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Los Angeles Water Resources

Monitoring Streamflow Regimes using NASA Sensor Data to Aid Classification-Based Decision Making for Stream Water Management in Los Angeles County

DEVELOP Technical Report

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I. Abstract

Resource agencies such as the Council for Watershed Health (CWH) and the Southern California Coastal Water Research Project (SCCWRP) rely on accurate knowledge of the entire watershed system to monitor, model and manage water resources. The current methods to detect streams and predict flow regimes (perennial/intermittent) in California's watersheds mostly use field measurements. Intermittent stream identification is challenging using these methods, and field verification is labor intensive and expensive. To assess the feasibility of using remote sensing, we determined which NASA sensors were compatible for our study and then we researched, created and executed methodologies to analyze both Landsat and UAVSAR data. We used Landsat 5 TM and Landsat 8 OLI to analyze the potential of imagery to detect surface water, soil moisture and vegetation-rich areas by performing band combinations, band math, classification and change detection. We used UAVSAR (PolSAR) to evaluate the potential of radar to detect soil moisture and vegetation by using different band polarizations, and by performing a land classification and change detection. Our findings indicate that UAVSAR data and Landsat data cannot effectively locate small intermittent streams, but can be useful in analyzing trends within larger water bodies such as reservoirs. Our results are useful to the CWH and the SCCWRP in understanding the potential use of these Earth observation sensors and analyses of their data, and in providing the potential of other sensors for moving forward with their inquiry.

Keywords

Remote sensing, UAVSAR, Landsat, detecting streams, intermittent, soil moisture, vegetation, NDVI

II. Introduction

Background Information

"Rivers and streams are the arteries of the earth, with water flowing through them. With pulses of flow in surface water networks are representative of the health of our planet. Some streams flow constantly, we say they are perennial and others only flow during part of the year we call those intermittent. The intermittent streams are hard to observe because they're located up in remote areas. This is one of the reasons why we at JPL are investigating potential capabilities to see those changes remotely using planes and satellites."

- Cedric David, Jet Propulsion Laboratory, Science Advisor

Intermittent streams comprise up to 90% of the stream length in arid regions (Levick et al., 2008), providing critical habitat to a wide range of plant and animal species, and acting as a link between human activities occurring on the landscape and downstream impacts. However, there is a lack of research on intermittent streams in upper watersheds due to issues with accessibility for field observation and variation in presence of water (Ode et al., 2011).

Current forms of stream identification include field surveys, analysis of topography, available modeled data, stream gauges and other in situ observations. Although these methods have been used in practice for many years, they have substantial limitations including cost, logistics, thoroughness, frequency of collection and inaccuracies (Gritzner and Millet, 2003).

Understanding stream flow characteristics over time is essential for a variety of regional monitoring and assessment programs. Knowing whether a stream is perennial, intermittent, or ephemeral can affect the choice of protocols, the assessment tools used and can also improve model performance (Gritzner, 2003).

California waterways are often contaminated and intermittent streams may be a source of water quality impairments. Accurately classifying streams as perennial or intermittent, as well as the degree that they are intermittent may help determine flow regimes and better quantify the amount of contamination a stream may be contributing (Brooks et al., 2006).

Riparian ecosystems are home to a variety of plants and animals, and provide aesthetic value to humans. At times, the demands of humans and other organisms may be at odds, and waterways may be contaminated. Resource agencies rely on specific statewide tools and on modeling to assess stream conditions when dealing with conflicting allocation needs, and for assessing water quality and environmental concerns (Levick et al., 2008).

Remote sensing can potentially be used to assess intermittent streams to eliminate the dependence on field measurements for stream identification, allow for more widespread, efficient and constant monitoring, as well as comparison and validation of current data.

Project Objectives

The overall objective of this project was to assess the potential of using NASA's remote-sensed data to identify intermittent streams and water flow in the upper watersheds of the Los Angeles River and San Gabriel River watersheds. To accomplish this overall goal, our sub-objectives were to determine which NASA sensors are compatible for this study, create and execute methodologies for these sensors to detect streams during wet and dry seasons, and determine the validity of our results based on known locations of intermittent and perennial streams.

Study Area

The study area included the Los Angeles River and the San Gabriel River watersheds. Within this study area, we established a smaller section to focus our analysis which corresponded to one Landsat scene and one UAVSAR flight path and included known intermittent streams and larger bodies of water. We used this smaller region to compare between methods and data sources. This study area section extended approximately 98 kilometers (60 miles) east to west, and between 17.5 kilometers (11 miles) to 21 kilometers (13 miles) north to south. The range is on the southern side of the Angeles National Forest (Figure 1).

Study Period

In order to define our study period and find desired flight dates, we downloaded stream gage data from the USGS to indicate times of high and low discharge, which directly indicates wet and dry months. It was useful to look at wet and dry months because intermittent streams may dry up or appear in these periods and analyzing these dates would yield the largest observable changes. We chose to use Arroyo Seco stream discharge data to select our target months for our UAVSAR analysis (Figure 2), and ultimately decided on using September 2009, and April 2010 to represent dry and wet periods, respectively.

Since Landsat data is readily available with a temporal resolution of 16 days, we used precipitation data obtained from the National Oceanic and Atmospheric Administration (NOAA) to determine the best dates for Landsat imagery analysis. For Landsat 5 TM, we chose November 2010 to reflect a wet scene with stream flow as there had been steady rain since October after a dry summer; March 2011 a continued wet scene showing water infiltration and snow in the upper mountain range; and September 2011 after a dry summer. For Landsat 8 OLI, we chose November 2014 to compare with the November scene of 2010.

Sensor	UAVSAR	Landsat 5 TM	Landsat 8 OLI
Dates Used	18 September 2009, 15 April 2010	13 November 2010, 5 March 2011, 29 September 2011	8 November 2014

National Application

Our project addressed the Water Resources National Application Area and can be used by water resource programs to better understand and characterize their local watersheds.

Project Partners

The Council for Watershed Health (CWH) is a nonprofit organization whose mission is to enhance the health of the region's watersheds through education, research and planning. CWH has managed watershed-wide monitoring programs in the Los Angeles and San Gabriel River Watersheds since 2005 and 2008, respectively (Steele, N., pers.com.). These programs monitor multiple indicators to measure the ecological health of the watersheds. The results of our project will help provide detailed and accurate information of the headwater streams in LA county watersheds to determine the flow regimes of streams that are unknown, particularly for the purpose of monitoring the effects on habitat, recreation, and climate change.

The Southern California Coastal Water Research Project (SCCWRP) is a publicly funded research agency focusing on monitoring and assessing the condition of watersheds and the effects of human activities on these resources. SCCWRP conducts coastal environmental research that is used by local governments to establish policies to better manage and protect Southern California's coastal aquatic resources (Stein, E., pers.com.). Access to the upper watershed is at times difficult, or impossible to reach, making it hard to accurately survey intermittent streams within upper watersheds. This DEVELOP project helps to understand streamflow characteristics over time (such as duration and persistence of flow), and provides an easier way for managers to locate intermittent streams.

III. Methodology

Our first step was to evaluate available earth observation data and determine which sources were compatible for our study (Figure 4). The sensors that had potential were highlighted in green, and those that did not were highlighted in red. After careful consideration of parameters such as availability within our study area, spatial and temporal resolution, and capabilities of the sensors, we decided to focus our analysis on Landsat 5 TM, Landsat 8 OLI, Unmanned Aerial Vehicle Synthetic Aperture Radar (UAVSAR), Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM), and USGS LiDAR.

Landsat 5 TM allowed for highlighting vegetation-rich areas and soil moisture by using both the near infrared and middle infrared bands (Bands 4 and 5 respectively), and Landsat 8 OLI's 15 meter grey scale panchromatic band was used for image sharpening and 3D imagery. UAVSAR was used to locate areas with increased soil moisture and vegetation with a resolution of 6 meters. The SRTM DEM was our main elevation raster which allowed us to correct for topography and hill shading, and for 3D imaging. The LiDAR data has a resolution of 10 feet which was used to create a slope raster from its DEM, locate streams, and to create our own stream network using ArcGIS.

Ancillary data: NHD and NAIP

The National Hydrography Dataset (NHD) represents the drainage network of the United States. It includes and delineates features such as rivers, streams, canals, lakes, ponds, coastline, dams and stream gages. The dataset was created using USGS topographic maps, USGS elevation data (digital elevation maps), stereo imagery, and extensive field-checking. The NHD line work follows the National Map Accuracy standards and the collection dates vary from the 1950s to the present. We used the NHD to determine a study area, to observe known locations of streams and reservoirs, and for comparison with our results. Ultimately, remote sensing could be used to match and improve the NHD with more frequent and widespread data collection.
We used high resolution and archived orthoimages from the National Agricultural Imagery Program (NAIP) to perform comparative analysis for our target years.

