VALIDATION OF SATELLITE DATASETS FOR THE OPERATION OF FLOOD AND DROUGHT INDICATORS IN CERTAIN REGIONS OF MYANMAR

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ABSTRACT

Remote sensing data and information can strengthen the basis for informed flood and drought management actions. The reliability of satellite data needs to be validated and compared against ground measurements to a specific area and temporal scales before it can be used in any subsequent application. Rainfall is an important component in the water balance and hydrological modelling. As ground data may be scarce, remote sensing datasets can be used to give spatially distributed data and fill in data gaps. In this study, Climate Hazards Group InfraRed Precipitation with Station (CHIRPS), Global Precipitation Measurement (GPM) and Tropical Rainfall Measuring Mission (TRMM) rainfall data are compared with ground measurements from rainfall gauges and the remote sensing datasets are also compared with each other. Along with the floods, there are drought-stricken areas in Myanmar, which have devastating impacts on agriculture, quality of life of farmers and national economy. The drought related indicators such as Standardized Precipitation Index (SPI), Normalized Difference Vegetation Index (NDVI), Soil Water Index (SWI), NDVI deviation and SWI percentile are the most interesting indexes to attempt validation. The findings of this study indicate that satellite rainfall estimates have a consistently good agreement with ground rainfall at different spatiotemporal scales. In addition, rainfall estimates from remote sensing at a large catchment scale is more accurate than single stations. For the drought index validation, the results show that they can be used as indicators because they have good performance not only in rainy season but also in drought years.

Keywords: Satellite rainfall products, Drought related indexes, Myanmar

1. INTRODUCTION

Myanmar is vulnerable to climate change with predictions of floods and droughts becoming more frequent and intense (UNEP, 2012). Data and hydro information is the basic for any planning activity and data availability is often one of the key constraints for planning especially for flood and drought management. Nowadays, remote sensing data is very useful as it has a large spatial coverage and especially in areas with lack of station-based data. It is also essential for verifying model results or creating water balance (Bello & Aina, 2014). As Myanmar is a developing country, there are limited hydro-meteorological ground stations and cannot provide full coverage for the whole country. To fill this gap, satellite datasets are necessary because they can offer real time or near real-time data, easy access by scientists, authorities and the public via internet, uninterrupted data supply during catastrophic events that may severely damage ground stations (Fotopoulos et al., 2011). This paper will use satellite rainfall related data (TRMM, CHIRPS, GPM), Temperature (MODIS), Vegetation related data (NDVI, NDVI deviation) and Soil Moisture data (SWI, SWI percentile). Satellite datasets need to be validated as their accuracy can be affected by geographical position, topography, and climate. This study examines the validation of selected satellite datasets from several sources to represent the actual conditions in the country and therefore be used for decisions aiming at increasing the adaptation capacity towards flood and drought.

2. STUDY AREA AND DATA

2.1 Study area

The study area is selected based on two categories; flood and drought. According to the information of severity of the flood and drought events from stakeholders and historical records (Department of Meteorology and Hydrology et al., 2009), the lower part of Myanmar especially in Bago, Kayin and Mon state for flooded areas and central dry zone of Myanmar for drought-affected area.

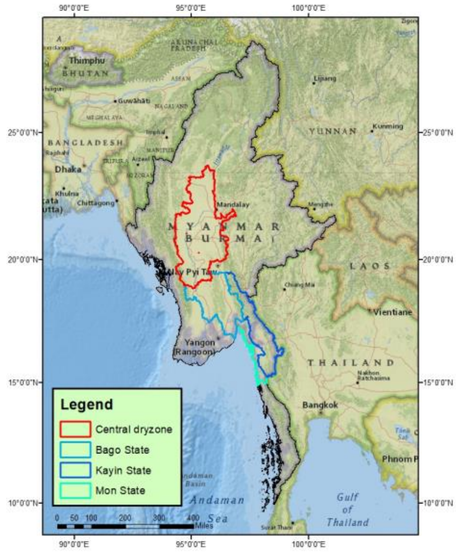


Figure 1. Location of flood affected regions and central dry zone in Myanmar

2.2 Datasets

For satellite rainfall validation, three satellite-based datasets such as CHIRPS, TRMM and GPM are used to compare with observed rainfall.

