A Comparison of Ground Vehicle Mobility Analysis Based on Soil Moisture Time Series Datasets from WindSat, LIS, and In Situ Sensors

Maria T. Stevens^a, George B. McKinley^b, Farshid Vahedifard^c

^a Research Geologist, U.S. Army Engineer Research and Development Center (ERDC), 3909
Halls Ferry Road, Vicksburg, MS 39180, USA. Email: Maria.T.Brown@erdc.dren.mil

^b Computer Scientist, U.S. Army Engineer Research and Development Center (ERDC), 3909
Halls Ferry Road, Vicksburg, MS 39180, USA. Email: George.B.Mckinley@erdc.dren.mil

^c Corresponding Author, Assistant Professor, Dept. of Civil and Environmental Engineering,
Mississippi State University, Mississippi State, MS 39762, USA. Email:
farshid@cee.msstate.edu

Abstract

Soil moisture is a key terrain variable in ground vehicle off-road mobility. Historically, models of the land water balance have been used to estimate soil moisture. Recently, satellites have provided another source of soil moisture estimates that can be used to estimate soil-limited vehicle mobility. In this study, we compared the off-road vehicle mobility estimates based on three soil moisture sources: WindSat (a satellite source), LIS (a computer model source), and in situ ground sensors (to represent ground truth). Mobility of six vehicles, each with different ranges of sensitivity to soil moisture, was examined in three test sites. The results demonstrated that the effect of the soil moisture error on mobility predictions is complex and may produce very significant errors in off-road mobility analysis for certain combinations of vehicles, seasons, and climates. This is because soil moisture biases vary in both direction and magnitude with season and location. Furthermore, vehicles are sensitive to different ranges of soil moistures. Modeled vehicle speeds in the dry time periods were limited by the interaction between soil

traction and the vehicles' powertrain characteristics. In the wet season, differences in soil strength resulted in more significant differences in mobility predictions.

Keywords: Soil moisture; Off-road mobility; Soft soil trafficability; Remote sensing

1. Introduction

Ground vehicle off-road mobility in soft soil has long been recognized as a significant factor in military mission planning and execution (US Army, 1947-1974; US Army, 1959; US Army, 1990; US Army, 2010). Low soil strength is among the top causes of terrain inaccessibility. Moreover, soil strength is a terrain variable that is not necessarily obvious from visual inspections. Other causes of vehicle restrictions (e.g., high slopes or dense vegetation) may be assessed more readily both remotely and on site. Other terrain factors such as visibility and surface roughness may still slow vehicle traffic but will not cause terrain inaccessibility.

Methods were developed to quantify the soft soil performance of military vehicles and to characterize the terrain over which the vehicle would operate (Nuttall et al., 1966). The US Army Corps of Engineers (USACE) developed a metric, referred to as vehicle cone index (VCI), that directly quantifies a ground vehicle's performance in soft soil (Priddy and Willoughby, 2006; Stevens et al., 2013). This metric describes the minimum soil strength needed for a vehicle to make a specified number of passes over terrain without becoming immobilized. The one-pass VCI, or VCI_1 , provides an index of the soil strength at which vehicle mobility begins. Similarly, the VCI_{50} is considered the soil strength above which vehicle mobility is unlikely to be significantly limited by soil strength.

VCI is quantified in terms of soil strength expressed by rating cone index (RCI), which is the product of cone index (CI) and remold index (RI). CI is measured as the tip resistance of a

standard hand-held trafficability cone penetrometer and gives an index of the shear strength of the soil. RI is a ratio of remolded soil strength to in situ soil strength and gives an index of the potential for strength loss during vehicle traffic. VCI can be both measured in the field (Stevens et al., 2013) and predicted based on vehicle characteristics (Priddy, 1995). VCI is heavily influenced by the vehicle's ground contact pressure among other factors (Priddy and Willoughby, 2006).

Once vehicle requirements are known, the challenge is to adequately represent the terrain in mobility models. The frequency of encountering low soil strength areas will vary with region and season. Meyer and Bohnert (1970) estimated that world-wide year-round about 25% of terrain has low enough soil strength (i.e., CI of less than 150 psi or 1034 kPa) to potentially impede mobility. More importantly, some regions and seasons have a much higher incidence of low trafficability conditions. For instance, in Southeast Asia approximately 55-73% (depending on season) of terrain will potentially impede traffic (i.e., CI of less than 150 psi). In the same area, 11% of terrain will be highly unfavorable (i.e., less than 45 psi or 310 kPa CI) in every season (Meyer and Bohnert 1970).

