RECLAMATION

Managing Water in the West

Fusion of In-Situ and Remotely Sensed Soil Moisture Data

Research and Development Office
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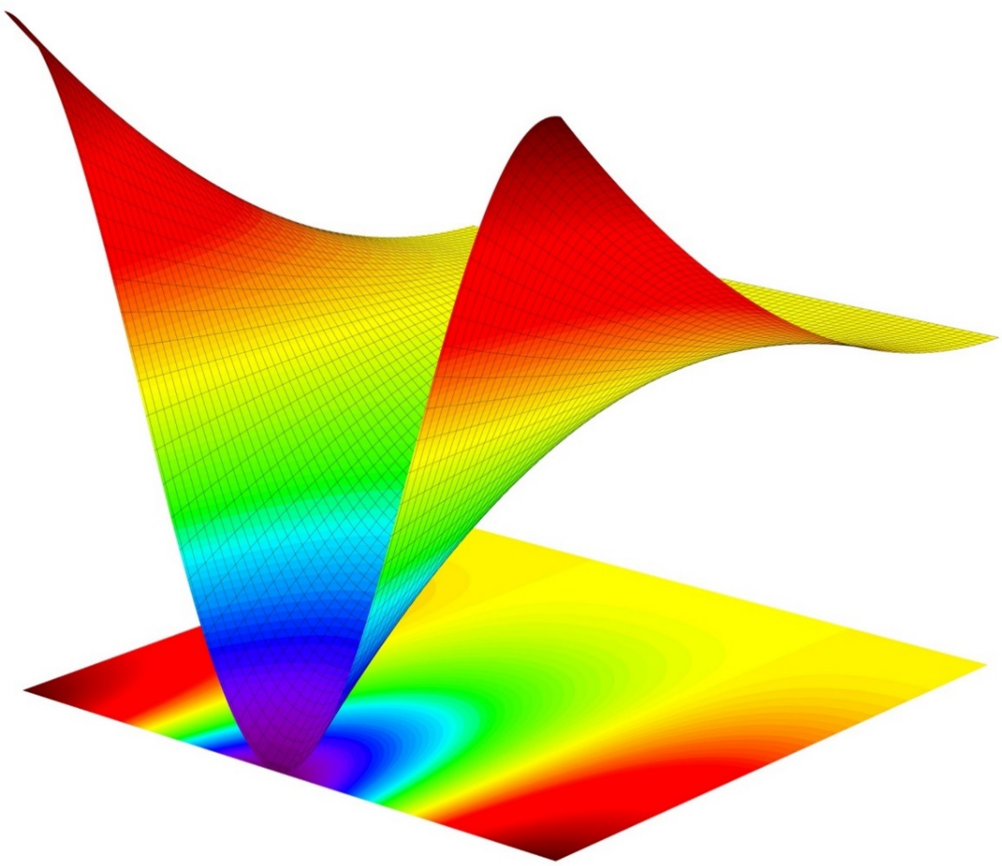

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Mission Statements

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14. ABSTRACT *(Maximum 200 words)* The US Bureau of Reclamation has developed a soil moisture monitoring network to create and maintain habitat for endangered species in designated conservation areas along the Colorado River in the Mojave Desert. Although soil moisture data loggers provide continuous and accurate information, their use is limited due to cost and logistics. Timely and accurate soil moisture information is vital to the effective water management of protected areas which have experienced drought for two decades.

The Enhanced Spatial and Temporal Adaptive Reflectance Fusion Model (ESTARFM) algorithm was evaluated for its utility in combining MODIS and LANDSAT satellite imagery with in-situ data to produce soil moisture data with increased resolution and accuracy beyond that of satellite data alone. The fusion of the best

characteristics of remotely sensed data and on-the-ground direct measurements can generate a product that is greater than the sum of its parts.