Table 1. Climate data for satellite rainfall validation

NO	DATA	SOURCE	RECORD	FREQUENCY	SPATIAL RESOLUTION	COVERAGE
1	Rainfall	**CHIRPS**	1981-2018	Daily	0.05	All
2	Rainfall	**TRMM**	2000-2018	Daily	0.25	All
3	Rainfall	**GPM**	2014-2018	Daily	0.1	All
4	Temperature	**MODIS**	2000-2018	8-Daily	1km	All
5	Rainfall	**DMH**	2010-2018	Monthly	Observed	Hpa-An
6	Rainfall	**DMH**	2010-2018	Monthly	Observed	Shwegyin
7	Rainfall	**DMH**	2010-2018	Monthly	Observed	Magway
8	Rainfall	**DOA**	2010-2018	Monthly	Observed	Mawlamyine
9	Rainfall	**DOA**	2010-2018	Monthly	Observed	Myingyan
10	Temperature	**DMH**	2010-2018	Monthly	Observed	Hpa-An
11	Temperature	**DMH**	2010-2018	Monthly	Observed	Shwegyin

Flooded years and flood impact data are collected from Department of Disaster Management (DDM). In Mawlamyine and Hpa-An cities, flood affected households and population were higher in 2018 than others. Therefore, it can be assumed that 2018 was a flooded year for Mawlamyine and Hpa-An cities. In addition, flood events periods are collected from Myanmar Information Management Unit (MIMU) flood hazard maps. Then, we choose the flooded years to perform validation based on all the data we have.

Along with floods, there are drought-stricken areas in Myanmar, which have devastating impacts on agriculture, quality of life of farmers and national economy (Yi, 2012). The drought related indicators which are the most interesting to attempt validation are: Standardized Precipitation index (SPI), Effective Drought Index (EDI), Soil Water Index (SWI), and Normalized Difference Vegetation Index (NDVI) based such as NDVI deviation.

Table 2. Types of drought related indicators for drought index validation.

NO	DATA	SOURCE	RECORD	FREQUENCY	SPATIAL RESOLUTION	COVERAGE
1	SPI1	TRMM	2000-2018	Daily	0.25degree	All
2	SPI3	TRMM	2000-2018	Daily	0.25degree	All

NO	DATA	SOURCE	RECORD	FREQUENCY	SPATIAL RESOLUTION	COVERAGE
3	SPI6	TRMM	2000-2018	Daily	0.25degree	All
4	NDVI	Terra-MOD13C1	2000-2018	16-Daily	5600m to 250m	All
5	NDVI deviation	NDVI	2000-2018	16-Daily	5600m to 250m	All
5	SWI	METOP-ASCAT	2007-2018	10-day	0.1 degree	All
5	SWI percentile	SWI	2007-2018	10-day	0.1 degree	All

3. METHODOLOGY

The most important aspect to consider when carrying out a validation, is what the data would be used for. The objective of this study is for activities supporting flood and drought management. Therefore, two methodologies are presented.

3.1 Satellite Rainfall and drought index Validation

Firstly, three satellite datasets (CHIRPS, TRMM and GPM) are chosen and observed rainfall data are collected from Department of Meteorology and Hydrology (DMH) and Department of Agriculture (DOA). Before comparing with observed data, satellite data itself are compared to see the correlation and deviation between them. After that, observed rainfall and satellite data are compared at each station. The comparisons are made in flooded years which are collected from MIMU flood hazard maps. Then, performance indicators are used to check the validation and the results discussed. For Drought index validation, yearly satellite and observed rainfall are analyzed to choose drought year by seeing the lowest rainfall period. Comparisons are made between SPI 1, 3, 6, NDVI, NDVI deviation, SWI and SWI percentile. The methodology for validating of satellite rainfall and drought indexes is schematized in Figure 2.