Trafficability kits have been deployed for operational use so that soldiers can measure RCI along anticipated travel routes (US Army, 1959). However, for mobility simulations and operations planning, it is often not possible to measure in situ RCI. Thus, RCI must be estimated remotely based on knowledge of soil and environment characteristics. Several USACE models have used soil and meteorological parameters to estimate RCI. Some of these models are Soil Moisture Strength Prediction (SMSP; Sullivan et al., 1997); Short-term Operational Forecasts of Trafficability (SOFT; Mason et al., 2001); and Fast All-season Soil STrength (FASST; Frankenstein and Koenig, 2004). Generally, these models involve first using meteorological data

to estimate soil moisture and then estimating RCI from soil moisture using empirical relationships. In the absence of meteorological data, soil strength can be approximated based on climate zone, terrain slope, and soil type (Bullock, 1994a), but this approach results in lower confidence estimates.

Recently, the availability of satellite soil moisture data has moved the US Army closer to its goal of fully characterizing terrain in a timely manner. Various types of satellites measure soil moisture and recent developments have focused on active and passive microwave sensors (Wang and Qu, 2009). Much of the current research in this area involves developing algorithms to: correctly retrieve soil moisture from these satellites (e.g., Owe et al., 2008; Li et al., 2010; Jackson et al., 2010; Jackson et al., 2012), blend the data appropriately with other data sources (e.g., Kumar et al., 2008; Y. Liu et al., 2011; Peters-Lidard et al., 2011), and quantify the error in the resulting soil moisture datasets (e.g., Harrison et al., 2011).

The US Army has been cooperating with other agencies to understand how satellite-derived soil moisture can be incorporated into existing terrain characterization models (Baylot et al., 2013; Frankenstein et al., 2015). Flores et al. (2014) demonstrated the usefulness of soil moisture data similar to that expected from the NASA Soil Moisture Active Passive (SMAP) mission. They simplified their analysis by considering only mobility limitations caused by soil strength, which, as Flores et al. (2014) noted, may overemphasize soil strength impacts.

The current research seeks to understand soil moisture impacts to ground vehicle mobility across several different locations using various soil moisture datasets. To accomplish this task, this paper compares vehicle mobility assessments conducted using three soil moisture sources of: WindSat, NASA's Land Information System (LIS), and in situ soil moisture measurements.

Three test sites (in Spain, France and Australia) and six vehicles, each with different ranges of sensitivity to soil moisture, are used in the mobility analyses.

2. Methodology

An overview of the study methodology is shown in Figure 1. The mobility analysis used entire time series of soil moisture data available from three sources. Each soil moisture value was used to estimate a corresponding RCI value based on the relationships of Sullivan et al. (1997). This produced RCI time series. Each study vehicle was analyzed with the NATO Reference Mobility Model (NRMM) Version 2.8.2 (Ahlvin and Haley, 1992) to produce a table of speed values corresponding to different RCI values. Finally, these look-up tables were used to convert RCI estimates to speed estimates. Each of these steps is discussed in detail in the following sections.

3. Study Vehicles

Six vehicle configurations were used to represent a cross-section of military ground vehicles. Relevant details of these vehicles are summarized in Table 1. W1 is a common light-weight, high-mobility wheeled vehicle. W2 was selected as a common medium-weight wheeled vehicle. W3 was selected as a heavy wheeled supply vehicle. W4, a heavily armored wheeled vehicle, was selected as a probable worst case for soft soil mobility. Vehicle T1 was selected to represent a relatively light-weight tracked vehicle, and T2 was selected to represent a heavy tracked vehicle.

As explained previously, VCI is a measure of the minimum soil strength required to achieve a specified number of passes. Lower VCI values indicate lower demand on the soil and better soft soil mobility. Generally, ground vehicle soft soil mobility is most closely related to

weight and ground contact area. Tracked vehicles usually have much larger contact areas, and consequently they tend to have better soft soil mobility compared to wheeled vehicles of the same weight. Also, it should be noted that adding weight to an existing vehicle configuration can degrade soft soil mobility. This is a common phenomenon as more armor or payload may be assigned during a vehicle's life-cycle.

