Bi-temporal Radiometric Normalization of Landsat 8 Images Using Pseudo-Invariant Features

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ABSTRACT:

Relative radiometric normalization (RRN) is one of the radiometric corrections for satellite imagery besides absolute radiometric normalization (ARN). In contrast to the absolute method that corrects various components such as atmospheric condition, earth-sun distance, illumination and viewing angle of satellite to find true reflectance, relative method does not find true reflectance but do the transformation of digital number to fit with reference image digital number or try to find common scale of digital number both of reference and target images instead. Several studies have conducted relative radiometric normalization to solve radiometric inconsistency issues by using pseudo-invariant features (PIFs). PIFs are reference objects that has an insignificant or near stable reflectance value change over time. This study is aimed to evaluate radiometric normalization result for Landsat 8 surface reflectance product that utilized Google Earth Engine platform for the computations. Normalization in this paper applied Multivariate Alteration Detection for PIFs selections. The selection of PIFs is based on data distribution of MAD result, the threshold values for selection are 10%, 15%, 20% and 25% of data distribution. Finally, the normalization used selected PIFs as sample data for calculate the slope and aspect of linear regression. On this study show the normalization result have the highest Pearson correlation value on 10% PIFs blue band which achieve 97.6% then the lowest Pearson correlation on 25% PIFs SWIR1 band which achieve 91.4%. The results suggest that developed approach have a potential solution to deal with inconsistency issues.

KEY WORDS: Relative Radiometric Normalization, PIFs, Multivariate Alteration Detection, Google Earth Engine

1. INTRODUCTION

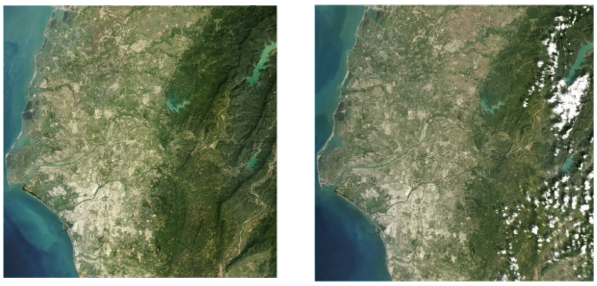
Satellite imagery usage for observation of objects on earth is a common task to do nowadays. Various information can be obtained through observation of periodic satellite imagery in the same area. The obtained information could be the information about land use and land cover changes (Celik 2018), information about the phenology of specific vegetation (Upadhyay, Ghosh, and Kumar 2016), even information about the natural disaster phenomenon satellite imagery can provide that (Said et al. 2019). As a matter of fact, it is difficult to obtain images with radiometric consistency. Inconsistency of radiometric due to shifting in atmospheric conditions, shifting in the earth-sun distance, shifting in illumination, and view angle. Consequently, it is important to remove unwanted effects on satellite imagery to obtain image radiometric consistency to support the quality of information.
Several corrections or normalization methods have been developed to control and reduce the radiometric inconsistency effect. There are two groups of normalization methods which are Absolute Radiometric Normalization and Relative Radiometric Normalization. Absolute Radiometric Normalization (ARN) corrects radiometric condition from various components such as atmospheric condition, earth-sun distance, illumination, and viewing angle of satellite to find true reflectance (Xu 2006), then Relative Radiometric Normalization method does not find true reflectance but does the transformation of the digital number to fit with reference image digital number or try to find the common scale of digital number both of reference and target image instead (de Carvalho et al. 2013). Pseudo-invariant Features have been used in some research to do relative radiometric normalization (PIFs). PIFs are reference objects with a relatively steady or minor reflectance value shifts over time (Lin et al. 2019).
This study is aimed to obtain radiometric consistency from Landsat 8 surface reflectance products. To achieve that, we applied radiometric normalization on Landsat 8 images by using Google Earth Engine. PIFs were used as reference objects in the normalization process in this research. The main challenge in this study is PIFs selection, so PIFs selection in this study according to MAD value distribution by measure the spectral distance from both multidimensional variables.

2. METHODS

Relative radiometric normalization in this study has four main steps. The first step is image acquisition by filtering images from the data catalog, then continue by register the images to match with each other. The third step is pseudo-invariant features selection and the last step is radiometric normalization of target images. To analyze the comparison of Pearson's correlation value and spectral response of selected PIFs was used.

Table 1 Surface Reflectance Product Landsat

	Landsat Image ID (T1_SR)	Cloud Cover Land (%)
Reference Image	LC08_118044_20200222	1.95
Target Image	LC08_118044_20200206	3.29



a. b.