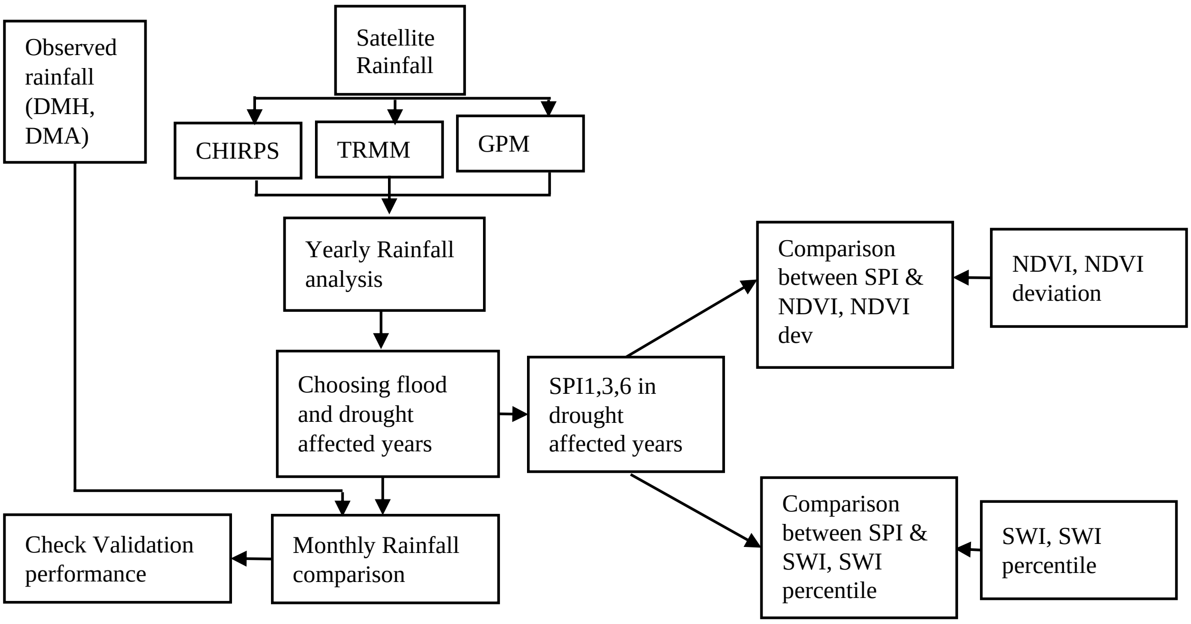


Figure 2. Overall methodology for satellite rainfall and drought index validation

3.2 Analysis of validation performance

To check the performance of validation, error parameters are calculated. Mean Absolute Error (MAE), Mean Absolute Deviation (MAD), Coefficient of determination (R^2) and Percentage Difference are calculated to see the correlation and deviation. The formulations of these error estimations are as follows;

(a) Mean Absolute Error (MAE)

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n} \quad (1)$$

where y_i is observed value and x_i is satellite value.

(b) Root Mean Square Error (RMSE)

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2} \tag{2}$$

where x_i is satellite value and y_i is observed values.

(c) Nash-Sutcliffe efficiency coefficient (NSE)

$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{n}(x_i - y_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{3}$$

where x_i is satellite value, y_i is observed values and $\bar{y}$ is average of observed values.

(d) Coefficient of determination (R^2)

$$R^2 = \frac{\sum_{i=1}^{n}[(x_i - \bar{x})(y_i - \bar{y})]^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{4}$$

where, x_i and y_i are observed and satellite data and $\bar{x}$ and $\bar{y}$ are average data of these two datasets.

(e) Pearson correlation coefficient

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\ \sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{5}$$

where x_i and y_i are precipitation by collected satellite and observed station, $\bar{x}$ and $\bar{y}$ are average of them.

4.RESULTS AND DISCUSSION

4.1 Analysis of satellite rainfall datasets

First of all, satellite data sets are compared for three states; Bago, Kayin and Mon and for three cities; Bago, Hpaan and Mawlawmyine. Annual rainfalls are compared in the states and select the highest rainfall year. After this, city level monthly rainfalls are compared in that year. In Bago state and its respective city; Bago, 2015 was the highest rainfall year which matched to the flooded year in the historical flood record. Also, the monthly rainfall trends are similar and TRMM had the highest peak. The same procedure is repeated for Kayin State, Hpa-an city and Mon state, Mawlamyine city. 2018 was the flooded year for both Kayin and Mon state. This can be proved by receiving the highest rainfall according to yearly rainfall comparison graphs. Also, in monthly rainfall comparison, three satellite datasets are in similar trend for all cities.

