A LAND COVER MAP ACCURACY METRIC FOR HYDROLOGICAL STUDIES

Brian Alan Johnson[1]*, Isao Endo[1], Akio Onishi[2], Milben Bragais[3], Damasa B. Magcale-Macandog[3], Emily Skeehan[1]

[1]Institute for Global Environmental Strategies, 2108-11 Kamiyamaguchi, Hayama, Kanagawa 240-0115, Japan
[2]Faculty of Environmental Studies, Tokyo City University, 3-3-1 Ushikubo-nishi, Tsuzuki-ku, Yokohama, Kanagawa 224-8551, Japan, [3]Institute of Biological Sciences, University of the Philippines Los Baños, College, Laguna 4031, Philippines
*Corresponding author: johnson@iges.or.jp

ABSTRACT

Land cover (LC) has a significant impact on rainfall-runoff dynamics of a watershed, so LC maps are often incorporated into hydrological models to simulate how changes in climate or land management will affect water quantity/water quality within the watershed. The accuracy of a LC map can thus affect the accuracy of hydrological modelling results. However, because LC maps are not typically produced specifically for hydrological studies, the conventional LC map accuracy metrics may not be the most relevant. In this study, we proposed a new metric for LC map accuracy assessment, calculated as the root-mean-square-deviation (RMSD) of the mapped (i.e. estimated) and "ground truth" runoff curve numbers (CN) at randomly-sampled locations. The new metric, CN-RMSD, assesses the accuracy of the direct runoff estimates derived from the LC map, and its benefit over the traditional LC accuracy assessment metrics is that it more heavily weights LC classification errors that cause greater errors in estimated runoff. Ground truth CN data can be collected much in the same way as ground truth data is collected for the traditional accuracy metrics, although a soil map can improve the accuracy of the ground truth CN values. Some potential applications of CN-RMSD, e.g. for LC map selection and LC map fusion, are also discussed.

Keywords: hydrological modelling, land cover accuracy assessment, rainfall-runoff, remote sensing, SCS curve number

INTRODUCTION

Hydrological models are often used to estimate the water quality and/or water quantity of lakes and rivers under different climate and land/water management scenarios (Thirel et al., 2015). In terms of watershed land management, land cover (LC) conditions have a significant impact on hydrological processes (e.g. rainfall runoff and infiltration), so many hydrological models incorporate LC maps as input datasets. For this reason, the accuracy of a LC map can also affect the accuracy of hydrological modelling results (Cotter, Chaubey, Costello, Soerens, & Nelson, 2004). LC maps are typically produced by classifying pixels in a satellite or aerial image into different LC classes using an image classification algorithm (Jensen, 2005), and the LC map's accuracy is then calculated by comparing the "classified" LC type with the "ground-truth" LC type at a number of randomly-sampled pixel locations (Congalton, 2009). Ground truth LC data for this accuracy assessment is either obtained in-situ (through a field survey) or remotely (by visual image interpretation). Accuracy assessment is an important research topic for both LC map producers and LC map users, and although we just briefly introduce the topic here, readers can refer to some recent studies for a better understanding of various issues related to accuracy assessment (Castilla, 2016; Congalton, 2009; Johnson, 2015; Olofsson et al., 2014).

Several conventional LC map accuracy metrics exist, with the most common being overall accuracy (# of correctly classified sample pixels / total # of sample pixels) (Congalton, 1991). However, the existing metrics do not take into account that some types of classification errors are more problematic than others when it comes to simulating hydrological processes. As an example, consider two cases: In Case 1, a pixel in a LC map is classified as "built-up/impervious area" but in truth contains "forest", and in Case 2, a pixel is classified as "built-up/impervious area" but in truth contains "bare soil". Of these two cases, Case 1 is the more serious error due to the greater difference in runoff rates of impervious and forested lands (Soil Conservation Service, 1986).