UAVSAR Data

UAVSAR has an L-band radar antenna that transmits and receives either vertical (V) or horizontal (H) radio waves, with the first letter indicating how the wave was sent and the second how it was received. We downloaded ortho-rectified grid files for UAVSAR's Polarimetric synthetic aperture radar (PolSAR) data using the NASA-JPL data portal for flight path 08525. We used the HH polarization, which highlights soil and urban areas, the VV polarization, which highlights surface water, and the HV polarization, which highlights vegetation. We downloaded the data for September 18, 2009 and April 15, 2010. We generated header files using a publicly available python script so that ArcGIS could read the data. We also radiometrically corrected the files, which is an important process for terrain correction, using the incidence angle file (Eq.1).

$$PolSAR.grd \times tan\ (Incidence\ angle) \quad (1)$$

After radiometrically correcting the images VV was divided by the HH. The polarizations VV, HH, and HV were converted into decibels to transform the data into a more usable scale (Eq.2), while it was unnecessary to convert VV/HH into decibels given that we were interested in the ratio between the two bands.

$$10x\ log10\ (PolSAR\_IncidentCorrected.grd) \quad (2)$$

We then made a red, green, blue composite image using the HH, HV, and VV polarizations. Where HH is red, VV is blue, and HV is green. The VV, HH, HV, and VV/HH images were further analyzed by applying a change detection algorithm where we subtracted a wet month from a dry month using the raster calculator.

Figure 5 is a flowchart of the methodology we used with the UAVSAR data in order to detect streams.

Landsat Data

The Landsat satellite program is a series of imagery that measure a range of frequencies along the electromagnetic spectrum (called bands). The amount of solar radiation that reflects, absorbs or transmits varies with wavelength and is specific to different materials. As a result, different aspects or elements of a scene can be identified by looking at an image's spectral signatures, or the relationship between reflectance versus wavelength. In our study, we were able to highlight water presence and vegetation using the near infrared, mid-infrared and visible bands due to known responses in these areas of the spectrum. Due to vegetation obstruction, shadowing, and small width stream size we decided to look at vegetation density and turgidity (amount of water in plants), and surface water as a means of identifying intermittent streams. We chose three methods to process the images: two band math ratio methods to detect streams: NDVI (Normalized Difference Vegetation Index) and NDWI (Normalized Difference Water Index), and a supervised classification and region of interest analyses to provide change detection to identify areas with potential intermittent stream flow. We obtained the Landsat imagery from the USGS EarthExplorer tool for relevant dates (Figure 6) and processed the imagery in ENVI Classic and ENVI 5.0, as well as ArcGIS.

Figure 7 is a flowchart of the methodology we used with the Landsat data in order to detect streams. All methods were processed using ENVI Classic unless otherwise noted.

Data Processing

Atmospheric Correction: First, we corrected the imagery for the effects from scattering and reflectance by using the dark object saturation tool in ENVI 5.0. This is a radiometric calibration tool that finds the darkest pixel value in each band of the scene and subtracts this value from every other pixel in the band. Since the dark object's value will only be a result of atmospheric scattering (because otherwise a dark object would return a value of zero), this method calibrates the other pixels to not include the effects of reflectance.

Shadow masking: Our study area is characterized by steep terrain enhancing shadow effects on the images. In order to reduce the effects on our analysis we created shadow masks for the NDVI and NDWI processes, and selected samples as a region of interest (ROI) for the Supervised Classification. We eliminated the effect of shadowing differently in each method, and the strategy behind each individual shadow mask will be outlined in each method's section.

Co-registering images: The resolution of the Landsat visible and infrared bands are 30 meters; however, Landsat 8 OLI has a panchromatic grayscale band with a 15 meter resolution that covers the area of visible bands and near infrared. We used the 15 meter Landsat 8 OLI panchromatic band as a base image to co-register (image-to-image) the Landsat 5 TM images (Figure 8). We first had to resample the spatial resolution of the 30 meter Landsat 5 TM images to 15 meters, and then selected Ground Control Points (GCP) which acts as tie points between the two images to create a warped file. The pseudo-higher resolution images created by co-registering the images with the 15 meter OLI band allowed for rigorous training sites to be made for classification purposes.

NDVI: We chose to perform an NDVI calculation because of the low resolution of Landsat. Although a thirty meter resolution might not be precise enough to pick up small intermittent streams, it has the potential to highlight 'vegetation corridors,' or strips of dense vegetation, associated with these small streams. The NDVI method determines the spatial distribution of vegetation by utilizing the phenomena that leaf cells scatter solar radiation in the near-infrared region and chlorophyll strongly absorbs visible light in order to photosynthesize. As a result of these qualities, the spectral signature of vegetation is characterized by high reflectance in the near-infrared wavelengths and, conversely, high absorption in visible wavelengths (red and blue). Using a Landsat 8 image from November of 2014, we performed an NDVI band math calculation by employing the NDVI tool in ENVI Classic (Transform → NDVI). This tool applies the following equation (Eq. 3) to highlight vegetation in a scene:

$$NDVI = \frac{NIR - VIS(red)}{NIR + VIS(red)} \tag{3}$$

The result of this process is a set of grayscale images representing the amount of vegetation present in the scene. We then used color mapping and ENVI Color Tables to make the values appear in a color gradient. The colors ranged from white to green with white representing areas with no vegetation, and green representing densely vegetated areas. Comparing these patterns to the NHD appeared to show a correlation between highly "vegetated" areas and places of known streamflow.

We performed a supervised classification of the scene by creating regions of interest (from the original Landsat image) using the spectral profiles of unique elements to properly classify the area. We observed the statistics information of our user-defined regions of interest in order to make sure they were cohesive and accurate. The spectral profile for shadows is shown in Figure 9.

Using the shadow region of interest, we created a shadow mask and applied it to an NDVI image. Once this mask was performed, much of the previously apparent correlations between dense vegetation and NHD flow lines disappeared, resulting in the conclusion that these patterns were actually a correlation between topography and the NHD flow lines.

<u>NDWI:</u> The co-registered November 2010 Landsat 5 TM image was used to perform the NDWI, and our first step was to create an NDWI image by using the following band math (Eq. 4):

$$NDWI = \frac{NIR - VIS(blue)}{NIR + VIS(blue)} \tag{4}$$

From this image we created a density slice to change the ranges and remove the water bodies by entering a minimum and maximum threshold value of -0.65 to -0.50 to create a water mask. Small gaps were filled in by using a morphology filter on the mask and selecting a kernel size of 5x5, this was saved as a .tif file to open it in ArcMap.

In the NDWI image the shadow regions and the water regions are similar, so we created a hill shade mask to remove shadow regions that were incorrectly assigned as water regions. This process was performed in ArcMap and required resampling of the SRTM's spatial resolution DEM from 30 meters to 15. We calculated the hill shade by using the sun's azimuth and elevation information from Landsat 5 TM image. The shadow mask was created by setting a null value to the hill shade reflecting shadow regions < 70. The next step was to change values in the attribute from NoData to 0. By reclassifying the mask to 0s and 1s instead of NoData and 1s, the 0 values can be selected and deleted from the mask by using the expression "GRIDCODE"=0. We then used the filtered NDWI water mask and the shadow mask to create a polygon file that reflected water regions in shadow that were not shadow. This process required using a conditional raster (the reclassified shadow mask) and an input file (the filtered NDWI water mask), and the expression "Value" = 0 to pull out the constant false value of 0. The results are the magenta polygons reflected in Figure 10.

<u>Supervised classification:</u> For the classification to be successful, a scrutinized set of training sites needed to be created to flush out the small streams and plants with high turgidity versus regular vegetation. Using the Landsat co-registered images, training sites were created through a rigorous classification process by which pixel values were sampled by studying their spectral bands associated to recognized profiles Figure 11. This required constant evaluation and adjustment to ROIs in order to create a classified image that somewhat resembled the features of the co-registered image. The legend in Figure 12 shows the features that were targeted to best represent the image.

The ROIs were then overlaid on each image and a supervised parallelepiped classification was then performed. The parallelepiped method classifies pixels based on the minimum and maximum limits on each class in each band. The values to the limits can be adjusted prior to the classification, and since the water pixels were fewer in comparison to other classes, a higher value was given to exaggerate their presence (Figure 13).