Figure 1 Reference Image (a) and Target Image (b)

2.1. Image Acquisition

The first step of all remote sensing study is image acquisition. At this part filtering image must be conducted to get the acceptable images. This study filtered the Landsat 8 surface reflectance products by range date from February 2020 to April 2020 when Taiwan in Spring season. Additional conditions for the filtering are path, row of Landsat image and cloud cover land percentage. For the path is 118 and the row is 44 both of which are in southern Taiwan. For the cloud cover land percentage is less than 10%. The reference and the target images as shown in table 1 and figure 1.

2.2. Co-Registration Image

Time series satellite imagery is almost impossible perfectly aligned so the displacement of image pixels may occur. Unregistered image observation becomes difficult to track the changes of pixels or areas through time(Leach, Coops, and Obrknezev 2019).Consequently in this research applied co-register the target image to the reference image to minimize the displacement errors.

2.3. Invariant Pixel Selection

Targets whose spectral reflectance has not changed over time are required for radiometric normalization of time series of pictures and as a basis for change detection in image pairs(Philpot and Ansty 2013). A fully automatic approach for determining time-invariant data has been developed, based on the invariance principles of the Multivariate Alteration Detection (MAD) transformation. Because of its robustness against differing atmospheric conditions from the images, the MAD transformation was chosen for invariant selection(Canty and Nielsen 2008). MAD is a method to calculate linear relationship between two multidimensional variables based on Canonical Correlation Analysis. MAD components have order images that highlight the decreased intercorrelation between canonical variates pair and increased noise interface, the first linear relationship is the canonical variates pair with the highest intercorrelation value and less noise. Higher order correlation defined large similarity (no-change probability) then lower order correlation defined a few similarity (change probability) (Nielsen, Conradsen, and Simpson 1998).

In this study, MAD transformation calculate the linear relationship between the reference and the target images. Determining invariant pixels by spectral distance metrics calculation of MAD components that is sum of the squares of the standardized MAD components it will be called Normalized MADas shown in equation 1 (Canty and Nielsen 2008).

$$NMAD = \sum_{i=1}^{N} \left(\frac{MAD_i}{\sigma_{MADi}} \right)^2 \qquad (1)$$

Where MAD_i is the multivariate components in each spectral band and σ_{MADi} is standard deviations of the multivariate components

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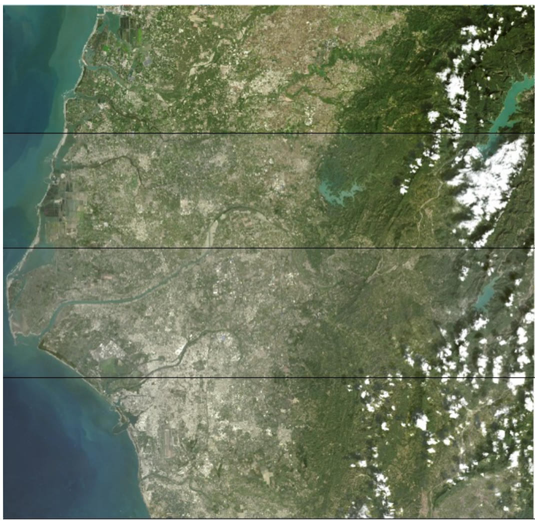
2.4. Radiometric Normalization

To complete the normalization process, the transformation of the target's radiometry to reference images must be calculated. A PIFs thresholds in this study are 10%, 15%, 20%, and 25% to select invariant features between reference and target images. Selected PIFs were converted to binary masks to remove target objects with high potential to change over time such as water bodies and clouds. The mask value will be 1 and 0, the value 1 will keep remain for further process and value 0 will be ignored. Then regression was used to transform the radiometry from both images.



a.
b.
c.
d.

Figure 2 (a.) Normalization Result by PIF consider 10% of NMAD components; (b 15% of NMAD components;(c.) 20% of NMAD components;(d 25% of NMAD components

3. RESULTS

3.1 Normalization Result

In this study we used normalized MAD for normalization due to NMAD describe the invariant pixels distribution by spectral distance metrics calculation of MAD components. Chosen invariant pixels depend on the image percentage threshold value(Canty, Nielsen, and Schmidt 2004). Figure 2 shows the normalization results from different levels of PIFs. According to the results, the different level of PIFs show the different normalization results.

Table 2 Root Mean Square and Correlation Coefficient on PIFs from NMAD

Bands	NMAD (PIFs 10%)		NMAD (PIFs 15%)		NMAD (PIFs 20%)		NMAD (PIFs 25%)	
	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE
2-blue	0.933	0.006	0.925	0.006	0.919	0.007	0.914	0.007
3-green	0.947	0.006	0.942	0.007	0.938	0.007	0.935	0.008
4-red	0.945	0.007	0.937	0.008	0.932	0.008	0.928	0.009
5-NIR	0.966	0.012	0.964	0.013	0.961	0.014	0.958	0.015
6-SWIR1	0.976	0.010	0.973	0.012	0.970	0.013	0.968	0.014
7-SWIR2	0.960	0.009	0.957	0.010	0.954	0.011	0.951	0.012

3.2 Evaluation of Spectral Measure

The correlation coefficient and root mean square error (RMSE) for regression on different levels of PIFs from the NMAD images are shown in Table 2. The removal of noise components provides a best-fit regression line that comes with a higher correlation coefficient and lower RMSE value for all bands. The increasing value of PIFs percentage followed by increased root mean square error. An inverse behavior is found for correlation coefficients, where the correlation coefficient decreasing when the PIFs percentage were increased.