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LCR MSCP

(Final Report) ST- 2019 (EN 19136)

Fusion of In-Situ and Remotely Sensed Soil Moisture Data

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Acronyms and Abbreviations

BOR	Bureau of Reclamation
ESTARFM	Enhanced Spatial and Temporal Adaptive Reflectance Fusion Model
FSDAF	Flexible Spatiotemporal Data Fusion
LANDSAT	Land Remote-Sensing Satellite
LCR	Lower Colorado Region
LiDAR	Light Detection and Ranging
LST	Land Surface Temperature
MODIS	Moderate Resolution Imaging Spectroradiometer
MSCP	Multi-species Conservation Program
NDVI	Normalized Difference Vegetation Index
NIR	Near Infrared
RTM	Radiative Transfer Model
SMAP	Soil Moisture Active Passive
SSM	Surface Soil Moisture
STARFM	Spatial and Temporal Adaptive Reflectance Fusion Model
Tb	Brightness Temperature
TIR	Thermal Infrared
UAS	Unmanned Aerial System

Executive Summary

Conservation areas managed by LCR MSCP are surrounded by landscapes which are often markedly different (e.g. agricultural land, raw desert) with respect to vegetation and terrain. Changes in soil moisture in these surrounding areas may impact LCR MSCP restored habitat but currently are not monitored by LCR MSCP. Imagery that overlaps both LCR MSCP and non-LCR MSCP areas and which has been integrated with localized soil moisture data can provide a means whereby local and regional soil moisture variables can be related. This “data fusion” approach seeks to leverage the large spatial extent, data quality, and derived products associated with satellite and/or aerial imagery with the accuracy and high temporal resolution of ground-based soil moisture monitoring equipment. The fusion of different datasets is further warranted when considering that the timing and resolution of imagery from satellites and aerial platforms is not always well suited to the system of interest, while the number of soil moisture loggers is limited due to cost and logistics.

A literature review of concepts, software, workflows, and algorithms was conducted to understand the current state of the science. Software packages (both commercial and open source) were evaluated and tested. Subject matter experts from within the BOR and other Federal and local agencies, software vendors, and academia were consulted.

The results identified work flows and algorithms which are most likely to produce a usable and robust soil moisture retrieval process for the LCR MSCP area of interest. The selected research uses free and publicly available imagery and data and utilizes well-established relationships between vegetation and temperature and is not directly dependent on ancillary data. Modifications are proposed to allow for the more realistic modelling of the areas of interest.

The original model inputs and equation coefficients will need to be quantified for LCR MSCP conservation areas. Vegetation, soil type, and other physical characteristics of the areas of interest may need to be mapped in more detail than is currently available through existing datasets to achieve this. Significant testing of the finalized work flow will be required to ensure a functional output and modifications to the selected algorithms may be necessary.

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Main Report

Background

The Lower Colorado Region Multi-Species Conservation Program (LCR MSCP) has developed a soil moisture monitoring network as part of its tasking to create and maintain habitat for covered species in designated conservation areas. This information is a component of management decisions directly related to (1) the surface soil moisture (SSM) needs for avian habitat requirements and (2) vegetation health requirements with respect to evapotranspiration (LCR MSCP). SSM is generally defined as the relative soil water content from 0 to 10 cm in depth. In addition to the efforts of LCR MSCP, the Bureau of Reclamation (BOR) employs soil moisture information to validate and monitor such environmental and operational parameters as water budgets, soil condition, and habitat condition as it pertains to management decisions regarding endangered species, invasive plants, and fire regime. Soil moisture is an input parameter used by the AgriMet network to monitor irrigation water management (BOR AgriMet). More generally, soil moisture indices are important components of hydrological modeling in forested (Hogg, Barr, and Black 2013), agricultural (Carrao et al. 2016), and arid landscapes (Halwatura et al. 2017). Soil moisture is broadly used in studying drought assessment and prediction (Zhang et al. 2016; Kathuria, Mohanty, and Katzfuss 2019).

Conservation areas managed by LCR MSCP are surrounded by landscapes which are often markedly different (e.g. agricultural land, open desert) with respect to vegetation and terrain. Changes in soil moisture in these surrounding areas may impact LCR MSCP restored habitat but currently are not monitored by LCR MSCP. Imagery that overlaps both LCR MSCP and non-LCR MSCP areas and which has been integrated with localized soil moisture data can provide a means whereby local and regional soil moisture variables can be related. This “data fusion” approach seeks to leverage the large spatial extent, data quality, and derived products associated with satellite and/or aerial imagery with the accuracy and high temporal resolution of ground-based soil moisture monitoring equipment. The fusion of different datasets is further warranted when considering that the timing and resolution of imagery from satellites and aerial platforms is not always well suited to the system of interest, while the number of soil moisture loggers is limited due to cost and logistics.