Due to the limitation of the existing LC map accuracy metrics, the objective of this study was to develop a new metric more relevant to hydrological processes. This new metric is based on the well-known U.S. Soil Conservation Service runoff curve number (CN) approach for calculation of direct runoff (i.e. surface and immediate subsurface runoff), which takes into account the LC and soil properties of the land (Soil Conservation Service, 1986). Before describing the new metric, we first briefly introduce the

CN. CN is related to the maximum potential soil moisture retention of the land (*S*), and the CN calculation method was developed by the USDA from an empirical analysis of rainfall (*P*) and runoff (*Q*) measurements at field test sites. *S* and CN values were calculated using the measured values of *P* and *Q* and an estimate of the initial abstraction (*I$_a$*), i.e. the amount of rainfall that could be retained in the soil or vegetation before runoff begins (assumed to be = 0.2*S*) (Soil Conservation Service, 1986). *CN* is given by:

$$Q = \frac{(P - Ia)^2}{P - Ia + S} = \frac{(P - 0.2S)^2}{P - 0.8S} \qquad P > Ia$$

and

$$CN = \frac{1000}{10 + S}$$

Higher CN values indicate higher potential runoff rates (see **Table 1** for some examples for different LC/soil types**)**. A spatially-explicit CN map can be produced by overlaying a LC map and a soil map using Geographic Information Systems (GIS) software. The CN is the foundation of many hydrology algorithms, including those in most simulation models developed by the U.S. Department of Agriculture for hydrology, soil erosion, and nonpoint water quality estimation (Garen & Moore, 2005).

Table 1. Runoff Curve Number (CN) values of four common types of land cover (LC), adapted from the Table 2-2 of Soil Conservation Service (1986). Higher CN values indicate higher runoff potential.

Land cover (LC)	Hydrologic Soil Group (HSG)			
	A	☐	C	D
Built-up/impervious area	98	98	98	98
Bare soil	77	86	91	94
Pasture, grassland, or range (>75% ground vegetation cover)	39	61	74	80
Forest (litter and brush covering the soil)	30	55	70	77

Because of the importance of the CN for various types of hydrological analysis, our proposed LC map accuracy metric is calculated as the root-mean-square-deviation (RMSD) of the mapped (i.e. predicted, or estimated) and ground truth (i.e. actual) CN values at randomly-sampled pixel locations. This new metric, CN-RMSD, assesses the accuracy of the direct runoff estimates derived from a LC map, making it a better indicator of the LC map's suitability for studies related to rainfall-runoff dynamics. To our knowledge, CN-RMSD is the first LC map accuracy metric developed specifically for hydrological applications. In the remainder of this paper, we provide a step-by-step approach to calculating CN-RMSD (Methods section) and identify some possible ways in which the new metric can be used in practice (Results and Discussions section).
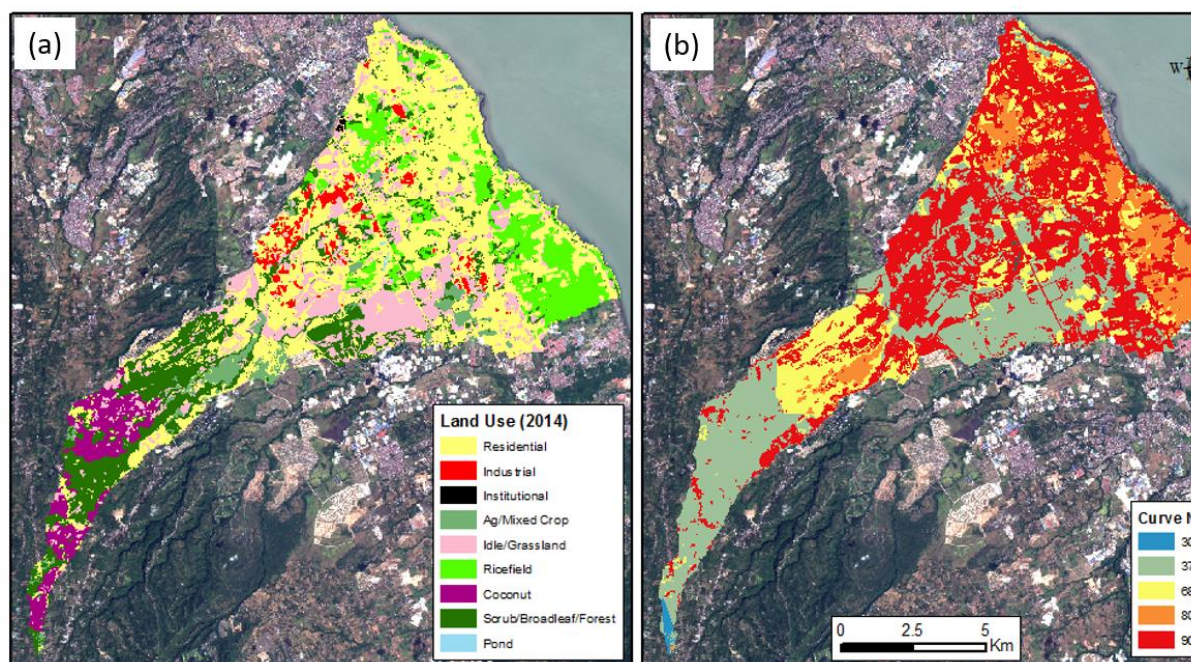
METHODS

