860 nm) and RED is the reflectance in the red band visible (VIS) channel (centered at 650 nm). A drawback of using NDVI for this application is that it saturates when vegetation coverage become dense (when leaf area index (LAI) reach around 5 [4], [11]) and is no longer sensitive to changes in vegetation. The saturation of NDVI was also observed by Chen *et al*. [6] for VWC $> 3\,\mathrm{kg/m^2}$ for corn. Moreover, RED and NIR are located, respectively, in the strong chlorophyll absorption region and the high reflectance plateau of vegetation canopies, meaning that NDVI represents chlorophyll rather than water content [6], [12]. Nevertheless, Jackson *et al*. [4] suggested that for specific canopy types (such as grasslands) within specific regions and when supported by ground sampling, it is still possible to establish useful VWC functions based on NDVI.

The normalized difference water index (NDWI), which utilizes the shortwave infrared (SWIR) together with NIR, has been shown to have a better correlation with leaf water content than the vegetation indices employing VIS and NIR [6], [12]. Compared to NDVI, it has been found that the saturation of this SWIR-based spectral index occurs later [6], [13]. The NDWI proposed by Gao [12] used a SWIR band centered at 1240 nm. This wavelength became available with the launch of MODIS. Previous to this the SWIR bands at 1640 and 2130 nm, which are available from Landsat, had been used to demonstrate that the water absorption was dominant and thus sensitive to VWC

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Y. Gao, J. P. Walker, and A. Monerris are with the Department of Civil Engineering, Monash University, Clayton 3800, Australia (e-mail: ying.gao@moansh.edu; jeff.walker@monash.edu; sandra.monerris-belda@monash.edu).

M. Allahmoradi and D. Ryu are with the Department of Infrastructure Engineering, University of Melbourne, Parkville 3010, Australia (e-mail: dryu@unimelb.edu.au).

T. J. Jackson is with U.S. Department of Agriculture ARS Hydrology and Remote Sensing Laboratory, Beltsville, MD 20705 USA (e-mail: tom.jackson@ars.usda.gov).

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TABLE I
SUMMARY OF LITERATURE USED FOR THIS STUDY, INCLUDING THE SOURCE OF VWC, SPECTRAL DATA, AND DERIVED VEGETATION INDICES

Publication by author names	Year	Data source				
		VWC	NDVI	$NDWI_{1240}$	$NDWI_{1640}$	$NDWI_{2130}$
T. Jackson *et al.*	2004	SMEX02 (interpolated)	Landsat TM/ETM+	-	Landsat TM/ETM+	-
D. Y. Chen *et al.*	2005	SMEX02	Landsat TM/ETM+, Terra-MODIS	-	Landsat TM/ETM+, Terra-MODIS	Terra-MODIS
V. Maggioni *et al.*	2006	NAFE'05	100BX Radiometer	-	Aqua-MODIS	MODIS
Y. H. Yi *et al.*	2007	Weishan Experiment	Terra, Aqua-MODIS	-	Terra, Aqua-MODIS	Terra, Aqua-MODIS
M. T. Yilmaz *et al.*	2008	SMEX05	-	-	Landsat TM, AWiFS, ASTER	-
J. Huang *et al.*	2009	SMEX02	Landsat TM/ETM+	MODIS	Landsat TM/ETM+	Landsat TM/ETM+
M. H. Cosh *et al.*	2010	NAFE'06	-	-	Landsat TM	-
M. Allahmoradi *et al.*	2013	NAFE'06	CROPSCAN multispectral radiometer (MSR-16)			
		AACES-1, -2	ASD field spectrometer (FieldSpec 3)			
		SMAPEx-1, -2, -3	CROPSCAN multispectral radiometer (MSR-16)			

variations [4], [6]. Therefore, the following NDWI indices are also considered in this work:

$$NDWI_{1240} = \frac{NIR_{860} - SWIR_{1240}}{NIR_{860} + SWIR_{1240}} \quad (2)$$

$$NDWI_{1640} = \frac{NIR_{860} - SWIR_{1640}}{NIR_{860} + SWIR_{1640}} \quad (3)$$

$$NDWI_{2130} = \frac{NIR_{860} - SWIR_{2130}}{NIR_{860} + SWIR_{2130}} \quad (4)$$

where the subscript refers to the wavelength (nm).

Although many empirical relationships between VWC and the aforementioned vegetation indices have been established for different vegetation categories and from different field campaigns around the world, there has been no study to synthesize or inter-compare the data and relationships derived from these different field campaigns, and to recommend a best relationship for global remote sensing applications, such as the soil moisture active passive (SMAP) satellite mission that needs a global VWC map as input for generating the soil moisture products. Currently, in order to obtain VWC information from optical sensing observations, many options are available as to which vegetation index and which model to apply based on the literature. Consequently, it is the intention of this investigation to synthesize the body of work available from literature and our own recently collected data sets into more robust models for VWC estimation. Statistical analysis is performed for both the new models and the existing models using the combined data sets, upon which a recommendation of vegetation index and model is made for both specific types of land cover and general categories.

II. DATA SOURCES

Data from eight different studies [4], [6]–[9], [14]–[16] are analyzed in this paper. These studies were chosen because 1) the vegetation indices they analyzed were either NDVI or/and NDWI, which have been found to be the best for VWC estimation and 2) the analysis was based on one or more specific land cover types and provided a vegetation type specific model to relate the index to VWC. The sources of VWC and vegetation index data provided in each study are summarized in Table I. The data were from the following field campaigns: SMEX02 and SMEX05 in the U.S.A. [9], [15], NAFE'05 [17], NAFE'06 [18], AACES-1 and -2 [19], SMAPEx-1, -2, and -3 [20] in Australia, and the Weishan experiment [16] in China. The locations of these experiments are indicated in Fig. 1.

