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Darwin A. Arrechea-Castillo[a], Yady T. Solano-Correa*[a,b], Julián F. Muñoz-Ordoñez[a,c], Edgar L. Pencue-Fierro[a,d], Estiven Sánchez-Barrera[b]

[a]Grupo de Óptica y Láser (GOL), Universidad del Cauca, Popayán – Cauca, Colombia; [b]Grupo de Investigación en Física Aplicada y Procesamiento de Imágenes y Señales (FAPIS), Universidad Tecnológica de Bolívar, Cartagena de Indias – Bolívar, Colombia; [c]Grupo de Investigación en Computación e Informática Aplicada (MIND), Corporación Universitaria Comfacauca – Unicomfacauca, Popayán - Cauca, Colombia; [d]Grupo de Estudios Ambientales (GEA), Universidad del Cauca, Popayán – Cauca, Colombia

ABSTRACT

The Sustainable Development Goal (SDG) number 11 aims at making cities and human settlements more inclusive, safe, resilient, and sustainable. Complying with SDG 11 is a difficult task, especially when considering rural settlements where: (i) population settles in a dispersed manner; and (ii) geography complexity and social dynamics of the area make it difficult to monitor and capture data. One example of such areas can be found in the South-West of Colombia, in the Las Piedras River sub-basin. The National Administrative Department of Statistics in Colombia (DANE in Spanish) aims at mapping the population and houses in dispersed and difficult-to-access rural settlements in an accurate and continuous way. Nevertheless, there are several difficulties (derived from the in-situ way of collecting the data) that prevent such data from being generated. This research presents a methodology to carry out an updated mapping of rural areas with high spatial resolution data coming from PlanetScope (3m). Such a mapping considers the dynamics of housing growth, focusing on dispersed and difficult-to-access rural settlements. To this aim, Convolutional Neural Networks (CNNs) are used together with PlanetScope data, allowing to account for average houses size ($\geq 12m^2$) in the study area. Preliminary results show a detection accuracy above 95%, in average, according to geography complexity.

Keywords: Rural settlement, House/building detection, PlanetScope, Deep learning, Remote sensing, SDGs

1. INTRODUCTION

The "Sustainable Development Goals" (SDGs) are a collection of 17 interconnected global objectives adopted by the United Nations (UN)[1] in 2015 to make a universal call to action to end poverty, protect the planet, and ensure that by 2030 all people enjoy peace and prosperity[2]. All countries and stakeholders that are part of the 2030 agenda must ensure compliance with the SDGs[3]. To achieve this, focused regional strategies and political initiatives that can be implemented by local entities must be put in place[2]. SDG number 11[2], called "Sustainable Cities and Communities", aims to make cities and human settlements more inclusive, safe, resilient, and sustainable. This SDG has 10 targets, which are measured through 15 indicators. Indicator 11.3.1, which measures the relationship between the rate of land consumption and the population growth[1], is difficult to quantify in dispersed rural areas. In such areas the population settles in distant areas, such as in the Las Piedras River sub-basin in Colombia[4]. Due to this fact, quantifying the demographic behavior of the population that settles in dispersed rural areas becomes a complex task. Not to mention the complexity added because of topography and social dynamics that occur in these regions[5]. In Colombia, the National Administrative Department of Statistics (DANE in Spanish)[6] is the entity responsible for carrying out the most complex and important statistical operation in the country: the National Population and Housing Census (CNPV in Spanish)[7]. Through the CNPV, the Country obtains firsthand data on the number of inhabitants, their distribution in the territory, and their living conditions[7]. This statistical information is the strategic basis for different public and private organizations in the country to plan and make decisions on public policy, economic development, social welfare, employment, housing, health, migration, among others[4]. At the general level, international dynamics recommend a CNPV to be conducted every 10 years[6]. However, due to the complexity of this operation, in Colombia, historically speaking, the CNPV has been carried out in a time frame larger

*tsolano@unicauca.edu.co

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than what recommended by international organizations[6]. For example, between the last two CNPVs, there is an interval of approximately 13 years (2005 and 2018)[7]. The information provided by the CNPV is the strategic basis for national and territorial planning and decision-making and for calculating Sustainable Development Indicators, such as indicator 11.3.1. To carry out the CNPV, the DANE needs previous information indicating the locations of the Homes, Households, and Special Accommodation Places (LEA in Spanish). This information is currently obtained through the national cadastral system and the different municipal cadastres[6]. In some cases, when the cadastral information is insufficient, DANE's technical team performs the manual labeling of the buildings where people may be living. In the first case, the information in the dispersed rural areas is imprecise and outdated; while, in the latter, carrying out this task demands quite a considerable additional consumption of time and human resources[8]. Therefore, the goal of this research is to introduce a methodology that exploits both Remote Sensing (RS)[9] and Deep Learning (DL)[10] techniques in order to detect buildings' locations automatically in the dispersed rural areas of the Las Piedras sub-basin.