There are seven main steps for calculating CN-RMSD, and they can be performed using many free (e.g. QGIS) or commercial (e.g. ESRI ArcGIS) GIS software packages:

1. Obtain or create a LC map of a study area watershed;
2. Overlay the LC map onto a hydrologic soil group (HSG) map of the study area (more information related to HSGs given below after the main steps);
3. Generate a CN map of the study area using the LC map, the HSG map, and the lookup table provided in Soil Conservation Service (1986);
4. Randomly generate *n* sample points within the study area;
5. Extract the "mapped CN values" at these sample point locations from the CN map;
6. Identify the "ground truth CN values" at these sample point locations. A field survey or visual image interpretation can be conducted to identify the ground truth LC. The HSG map can be used to identify the ground truth soil properties (although the HSG map is unlikely to be 100% accurate, it is usually the best reference data available); and
7. Calculate the RMSD of the mapped (*CN$_{mapped}$*) and ground truth CN (*CN$_{GT}$*) values at these *n* sample point locations. CN-RMSD is calculated as:

$$CN\text{-}RMSD = \sqrt{\frac{\sum(CN_{mapped} - CN_{GT})^2}{n}}$$

Regarding the HSG map (step 2), soils can be generally classified into one of four HSGs – '*A*' ("sand, loamy sand, or sandy loam"), '*B*' ("silt loam or loam"), '*C*' ("sandy clay loam"), or '*D*' ("clay loam, silty clay loam, sandy clay, silty clay, or clay") – based on the minimum infiltration rate of the soil (Soil Conservation Service, 1986). A lookup table for identifying the HSG of many different soil types has also been provided by the U.S. Soil Conservation Service (1986). If a reliable soil map is not available for a watershed, the entire watershed area can alternatively simply be assigned to the dominant HSG of the watershed based on the hydrologist's knowledge of the typical soil conditions of the area. For easier understanding of the CN map generation process, a CN lookup table for a few selected LC classes is shown below in **Table 1**, and a LC map and its corresponding CN map are shown in **Fig. 1** to allow for a visual comparison. Regarding the appropriate number of sample points needed for calculating CN-RMSD (i.e. value of *n* in step 4), although no hard rules exist, for conventional LC map accuracy assessments a good "rule of thumb" is to collect a minimum of 50 samples for each LC class (Jensen, 2005), so this same rule of thumb could probably also be applicable for accuracy assessments based on CN-RMSD.
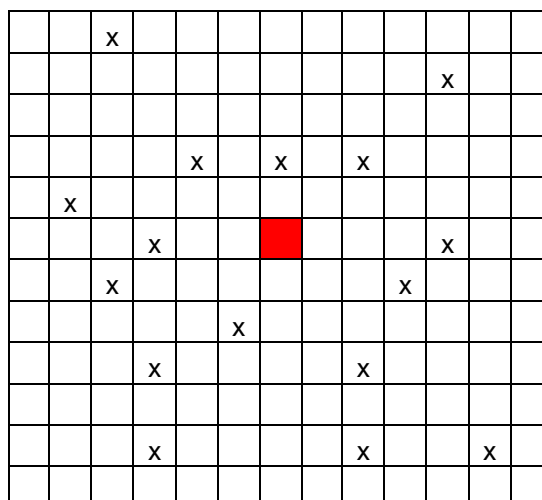