This exaggeration can be seen in particular in the November scene during which time there had been rainfall since October (Figure 14). March shows snow and scattered water bodies, an increase in vegetation turgidity, full reservoirs, and fewer large water areas (Figure 15); September shows very few water pixels and significantly reduced reservoirs (

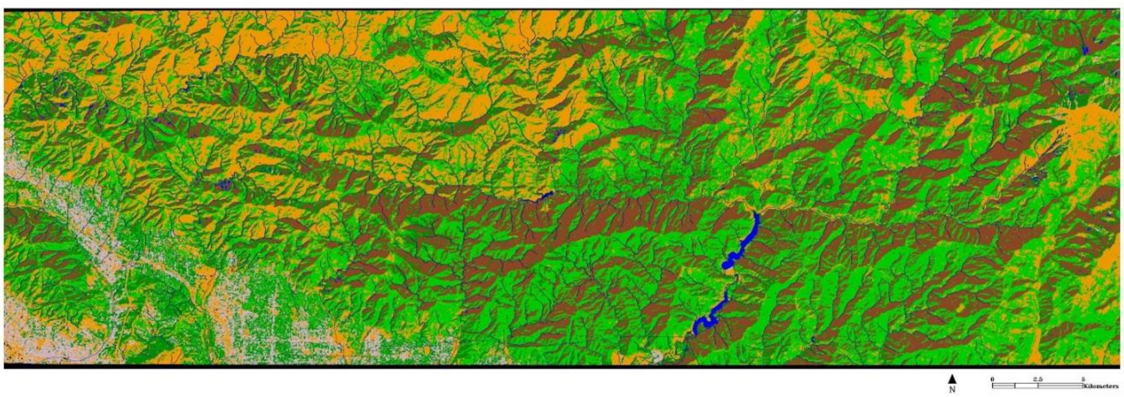

Figure 16).

Data Analysis

No data analysis was performed for the NDVI calculation because the analysis found a correlation between shadowing and the NHD lines rather than vegetation and the NHD lines.

The NDWI data analysis showed magenta polygons as created from the NDWI water mask to total 5.39 km^2. We overlaid the NDWI water mask on the November 2010 supervised classification image (Figure 17) to impose the water mask along potential streams as shown in the exaggerated water bodies. Most water mask polygons are along or near the NHD stream flow lines, further study of these areas to determine whether there is any potential in the analysis require in-situ observation.

The Supervised Classification of a wet to dry year (2010-2011) showed water bodies in exaggeration. We used the percent of vegetation high turgidity (VHT), and water bodies, to evaluate change in water bodies over certain times of the year (Figure 18). Between the three scenes, November 2010 shows the largest total area of water bodies throughout the upper watershed at 86.2 km^2 and VHT at its lowest 225.17 km^2; while March 2011 reflects the lowest area of VHT (240.39 km^2) it is during the winter time with snow along the higher range; and while September 2011 lists the lowest total area of water bodies as 5.67 km^2 it has the highest area of VHT 255.42 km^2 . The lower amount of VHT in November 2010 could be due to the late arrival of rain while September 2011 was a wet winter and the melted snow would have contributed to consistent water availability throughout the summer. Further comparison of dry or drought years is required to evaluate water availability in the upper watershed; and in-situ observations to confirm this analysis is suggested.

LiDAR Data

We used a 10 foot resolution LiDAR DEM for Los Angeles County, which is available through the Los Angeles County GIS web page, to create a stream network map. We used ArcGIS for this analysis. First we "sink filled" the DEM to remove any holes that would screw the analysis. The second step we did was determine the direction water flows within the area, to do this we used the "flow direction" tool within ArcGIS and used the DEM as the input raster. Next we created a flow accumulation raster using the "flow accumulation" tool. This allowed us to determine where and how many water parcels accumulate in a given area. The final step we did was to create a stream network. We set a minimum stream threshold of 0.8 km^2 using map algebra, then converted this raster to a feature using the "stream to feature" tool with the input raster as the flow accumulation raster with the minimum threshold. The output was a stream network.

SRTM Data

The SRTM file was downloaded from JPL/NASA's database. The SRTM DEM was our main elevation raster which allowed us to correct for topography and hill shading, and for 3-D imaging.

IV. Results & Discussion

UAVSAR Results

The RGB composite, polarizations (VV, HH, HV, and VV/HH), and change detection images were all analyzed using the ancillary data. The RGB image highlights various features and allowed us to see where water or moist areas are more prominent. We observed dark blue colors within the large reservoirs, red in the urban areas, and green in the vegetated areas (Figure 19a). The topography within the area impacted the results of the analysis which is distinguished with the same dark blue colors on mountain ridge lines (Figure 19b). The VV/HH polarizations highlight soil moisture, however for the dry and wet months we were unable to discern any patterns indicating the river presence (Figure 20). This is the case for the VV, and HV images as well (Figure 20). We also were unable to see these rivers using the change detection of VV/HH, VV, or HV (Figure 21). We did however observe that the change detection of VV/HH and VV images captured changes in large reservoirs (i.e., imagery displays increased soil moisture in the wetter months).

Landsat Results

Upon first conducting the NDVI analysis and color mapping the band math return so that white corresponded to no vegetation and green corresponded to dense vegetation, there appeared to be a strong a correlation between highly "vegetated" areas and places of known streamflow shown by the NHD (Figure 22). However, after applying a shadow mask to eliminate the effects of topography, much of the previously apparent correlations between dense vegetation and NHD flow lines disappeared, resulting in the conclusion that these patterns were actually a correlation between topography and the NHD flow lines (Figure 23). This methodology would work well with higher resolution imagery because even though we were observing the larger vegetation index, some of the small streams in the study might have associated vegetated areas much smaller than the Landsat resolution.

LiDAR Results

The stream network generated using the LiDAR DEM closely matched the NHD. This indicates that the NHD does not have any grossly inaccurately classified streams. Furthermore the NHD categorizes the stream networks as perennial and intermittent, making the NHD dataset more detailed than the stream networks we generated. Given the close match between the NHD and the stream network generated using a high resolution DEM, we felt the NHD was appropriate to use as a guideline in finding streams using other remote sensing techniques.

Challenges

The results from the UAVSAR, Landsat 5, and Landsat 8 images all indicate that we were unable to identify intermittent streams. The main challenge during our analysis to detect streams was the resolution. The UAVSAR images had a resolution of 6 meters and the Landsat 5 and Landsat 8 images had a resolution of 30 meters (Figure 24). Given that most intermittent streams are smaller than 6 meters, UAVSAR and Landsat pixels will display an average value of the water and dry soil.

The second factor that caused uncertainty was the topography. Because our study area was located in the upper watersheds, steep terrain and shaded slopes had a large effect on our analyses (Figure 25). For UAVSAR, the shaded areas within valley and ridges caused "stream-like" patterns to occur on our images. For Landsat, shaded areas had similar returns to dense vegetation and water which makes these areas difficult to differentiate and eliminate.

Future Work

Given that resolution was the main challenge with this project, we believe that our methodology could be used to yield more conclusive results using higher resolution data. The following table shows potential sources of higher resolution data and the parameters for each.

Sensor	Source	Availability	Resolution	Capabilities
SWOT	NASA	Launch Date: 2020	2 meter	Will survey Earth's surface water, observe the fine details of the ocean's surface topography, and measure how water bodies change over time
AirSWOT	NASA	Current; missions	< 1 meter	Airborne testing for the SWOT mission

		must be requested		
Green LiDAR	Private	Must be privately purchased	~ 2 m	Detects, delineates and penetrates water surfaces

V. Conclusions

The methodology that we developed for Landsat and UAVSAR data was unable to effectively map intermittent streams or determine the degree that streams are intermittent within our study area. Our Landsat results show areas with increased moisture and how these areas change over seasons, and our UAVSAR results show changes in reservoir size at a relatively high resolution (6 meters). Both data sources were able to detect large, year-round streams and other large bodies of surface water. Detecting these water bodies and reservoirs and their changes throughout seasons and years is useful for monitoring water storage, especially in the current state of California's drought. Using higher resolution data such as AirSWOT, SWOT, or Green LiDAR may be more appropriate for this study and could potentially be more effective at detecting intermittent streams.