There are several methods to generate automatic rural houses mapping using RS and DL available in literature. Sun et al.[11] identified building rooftop in rural areas in north China to determine the spatial distribution of photovoltaic power generation potential. They used U-Net DL network and publicly available Very High spatial Resolution images (VHR) of 0.3 m/pixel and 0.6 m/pixel. This work has a limitation since it only maps conglomerated rural areas rather than dispersed rural areas. Additionally, the Convolutional Neural Network (CNN) architecture used, and the type of satellite data chosen to make it infeasible to map large spatial extensions. In the research done by Leonard et al.[12], they applied citizen science through a project called "Power to the People", paired with satellite imagery and computer vision to map remote off-grid homes for electrical system design. This research shows citizen science and computer vision to be a promising pipeline for rural home-level mapping. However, the research was limited by the need to involve over 6000 participants and the six-month duration required to annotate houses in rural areas of certain African countries. Monna et al.[13] detected vernacular houses automatically in Sumba Island (Indonesia), using satellite imagery and several DL powerful architectures, such as Inception v2[14] and ResNet 50[15]. A weakness of this research is that they rely on satellite images obtained from Microsoft Bing, which may have limitations in terms of geometric and radiometric consistency across the study area. Moreover, the use of a semantic segmentation approach with VHR images also makes it challenging to apply this methodology to map large spatial extensions in a reasonable amount of time. In this 3 research works[8,16,17], they used PlanetScope imagery to map individual houses. In[8], Gordana and Onur explored a high spatial resolution PlanetScope dataset for extracting houses inventory information in order to prevent serious damages and to determine the possible loses from earthquakes. The authors employed a DL-based approach that uses a U-Net architecture[18] for houses segmentation in settlements under earthquake risk. In[16], Li et al., presented a method for generating houses footprints using a CNN combined with feature pairwise conditional random fields. The approach aimed to overcome the challenges of existing methods, such as limited contextual information. Li et al.[17] proposed a semi-supervised approach to houses footprint generation that uses features and outputs consistency training. The method aimed to improve the accuracy of houses footprint generation while reducing the need for manual labeling of training data. Even though the last 3 studies employed PlanetScope imagery, which has the potential to map rural buildings across large spatial extensions, these investigations are not primarily aimed at mapping dispersed rural areas. Furthermore, the use of complex techniques such as semantic segmentation makes large-scale mapping impracticable. In summary, after conducting a literature review[19–23], we could not find any research that has developed a methodology capable of mapping houses at an individual level on a large scale and in dispersed rural areas using PlanetScope imagery. Therefore, this research aims at addressing this gap in literature.

2. STUDY AREA AND RS DATA

The study area selected for this research is within the Las Piedras River sub-basin, as shown in Figure 1 and covering a total area of approximately $66km^2$[24]. It is located within the municipalities of Popayán and Totoró in the southwest of Colombia. The basin is composed by two townships: Quintana and Las Piedras, where small peasants and indigenous communities (Puracé and Quintana councils) are located[4]. This sub-basin is characterized by a rugged topography, with steep slopes and narrow valleys. The sub-basin is home to a rich array of flora and fauna, including several endemic species, and provides important ecosystem services such as water supply for agricultural and domestic use[4]. In order to better show the results, the three tiles highlited in Figure 1 were considered.

The proposed approach is applied over images acquired by the PlanetScope satellite constellation. The PlanetScope imagery[25] is a collection of high spatial resolution satellite imagery captured by the Planet company. It consists of a constellation of satellites equipped with multi-spectral sensors capable of capturing imagery at a resolution of 3m per pixel[25]. For the development of this research, an 8 band PlanetScope[25] image acquired on January 28, 2023 was used.