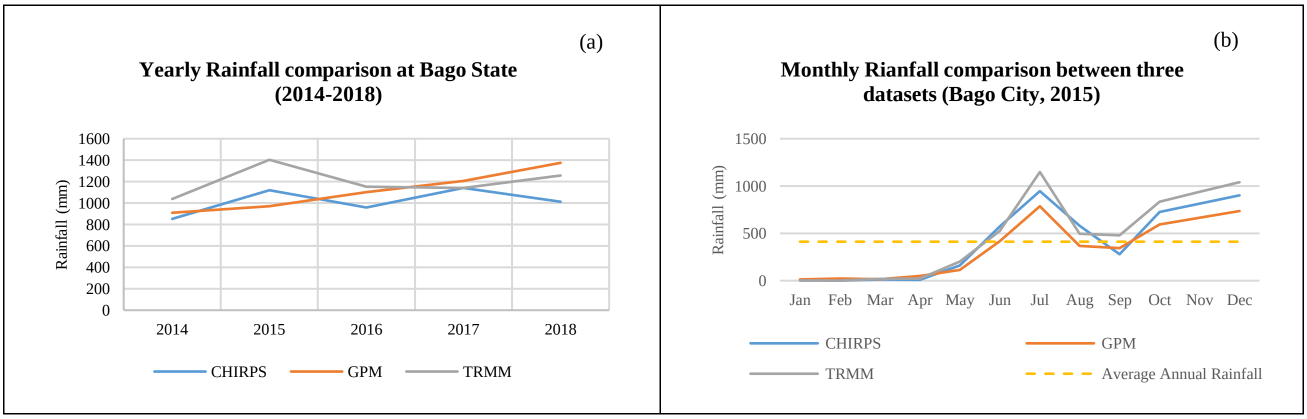


Figure 3. (a) Yearly rainfall at Bago State. (b) Satellite Monthly Rainfall comparison for Bago in 2015.

4.2 Validation performance with satellite rainfall data

The correlation between three satellite datasets is good because the R^2values range between 0.7 to 0.95. When checking with mean absolute error and mean absolute deviation, the results are higher in the cities than in states. Therefore, rainfall estimates from remote sensing at a large catchment scale might actually be more accurate than from single stations.

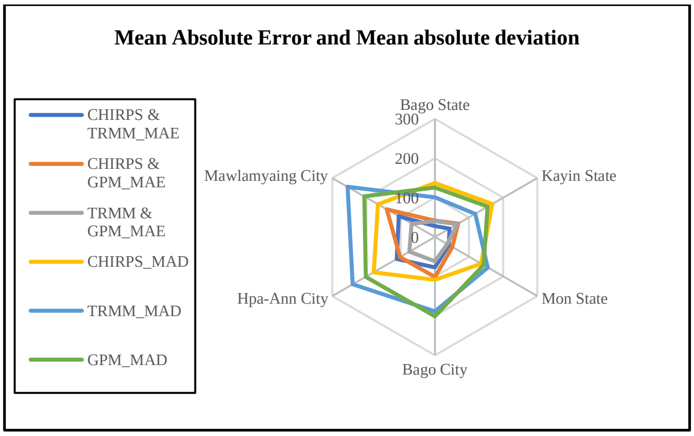


Figure 4. Mean absolute error and mean absolute deviation between satellite datasets for state and city level

4.3 Analysis of satellite and Observed rainfall data

There are monthly rainfall and temperature for five observed stations so that satellite data and observed rainfall are compared to check the correlation between them. Hpa-An, Shwegyin and Mawlamyine stations are located in flooded regions and Magway and Myingyan stations are located in drought affected area. Overall, all observed and satellite rainfall are in good correlation with acceptable coefficient of determination. For Hpa-An station, CHIRPS and TRMM data show a similar trend which are underestimated only in the period of rainfall peaks. As 2018 was observed flooded period according to flood records, the gap between GPM and observed rainfall peaks was small which can be assumed that GPM can estimate close to observed data. For Shwegyin station, the trend was similar when comparing with observed and satellite data. It is the same pattern with Hpa-An and Mawlamyine case, where satellite rainfall was underestimated only in the period of rainfall peaks occurred. For Magway station, which is located in drought-affected area, the comparison showed that the trend was in a similar shape and satellite data still underestimated in the period of rainfall peaks occurred. There is also a similar result for Myingyan station.