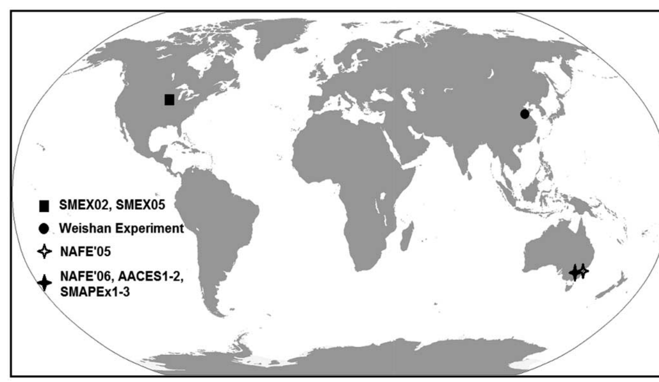

Fig. 1. Locations of the field campaigns compiled in this study.

The basic information of these field campaigns, including location, season, major crop types, and ancillary data measured are summarized in Table II. Most of the campaigns were conducted in spring or summer, except AACES-2 and SMAPEx-1, which were in winter. In terms of crop types, the experiments in Australia had a more diverse range, including barley, wheat, corn, Lucerne, and grasslands. For the two campaigns in the U.S.A., SMEX02 and 05, the crop types included corn and soybean, being the only major crops in the experiment

TABLE II
SUMMARY OF CAMPAIGN INFORMATION

Experiment (source)	SMEX 02, 05 [9, 14]	NAFE'05 [17]	NAFE'06 [16]	Weishan [15]	AACES 1, 2 [18]	SMAPEx-1, -2, -3 [19]
Location	Walnut Creek watershed, Iowa, USA	Goulburn River catchment, NSW, Australia	Kyeamba/ Yanco/ Yenda, NSW, Australia	Weishan Irrigation Zone, China	Murrumbidgee catchment, NSW, Australia	Yanco, NSW, Australia
Season	Summer	Spring		Spring	Summer and winter, respectively	Winter, summer, and spring, respectively
Major crop types	Corn, soybean	Barley, wheat, corn, canola		Winter wheat	Barley, wheat, corn, canola	Barley, wheat, corn, canola, lucerne
Available ancillary data	VWC, LAI, dry biomass	VWC, LAI, vegetation height, surface reflectance		VWC, LAI, dry biomass	VWC, LAI, dry biomass, surface relectance	VWC, LAI, dry biomass, surface reflectance

TABLE III
SUMMARY OF SPECTRAL BANDS FROM FIELD SPECTROMETERS USED IN THE FIELD CAMPAIGNS OF THIS PAPER, AND CURRENT SATELLITES THAT CAN BE USED FOR CALCULATING THE VEGETATION INDICES

Field Spectrometer or Satellite	Wavelength (nm)				
	RED_{650}	NIR_{860}	$SWIR_{1240}$	$SWIR_{1640}$	$SWIR_{2130}$
100BX	630-690	760-900	NA	NA	NA
FieldSpec 3	630-670	820-880	1234-1246	1632-1648	2122-2138
MSR-16	630-670	820-880	1234-1246	1632-1648	NA
Landsat TM/ETM+	Band 3 630-690	Band 4 760-900	NA	Band 5 1550-1750	Band 7 2080-2350
MODIS	Band 1 620-670	Band 2 841-876	Band 5 1230-1250	Band 6 1628-1652	Band 7 2105-2155

area. While all the campaigns sampled VWC, LAI, and dry biomass, however, ground-based surface reflectance was only measured in the NAFE, AACES, and SMAPEx campaigns. As a result, except for Maggioni *et al*. [8] and Allahmoradi *et al*. [14] which used calculated vegetation indices from field spectrometer measurements, the rest of the studies relied on either Landsat or MODIS to provide spectral data for calculation of the vegetation indices.

Landsat 5 (TM sensor) and Landsat 7 (ETM+ sensor) have eight frequency bands. Apart from bands 6 and 8, which have a resolution of 60 and 15 m, respectively, all other bands have a resolution of 30 m. In (1), RED and NIR correspond to band 3 (630–690 nm) and band 4 (760–900 nm), respectively. For SWIR in (2)–(4), band 5 (1550–1750 nm), and band 7 (2080–2350 nm) are used to cover SWIR_{1640} and SWIR_{2130}. SWIR_{1240} is not available from Landsat. Moreover, because of the infrequent temporal coverage of TM and ETM+, it is difficult to rely on them for estimating VWC for most applications [4]. However data from MODIS on the Terra and Aqua satellites are available daily, and are free to access. The resolution of MODIS is 250 m for bands 1 and 2 (centered at 648 and 858 nm), and 500 m for bands 3–7 (centered at 470, 555, 1240, 1640, and 2130 nm). RED and NIR correspond to bands 1 and 2, respectively, whereas SWIR_{1240}, SWIR_{1640}, and SWIR_{2130} correspond to bands 5, 6, and 7, respectively. A summary of the spectral wavelengths used by the hand spectrometers for the field campaigns considered in this study and their associated satellite bands for calculating vegetation indices is presented in Table III. For more details on the satellite data processing, refer to the original publications listed in Table I.

III. METHODOLOGY

Existing equations for NDVI and NDWI are summarized in Table IV. Lucerne in Allahmoradi *et al*. [14] is grouped with soybean in a category referred to as legumes, due to their similar spectral behavior. In addition to the equations, the data series of sampled VWC and calculated vegetation indices have also been digitized from their original graphs and replotted in Figs. 2–5, according to the category of vegetation type and vegetation index. The red-dotted lines indicate the newly established equation based on all the available data sets. It should be noted that the equations and data sets from Huang *et al*. [15] are not included in the NDVI and NDWI_{1640} plots for corn and soybean, since the same SMEX02 data sets as Chen *et al*. [6] were used.