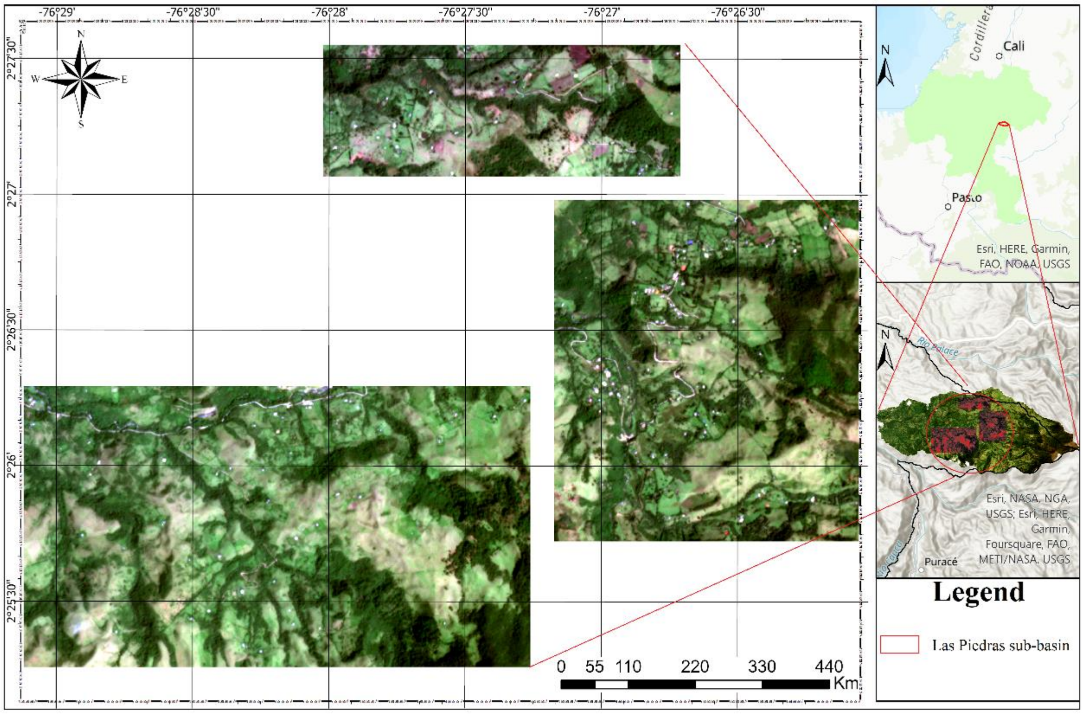


Figure 1. Study area location with a true color composition of PlanetScope images showing three tiles to work with.

3. PROPOSED APPROACH FOR DISPERSED HOUSE MAPPING

In this study, we propose an approach that combines PlanetScope RS data and DL to perform rural area dispersed house mapping. The proposed approach (see Figure 2) consists of several stages. The first stage involves selecting the area of interest and downloading the satellite information that covers it. The next stage is the pre-processing of the information. Here, an initial clipping of the Las Piedras sub-basin and image normalization is performed to make the image spectral range between 0 and 1; which benefits the model performance. Next, three test zones are extracted within the sub-basin to qualitatively assess the model final performance (Figure 1). Afterwards, the NDVI Index is calculated since it can help differentiate the two classes of interest: Houses and Non Houses[27]. The next step is to combine the original 8 spectral bands image plus the calculated index to form the feature set from which 2000 training samples are selected, resulting in a dataset of 4000 images in total, each with 9 bands (feature set). The next step in the scheme is to train, validate, and test the model. For this, 200 images are selected for each class to perform the test, and the remaining 1800 images per class are divided into 80% for training and 20% for validation. The last step is to map the houses.