Remote Sensing of Soil Moisture

All things being equal, microwave emissivity has a nearly linear relationship to soil moisture (Mattikalli et al. 1998). Within the general category of Radiative Transfer Models (RTM) (Mohanty et al. 2017), the remote sensing of soil moisture information via satellite systems (Figure 1) measures the microwave radiance, or brightness temperature (Tb), primarily in the C, L, and S bands received at the platform's radiometer. The observed brightness temperature of the surface is determined by soil moisture, soil composition and surface roughness (Brubaker and Entekhabi 1996) and attenuated by vegetation canopy effects (Gillies and Carlson 1995). Due to the physical characteristics of a passive satellite system, the spatial resolution of soil moisture data is generally coarse, typically on the scale of tens of kilometers. This is often too large a resolution for analysis of many landscapes, including the study area herein where the mean area of sites is just under three square kilometers. Roy et al. (2016) demonstrated the importance of sub-pixel heterogeneity with respect to soil temperature and vegetation composition when estimating soil moisture content, with the subsequent implication for reducing pixel size.

In order to increase the initial spatial resolution of soil moisture retrieval algorithms (downscaling), two general approaches are used: (1) visible and near infrared satellite observations and their associated data products to increase resolution and accuracy of SSM retrieval (Mallick, Bhattacharya, and Patel 2009). and (2) use of active sensors (e.g. radar) to estimate soil moisture at a finer scale (Dubois et al. 1995; Oh et al. 1992). The concept of downscaling is discussed in subsequent sections as it is a primary consideration for conducting this research.

Instrument	Satellite	Frequency	Band	Spatial resolution	Temporal resolution	Sensor type
		GHz			d	
AMSR-2	GCOM-W1	6.9–89	S, X	25–50 km	2	passive
AMSR-E	Aqua	6.9–89	C, X	25–50 km	2	passive
Aquarius	Aquarius	1.26	L (active)	76–156 km	7	active/passive
		1.41	L (passive)			
ASAR	ENVISAT	5.33	C	30–1000 m	5	active
ASCAT	MetOp	5.25	C	25–50 km	2	active
MIRAS	SMOS	1.4	L	35–60 km	3	passive
NISAR	NISAR		L and S	0.1–50 km	12–60	active
PALSAR	ALOS	1.27	L	10–100 m	46	active
RADARSAT-1 & -2		5.40	C	10 m	24	active
Tandem-L	Tandem-L	1.2	L	3–20 m	8	active
Sentinel-1A & -1B			C	5–20 m	6–12	active
SMAP	SMAP	1.41	L (passive)	40 km (passive)	2–3	active/passive
		1.26	L (active)	3 km (active)	2–3	
SSM/I	SSM/I	19.35	K	13–69 km	0.5	passive
WindSAT	Coriolis 6.8–37		C,X, and K	8–71 km	8	passive

Figure 1. From Mohanty et al. 2017: Remote sensing instruments and satellite platforms (past and current) for soil moisture retrieval.

In addition to RTMs; the primary methods for estimating soil moisture via passive remote sensing can be grouped as: Universal Triangular Relationship Method, statistical analysis technique (e.g. linear regression), and the application of neural networks (Ahmad, Zhang, and Nichols 2011). The Universal Triangular Relationship Method refers to the formalized regression between the parameters of soil moisture, Normalized Difference Vegetation Index (NDVI), and land surface temperature (LST) (Carlson 2007). Neural networks are artificial intelligence algorithms which incorporate a series of complex, complementary mathematical functions which direct the output towards a user -defined result. The back propagation neural network is a primary application in remote sensing for pattern recognition and time series data and in estimating soil moisture (Chai et al. 2008).

Visible and Infrared

Visible spectrum wavelengths (red, green and blue) as well as near-infrared (NIR) and thermal infrared (TIR) pixel values are integrated with vegetation indices such as NDVI (red and NIR wavelengths are its components), Enhanced Vegetation Index, and Vegetation Condition Index to estimate soil moisture (Esfahani et al. 2015). Similarly, Shafian and Maas (2015) have used raw image pixel digital count data in the red, NIR, and TIR spectral bands evaluated against LANDSAT ground cover data to create a soil moisture index. Haijun et al. (2017) produced hyperspectral images (400 - 1000 nm; 339 spectral channels) of soil samples and identified 256 optimal wavelengths. Analysis of this data produced several model variables which showed highly significant and accurate responses to soil moisture variability.