A recommended function is provided for the categories where multiple data sets are present (Table IV). These functions were developed based on all the available data sets for a certain category. For NDVI, exponential equations were chosen due to the notable upward trend which matches with the saturating behavior of NDVI over the higher range of VWC. For the rest of vegetation indices, either linear or quadratic equations were provided. It should be noted that no recommended equation is given for NDVI_{2130} for corn, because the two available studies applied the same data set but with different source

TABLE IV

EQUATIONS FOR ESTIMATING VWC ('Y') USING THE RESPECTIVE VEGETATION INDEX ('X') ACCORDING TO INDIVIDUAL STUDIES IN LITERATURE

	Publication by first author names	Equations and statistics															
		NDVI	RMSE – org. data	R^2 – org. data	RMSE - all data	$NDWI_{1240}$	RMSE – org. data	R^2 – org. data	RMSE - all data	$NDWI_{1640}$	RMSE – org. data	R^2 – org. data	RMSE - all data	$NDWI_{2130}$	RMSE – org. data	R^2 – org. data	RMSE - all data
Corn	T. Jackson	$y = 192.64x^5 - 417.46x^4 + 347.96x^3 - 138.93x^2 + 30.7x - 2.82$	0.05	0.99	0.89	–	–	–	–	$y = 9.82x + 0.05$	0.05	0.98	0.61	–	–	–	–
	D. Y. Chen	$y = -17.75x^5 + 75.71x^4 - 73.46x^3 + 25.42x^2 - 0.83x - 0.37$	0.62	0.72	0.75	–	–	–	–	$y = 7.88x + 0.58$	0.46	0.84	0.56	$y = 6.67x + 0.1$	0.61	0.72	–
	M. T. Yilmaz	–	–	–	–	–	–	–	–	$y = 7.69x + 0.75$	0.47	0.89	0.52	–	–	–	–
	J. Huang	–	–	–	–	$y=25.29x +1.31$	0.79	0.31	0.90	$y = 7.71x + 0.26$	0.25	0.62	2.31	$y = 10.51x - 4.11$	0.85	0.48	–
	M. H. Cosh	–	–	–	–	–	–	–	–	$y = 9.39x + 1.26$	0.34	0.71	1.21	–	–	–	–
	M. Allahmoradi	$y = 68.22x^2 - 97.19x + 35.37$	0.72	0.85	3.40	$y = 19.66x + 0.38$	0.64	0.89	1.51	$y = 11.47x - 1.23$	0.68	0.67	1.19	–	–	–	–
	Recommended	$y = 0.098e^{4.225x}$	–	0.80	0.69	$y = 25.37 + 1.1$	–	0.50	0.88	$y = 7.84x + 0.6$	–	0.87	0.51	–	–	–	–
Cereal grains	Y. H. Yi	$y = -51.73x^2 + 70.48x - 20.24$	0.83	0.69	3.26	–	–	–	–	$y = 12.5x - 0.44$	0.74	0.76	2.23	$y = 10.29x -1.98$	0.44	0.84	0.67
	V. Maggioni	$y = 4.81x - 0.55$	0.18	0.83	1.65	–	–	–	–	$y = 13.2x^2 + 1.62x$	0.38	0.79	0.92	$y = 10.99x -3.07$	0.45	0.75	0.72
	M. H. Cosh	–	–	–	–	–	–	–	–	$y = 2.1x - 0.51$	1.10	0.69	1.22	–	–	–	–
	M. Allahmoradi	$y = 1.9x^2 + 0.02x + 0.09$	0.42	0.54	0.48	$y = 3.25x^2 + 5.31x + 0.89$	0.40	0.62	–	$y = -0.82x^2 + 2.49x + 0.62$	0.41	0.57	0.43	–	–	–	–
	Recommended	$y = 0.078e^{3.510x}$	–	0.59	0.50	–	–	–	–	$y = 2.45x + 0.57$	–	0.57	0.43	$y = 12.38 x-3.26$	–	0.84	0.55
Legumes	T. Jackson	$y = 7.63x^4 - 11.41x^3 + 6.87x^2 - 1.24x + 0.13$	0.03	0.99	0.45	–	–	–	–	$y = 1.44x^2 + 1.36x + 0.34$	0.02	0.97	0.17	–	–	–	–
	D. Y. Chen	$y = 2.06x - 0.86$	0.22	0.46	0.43	–	–	–	–	$y = 1.78x + 0.28$	0.21	0.52	0.19	–	–	–	–
	M. T. Yilmaz	–	–	–	–	–	–	–	–	$y = 2.22x + 0.38$	0.12	0.87	0.20	–	–	–	–
	J. Huang	$y = 0.89x - 0.30$	0.29	0.08	0.35	$y = 3.30x + 0.63$	0.22	0.48	0.22	$y = 0.85x + 0.33$	0.17	0.31	0.25	$y = 0.97x - 0.01$	0.25	0.31	–
	M. Allahmoradi	$y = 0.88x^2 + 0.18x - 0.06$	0.36	0.96	0.31	$y = 11.42x^2 + 5.29x + 0.59$	0.24	0.96	0.23	$y = 0.29x^2 + 1.36x + 0.26$	0.22	0.96	0.20	–	–	–	–
	Recommended	$y = 0.059e^{2.573x}$	–	0.51	0.31	$y = 4.03x + 0.68$	–	0.76	0.21	$y = 1.74x + 0.34$	–	0.76	0.18	–	–	–	–
Grassland	V. Maggioni	$y = 0.21x + 0.24$	0.03	0.92	0.34	–	–	–	–	$y = 0.19x + 0.32$	0.07	0.04	0.33	$y = 0.78x + 0.01$	0.02	0.9	0.38
	M. H. Cosh	–	–	–	–	–	–	–	–	$y = 0.98x + 0.28$	0.07	0.35	0.33	–	–	–	–
	M. Allahmoradi	$y = 1.93x^2 - 0.21x + 0.01$	0.29	0.56	0.30	$y = 3.63x + 0.80$	0.22	0.43	–	$y = 0.17x^2 + 1.79x + 0.5$	0.30	0.51	0.31	$y = 0.94x + 0.25$	0.33	0.37	0.32
	Recommended	$y = 0.017e^{5.866x}$	–	0.52	0.33	–	–	–	–	$y = 1.16x + 0.45$	–	0.20	0.30	$y = 0.74x + 0.23$	–	0.31	0.31

Also shown is the recommended equation for each vegetation category where more than a single data set exists. Performance statistics are also provided.
*Literature that used interpolated data.
**Equation should be used with caution due to lack of data.
***No data sets were presented in the original paper.

of spectral data. Also, for those categories with only one data set available ($NDVI_{1240}$ for cereal grains and grassland, and $NDVI_{2130}$ for legumes), the recommended equation would be the same as the one developed from its original study.