4. Study Sites

To assure that satellite data and in situ soil moisture data were available for the study, three locations in Spain, France, and Australia were selected for analysis. These locations are expected to provide good conditions for accurate satellite data, in that they are relatively free of radio frequency interference, have low surface roughness, and are not densely covered with vegetation. Furthermore, these sites are established soil moisture validation sites with in situ data available. Each site is represented only by a single moisture series (per data source) averaged across the site.

4.1. France

The site in France is a part of the Surface Monitoring of the Soil Reservoir Experiment (SMOSREX; De Rosnay et al., 2006), an experiment intended to provide ground truth data to validate measurements from the SMOS satellite. The site is located at 43°23'N, 1°17'E, approximately 30 km south of Toulouse, France. The site has strong seasonal trends in soil moisture and it generally experiences dry, hot summers and wet, cool winters. Average annual precipitation in the area is approximately 630 mm.

4.2. Australia

The site in Australia is the 60 km by 60 km Yanco study area, which is a part of the Australian Moisture Monitoring Network (OZNet; Smith et al. 2012). The Yanco area is located at approximately 34°51'S, 146°7'E in an agricultural area with an average annual rainfall of about 400 mm.

4.3. Spain

The site in Spain is located at 41°25'58"N 5°22'47"W at the REMEDHUS (Red de MEDicion de la HUmedad del Suelo) soil moisture network, which has been used as a validation site for the European Space Agency's Soil Moisture and Ocean Salinity (SMOS) satellite (Sanchez et al. 2012). The site is a 35 by 35 km area in a semi-arid agricultural region with an average annual precipitation of 385 mm.

5. Soil Moisture Data Sources

Soil moisture data was derived from three sources: WindSat (a satellite source), LIS (a computer model source), and in situ ground sensors (to represent ground truth). The data processing is detailed in Eylander et al. (2016). For each case, the site was represented by a single soil moisture value for each time step. In the case of the coarse WindSat and LIS data, the single value was that of a single pixel. For the results obtained from in situ sensors, data was averaged to best represent the pixel.

5.1. WindSat

WindSat is a passive microwave sensor that was launched in 2003 primarily for the purpose of measuring ocean surface winds from space (Gaiser et al., 2004). However, the satellite data has also been used to measure surface soil moisture (Li et al., 2010). The soil moisture retrieval algorithm relies on the large difference between soil and water dielectric

constants at microwave frequencies. Challenges in this method include accounting for effects of vegetation water content, vegetation structure, soil roughness, land surface temperature, and radio frequency interference (Li et al., 2010). The retrieval algorithms for this study were based on the algorithms of Li et al. 2010 (which included only 10.7, 18, and 37 GHz channels) and were modified to create new site-specific algorithms that include the 6.8 GHz channel (Eylander et al., 2016).

With a cell size of about 50 km and an average revisit time of approximately three days, WindSat data is spatially and temporally coarse for many purposes including ground vehicle mobility. Efforts are currently underway to address these issues by assimilating WindSat into other soil moisture models. Furthermore, the soil moisture measurement is representative of different depths depending on sensor frequency and local soil conditions. Measurement depth ranges from about 1 cm for extremely wet conditions to about 1 m for extremely dry conditions. For practical reasons, it is standard practice to assume that the microwave sensor measurement represents soil moisture at 5 cm depth (Eylander et al., 2016).

5.2. Land Information System (LIS)

The Noah Land Surface Model (LSM, version 3.3) within the NASA LIS (Peters-Lidard et al., 2007) was used as a representation of baseline capabilities. This source of soil moisture data has been used for ground vehicle mobility estimates (Baylot et al. 2013). LIS is a data assimilation framework that uses many data sources including temperature, humidity, pressure, wind, and precipitation to estimate soil moisture and other land surface conditions. LIS estimates mass and energy balances through a series of time steps wherein each ground state estimate is dependent on the previous time step.

The LIS framework can be used to assimilate satellite soil moisture estimates such as those from WindSat. However, the current baseline for mobility predictions does not include WindSat. Therefore, for this study LIS was used in “open-loop” mode. That is, soil moisture observations were not assimilated into the model.