VI. Acknowledgments

Advisor

- Cedric David (JPL)

Partners

- Council for Watershed Health (CWH)
- Southern California Coastal Water Research Project (SCCWRP)

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VIII. Appendices

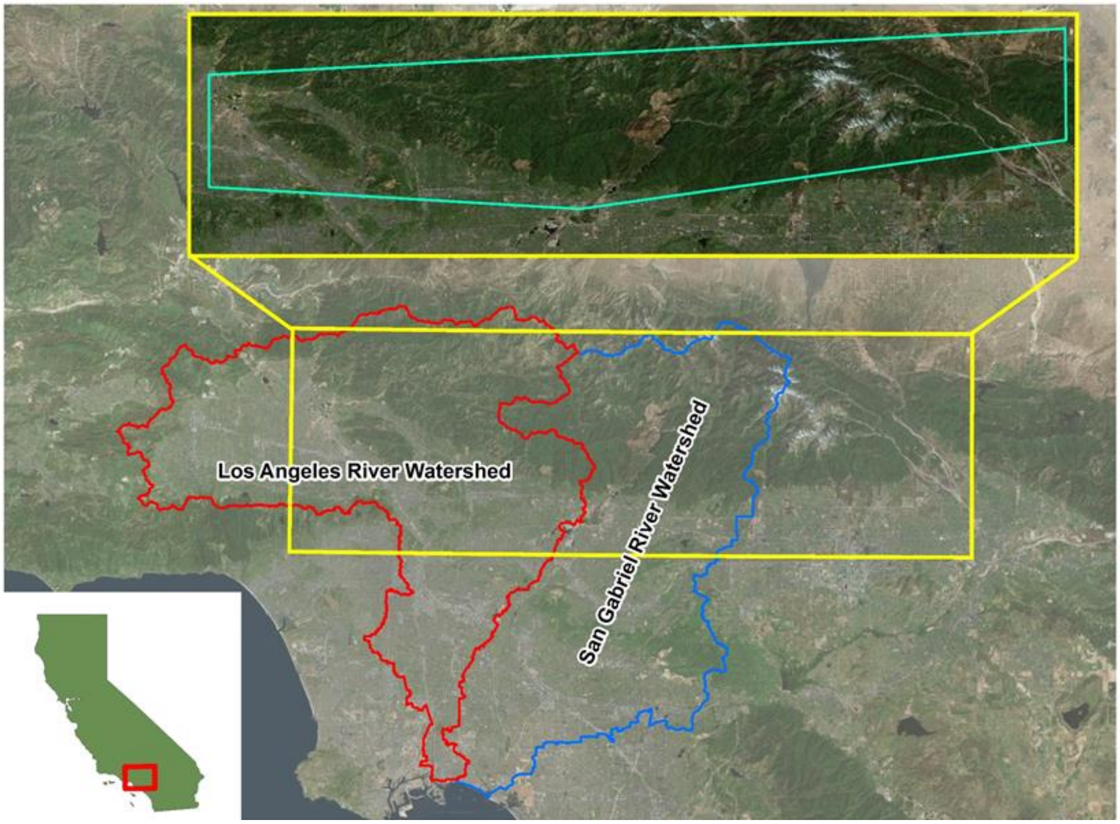


Figure 1. Study Area

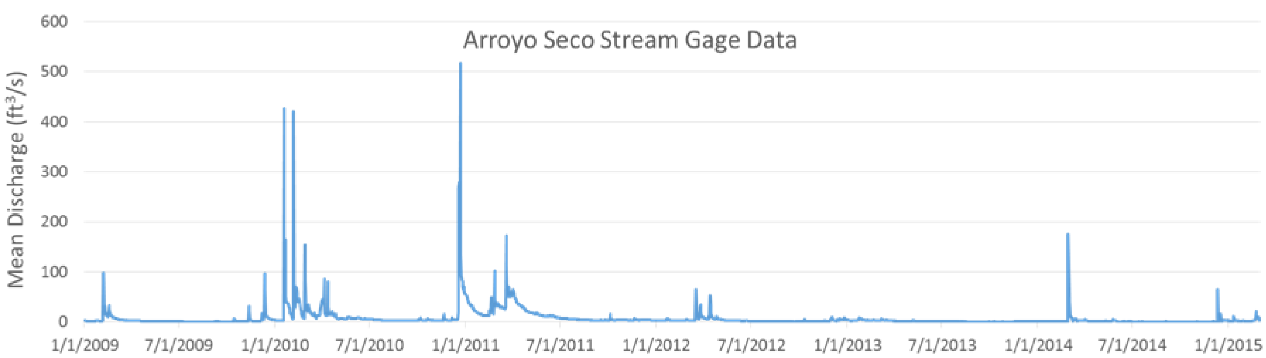


Figure 2. Arroyo Seco Stream Gage Mean Discharge vs. Dates

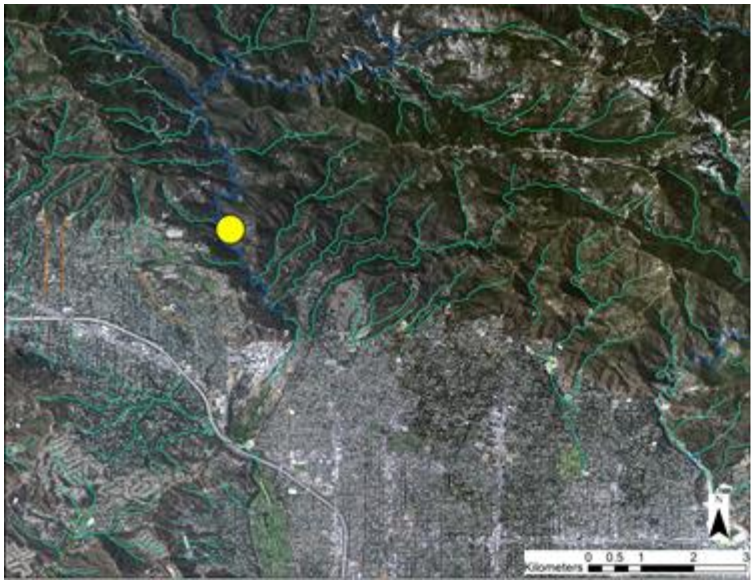


Figure 3. Arroyo Seco Stream Gage Location

Platform	Sensor	Active period	band	swath	Spatial resolution	Data available for LA?	What it measures
NASA: Gulfstream-III	UAVSAR-active (airborne radar)	2007-present	L-Quad polarization	>60km	~5m	Yes	Polarization (hh, hv, vv)
Airborne	Lidar	2006-present	NIR	varies	10 ft	Yes	Digital elevation model (DEM)
NASA: Space Shuttle Endeavor	SRTM-active	2/11-21/2000	C-band (DEM) and X-band	225km	Digital elevation model (DEM) in 30m	Yes	Earth's topography (elevation) between 60 degrees N and S lats
NASA: Landsat 5	Thematic Mapper	18984 - 2013	7 bands (Visible, NIR, Thermal, Mid-Infrared)	185 km	30m, thermal at 120 m	Yes	Spatial resolution and spectral characteristics from current and historical data (Landsat missions date back to 1972) will allow for
NASA: Landsat 8 (2 sensors)	OLI-passive	2013-present	9 bands (Coastal/aerosol, 3-Visible, NIR, 2-SWIR, Panchromatic, Cirrus)	185 km	30m; panchromatic band at 15m	Yes	spectral characteristics from current and historical data (Landsat missions date back to 1972) will allow for measuring water availability
	TIRS-passive		2 thermal IR bands	185 km	Data collected 100m, resampled to 30 m	Yes	in vegetation and land cover change
JAXA: ALOS-2 (renamed "Diachi-2") 3 sensors	AVINIR-2, PALSAR, PRISM	2014 life expectancy 3-5 years	VNIR, L-Band polarization (HH, HV, VH, VV), Panchromatic	350 km	10m VNIR, SAR-L 10 and 100m, 2.5m PRISM Panchromatic,	Yes, But this is a Japanese satellite	Global Digital 3-D map (2016); GDEM; damage prediction for natural disaster; monitoring of rain forests for carbon sink; urban
TERRA	ASTER-passive	1999-present	14 bands (Visible to thermal IR)	60 x 60km	VNIR-15m; SWIR-30m; TIR-90m	Yes	Land, air, oceans, ice, volcanoes, hydrology, disasters, GDEM
NASA: ER-2, Twin Otter, WB-57, Scaled Composites' Proteus	AVIRIS-passive	1992-present	imaging spectroscopy (hyperspectral) 224 bands ~400-2500 nm	11km	~4m	Yes, must be ordered	Earth's surface and atmosphere based on molecular absorption and pattern scattering signatures
NASA: King Air B200 (testing platform)	AirSWOT-active	2013 - present	Interferometer) contains 2 Ka-band SPAR antenna	120km	<100m	N/A	Sea surface heights; mask terrestrial water bodies to measure hydrology and changes