Statistical analysis is carried out to assess the correlation and VWC retrieval performance of all equations. Since R^2 was provided with most existing equations, they are directly quoted here in Table IV. However, not all studies gave RMSE as the VWC retrieval error. Therefore, RMSE is calculated here for all existing equations, based on their digitized data sets, both against their own data sets and against the entire synthesized data sets for each vegetation category (Table IV).

IV. DATA COMPARISONS

A. NDVI

It can be seen in Fig. 2(a) that both the data and the equations from Jackson *et al*. [4] and Chen *et al*. [6] agree well for corn, especially in the higher VWC range ($3-5\,\mathrm{kg/m^2}$). In comparison, the data from Allahmoradi *et al*. [14] are focused on a lower range of VWC ($1-2\,\mathrm{kg/m^2}$) and a limited number of samples were used in its equation derivation. However, these data still fall approximately into the range of the data from [4] and [6]. It is also clear that NDVI becomes saturated for VWC above about $3\,\mathrm{kg/m^2}$, which is consistent with most previous studies (e.g., [4], [6], [12]).

For cereal grains [Fig. 2(b)], Allahmoradi *et al*. [14] had a greater number of samples, including barley, wheat and oats. While the winter wheat data sets from Yi *et al*. [16] agree with the data from [14] in the lower range of VWC ($<1.5\,\mathrm{kg/m^2}$), the VWC of winter wheat reached to $3-4\,\mathrm{kg/m^2}$ with an NDVI of 0.6–0.8, making it significantly higher compared with [14] ($0.5-2.5\,\mathrm{kg/m^2}$) for the same NDVI range. To explain this, Yi *et al*. [16] pointed out that there were significant solar and zenith angular effects on the surface reflectance data from MODIS after the wheat heading stage, meaning that NDVI would be unable to detect crop growth during this phase. As a result, the data with high VWC values [circled in Fig. 2(b)] from [16] are considered to be outliers, and not used in the subsequent analysis.

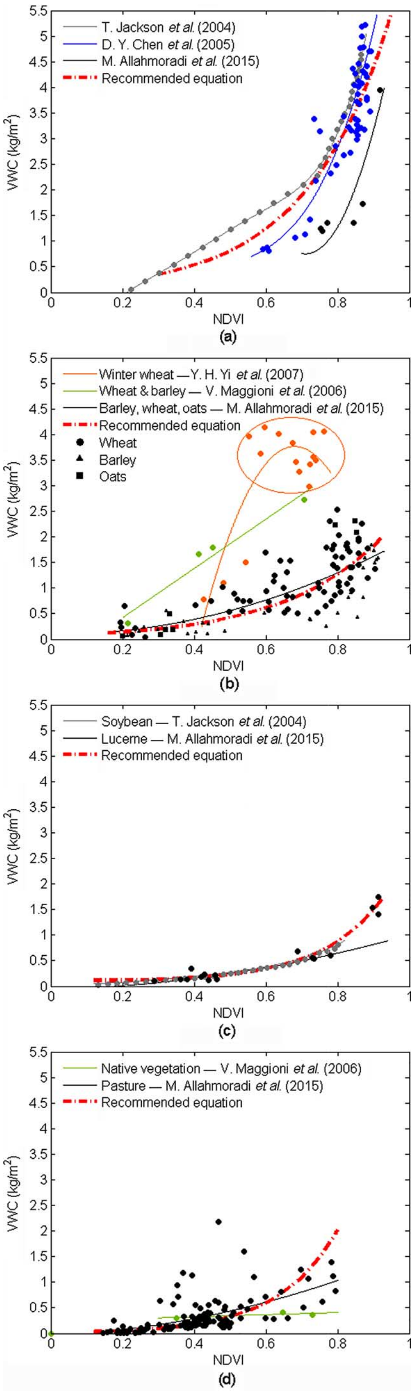

Fig. 2. Data sets and models for VWC estimation using NDVI. (a) Corn. (b) Cereal grains. (c) Legumes. (d) Grassland.

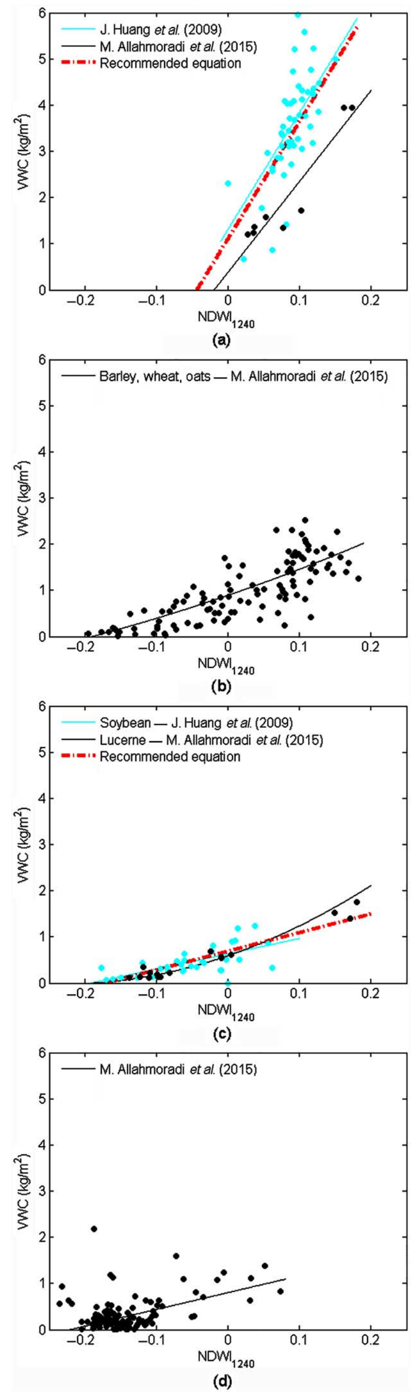

Fig. 3. Data sets and models for VWC estimation using NDWI_{1240}. (a) Corn. (b) Cereal grains. (c) Legumes. (d) Grassland.

For legumes [Fig. 2(c)], the equations from Jackson *et al*. [4] and Allahmoradi *et al*. [14] are similar to each other, as are the underlying data sets. For grassland [Fig. 2(d)], the equations from Maggioni *et al*. [8] and [14] are the only ones available for estimating VWC. Although the number of data points of [8] is very limited, they still fall into the same range as the data of [14].