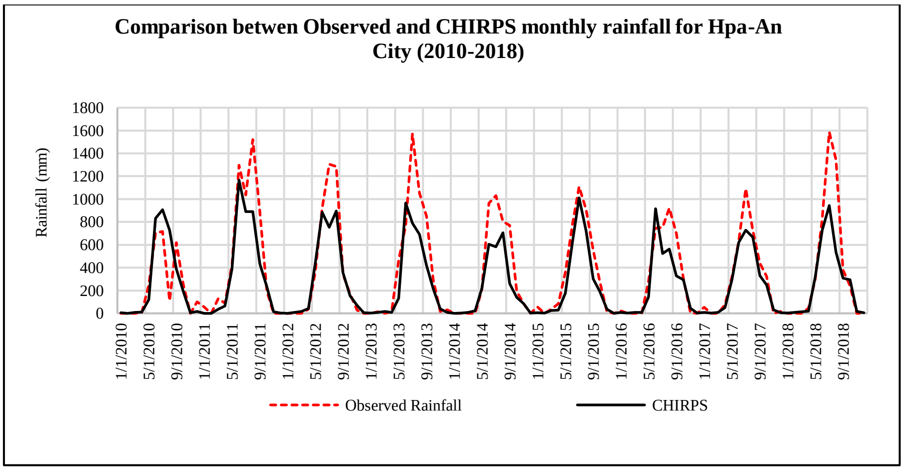


Figure 5. Comparison between CHIRPS and Observed rainfall for Hpa-An Station

4.4 Validation performance between satellite and observed rainfall

In case of correlation, TRMM and GPM has the highest R^2 value among others in all three observed stations. Nash-Sutcliffe efficiency coefficient (NSE) can range between $-\infty$ and 1, where the value 1 corresponds to a perfect match between the datasets. NSE values in flood affected areas are higher than in the drought affected areas. Likewise, flood affected regions had high Pearson's Correlation Coefficient (r) which is closed to 1. Therefore, overall correlation of three datasets and observed data is quite good. Mean Absolute Error (MAE) is used to determine the prediction quality of the satellite data based on the prediction errors and it can tell us how big of an error we can expect from the forecast on average. According to the result, MAE values are acceptable because (Singh et al., 2004) stated that RMSE and MAE values less than half the standard deviation of the measured data are considered low and that either is appropriate for model evaluation. MAE values of Magway station are less than other stations because rainfall is very less in Magway where drought occurred according to the record.

Table3.Performance Indicators for the validation of satellite rainfall with observed data.

STATION	PERFORMANCE INDICATORS	OBSERVED AND CHIRPS	OBSERVED AND TRMM	OBSERVED AND GPM
Hpaan	MAE	89.98	117.13	106.50
	RMSE	145.15	202.78	173.72
	NSE	0.89	0.79	0.85
	R^2	0.85	0.62	0.71
	r	0.95	0.95	0.93
Mawlamyine	MAE	94.42	105.44	137.29
	RMSE	162.93	180.50	229.73
	NSE	0.89	0.86	0.77
	R^2	0.84	0.70	0.60
	r	0.94	0.96	0.92
Shwegyin	MAE	117.22	93.81	130.06
	RMSE	203.38	172.93	213.19
	NSE	0.68	0.77	0.65
	R^2	0.51	0.60	0.48
	r	0.89	0.90	0.89
Magway	MAE	32.48	43.25	28.95
	RMSE	53.77	80.55	46.68
	NSE	0.72	0.73	0.79
	R^2	0.56	0.59	0.76
	r	0.86	0.84	0.89
Myingyan	MAE	34.29	35.67	30.13
	RMSE	53.89	58.03	48.60
	NSE	0.57	0.51	0.65
	R^2	0.47	0.62	0.70
	r	0.77	0.82	0.87

4.5 Analysis of Observed rainfall, Soil Water Index and Normalized Difference Vegetation Index

NDVI and SWI trends are drawn in drought years. In Myanmar the summer season starts from March to Mid May, the rainy season starts from Mid-May to October and the winter season starts from November to February (Aung et al., 2017). Therefore, NDVI and SWI increased significantly in rainy season.