For this study, LIS was forced with meteorological data from AFWA’s Agricultural Meteorological Modeling System (AGRMET); the details of the LIS setup are described in Eylander et al. (2016). For this study, LIS produced data at 25 km spatial resolution and daily temporal resolution. However, LIS can be used to produce much higher resolution data (sub-1 km and sub-hour intervals). LIS with Noah usually outputs soil moisture for four layers: 0-10 cm, 10-40 cm, 40-100 cm, and 100-200 cm. The 0-10 cm depth was analyzed in the current study.

5.3. In Situ Measurements

In situ data were processed as noted in Eylander et al. (2016) for the sites in Spain, France, and Australia, respectively. Where multiple depths were available, 5 cm soil moisture was used. In cases where multiple in situ sensors were available, these were averaged to provide a representative condition. The in situ soil moisture is assumed to represent the ground truth against which LIS and WindSat should be evaluated.

6. Soil Strength versus Soil Moisture Relationships

RCI was estimated from soil moisture based on the relationships in Sullivan et al. (1997), shown in Figure 2. These empirical relationships require only gravimetric soil moisture and USCS soil type as inputs. Because the soil moisture data in this study was expressed volumetrically, assumptions were made for soil porosity and specific gravity for each soil type so that the volumetric soil moisture could be converted to gravimetric soil moisture (Baylot et al.,

203 2013). Relationships are shown in for the following USCS soil types: SP (poorly graded sand),
204 SM (silty sand), SC (clayey sand), ML (low plasticity silt), CL (low plasticity clay), and CH
205 (high plasticity clay).

206 **7. Mobility Modeling and Estimating Vehicle Speed using NRMM**

207 NRMM (Ahlvin and Haley, 1992) is a mobility model that predicts maximum vehicle
208 speed based on vehicle parameters (such as weight and tire dimensions), static terrain conditions
209 (such as soil type and slope), seasonally-varying terrain conditions (such as visibility and soil
210 strength), and human factors (such as ride comfort and shock requirements). Its primary outputs
211 are vehicle speeds and reason codes explaining what factor controls the speed. Commonly,
212 NRMM is used to simulate either a real-world area or a parametric terrain representing a range of
213 possible conditions. For this study, a parametric terrain was used in NRMM to create a table of
214 vehicle speeds based on RCI. For this process, several simplifying assumptions were made.

215 First, it was assumed that soil strength was the only terrain factor that affected speed; all
216 other terrain factors were modeled as benign. This assumption was intended to isolate soil
217 strength as the only variable and can be considered as the key assumption/limitation to the
218 analysis presented in this paper. However, tire speed limits and other vehicle-related speed
219 limiting factors were included just as they would be in a more rigorous mobility analysis.
220 (Wheeled military vehicles often change tire pressure settings for different terrain types:
221 highway, cross country, and mud/sand/snow. Lower tire pressures allow greater contact areas
222 and lower contact pressures. This provides greater mobility; however, the tires have lower
223 recommended maximum speed at these lower tire pressures.)

224 Second, only CH (high plasticity clay) soil was modeled. A similar analysis could be
225 performed with other soil types, but only CH soil is included in this study. CH is considered the

worst-case soil type for soft soil mobility (Stevens et al. 2013). Flat, wet CH soil can reasonably be expected to cause a mobility challenge. Furthermore, this represented a significant percentage of the total area in each of the areas of interest including 100% in Australia, 29% in France, 15% in Spain according to the National Geospatial-Intelligence Agency (NGA) 1 km soil type map.

Third, the surface condition was assumed to be non-slippery. Surface slipperiness, which is caused by the presence of free water on the surface, can be a major factor in degrading ground vehicle mobility. Clearly, the causes of soil moisture and surface condition are related; however, high soil moisture does not necessarily imply surface slipperiness. Schreiner (1985) and Bullock (1994b) describe the convention for slipperiness consideration in mobility studies. Usually it is assumed that the surface is slippery if precipitation has occurred within the last 6 hours on a soil with significant fines content. For this simplified time series analysis, non-slippery analysis was used for convenience only. It is likely that some time windows would be better represented with a slippery surface condition. Further work is needed to automate an appropriate choice surface condition based on the precipitation and soil moisture data. The speed-versus-RCI look-up table produced by NRMM was used to convert the time series of RCI into speed estimate time series for each combination of vehicle, soil moisture source, and study area.