Figure 2. Land use/land cover map of the Silang-Santa Rosa sub-watershed in The Philippines (a) and the corresponding CN map (b) [soil map not shown for illustration simplicity]. LC classes with greater impervious surface area (e.g. "Residential" and "Industrial") appear red in the CN map (high CN values), while LC classes with greater vegetation cover (e.g. "Scrub/broadleaf forest" and "Coconut") appear green or yellow (very low CN values) depending on the hydrologic soil group of the underlying land.

RESULTS AND DISCUSSIONS

In this section, we discuss some ways in which the proposed metric, CN-RMSD, could be used in practice for hydrological studies.

If multiple LC maps exist for a watershed of interest, a commonly occurrence nowadays with the growing number of global/regional/national LC maps available, there are a few ways in which the CN-RMSD metric can be useful. As one example, CN-RMSD values could be calculated for each of the available LC maps, and the map with the lowest CN-RMSD value could be selected as the most appropriate map to use for hydrological analysis. Alternatively, CN-RMSD could be utilized for fusing, or combining, the CN_{mapped} values derived from multiple LC maps (i.e. CN_{mapped_1}, CN_{mapped_2}, …). As a simple example, if CN-RMSD is calculated locally pixel-by-pixel, e.g. based on the nearest 10 sample points with CN_{GT} information as shown in **Fig. 2**, then the most locally-accurate CN map can be identified at each pixel location. All of the most locally-accurate CN_{mapped} values could then be combined to produce a "fused" CN map with higher accuracy (lower CN-RMSD). Aside from this simple example, various other methods for geographic data fusion exist, including geographically-weighted regression based fusion

methods (See et al., 2015) and machine-learning based fusion methods (Johnson, Scheyvens, & Shivakoti, 2014). For all of the map fusion methods, the different LC maps would first need to be resampled to a common spatial resolution and coordinate system.

Figure 2. Simple approach for fusing multiple CN maps based on local CN-RMSD calculations. The red cell indicates the pixel for which the local calculation is being performed, and cells with "x" indicate sample pixels containing ground truth CN information. The 10 nearest sample pixels (shown in red) could be used to calculate CN-RMSD locally, and the map with the lowest CN-RMSD value could be identified as the most accurate at the red pixel location. [Note: we use the nearest 10 sample points for demonstration purposes only].

In addition to its usage to select or combine information from multiple LC maps, CN-RMSD could also be used to help better understand sources of uncertainty in a hydrological model's results, which may be affected by various other factors including errors in the precipitation data, errors in the digital elevation model, and errors in water level or streamflow data. Finally, CN-RMSD may be helpful for the calibration of hydrological models with parameters related to CN. For hydrological model calibration, it is useful to have an idea before-hand of the realistic range of values of different model parameters (to avoid setting parameter values that are physically unrealistic or impossible), so CN-RMSD could be used to define a realistic range of values for the CN parameter(s) in a hydrological model. Several commonly-used hydrological models have CN parameters (e.g. The Soil and Water Assessment Tool (Neitsch, Arnold, Kiniry, & Williams, 2011)).