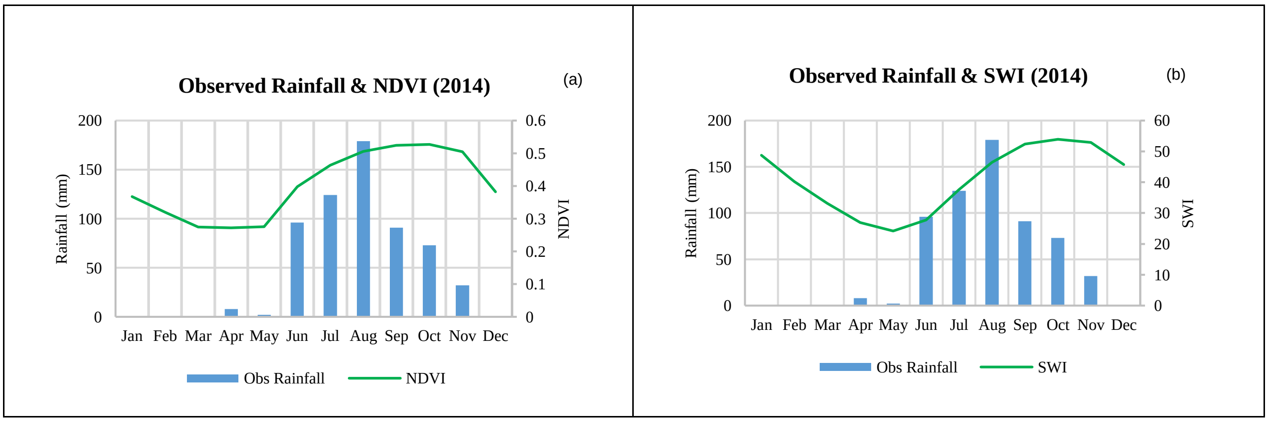
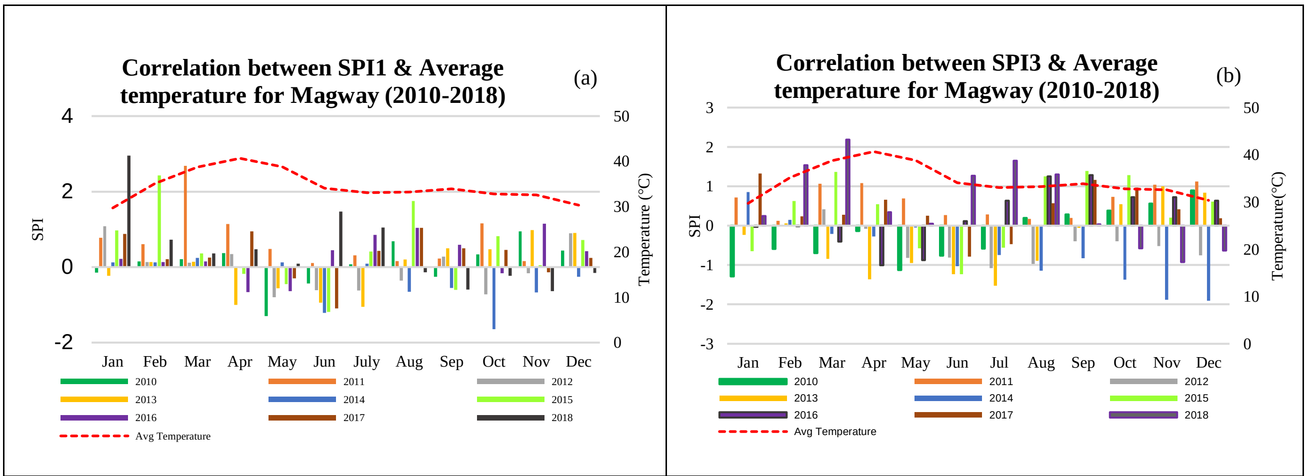
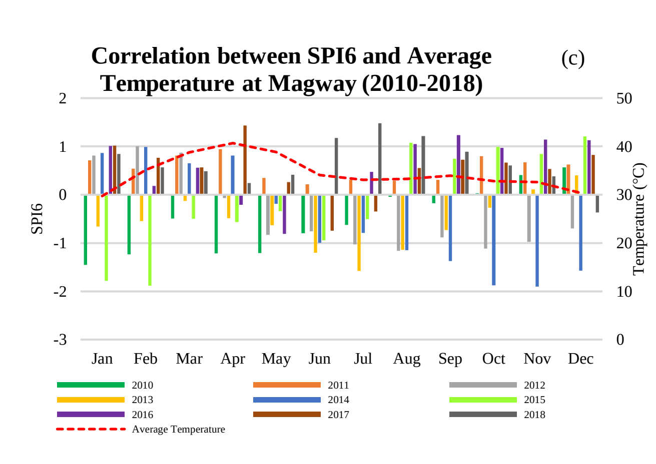