8. Results

8.1. France

The results for the study site in France are shown in Figure 3 and Figure 4. Figure 3 shows that WindSat generally estimated higher soil moisture compared to the in situ measurements during the dry season and approximately the same soil moisture as in situ during the wet season. LIS without satellite data tended to be biased toward wetter soil in the dry season and drier soil in the wet season. However, the bias during the dry season generally had

limited effect on vehicle mobility; the soil was usually predicted to be well above VCI₅₀ for all vehicles (Figure 3). Figure 4 depicts the speed estimates over time. As shown, during the wet season, the dry bias of LIS resulted in modeled speeds higher than those expected based on the in situ soil moisture. To a lesser extent, WindSat also resulted in higher predicted speeds in the wet season. These trends apply to all vehicles. The W1 speed estimates based on LIS (Figure 4a) illustrate the extreme case; soil moisture was never high enough to limit this vehicle's speed.

Pair-wise comparisons of predicted vehicle speeds for France (Table 2) showed that LIS and WindSat both performed well in the dry period (with 99% and 86%, respectively, of their speeds within a 5 km/h tolerance of the speed predicted based on in situ moisture). WindSat's performance in the dry period was worse for the vehicles with higher VCI (W2 and W4); only 71% of its speeds were within the 5 km/h threshold for these vehicles.

In the wet season, speed predictions obtained using both LIS and WindSat were worse compared to the dry season. Results varied by vehicle, but the speeds from LIS had an average of 22% and a range of 14 to 45% of the speeds within the 5 km/h threshold. The speed predictions using WindSat had an average of 46% and a range of 32 to 70% within the same. Most of the LIS-based speed predictions in the wet season were higher than in situ-based speed predictions (77%) with a significant percentage more than 15 km/h higher (58%). In comparison, 41% of WindSat-based speed predictions were higher than the in situ and few (13%) were more than 15 km/h higher; 13% of WindSat-based speeds were lower than in situ and some (3%) were more than 15 km/h lower. For both sources, the speed predictions for the W1 vehicle were considerably better than the average; the reason for this is shown in Figure 4a. W1 is a high mobility vehicle with low VCI and low sensitivity to soil strength, so it achieved its maximum off-road speed on much of the time series. Based on VCI alone, it may appear that T1 should

have had a similar performance, but other characteristics of the T1 vehicle (mostly the powertrain characteristics) prevented it from reaching maximum speed for as much of the period.

8.2. Australia

Figure 5 and Figure 6 show the results for the site in Australia. For this site, most of the period of record was not wet enough to limit ground vehicle mobility. As with the site in France, the errors in soil moisture during the dry periods were not significant to the modeled speeds; maximum speed was predicted for most of the dry period. Generally, in this time period during which soil moisture was high enough to affect mobility, both LIS and WindSat provided lower estimates of soil moisture compared to the in situ measurement. As a result, some soil strength and modeled speeds for both LIS and WindSat were higher than those for in situ (Table 3). Even so, wet season predicted speeds for both LIS and WindSat were within the 5 km/h threshold over 80% of the time for all vehicles (Table 3).

8.3. Spain

The results for the site in Spain are shown in Figure 7 and Figure 8. WindSat and the in situ soil moisture inputs indicate very limited impact of soil moisture on mobility. Even in the wet season, maximum speeds were usually predicted. As a result, most of the predicted speeds from both LIS and WindSat matched those based on in situ soil moisture. However, LIS provides wetter soil moisture estimates overall, which result in predictions of lower soil strengths and degraded speeds in the wet season (Figure 8). The wet season speed bias from LIS did not affect all vehicles equally (Figure 8); W1 (Figure 8a) was completely unaffected and had maximum speed predictions across the entire time series for all three soil moisture sources. W2 (Figure 8b), W3 (Figure 8c), and W4 (Figure 8d) were most affected with 86%, 65%, and 85% (respectively) of their predicted speeds at least 5 km/h slower than the speeds predicted based on in situ. T1

(Figure 8e) and T2 (Figure 8f) speed predictions were only moderately affected, with 16% and 11%, respectively, of LIS speeds being slower than in situ speeds.