Figure 4. Table of potential sensors and their parameters

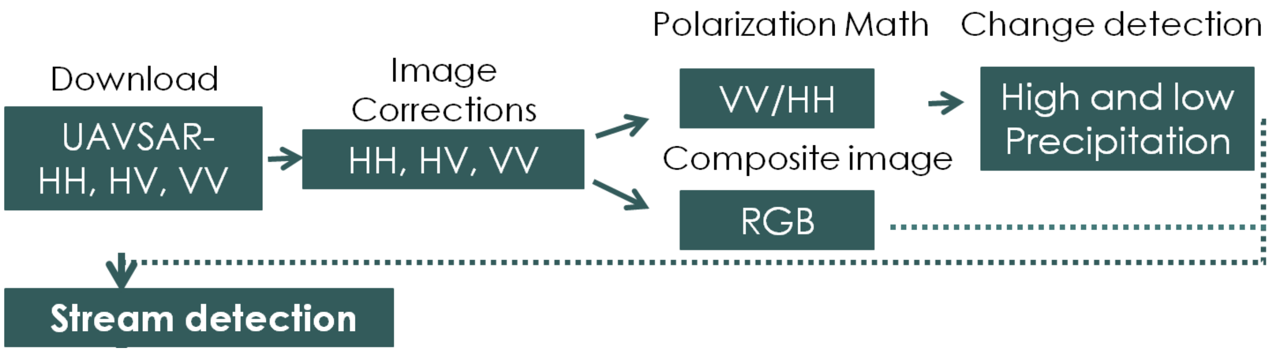


Figure 5. UAVSAR Methodology Flowchart

Figure 6. Landsat data (green) overlapping LA County (red) in USGS EarthExplorer

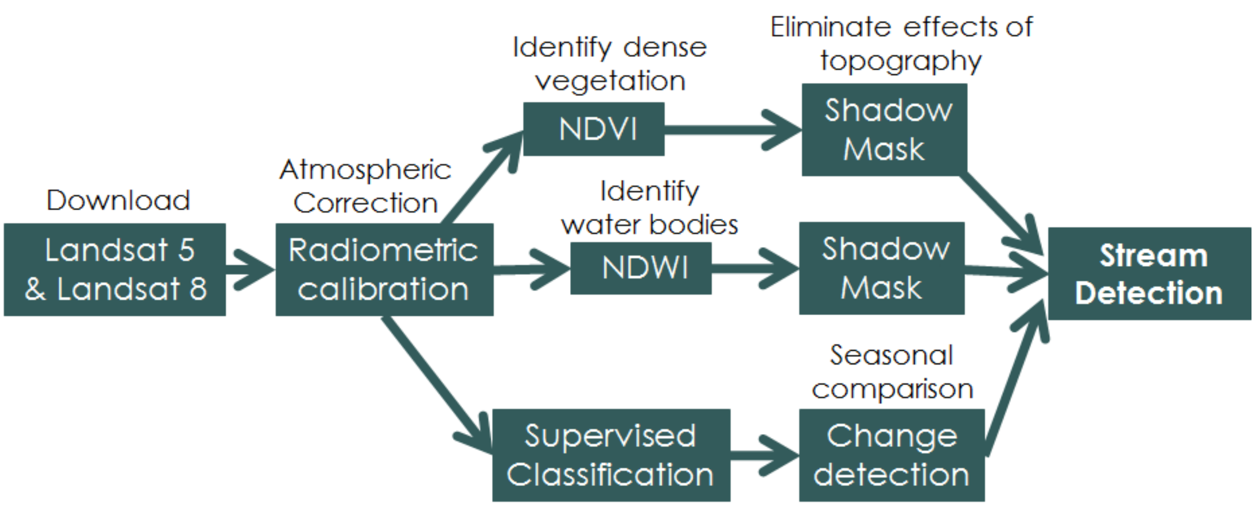


Figure 7. Landsat Methodology Flowchart

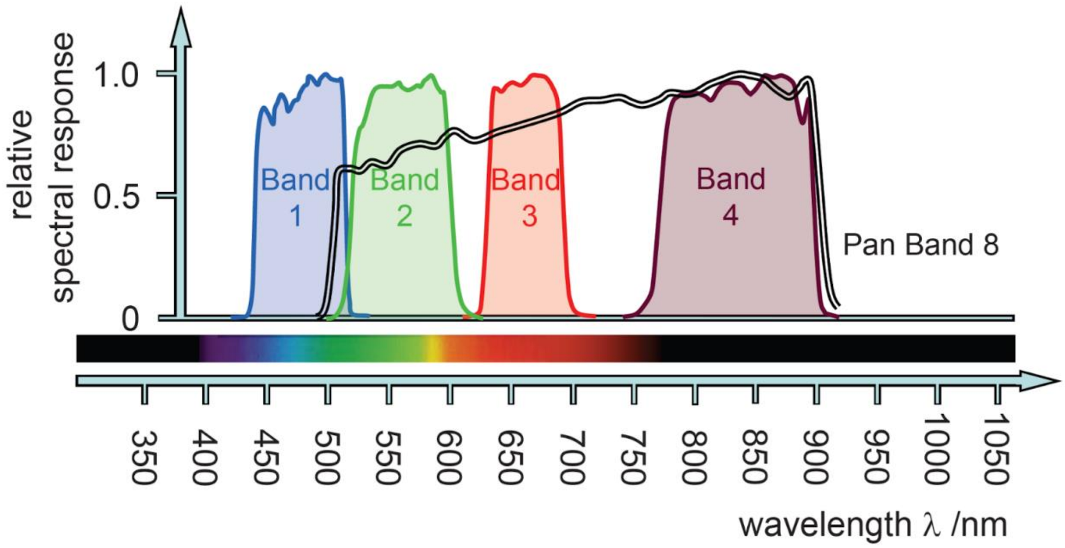


Figure 8. Landsat 5 TM and 8 OLI Panchromatic overlapping bands (Source: SEOS)

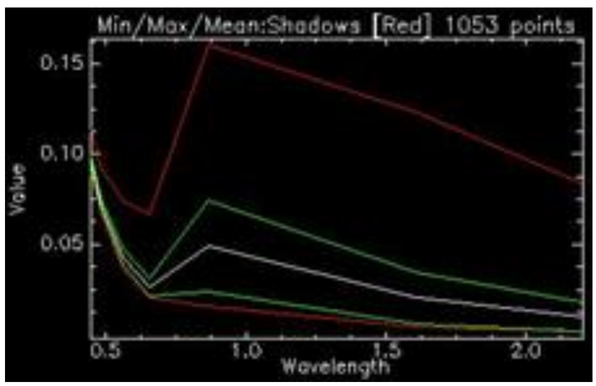
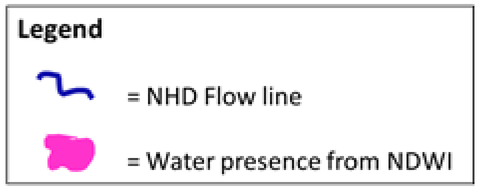


Figure 9. Spectral Profile of Shadow Region of Interest



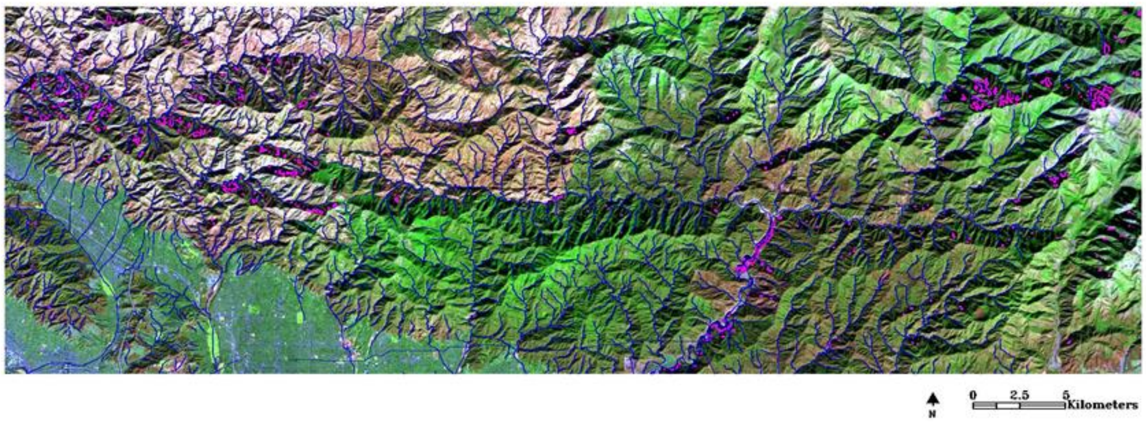


Figure 10. NDWI, November 2010 (RGB = 542)