B. $NDWI_{1240}$

For the land cover categories of corn and legumes [Fig. 3(a) and (c)], only two studies are available for comparison: Huang *et al*. [15] and Allahmoradi *et al*. [14]. Although their NDWI was calculated from different sources, MODIS and field spectrometer MSR-16, the equations and underlying data sets match well with each other. This is because the MSR-16 was set to match with the MODIS bands during the NAFE and SMAPEx experiments. As noted previously, Reference [14] is the only study to have used NDWI_{1240} to estimate VWC for both cereal grains and grassland [Fig. 3(b) and (d)]. Thus, until now the MODIS SWIR bands, especially at the 1240 nm recommended by Gao [12], have not been fully assessed and evaluated for estimating VWC.

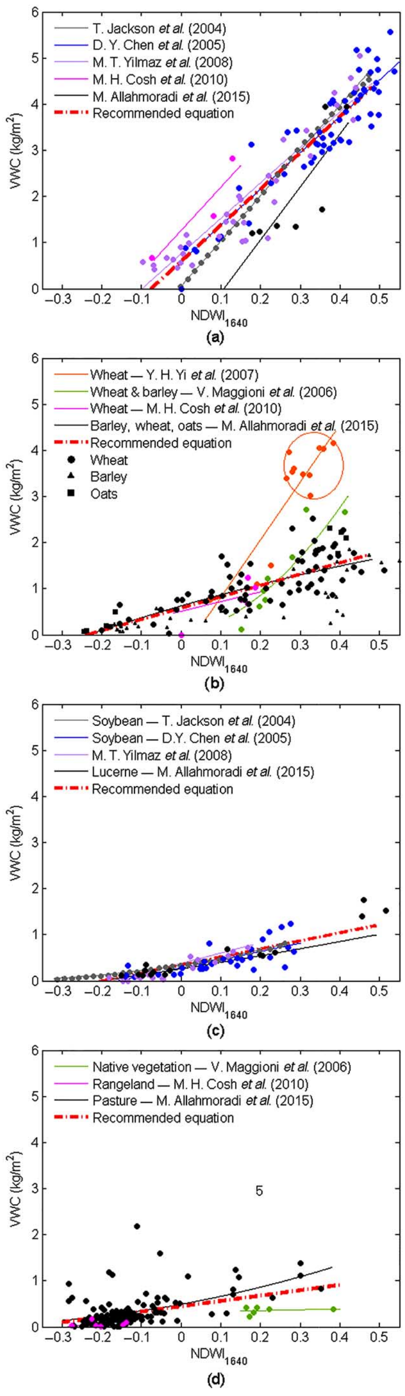

Fig. 4. Data sets and models for VWC estimation using NDWI_{1640}. (a) Corn. (b) Cereal grains. (c) Legumes. (d) Grassland.

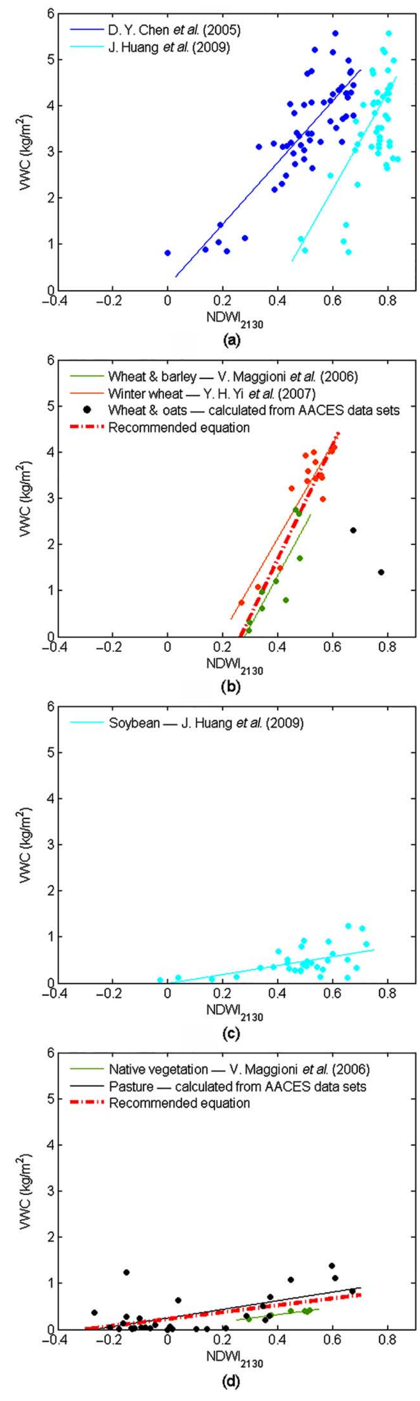

Fig. 5. Data sets and models for VWC estimation using NDWI_{2130}. (a) Corn. (b) Cereal grains. (c) Legumes. (d) Grassland.

C. $NDWI_{1640}$

The most frequently used index for VWC estimation is NDWI_{1640}. It is also the preferred index for estimating VWC, mainly because SWIR bands are sensitive to changes in water content of plant canopies, and SWIR_{1640} has been available on Landsat for many years. For corn [Fig. 4(a)], all studies obtained NDWI_{1640} from Landsat except for Allahmoradi *et al*. [14]. However, Chen *et al*. [6] applied both Landsat and MODIS data to calculate NDWI_{1640} and compared the two sets of data. Although only the Landsat data sets are included here [Fig. 4(a)], the analysis in [6] showed that the data sets derived from MODIS were similar to those derived from Landsat, but with a small shift. This shift could be due to that the center wavelength of Landsat Band 5 being slightly higher than MODIS Band 6, which were used to calculate SWIR_{1640}. It can be seen in Fig. 4(a), that all equations and data sets match well.

The data sets for legumes [Fig. 4(c)] and grassland [Fig. 4(d)] also have a good agreement. For cereal grains [Fig. 4(b)], similar winter wheat outliers as those of the NDVI analysis can be observed. This is consistent with the previous discussion that the outliers could be due to the angular effects at late growth stage during the experiment period.