Figure 6. (a) Correlation between observed rainfall and NDVI for Magway (2014), (b) Correlation between observed rainfall and SWI for Magway (2014).

4.6 Analysis of Standard precipitation index (SPI)

According to the 8 years period SPI1 trend (2010-2018) in Magway, (April to Oct) are dry periods mostly in 2014 because it was considered as drought year from rainfall analysis. SPI3 graph can show that 2014 has severe drought (-2 index value) which is assumed to be severe drought according to the SPI classification. Temperature is also around 30 °C during the drought periods. Also, for SPI6 graph (2010-2018), it can be seen clearly that end of 2014 and start of 2015 had severe drought with the value of nearly -2 index value. Therefore, the assumption of drought year 2014 is correct. In addition, SPI has been analysed in Mandalay and Myingyan. The results are quite similar to Magway. In Myingyan, the SPI values dropped in the assumed drought years and can be crosschecked with the increasing number of damage crop acres according to the record of annual damage crops in Myingyan.





SPI Index value	Classification
>2.0	Extremely wet
1.5 to 2.0	Very wet
1.0 to 1.5	Moderately wet
-1.0 to 1.0	Near normal
-1.5 to -1.0	Moderately dry
-2 to -1.5	Severely dry
<-2	Extremely dry

Figure 7. (a) Correlation between SPI1and averaged temperature for Magway (2010-2018), (b) Correlation between SPI1and averaged temperature for Magway (2010-2018), (c) Correlation between SPI1and averaged temperature for Magway (2010-2018)

4.7 Comparison of NDVI deviation, SWI percentile with SPI

NDVI deviation is calculated as the deviation from the long-term mean. It expresses the current vegetation growth compared to the long -term mean for the same period. It can be used to define a drought as it is defined as the difference between NDVI for the current time step and long term NDVI for the same month. When NDVI deviation is negative, it indicates the below normal vegetation condition and suggests a prevailing drought situation (Tucker, 1979). The greater the negative departure, the greater the magnitude of a drought. When comparing with SPI values and NDVI deviation, SPI trend matches with NDVI deviation. In case of Mandalay and Myingyan regions, there is a correlation between SPI and NDVI deviation. SPI negative values meet in the moderately dry range of NDVI deviation.

SWI percentile expresses the percentage of soil moisture that is equal to or below a certain amount of each year in the entire record. A drought or water scarcity is often defined when the soil moisture percentile drops below 30 or 20% (Sehgal & Sridhar, 2019). Therefore, SPI and SWI percentile are compared and as a result, the SPI trend match with the lower SWI percentile, which is regarded as drought. Comparison charts are drawn as follows. When comparing SPI and SWI percentile for Mandalay and Myingyan, the result is similar to Magway. The drop of SWI percentile coincide with negative values of SPI so that this comparison can be the indicator of drought happened in central dry region.