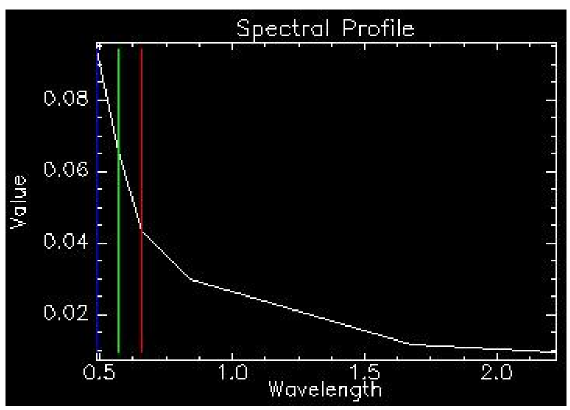


Figure 11. Spectral Profile of Shadow

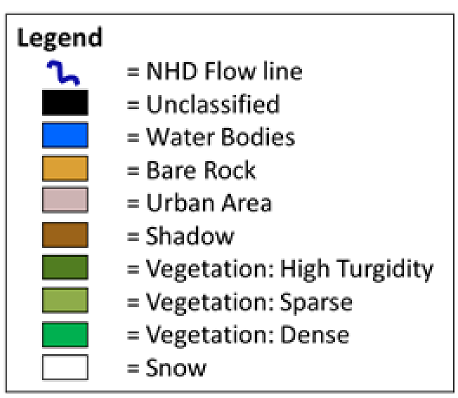


Figure 12. Legend showing ROIs

Figure 13. Exaggeration Values

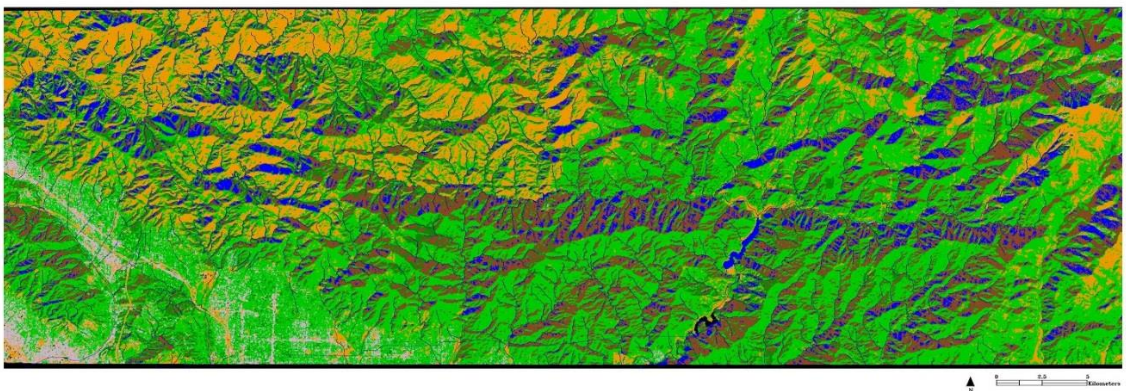


Figure 14. November 2010 Supervised Classification Landsat 5TM

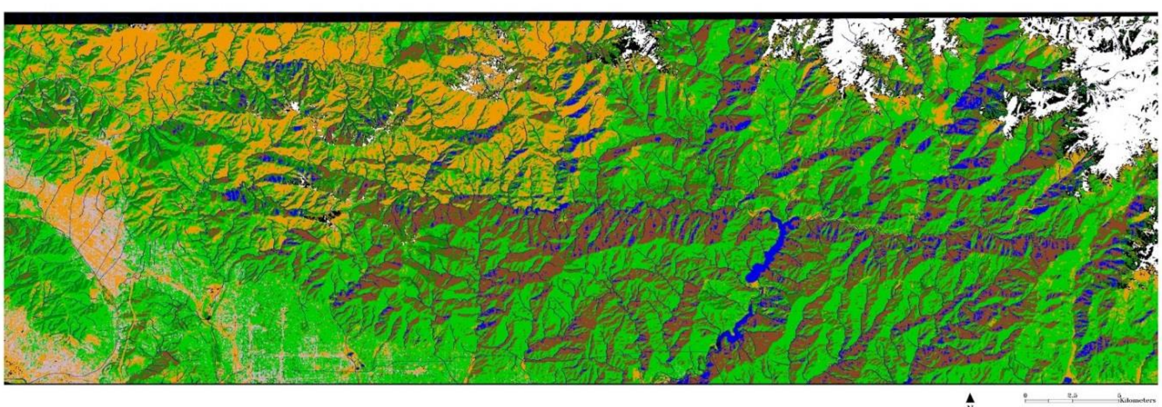


Figure 15. March 2011 Supervised Classification Landsat 5TM

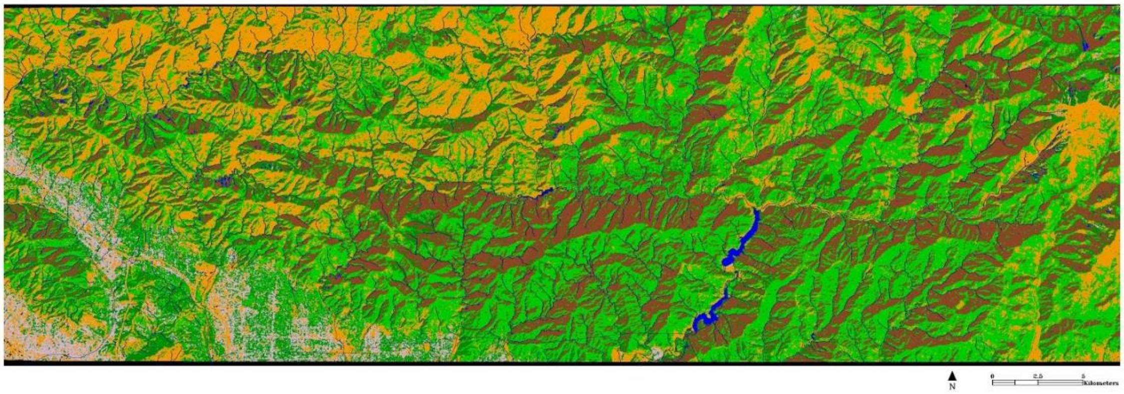


Figure 16. March 2011 Supervised Classification Landsat 5TM

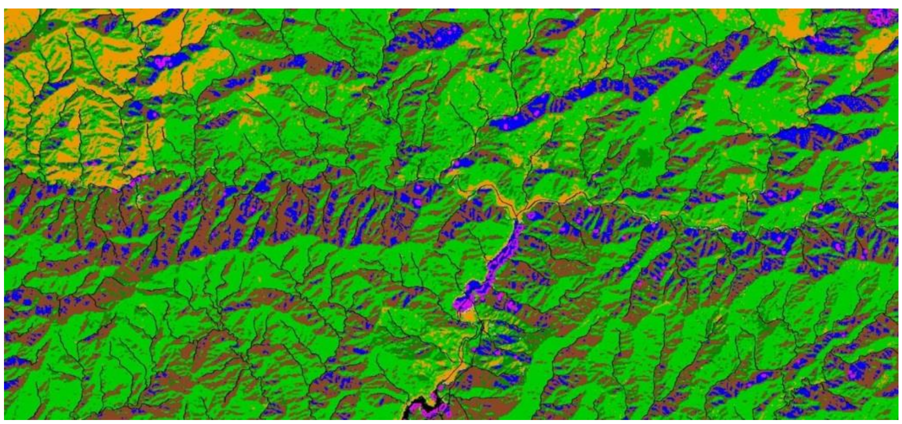


Figure 17. NDWI water mask overlaid on November 2010 supervised classification

Date	Water Bodies (km^2)	Veg: High Turgid (km^2)
11/1/2010	86.2	225.17
3/1/2011	47.56	240.39
9/1/2011	5.67	255.42