D. $NDWI_{2130}$

The NDWI_{2130} index has not received as much attention in the literature as NDWI_{1640}. However, it is also a valuable index in estimating VWC since it is available from both Landsat and MODIS. In Fig. 5(a), both the VWC field data of Chen *et al*. [6] and Huang *et al*. [15] are from SMEX02, while the NDWI_{2130} were derived from MODIS and Landsat, respectively. This graph confirms the phenomenon noted in [6]: that the data sets derived from MODIS are consistent with those derived from Landsat, but with a small shift (approximately 0.1–0.4 for NDWI) toward the left. This means that MODIS-derived NDWI is generally larger than the Landsat-derived value for the same type of vegetation in the same area. This is due to the larger center wavelength of Landsat (Landsat Band 7 compared with MODIS Band 7 for calculating SWIR_{2130}).

For the remaining categories, a separate calculation of NDWI_{2130} was performed using field data from the AACES campaigns because NDWI_{2130} was not considered in Allahmoradi *et al*. [14]. This is the only experiment that has NDWI_{2130} data available. For cereal grains [Fig. 5(b)], there were not enough data from AACES to establish an equation for barley and wheat. Similarly for the studies conducted by Maggioni *et al*. [8] and Yi *et al*. [16], a limited number of samples were presented, although they still provided equations. However, it is suggested that the newly established equation based on the combined data sets from [8] and [16] should still be used with caution. Conversely, there are enough samples from AACES to establish a relationship for grassland [Fig. 5(d)], with several samples from [8] also falling in the similar range.

V. Results and Discussion

The performance statistics of all equations, including R^2 and RMSE are listed in Table IV. Comparing the two RMSE values of the existing equations, the RMSE for the original data sets and RMSE for the combined data sets, it can be seen that the latter is generally much larger. This means that each of these equations may be representative for a specific data set at a specific location, but fail to capture well the conditions of other areas. Therefore, the proposed new equations, with smaller error against the combined data sets, are expected to be more robust when used for VWC estimation globally, as required by satellite soil moisture missions.

Comparing the R^2 and RMSE of different indices for each type of land cover, the most suitable index for estimating VWC was identified for that specific land cover. As can be seen in Table IV, the recommended equation for NDWI_{1640} performs the best in estimating VWC for corn, providing the highest R^2 (0.87) and the lowest RMSE ($0.51\,\mathrm{kg/m^2}$). NDVI also works well for corn based on the large range of available data sets and the relatively high correlation ($\mathrm{R}^2 = 0.8$). In the case of cereal grains, the recommended equation for NDWI_{2130} performs the best in terms of R^2 (0.84), although the retrieval error is slightly higher than other indices ($\mathrm{RMSE} = 0.55\,\mathrm{kg/m^2}$ compared with $0.4 - 0.5\,\mathrm{kg/m^2}$ for other indices). For legumes, NDWI_{1240} and NDWI_{1640} performed much better than the other two indices, both with an R^2 of 0.76 and a RMSE of around $0.2\,\mathrm{kg/m^2}$. While for grassland NDVI worked the best according to its highest R^2 (0.52 compared with $0.2 - 0.4$ for other indices), although all indices had a similar retrieval accuracy ($\mathrm{RMSE} \approx 0.3\,\mathrm{kg/m^2}$).

Disregarding the vegetation types, the new equations for NDVI and NDWI_{1640} are considered to be best for VWC estimation in general at the current stage. This is because: 1) the amount of historical data for these two indices are larger and therefore allow a more reliable equation to be established and 2) performance statistics show a better correlation for NDVI and NDWI_{1640} in general. There are at least three studies for NDVI for each land cover type, and as many as six studies for NDWI_{1640}, while for NDWI_{1240} and NDWI_{2130}, there are only one or two studies available. Among these, there is a preference for using NDVI, as the R^2 for all the NDVI equations are above 0.5, even for the highly scattered grassland data, while for NDWI_{1640} the R^2 ranges from 0.57 to as high as 0.87, but is only 0.2 for grassland. Moreover, since NDVI is readily available from MODIS satellite, it is more convenient for VWC retrieval than NDWI_{1640}. Nevertheless, it should be noted that the model performance might vary over time or throughout the growing season of the crops. However, there are insufficient data sets to demonstrate this. Therefore, long-term experiments are needed to address this issue.

An important consideration is the impact of VWC error on soil moisture retrieval accuracy. According to the analysis in Parinussa *et al*. [21], the higher the vegetation optical depth is, the greater the influence on soil moisture retrieval error. As vegetation optical depth can be linearly related to VWC through a vegetation parameter 'b' (the slope of the regression line for VWC versus vegetation optical depth) [5], thus a higher VWC can also result in a higher soil moisture retrieval error. Combining the results of Jackson and Schmugge [5] and Parinussa *et al*. [21], it can be inferred that for vegetation such as corn, which can reach a VWC of as high as $4{-}5\,\mathrm{kg/m^2}$ during its mature stage, a VWC error of $0.5\,\mathrm{kg/m^2}$ will lead to a change of approximately $0.2\ \mathrm{m^3/m^3}$ for soil moisture retrieval accuracy for C-band, X-band, or Ku-band microwave instruments. However, for VWC less than $1.5\,\mathrm{kg/m^2}$ such as legumes and grassland, a $0.5\,\mathrm{kg/m^2}$ VWC error has almost no influence on the error of soil moisture retrieval. Therefore, for soil moisture related remote sensing applications, special attention needs to be paid for vegetation types such as corn and cereal grains, especially as they approach maturity. An example VWC map from MODIS-derived NDVI and the recommended equations from this paper is given in Fig. 6 for the SMAPEx-3 campaign. The VWC equations are applied on the basis of a Landsat derived landcover map, which is strongly reflected in the VWC distribution across the study site.