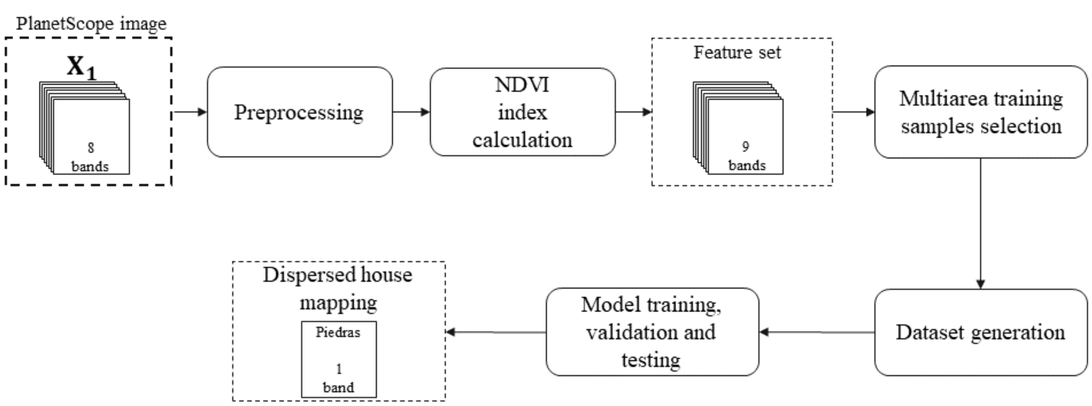


Figure 2. General block scheme of the proposed approach for rural area dispersed house mapping in the Las Piedras sub-basin.

Regarding the DL architecture, a CNN architecture is considered and build with Tensorflow API, Keras[28]. The architecture comprises a total of 7 layers, which include 4 convolutional layers and 3 fully connected layers. To optimize the performance of the model, several hyperparameters were carefully selected. The batch size was set to 64. The number of epochs was set to 50. Additionally, the learning rate was set to 0.001. Further information regarding the configuration of the model can be found in Table 1Table 1. CNN parameters for the feature extraction network..

Table 1. CNN parameters for the feature extraction network.

CNN parameters Input shape = (3,3,9)	**Convolutional layer**			
	Convolution 1	**Convolution 2**	**Convolution 3**	**Convolution 4**
Number of filters	100	150	300	530
Kernel size	(3,3)	(3,3)	(3,3)	(3,3)
Activation	ReLu	ReLu	ReLu	ReLu
Padding	Same	Same	Same	Same
Stride	1	1	1	1
Pooling	Max Pooling	Max Pooling	Average Pooling	Average Pooling
Dropout	0.25	0.25	None	0.25

The evaluation of the proposed method was based on four metrics: Overall Accuracy (OA), precision, recall, and kappa coefficient. OA provides an overall measure of how well the model performs[8], but it can be misleading if the dataset is imbalanced, meaning that one class is more represented than the other[29]. Precision evaluates how well the model identifies the positive samples. High precision indicates that the model has a low number of false positives[13]. Recall evaluates how well the model detects the positive samples. High recall indicates that the model has a low number of false negatives[8]. The kappa coefficient is a statistical measure that assesses the agreement between the predicted and true labels, considering the agreement that would be expected by chance. The kappa coefficient ranges from -1 to 1, where values closer to 1 indicate higher agreement between predicted and true labels[30]. By employing these four metrics, it is possible to obtain a comprehensive evaluation of the performance of the proposed DL model.

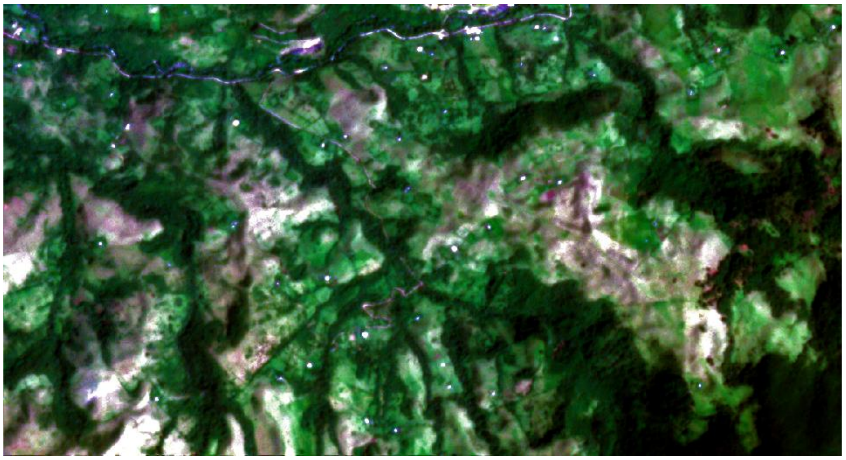
4. RESULTS AND DISCUSSION

The proposed DL model underwent 30 training sessions to assess its performance. The model results obtained a mean OA of 97.06% in the validation data for all the training sessions[31]. In the best case, our model achieved an OA of 97.31% on the training data and an OA of 97.50% on the validation data. The top-performing model was also tested on a previously unseen datasets (the three tiles highlited in Figure 1, for which no training samples were selected), yielding favorable results with an OA of 92.75%, an Overall Precision (OP) of 92.75%, an Overall Recall (OR) of 93.14%, and a kappa coefficient of 0.855, as shown in Table 2. The numerical results suggest that the model is capable of effectively recognizing dispersed houses in the rural areas of the Las Piedras sub-basin, demonstrating its ability to generalize.