Figure 18. Water bodies and VHT total area in km^2

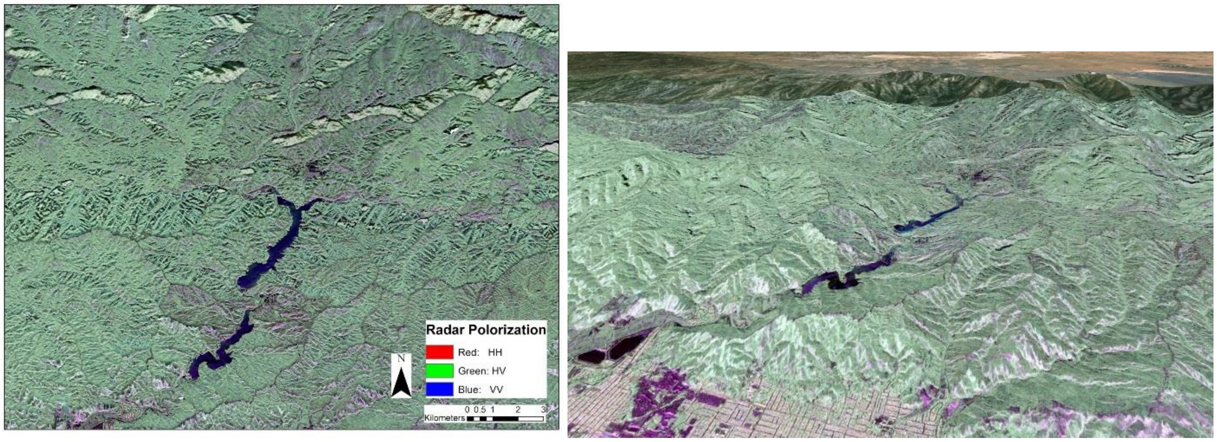
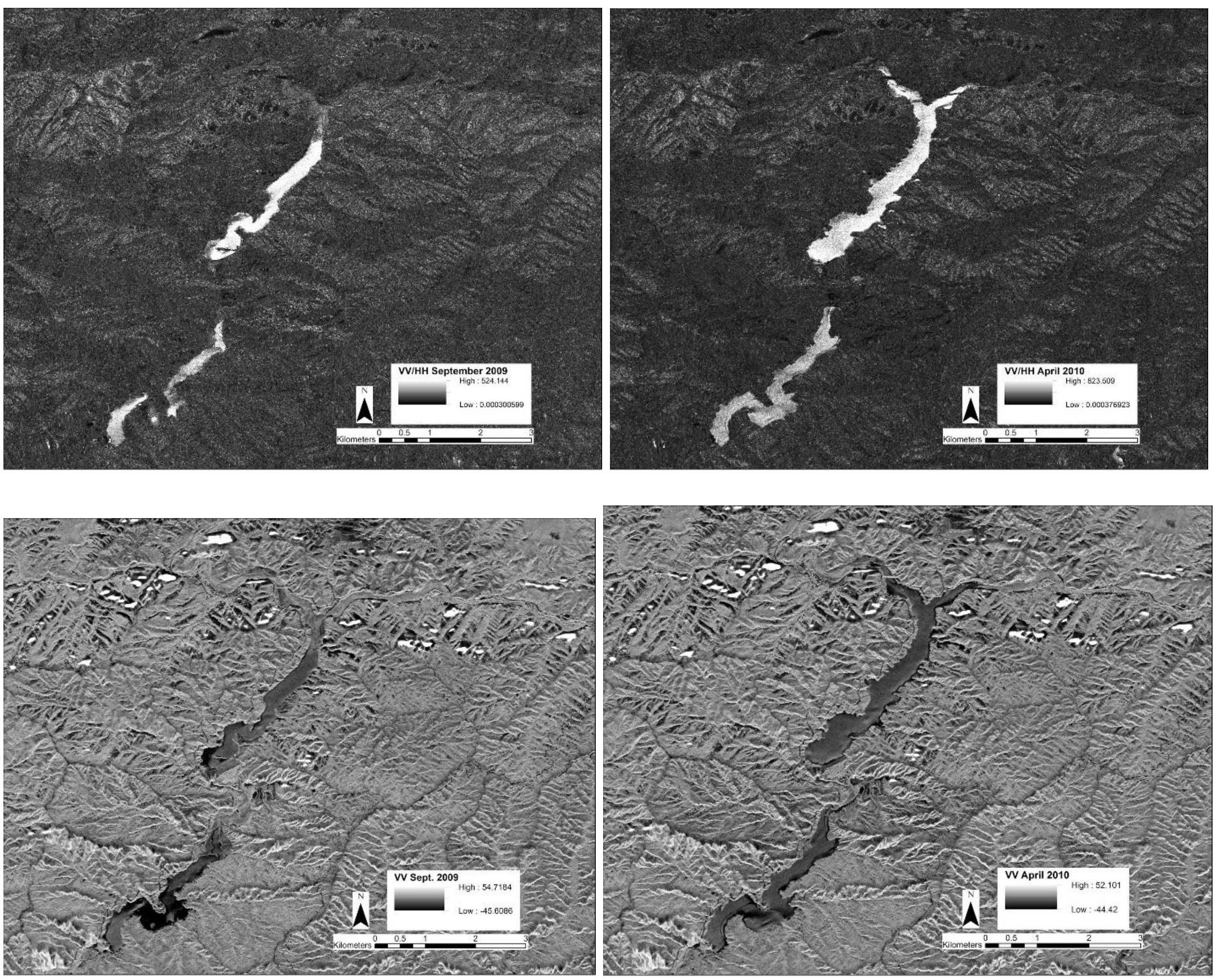