9. Discussion

The results shown in the previous section indicate that both directions and magnitudes of biases are different from site to site. In France, LIS had a dry bias, resulting in higher speeds. In Australia, moisture effects were minimal because of low soil moisture. In Spain, LIS had a wet bias, resulting in lower speeds. Also, the time series and pair-wise comparisons show that the biases can have different effects on the predicted speeds seasonally, especially in France and Spain.

Furthermore, the effect on speed estimates is different from vehicle to vehicle. VCI provides some estimate of the range of soil strengths to which the vehicle will be sensitive, but it is not the only indicator because mobility is also influenced by other vehicle characteristics. This explains why W1 was able to reach its maximum off-road speed more often than T1, a vehicle with better VCI metrics.

The simplified time series approach to analyzing ground vehicle mobility provides an advantage in that it allows relatively quick analysis over a period of record to consider differences across seasons. However, in considering this analysis, the simplifying assumptions mentioned in Section 4 must be remembered. In particular, the speeds used here assume that only soil strength (and no other terrain factors) influence ground vehicle speed. Also, the time series analysis treats each site as a single point; spatial distribution of soil strengths and other terrain characteristics is completely ignored. A more detailed model of the terrain could show the relative importance of soil strength in the context of other terrain characteristics, such as slope and vegetation.

10. Conclusions

Satellite soil moisture data can be used to characterize terrain for mobility modeling purposes. The current study conducted a comparison between vehicle mobility assessments conducted using three soil moisture sources: WindSat (a satellite source), LIS (a computer model source), and in situ ground sensors (to represent ground truth). Three test sites (Spain, France and Australia) and six vehicles were used in the mobility analyses with NRMM. It was assumed that soil strength was the only terrain factor that affected the vehicle mobility.

Comparison of the simplified, time-series-based analysis for the study sites at France, Australia, and Spain demonstrate the complex nature of the soil trafficability issue. Namely, biases in mobility predictions will vary based on location and time of year. This is the case even before accounting for other terrain factors such as slope and vegetation. In addition, ground vehicles are sensitive to different ranges of RCI changes. An error in soil moisture estimates may not affect one vehicle but may drastically change expected performance for another.

Modeled vehicle speeds in the dry time periods were limited by the interaction between soil traction and the vehicles' powertrain characteristics. In the wet season, differences in soil strength resulted in more significant differences in mobility predictions. This simplified time series analysis shows that soil moisture errors may produce very significant errors in mobility analysis for certain combinations of vehicles, seasons, and climates. Further work is needed to fully quantify these errors worldwide and year-round.

Research is ongoing to properly assimilate WindSat into the LIS framework. The advantage of a data assimilation framework such as LIS is that it can provide better spatial and temporal resolution than satellite systems (like WindSat) alone. LIS also is able to represent soil layers, unlike WindSat, which provides only a surface moisture estimate. However, each LIS soil

moisture estimate depends on correctly estimating mass and energy balances for the previous time step. Assimilating WindSat measurements into LIS could improve overall accuracy by providing independent soil moisture estimates to offset model biases. Ideally, this assimilation would provide soil moisture estimates that have spatial, temporal, and soil layering resolution of LIS with added accuracy contributed by WindSat.

Acknowledgements

Soil moisture datasets were provided by Dr. Li Li of the US Naval Research Laboratory. Further data support was provided by the DoD Soil Moisture Applications Consortium: John Eylander and Michael Shaw (US Army Engineer Research and Development Center), Andrew Jones (Colorado State University), and Gary McWilliams (US Army Research Laboratory). Funding was provided by the US Office of the Under Secretary of Defense for Acquisition Technology and Logistics (OUSD A&TL). Permission to publish this information was granted by the Director, Geotechnical and Structures Laboratory.

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List of Tables:

Table 1. Study vehicle configuration characteristics related to soft soil mobility.

Table 2. Pair-wise comparisons of NRMM speed predictions using WindSat and LIS versus in situ moisture data (France).

Table 3. Pair-wise comparisons of NRMM speed predictions using WindSat and LIS versus in situ moisture data (Australia).

Table 4. Pair-wise comparisons of NRMM speed predictions using WindSat and LIS versus in situ moisture data (Spain).