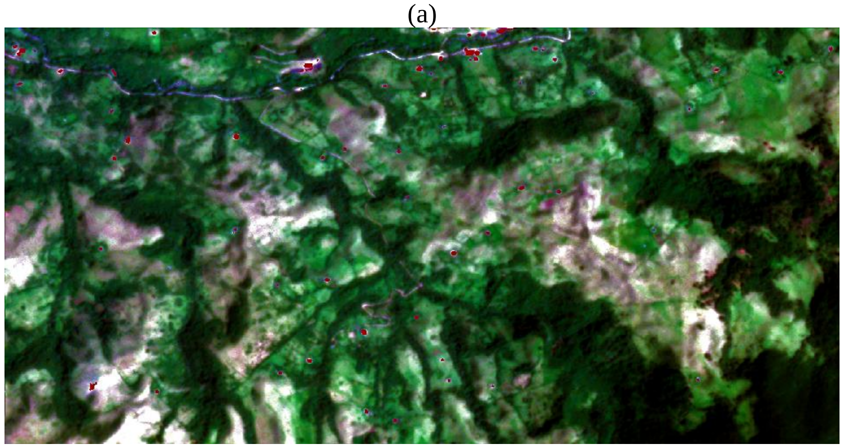
Table 2. Confusion matrix metrics for an unseen dataset.

	2023 PlanetScope Image		
	Houses	**Non houses**	
Precision	97.5%	88%	**OP:** 92.75%
Recall	89.041%	97.238%	**OR:** 93.14%
	OA: 92.75%		
	Kappa: 0.855		

To conduct a qualitative evaluation of the results obtained from the proposed DL model, a mapping exercise was carried out. The aim of this exercise was to qualitatively analyze the performance of the model in identifying dispersed houses in the study area. For this purpose, 3 tiles were selected within the Las Piedras sub-basin and the implemented model was able to map the dispersed houses present in them. The results are shown in Figure 3, Figure 4 and Figure 5, where both the true color composition of each tile and the detected houses (in red) can be seen. The study results suggest that the proposed model has a good performance in identifying dispersed houses in rural areas. In particular, the model demonstrated satisfactory results when applied to tiles 1 and 3. Interestingly, the model ability to detect houses was not limited to sparsely populated areas. It was also able to successfully identify houses in more dense areas. This indicates that the model accuracy is not affected by changes in the density of houses in the area that is mapped. These findings suggest that the proposed model has a great potential for practical use in rural area mapping and management, as it can provide accurate and reliable information regardless of the level of house dispersion.



(a)



(b)

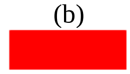
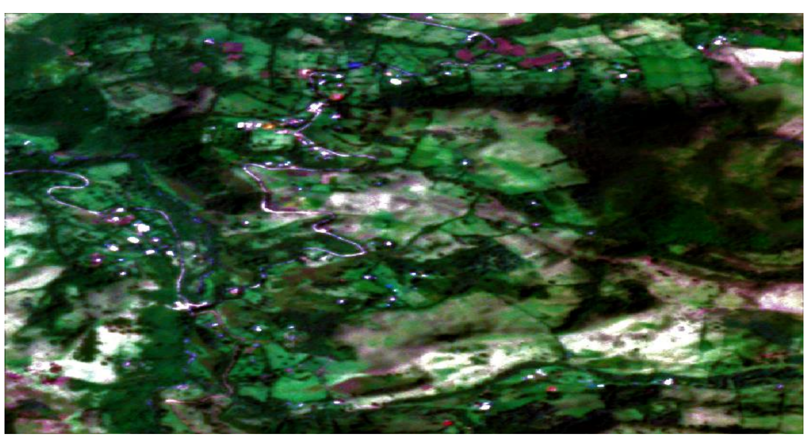
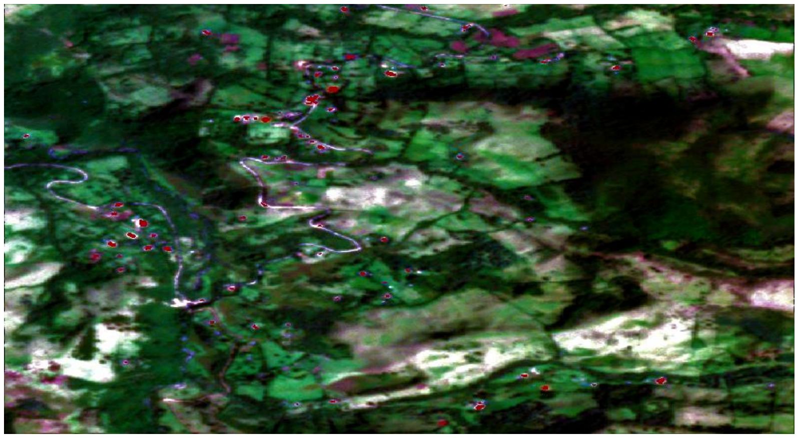