Figure 19. a. RGB image b. RGB image projected on 3D image using SRTM DEM



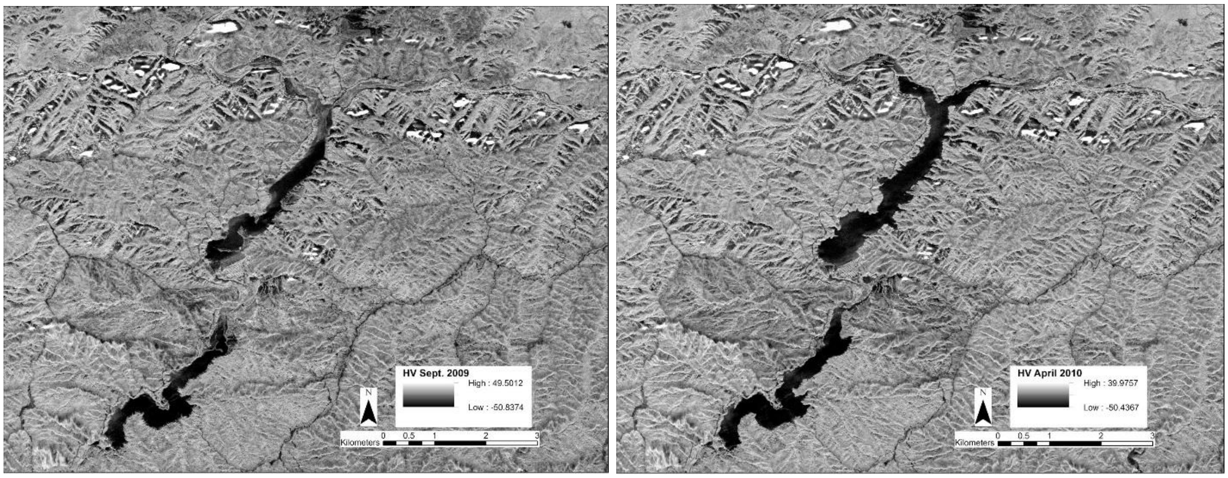


Figure 20. A-C "Dry" months D-F "Wet" months

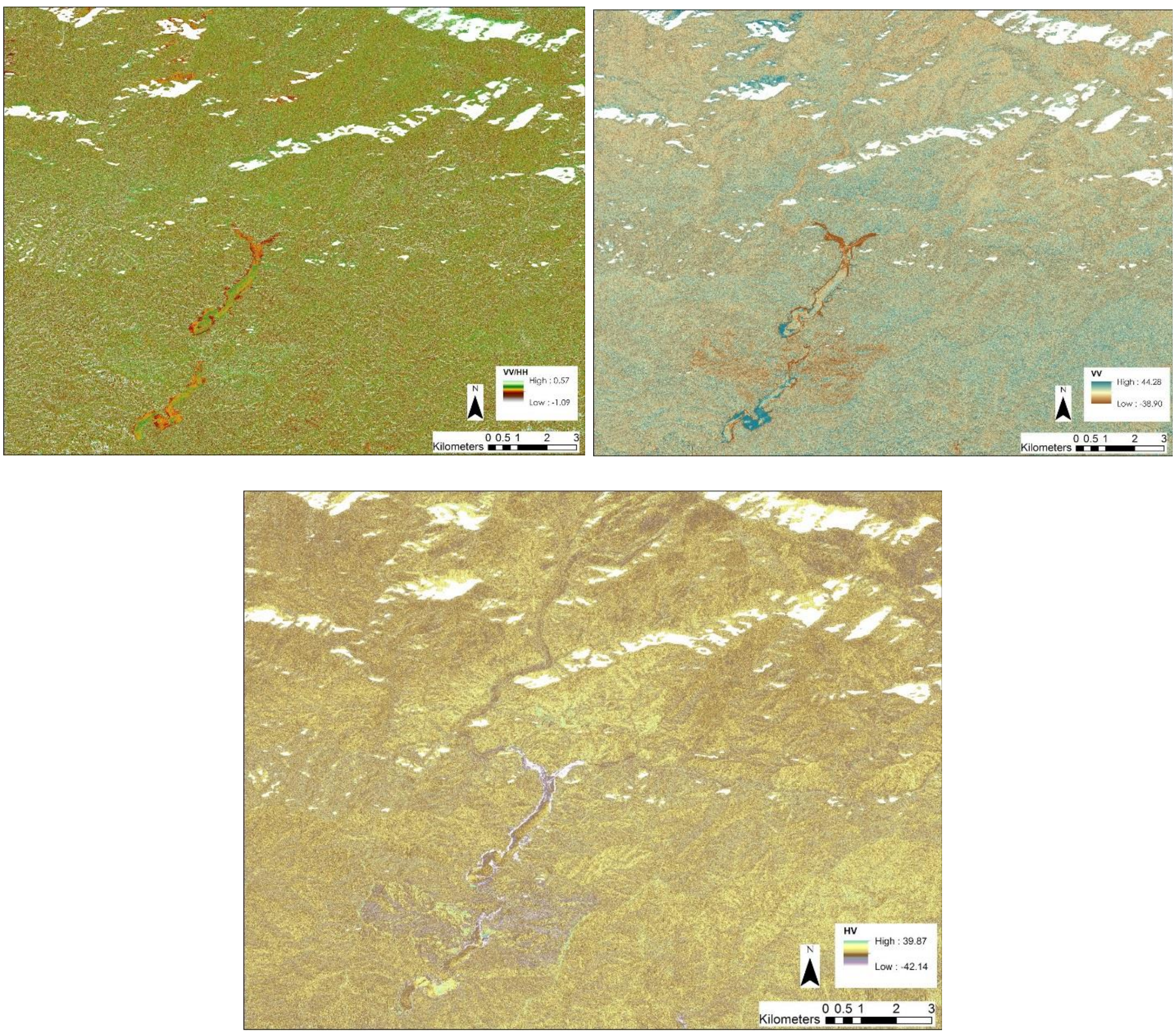


Figure 21. Change detection using dry and wet month of VV/HH(a), VV(b), and HV(c)

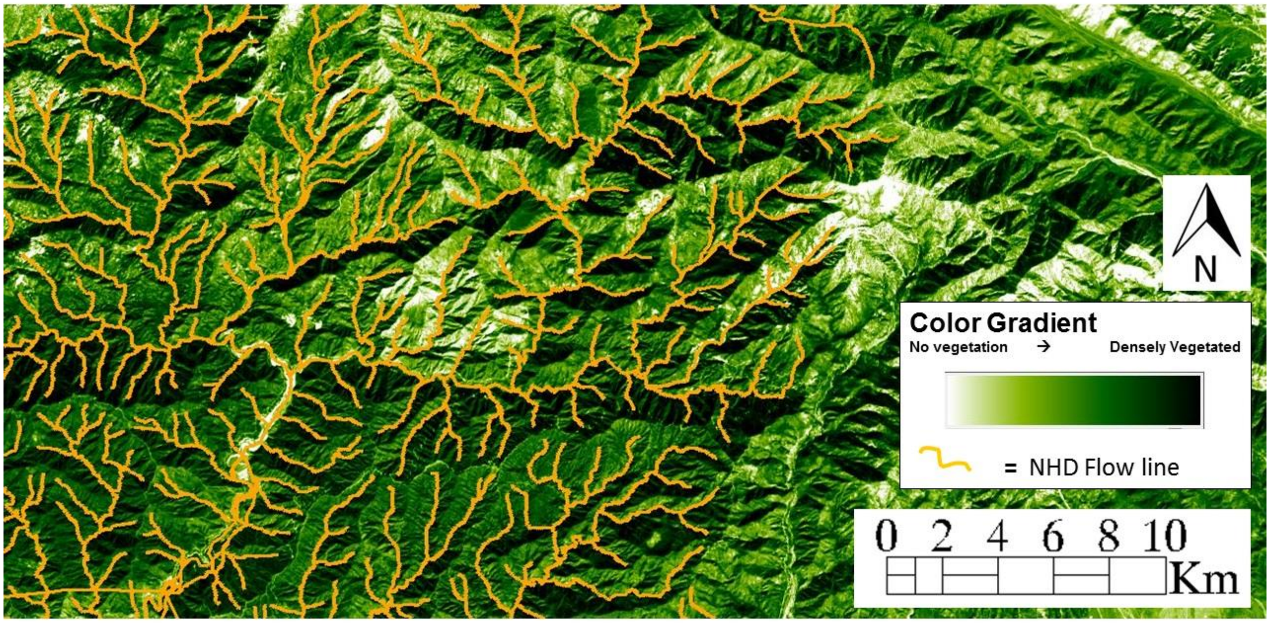


Figure 22. NDVI with NHD lines

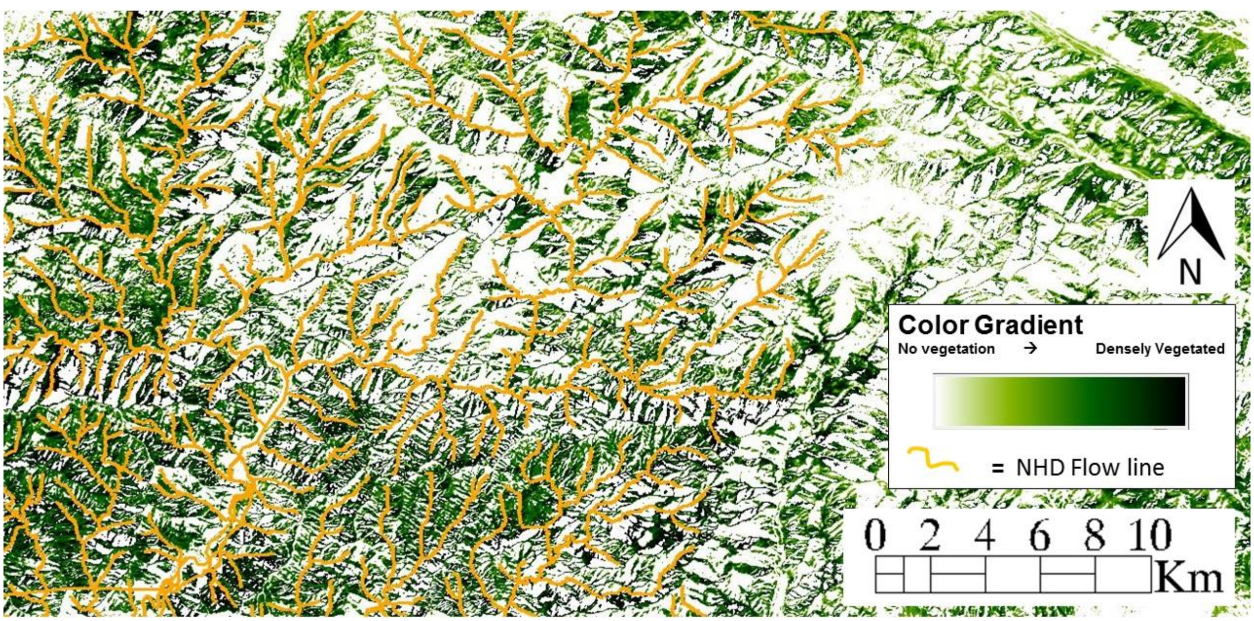


Figure 23. NDVI with Shadow Mask and NHD lines

Figure 24. Landsat and UAVSAR resolution compared to intermittent stream size

Figure 25. Topography of Study Area (3D Surface View using Landsat 8 and SRTM DEM)