List of Figures:

Figure 1. Study methodology overview.

Figure 2. Soil moisture-strength relationships used in the study

Figure 3. Time series of volumetric soil moisture and soil strength at the France study site.

Figure 4. Speed estimates of vehicles over time at France study site.

Figure 5. Time series of volumetric soil moisture and soil strength at the Australia study site.

Figure 6. Speed estimates of vehicles over time at Australia study site.

Figure 7. Time series of volumetric soil moisture and soil strength at the Spain study site.

Figure 8. Speed estimates of vehicles over time at Spain study site.

Table 1. Study vehicle configuration characteristics related to soft soil mobility.

Vehicle	Description	VCI ₁ , kPa	VCI ₅₀ , kPa
W1	Light Wheeled	150	350
W2	Mid-weight Wheeled	230	500
W3	Heavy Wheeled	260	560
W4	Very Heavy Wheeled	450	990
T1	Light Tracked	130	300
T2	Heavy Tracked	170	400

Table 2. Pair-wise comparisons of NRMM speed predictions using WindSat and LIS versus in situ moisture data (France).

Speed Range (km/h)	Wet Season						Dry Season					
	WindSat			LIS			WindSat			LIS		
	Avg.	Min	Max	Avg.	Min	Max	Avg.	Min	Max	Avg.	Min	Max
> 20	2	0	0	35	0	61	0	0	0	0	0	0
15 20	11	0	8	23	8	51	0	0	0	0	0	0
10 15	12	9	30	11	1	23	0	0	0	0	0	0
5 10	16	1	25	8	3	16	0	0	0	0	0	0
-5 5	46	32	70	22	14	45	86	71	100	99	98	100
-10 -5	6	0	11	1	0	2	12	0	25	1	0	2
-15 -10	4	3	5	0	0	0	0	0	0	0	0	0
-20 -15	2	0	5	0	0	0	2	0	4	0	0	0
< -20	1	0	3	0	0	0	0	0	0	0	0	0

507 **Table 3. Pair-wise comparisons of NRMM speed predictions using WindSat and LIS versus**
508 **in situ moisture data (Australia).**

	Speed Range (km/h)	Wet Season						Dry Season					
		WindSat			LIS			WindSat			LIS		
		Avg.	Min	Max	Avg.	Min	Max	Avg.	Min	Max	Avg.	Min	Max
>	20	1	0	3	2	0	4	0	0	0	0	0	0
15	20	1	0	3	3	0	7	0	0	0	0	0	0
10	15	3	0	5	2	0	3	0	0	0	0	0	0
5	10	4	0	8	4	0	7	0	0	0	0	0	0
-5	5	88	80	99	88	81	99	100	100	100	100	99	100
-10	-5	2	0	3	1	0	1	0	0	0	0	0	1
-15	-10	0	0	1	0	0	0	0	0	0	0	0	1
-20	-15	0	0	1	0	0	0	0	0	0	0	0	0
<	-20	0	0	0	0	0	0	0	0	0	0	0	0

509

510 **Table 4. Pair-wise comparisons of NRMM speed predictions using WindSat and LIS versus**
511 **in situ moisture data (Spain).**

	Speed Range (km/h)	Wet Season						Dry Season					
		WindSat			LIS			WindSat			LIS		
		Avg.	Min	Max	Avg.	Min	Max	Avg.	Min	Max	Avg.	Min	Max
>	20	0	0	0	0	0	0	0	0	0	0	0	0
15	20	0	0	0	0	0	0	0	0	0	0	0	0
10	15	0	0	0	0	0	0	0	0	0	0	0	0
5	10	0	0	0	0	0	0	0	0	0	0	0	0
-5	5	99	99	100	56	14	100	100	100	100	95	87	100
-10	-5	1	0	1	24	0	50	0	0	0	4	0	11
-15	-10	0	0	1	10	0	32	0	0	0	1	0	2
-20	-15	0	0	0	9	0	25	0	0	0	0	0	1
<	-20	0	0	0	1	0	3	0	0	0	0	0	0

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Figure 1.

Figure 2.

Figure 3.

Figure 4

Figure 5

Figure 5.

Figure 6

Figure 7

Figure 7.

Figure 8