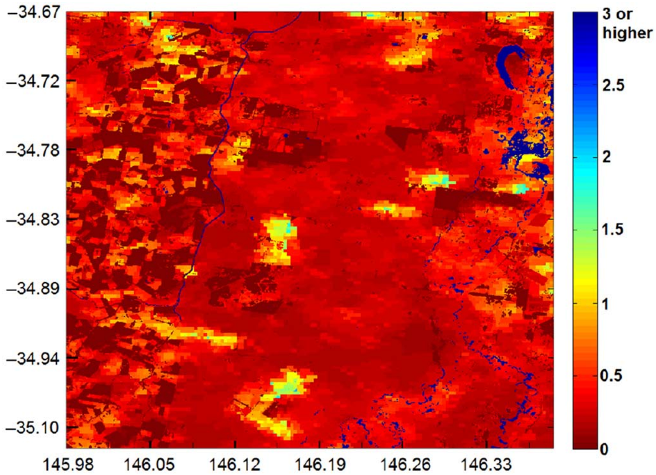

Fig. 6. Example VWC map (kg/m^2) from SMAPEx-3 for September 23, 2011, retrieved from a combination of MODIS-derived NDVI and a Landsat-derived land classification map.

VI. Conclusion

This study combined and inter-compared all available data sets and developed equations for estimating VWC from NDVI, $NDWI_{1240}$, $NDWI_{1640}$, and $NDWI_{2130}$, based upon land cover type. Analyses led to several conclusions.

1) There were marked similarities among the data sets and equations developed from most field campaigns for each type of vegetation, but some significant differences exist, especially for cereal grains.
2) According to the performance statistics and the number of data sets available, $NDWI_{1640}$ and NDVI are the two preferred vegetation indices for VWC estimation. Despite that NDVI is theoretically less suitable for estimating VWC when compared with the NDWI, it still provided a reliable estimate for VWC. Moreover, NDVI maps are readily available from the MODIS satellite, making operational implementation a relatively simple task.
3) The MODIS SWIR bands, especially at 1240 nm wavelength, have not been fully utilized for estimating VWC. More studies with larger number of VWC samplings are still needed, especially for cereal grains and grassland, to further evaluate the relationship between $NDWI_{1240}$ and VWC.

Additionally, this synthesis study recommended a new set of equations for VWC estimation of four different vegetation types (corn, cereal grains, legumes, and grassland), which will be more reliable than the equations developed from single data sets. These equations can be directly applied to satellite data in order to obtain VWC information for soil moisture retrieval or other climatic and agricultural applications.

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References

[1] C. J. Tucker, "Remote sensing of leaf water content in the near infrared," *Remote Sens. Environ.*, vol. 10, pp. 23–32, 1980.
[2] J. Peñuelas, I. Filella, C. Biel, L. Serrano, and R. Savé, "The reflectance at the 950–970 nm region as an indicator of plant water status," *Int. J. Remote Sens.*, vol. 14, pp. 1887–1905, 1993.
[3] S. J. Pyne, P. L. Andrews, and R. D. Laven, *Introduction to Wildland Fire*. Hoboken, NJ, USA: Wiley, 1996.
[4] T. J. Jackson *et al.*, "Vegetation water content mapping using Landsat data derived normalized difference water index for corn and soybeans," *Remote Sens. Environ.*, vol. 92, pp. 475–482, Sep. 2004.
[5] T. J. Jackson and T. J. Schmugge, "Vegetation effects in the microwave emission of soils," *Remote Sens. Environ.*, vol. 36, pp. 203–212, Jun. 1991.
[6] D. Y. Chen, J. F. Huang, and T. J. Jackson, "Vegetation water content estimation for corn and soybeans using spectral indices derived from MODIS near- and short-wave infrared bands," *Remote Sens. Environ.*, vol. 98, pp. 225–236, Oct. 2005.
[7] M. H. Cosh, J. Tao, T. J. Jackson, L. McKee, and P. O'Neill, "Vegetation water content mapping in a diverse agricultural landscape: National Airborne Field Experiment 2006," *J. Appl. Remote Sens.*, vol. 4, May 2010.
[8] V. Maggioni, R. Panciera, J. P. Walker, M. Rinaldi, and V. Paruscia, "A multi-sensor approach for high resolution airborne soil moisture mapping," presented at the 30th Hydrology and Water Resource Symp. [CD-ROM], Dec. 4–8, 2006.
[9] M. T. Yilmaz, E. R. Hunt, and T. J. Jackson, "Remote sensing of vegetation water content from equivalent water thickness using satellite imagery," *Remote Sens. Environ.*, vol. 112, pp. 2514–2522, May 2008.
[10] J. W. Rouse, R. H. Haas, J. A. Schell, and D. W. Deering, "Monitoring vegetation systems in the Great Plains with ERTS," in *Proc. 3rd Earth Resour. Technol. Satell. Symp.*, Washington, DC, USA, 1973, pp. 309–317.
[11] J. A. Gamon *et al.*, "Relationships between NDVI, canopy structure, and photosynthesis in 3 Californian vegetation types," *Ecol. Appl.*, vol. 5, pp. 28–41, Feb. 1995.
[12] B.-C. Gao, "NDWI—A normalized difference water index for remote sensing of vegetation liquid water from space," *Remote Sens. Environ.*, vol. 58, pp. 257–266, 1996.
[13] D. A. Roberts, R. O. Green, and J. B. Adams, "Temporal and spatial patterns in vegetation and atmospheric properties from AVIRIS," *Remote Sens. Environ.*, vol. 62, pp. 223–240, 1997.
[14] M. Allahmoradi, J. P. Walker, A. W. Western, D. Ryu, and T. Jackson, "Estimating vegetation water content using optical remote sensing: Application for soil moisture retrieval," *IEEE Trans. Geosci. Remote Sens.*, 2015, to be published.
[15] J. Huang, D. Y. Chen, and M. H. Cosh, "Sub-pixel reflectance unmixing in estimating vegetation water content and dry biomass of corn and soybeans cropland using normalized difference water index (NDWI) from satellites," *Int. J. Remote Sens.*, vol. 30, pp. 2075–2104, 2009.
[16] Y. H. Yi, D. W. Yang, D. Y. Chen, and J. F. Huang, "Retrieving crop physiological parameters and assessing water deficiency using MODIS data during the winter wheat growing period," *Can. J. Remote Sens.*, vol. 33, pp. 189–202, Jun. 2007.
[17] O. Merlin *et al.*, "The NAFE'06 data set: Towards soil moisture retrieval at intermediate resolution," *Adv. Water Resour.*, vol. 31, pp. 1444–1455, Nov. 2008.
[18] R. Panciera *et al.*, "The NAFE'05/CoSMOS data set: Toward SMOS soil moisture retrieval, downscaling, and assimilation," *IEEE Trans. Geosci. Remote Sens.*, vol. 46, no. 3, pp. 736–745, Mar. 2008.
[19] S. Peischl *et al.*, "The AACES field experiments: SMOS calibration and validation across the Murrumbidgee River catchment," *Hydrol. Earth Syst. Sci.*, vol. 16, pp. 1697–1708, Jun. 22, 2012.