LiDAR

LiDAR (Light Detection and Ranging) intensity responds to soil moisture variability most strongly for bare soil; soil moisture has greatly less influence on received pulse intensity where vegetation is present (Garroway, Hopkins, and Jamieson 2011). For vegetated land cover types, airborne LiDAR data can be used indirectly to measure soil moisture as an input in terrain analysis models (Hardy 2010) and in the creation of indices ancillary to soil moisture such as topographic wetness and canopy height (Southee, Treitz, and Neal 2012).

Data Fusion

Data fusion is defined in Chang and Bai (2018) as any process which creates an integrated dataset through the synergistic merging of numerous data sources that produces more information than any one of the inputs. Hall and Llinas (1997) expands on this in noting increased accuracy and greater ability to infer relationships and trends through data fusion. More specifically (and for the purposes of this project), image fusion involves the integration of two or more images from different sensors and is categorized by Pohl and Van Genderen (1998) into three levels depending on what stage the fusion is performed: pixel, feature, and decision (Figure 2); Chang and Bai (2018) describe these as low level, intermediate level and advanced level, respectively. As the name implies, pixel level fusion is the blending of pixel information after some mathematical operation is applied on each pixel and /or for each image. Image sharpening is an example of fusion at the pixel level. Feature level fusion begins with the extraction of features from each image based on classification and/or extraction algorithms with respect to geometry, radiometric value, etc. Land use/land cover maps are produced utilizing this type of fusion process. Decision level fusion follows similar procedures as feature level fusion with respect to feature extraction. Features are then identified and the data fused following external decision rules based on mathematical operators, including the use of Bayesian and “fuzzy logic “methods (Waltz 2001).

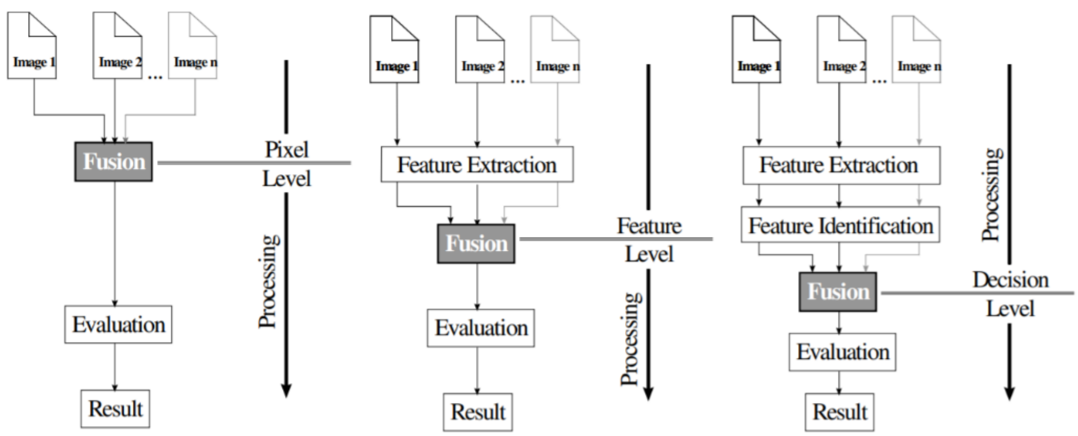

Figure 2. From Pohl and Van Genderen (1998): Diagram of fusion levels.

In-Situ Soil Moisture Data

In-situ SSM data has been used to evaluate and validate satellite soil moisture retrieval products such as the NASA Soil Moisture Active Passive mission (SMAP) (Zhang, Kim, and Sharma 2019; Velpuri, Senay, and Morisette 2016.) The SMAP mission was in itself a data fusion exercise in that a passive microwave radiometer was paired with an active radar sensor in order to downscale the microwave soil moisture data from 36 km to 3 km Due to the failure of the radar sensor soon after launch, available SMAP products range from 9 to 36km in resolution (NASA SMAP). Senanayake et al. (2019) incorporated in-situ SSM data in a regression tree model which accurately downscaled the SMAP Enhanced 9 km radiometric product to an output 1km resolution.