Figure 3. Experimental results for tile 1. (a) True color PlanetScope, (b) obtained results by the proposed method.



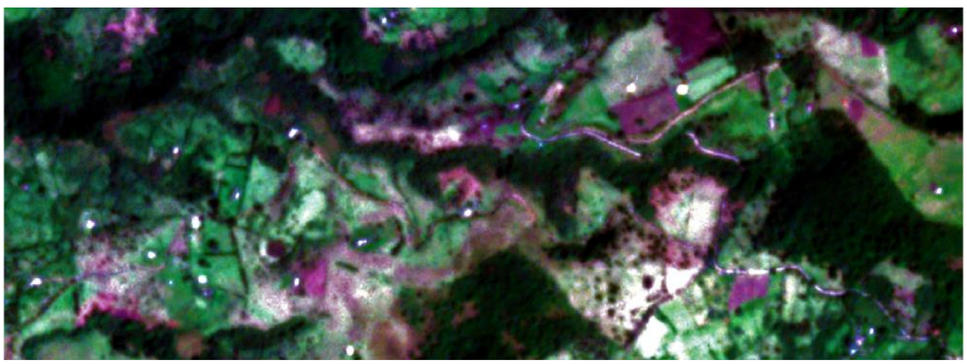
(a)



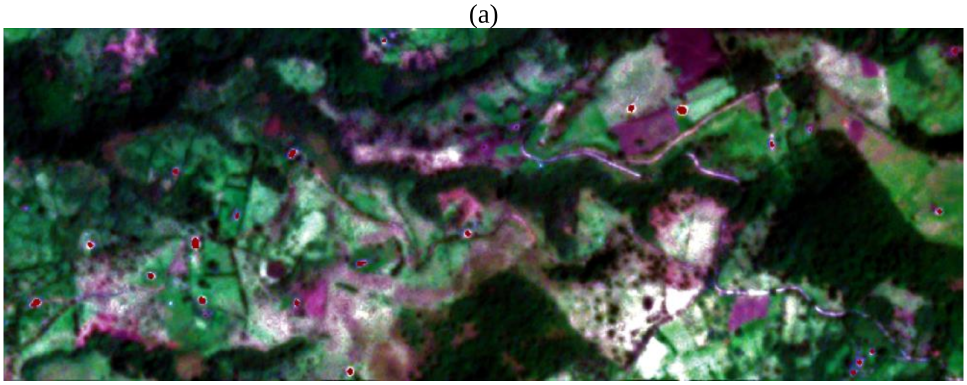
(b)

Houses

Figure 4. Experimental results for tile 2. (a) True color PlanetScope, (b) obtained results by the proposed method.



(a)



(b)

Houses

Figure 5. Experimental results for tile 3. (a) True color PlanetScope, (b) obtained results by the proposed method.

5. CONCLUSIONS

A DL model able to map dispersed houses in rural areas using new 8 band PlanetScope imagery in the Las Piedras sub-basins in Colombia has been presented. Results demonstrated great potential for practical use in rural area mapping and management. The study findings showed that the model can generalize and identify dispersed houses in rural areas accurately and reliably, regardless of the level of house dispersion. The model also showed to perform well in places where houses are closer together, which is an important consideration for rural areas with varying levels of housing density. In terms of future works, there is a need to extend the proposed model to other dispersed rural areas in Colombia to further test its performance and to assess the feasibility of using it on a larger scale. The feasibility of incorporating additional radiometric indices to enhance the accuracy of rural dispersed house detection could be also explored.

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