[20] R. Panciera *et al*., "The soil moisture active passive experiments (SMAPEx): Toward soil moisture retrieval from the SMAP mission," *IEEE Trans. Geosci. Remote Sens*., vol. 52, no. 1, pp. 490–507, Jan. 2014.

[21] R. M. Parinussa *et al*., "Error estimates for near-real-time satellite soil moisture as derived from the land parameter retrieval model," *IEEE Geosci. Remote Sens. Lett*., vol. 8, no. 4, pp. 779–783, Jul. 2011.

Ying Gao (S'13) received the B.E. degree in civil engineering (Hons. 1) from Monash University, Melbourne, Australia, and Central South University, Changsha, China, in 2010.

She was awarded the Faculty Scholarship to continue her Ph.D. in civil engineering with Monash University in 2011. She was involved in the SMAPEx field campaigns as part of NASA's SMAP mission. Her research interests include active and passive microwave remote sensing, optical sensing of vegetation, soil moisture retrieval, and surface roughness parameterization.

Jeffrey P. Walker (M'13) received the B.E. degree in civil engineering and the Bachelor of Surveying (Hons. 1 and University Medal) degree from the University of Newcastle, Callaghan, Australia, in 1995, and the Ph.D. degree in water resources engineering from the same University in 1999.

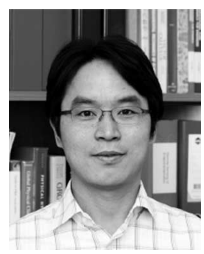
He then joined NASA Goddard Space Flight Centre to implement his soil moisture work globally. In 2001, he moved to the Department of Civil and Environmental Engineering, University of Melbourne, Melbourne, Australia, as a Lecturer. In 2010, he was appointed as a Professor with the Department of Civil Engineering, Monash University, Melbourne, Australia, where he is continuing this research. He is contributing to soil moisture satellite missions at NASA, ESA, and JAXA, as a Science Team Member for the Soil Moisture Active Passive (SMAP) mission and Cal/val Team Member for the Soil Moisture and Ocean Salinity (SMOS), and Global Change Observation Mission–Water (GCOM-W), respectively.

Mahdi Allahmoradi received the B.Sc. and M.Sc. degrees in natural resources engineering from the University of Tehran, Tehran, Iran, in 2003 and 2006, respectively. He is currently pursuing the Ph.D. degree at the Infrastructure Engineering Department, University of Melbourne, Melbourne, Australia.

He worked as a Research Associate with the University of Tehran, before being awarded the fullbright scholarship to study Ph.D. on environmental remote sensing in 2008. He has been involved in AACES 1-2 field experiments sponsored as part of ESA's SMOS mission. His research interests include environmental remote sensing, hydrology, and water resources management.

Alessandra Monerris (S'04–M'10) received the B.E. and degree in telecommunication from the Universitat Politècnica de València, València, Spain, and the Ph.D. degree in telecommunication from the Universitat Politècnica de Catalunya, Barcelona, Spain.

In 2006, she was a Visiting Ph.D. Student at the Università Tor Vergata, Rome, Italy. From 2007 to 2011, she was Executive Director of SMOS-BEC, the Soil Moisture and Ocean Salinity Mission Expert Centre, Barcelona, Spain. Since 2011, she has been a Research Fellow with the Department of Civil Engineering, Monash University, Melbourne, Australia. She has extensive experience in the preparation and coordination of field experiments for the validation of soil moisture satellite data, both for ESA's SMOS and NASA's SMAP missions (she led the third Soil Moisture Active Passive Experiment, SMAPEx-3). Since 2012, she has been responsible of the OzNet soil moisture monitoring network in the Murrumbidgee River Catchment, as well as the CosmOz tower, Yanco, Australia. Her research interests include the estimation of soil moisture and vegetation parameters from airborne and ground-based L-band passive microwave observations, cosmic-ray probes, and Global Navigation Satellite Systems Reflectometry (GNSS-R).



Dongryeol Ryu is a Senior Lecturer with the Melbourne School of Engineering, University of Melbourne, Melbourne, Australia. He is the Leader of the Hydrology and Remote Sensing Group and the UAV Research Unit of the Centre for Disaster Management and Public Safety (CDMPS). His research interests include innovative use of remotely sensed land surface features, water and vegetation parameters in hydrological modeling, and land surface processes.

Dr. Ryu was the recipient of a NASA Earth System Science Fellowship and the University of California, Irvine Medal.

Thomas J. Jackson (SM'96–F'02) received the Ph.D. degree from the University of Maryland, College Park, MD, USA, in 1976.

He is a Research Hydrologist with the U.S. Department of Agriculture, Agricultural Research Service, Hydrology and Remote Sensing Laboratory. His research interests include the application and development of remote sensing technology in hydrology and agriculture, and primarily microwave measurement of soil moisture. He is or has been a Member of the science and validation teams of the Aqua, ADEOS-II, Radarsat, Oceansat-1, Envisat, ALOS, SMOS, Aquarius, GCOM-W, and SMAP remote sensing satellites.

Dr. Jackson is a Fellow of the Society of Photo-Optical Instrumentation Engineers, the American Meteorological Society, and the American Geophysical Union. In 2003, he was the recipient of the William T. Pecora Award (NASA and Department of Interior) for outstanding contributions toward understanding the Earth by means of remote sensing and the AGU Hydrologic Sciences Award for outstanding contributions to the science of hydrology. He also received the IEEE Geoscience and Remote Sensing Society Distinguished Achievement Award in 2011.