Methods

A literature review of concepts, software, workflows, and algorithms was conducted to understand the current state of the science. Software packages (both commercial and open source) were evaluated and tested, such as Geomatica (PCI Geomatics), eCognition (Trimble), and ENVI/IDL (L3 Harris Geospatial Solutions). Subject matter experts from within the BOR and other Federal and local agencies, software vendors, and academia were consulted.

With the definitions and concepts regarding data fusion and the remote sensing of soil moisture taken into consideration, this research will determine the feasibility of estimating soil moisture by combining in-situ measurements with remotely sensed data such as aerial and satellite multi-spectral imagery. The priority for this scoping project has been to utilize open source software and publicly available imagery and data. The overall goal is to provide a foundation and framework from which soil moisture metrics and/or predictive model(s) for the areas of interest can be created as a next step.

Results

A review of what are known as spatio-temporal fusion models revealed half a dozen or so different versions (e.g. STAARCH, SPSTFM, STDF, etc.); each has its specific applications and limitations. Spatio-temporal fusion compares pairs of different datasets at the same location and time in order to quantify the correlation of physical characteristics of each. There are three general categories of this type of data fusion: weighted function based, unmixing based, and dictionary-pair learning based (Zhu et al. 2016). The workflow and approach found in Xu et al. (2018) have been determined here to be the most likely to produce a usable and robust soil moisture retrieval process for the LCR MSCP area of interest. It uses free and publicly available imagery and data and utilizes well-established relationships between vegetation and temperature and is not directly dependent on ancillary data. This research fused MODIS and LANDSAT data (Figure 3) to create a non-linear model for SSM values using NDVI and LST.

The imagery fusion model was implemented via the Spatial and Temporal Adaptive Reflectance Fusion Model (STARFM) developed by Gao et al. (2006). This pixel-level algorithm fuses spatial information from LANDSAT with temporal information from MODIS by comparing one or more pairs of LANDSAT and MODIS images; each pair taken from the same date. The Universal Triangle relationship between LST and NDVI is incorporated with the downscaled imagery to produce SSM data at 120m resolution (Figure 4).

MODIS		Landsat 8	
Band 1	Band 1, 620 nm to 670 nm, is primarily used for land, cloud, and aerosols boundaries.	Band 4	Band 4, 636 nm to 673 nm, is a red band.
Band 2	Band 2, 841 nm to 876 nm, is primarily used for land, cloud, and aerosols properties.	Band 5	Band 5, 851 nm to 879 nm, is a near infrared band.
Band 32	Band 32, 11.77 um to 12.27 um, is primarily used for surface and cloud temperature.	TIR2	TIR2, 11.50 um to 12.51 um, is a thermal infrared band.

Figure 3. From Xu et al. 2018: MODIS (1000 m) and LANDSAT 8 (30 m) corresponding bands.

The single channel method of Jimenez-Munoz et al. (2009) derives LST from the fused thermal infrared data. SSM values are produced using the regression equation (Equation1):

$$\text{SSM} = \sum_{i=0}^{i=n} \sum_{j=0}^{j=n} a_{ij}\, NDVI^{*(i)} T^{*(j)}$$

(1)

where NDVI* and T* are scaled values of NVDI and LST. The regression coefficients a_{ij} are quantified from the in-situ soil moisture data.

A modification to the above workflow is considered herein where the STARFM fusion model for each band is replaced with the Enhanced Spatial and Temporal Adaptive Reflectance Fusion Model (ESTARFM). Developed by Zhu et al. (2010), ESTARFM analyzes at least two pairs of pre-processed (geometric and radiometric) images, from one fine resolution (in this case LANDSAT) and one coarse resolution (MODIS) sensor, each image pair taken at the same date (or as close as possible) (Figure 5). Utilizing spectral unmixing of the coarse resolution data, the difference in time between the two image pairs establishes an observed reflectance trend between sensors, essentially as training data, which then is applied to a third pair of images to produce the final result (Chang and Bai 2018). The motivation for choosing ESTARFM is that STARFM does not accurately quantify surface reflectance for heterogenous landscapes (Chang et al. 2016), whereas ESTARFM was developed for that particular application (Zhu et al. 2010) and has improved performance compared to STARFM (Emelyanova et al. 2013).