Table 3 Mean Surface Reflectance Value

NMAD (PIFs 10%)	2-blue	3-green	4-red	5-NIR	6-SWIR1	7-SWIR2
Reference	0.055	0.076	0.067	0.189	0.137	0.086
Target	0.058	0.079	0.071	0.198	0.141	0.090
Normalized	0.057	0.078	0.071	0.194	0.141	0.091
Differences	0.001	0.001	0	0.004	0	0.001

NMAD (PIFs 20%)	2-blue	3-green	4-red	5-NIR	6-SWIR1	7-SWIR2
Reference	0.055	0.076	0.067	0.189	0.137	0.086
Target	0.058	0.079	0.071	0.198	0.141	0.090
Normalized	0.061	0.081	0.072	0.195	0.141	0.092
Differences	0.003	0.002	0.001	0.003	0	0.002

NMAD (PIFs 15%)	2-blue	3-green	4-red	5-NIR	6-SWIR1	7-SWIR2
Reference	0.055	0.076	0.067	0.189	0.137	0.086
Target	0.058	0.079	0.071	0.198	0.141	0.090
Normalized	0.059	0.080	0.072	0.194	0.141	0.092
Differences	0.001	0.001	0.001	0.004	0	0.002

NMAD (PIFs 25%)	2-blue	3-green	4-red	5-NIR	6-SWIR1	7-SWIR2
Reference	0.055	0.076	0.067	0.189	0.137	0.086
Target	0.058	0.079	0.071	0.198	0.141	0.090
Normalized	0.062	0.081	0.073	0.195	0.141	0.092
Differences	0.004	0.002	0.002	0.003	0	0.002

Table 3 illustrates the mean value of PIFs surface reflectance comparison. The comparison between the reference image (2020-02-22) and the target image (2020-02-06) before and after regression normalization. The difference between the target before and after normalization is almost zero, also with the largest difference at 0.004.

4. DISCUSSION

In this study, we demonstrate the relative radiometric normalization method for medium resolution satellite imagery. Relative radiometric normalization can risk overcorrection if the image contains a lot of distorted information. Distorted information can be caused surface reflectance of the surface that always changes with time it could be water body, phenology of vegetation, clouds, and shadows. Considering the risk, the selection of unchanged pixels (PIF) from the paired image is a possible alternative to do in the normalization process. The method we used for PIF selection is Multivariate Alteration Detection. This technique is considered since MAD is an automatic PIF selection that is easier and faster to apply than manual selection.
According to the result in this study, varied range of PIF percentages have different impact on normalization result. To analyze the results, Root Mean Square Error and correlation coefficient of pair image was used in this research. The RMSE and correlation coefficient suggests that the normalization method generated a more reliable transformation for the Landsat image. In table 2 shows that correlation coefficient decreases for the larger PIF, while RMSE value increases for the larger PIF. The 10% PIFs normalization shows the highest correlation coefficient and the lowest RMSE value.
Multivariate Alteration Detection method is pixel by pixel approach in normalization process. It means that every pixel can have a varied contribution to the final result. As a result, the increasing percentage in PIF selection may allow regression normalization to use change information as a reference. While reducing percentage in PIF selection may loss the fundamental information for regression normalization, and small number of samples for normalization may cause

under-correction.

The means value of PIF surface reflectance also used for evaluation. This evaluation was considered to compare the differences in surface reflectance value before and after normalization. In this normalization, the surface reflectance value of target image should be the same or almost the same to the reference image. The errors that caused by overcorrection occurs on band blue, band green, band red and band shortwave infra-red 2 as shown in table 3. The surface reflectance value of normalized image is larger than before normalization.

5. CONCLUSION

Inconsistency radiometric of the temporal image is a problem that needs to be addressed since it can contribute to information bias in temporal monitoring applications like land cover change detection and monitoring. By normalizing images with PIFs, the method presented in this research gives a potential solution to deal with radiometric inconsistency issues. The number of PIF represents the total unchanged information from the pair images. The invariant features selected in this investigation produce a different outcome. The different results are related to the regression model normalization, which states that the number of samples plays the most important role in transformation. Under-correction can occur if the samples are too few, while overcorrection can occur if the samples are too many.

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