CONCLUSIONS
In this study, a new land cover (LC) map accuracy metric was developed with hydrological studies in mind. The metric is calculated as the root-mean-square deviation (RMSD) of the mapped (i.e. estimated) and ground truth runoff curve numbers (CN_{mapped} and CN_{GT}, respectively) at randomly-sampled locations in the LC map. Unlike conventional LC map accuracy metrics, the new metric, CN-RMSD, more heavily penalizes LC classification errors that cause greater errors in predicted runoff, making it a better indicator of a LC map's suitability for hydrological analysis. Some potential uses of CN-RMSD for LC map selection, map fusion, and uncertainty analysis are also discussed.

ACKNOWLEDGEMENT

REFERENCES

1. Castilla, G. (2016). We Must All Pay More Attention to Rigor in Accuracy Assessment: Additional Comment to "The Improvement of Land Cover Classification by Thermal Remote Sensing". Remote Sens. 2015, 7, 8368–8390. *Remote Sensing*, *8*(4), 288. http://doi.org/10.3390/rs8040288
2. Congalton, R. G. (1991). A review of assessing the accuracy of classifications of remotely sensed data. *Remote Sensing of Environment*, *37*(1), 35–46.
3. Congalton, R. G. (2009). *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices.* Boca Raton, USA: CRC Press.
4. Cotter, A. S., Chaubey, I., Costello, T. A., Soerens, T. S., & Nelson, M. A. (2004). Water Quality Model Output Uncertainty As Affected By Spatial Resolution of Input Data. *Knowledge Creation Diffusion Utilization*, *72701*(August), 977–986. http://doi.org/10.1111/j.1752-1688.2003.tb04420.x
5. Garen, D. C., & Moore, D. S. (2005). Curve number hydrology in water quality modeling: Uses, abuses, and future directions. *Journal of the American Water Resources Association*, *41*(6), 1493–1494. Retrieved from <Go to ISI>://000234615100018
6. Jensen, J. R. (2005). *Introductory Digital Image Processing - A Remote Sensing Perspective* (3rd ed.). Upper Saddle River, USA: Pearson Prentice Hall.
7. Johnson, B. A. (2015). Scale Issues Related to the Accuracy Assessment of Land Use/Land Cover Maps Produced Using Multi-Resolution Data: Comments on "The Improvement of Land Cover Classification by Thermal Remote Sensing". Remote Sens. 2015, 7(7), 8368–8390. *Remote Sensing*, *7*(10), 13436–13439. http://doi.org/10.3390/rs71013436
8. Johnson, B. A., Scheyvens, H., & Shivakoti, B. R. (2014). An ensemble pansharpening approach for finer-scale mapping of sugarcane with Landsat 8 imagery. *International Journal of Applied Earth Observation and Geoinformation*, *33*, 218–225.
9. Neitsch, S. ., Arnold, J. ., Kiniry, J. ., & Williams, J. . (2011). *Soil & Water Assessment Tool Theoretical Documentation Version 2009. Texas Water Resources Institute, TR-406.* Retrieved from http://swat.tamu.edu/media/99192/swat2009-theory.pdf
10. Olofsson, P., Foody, G. M., Herold, M., Stehman, S. V, Woodcock, C. E., & Wulder, M. A. (2014). Good Practices for Assessing Accuracy and Estimating Area of Land Change. *Remote Sensing of Environment*, *148*, 42–57.
11. See, L., Schepaschenko, D., Lesiv, M., McCallum, I., Fritz, S., Comber, A., … Obersteiner, M. (2015). Building a hybrid land cover map with crowdsourcing and geographically weighted regression. *ISPRS Journal of Photogrammetry and Remote Sensing*, *103*, 48–56. http://doi.org/10.1016/j.isprsjprs.2014.06.016
12. Soil Conservation Service. (1986). Urban Hydrology for Small Watersheds. In *Technical Release 55.*
13. Thirel, G., Andréassian, V., Perrin, C., Audouy, J.-N., Berthet, L., Edwards, P., … Vaze, J. (2015). Hydrology under change: an evaluation protocol to investigate how hydrological models deal with changing catchments. *Hydrological Sciences Journal*, *60*(7-8), 1184–1199. http://doi.org/10.1080/02626667.2014.967248