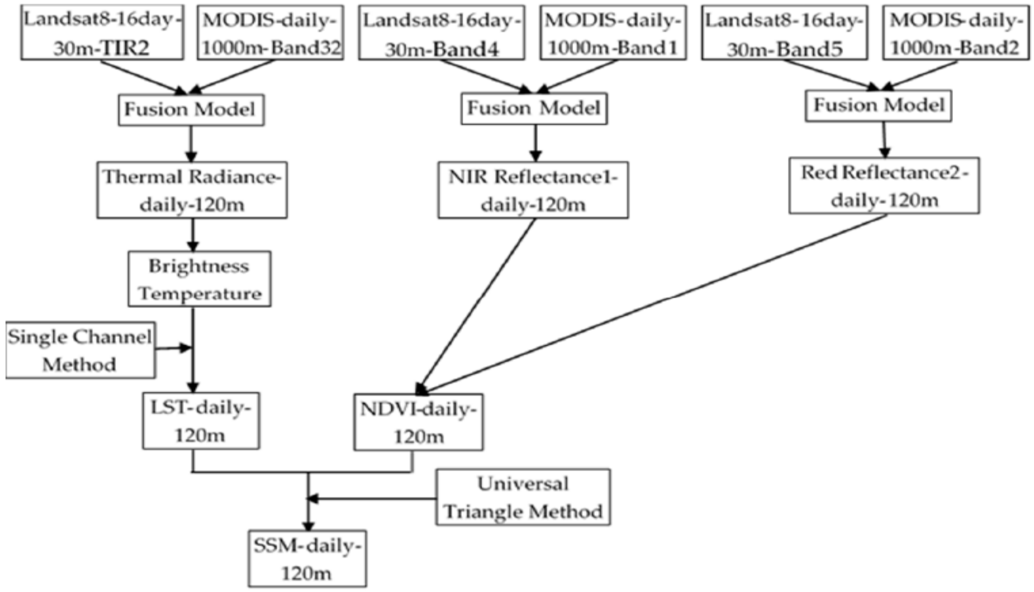

Figure 4. From Xu et al. (2018): Flow chart for fusion of MODIS and LANDSAT 8 measurements for SSM retrieval.

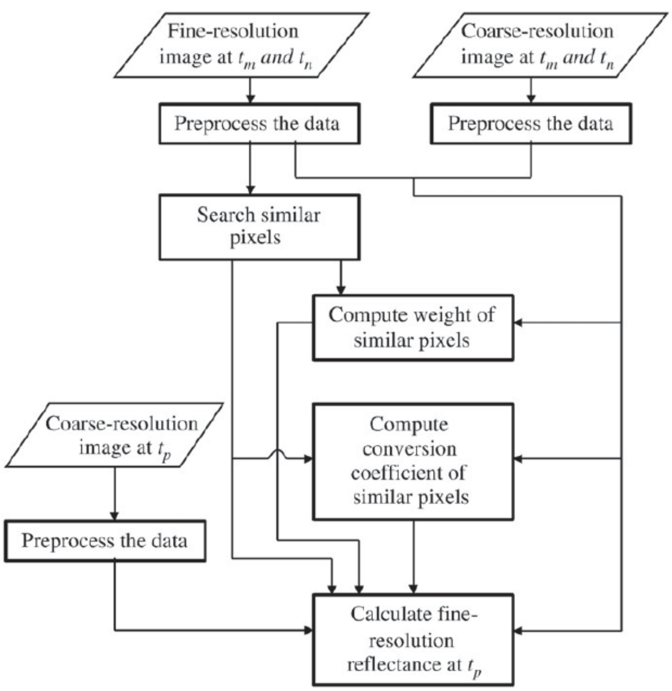

Figure 5. From Zhu et al. (2010): ESTARFM algorithm flowchart.

Preliminary testing of ESTARFM of LANDSAT and MODIS images used ENVI 5.5.2 tools (e.g. Image Registration) to pre-process the data. The ESTARFM algorithm was run in IDL 8.7.2.

a. b.