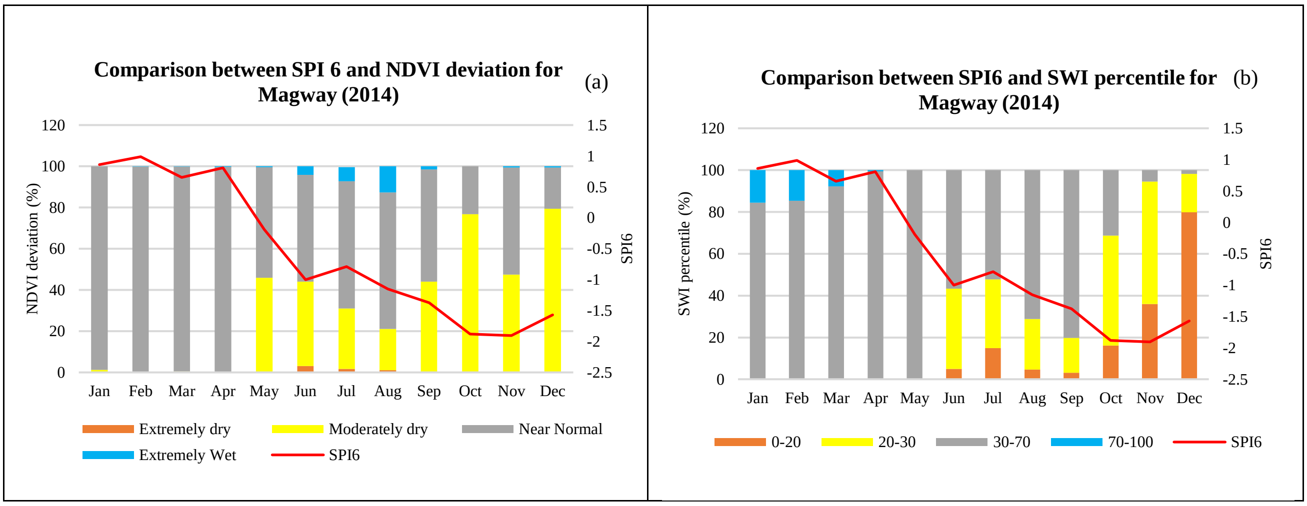


Figure 8. (a) Comparison between SPI6 and NDVI deviation for Magway (2014), (b) Comparison between SPI6 and SWI percentile for Magway (2014)

5. CONCLUSION

This paper describes the validation of satellite datasets with observed historical data in selected locations in Myanmar. It includes two main parts; satellite rainfall validation and satellite drought index validation. In statistical validation of satellite data, R square values represent all datasets are in good correlation. While MAE and MAD represent the deviation of each datasets, results are better in state level than in point location. For comparing with observed rainfall data in five stations, satellite data had a same pattern with monthly observed rainfall. However, they did not capture a peak of rainfall in which satellite data was lower than observed data. NSE, R^2 and r values are higher in flood affected stations than in drought. On the other hand, MAE and RMSE values are lower in drought situation than in flood because rainfalls were very less in drought affected places. As vegetation activity is highest in July and August (rainy season) and lowest in March and April (summer), NDVI trend can prove it with increasing in rainy season and decreasing in summer. The drought years are selected based on rainfall analysis whereas lowest rainfall periods are assumed drought. It was checked with the analysis of SPI index whereas the assumed drought year has negative SPI values which has moderately and severely drought. Furthermore, SPI trend dropped significantly in the moderately and extremely dry ranges of NDVI deviation. Along with SWI percentile, SPI dropdown points fell in the range 0-20% and 20-30% which is defined as drought. Therefore, satellite drought indexes; SPI, NDVI, NDVI deviation, SWI and SWI percentile can be used as indicators for drought monitoring. In addition, CHIRPS rainfall has low resolution, long period dataset whereas TRMM has high resolution. GPM is an improved product from TRMM and has low resolution. So, they can be used depending on the purpose of the projects. As a result, remote sensing rainfall are more likely to be accurate at catchment level than at station level. Overall, those three satellite rainfalls can be used as indicators for flood and drought operations.

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