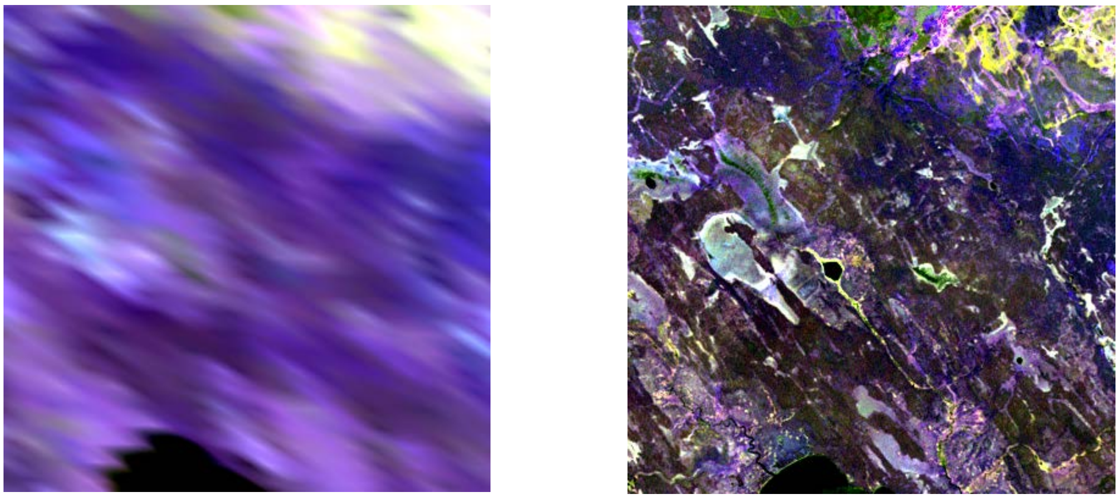

Figure 6. Original MODIS image (a) and ESTARFM output (b).

Conclusions

If the proposed workflow leads to accurate, detailed, and frequently updated soil moisture information over large areas, then all activities using such data will be enhanced. Producing soil moisture data products that are coherent across different scales will allow for analyses to be conducted at different scales as well. Any Reclamation entity which uses field data could conceivably adopt data fusion methodology for its particular needs. Data products derived in such a way could greatly increase the accuracy and utility of existing models and analysis tools. This in turn would guide and improve adaptive management decision making processes.

Next Steps

With respect to the workflow shown in Figure 4, Xu et al. (2018) note the importance of scaling NDVI and LST inputs to a particular landscape. Vegetation, soil type, and other physical characteristics of the areas of interest may need to be mapped at a higher resolution than is currently available through existing datasets to achieve this. Additionally, the coefficients in Equation 1 will need to be quantified from the in-situ soil moisture data. Zhu et al. (2018) describe the moving search window which is an essential part of the correlation of pixel information between coarse and fine imagery pairs in the ESTARFM algorithm. The size of the search window is dependent on landscape heterogeneity and this parameter may similarly need to be categorized by conservation area.

Currently, LCR MSCP acquires multispectral aerial imagery (15cm resolution) as well as LiDAR data and products nearly annually. These datasets may be used to establish additional fusion processes with the possibility of increased downscaling of data. The ESTARFM program can be modified to incorporate aerial imagery into its workflow (Dr. Xiaolin Zhu, personal communication; August 7, 2019). Alternatively, aerial imagery can be used as one of two required datasets (with LANDSAT/MODIS processed through ESTARFM as the second) in the Flexible Spatiotemporal Data Fusion (FSDAF) method (*ibid.*). FSDAF is similar in approach to ESTARFM; it adds spatial interpolation techniques to allow for abrupt landscape changes (Zhu et al. 2016). Considering that some LCR MSCP conservation areas experience seasonal flooding in certain sections, FSDAF may also be considered as a substitute fusion model in the workflow shown in Figure 4 in those instances.

In the expectation that BOR will increase the use and availability of Unmanned Aerial Systems (UAS), the temporal resolution of high resolution multispectral, hyperspectral, and LiDAR imagery can be matched to that of satellite systems, at least over short time periods. UAS data can be fused either on its own (Sankey et al. 2018) or as a more detailed level of downscaling as part of the workflow suggested here. The capability and cost-effectiveness of UAS data is also expected to increase, as evidenced by development of drones with integrated

LiDAR and visible sensor payloads (Analityk). Finally, Larson et al. (2008) demonstrated the significant and accurate response of GPS signals to soil moisture and proposed the use of GPS base stations as proxy soil moisture monitors, therefore providing a potential source of additional in-situ SSM data.

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