INTEGRATING REMOTE SENSING AND CENSUS INFORMATION FOR LAND SECURING IN NORD KIVU, DRC

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Sommario

La competizione per l'uso della risorsa territoriale è considerata motivo scatenante e fattore perpetuante dei conflitti nella parte orientale della Repubblica Democratica del Congo (RDC). La letteratura esistente dimostra che il telerilevamento (RS) è uno strumento utile per monitorare sistematicamente le dinamiche spazio-temporali di uso e copertura del suolo in molte regioni del mondo. Per tale ragione in questo studio proponiamo una metodologia per l'integrazione di informazioni provenienti da diverse fonti, in particolare il telerilevamento e le interviste condotte in campo, volta alla messa a punto di un sistema spaziale di supporto alle decisioni finalizzato alla valutazione multicriteriale di potenziali siti pilota per lo sviluppo agricolo e il re-insediamento di rifugiati congolesi.

Abstract

Land disputes are considered both key sources and perpetuating factors of conflict in the eastern Democratic Republic of the Congo (DRC). Existing literature demonstrates that remote sensing (RS) is a useful tool for systematically monitor the spatial-temporal land use/land cover dynamics in many regions of the world. For this reason, in this paper we propose a methodology for the integration of different sources of information, namely satellite imagery and census information, in order to set up a Spatial Decision Support System aimed at Multi-Criteria Evaluation of potential pilot sites for agricultural development and refugees resettlement.

Introduction

East-DRC : Historical background

Since the Democratic Republic of Congo (DRC) is one of the richest countries in the world in terms of natural resources (ADB, 2009; Bwana, 2011), the control of lands in the region has always been at the core of profound disputes (Naidoo, 2003).

In such a context of internal and external economic interests, land disputes can be considered obviously both as sources and perpetuating factors of conflict in the eastern DRC (Verweijen &

Marijnen, 2016). The most visible land-related conflicts, contributing to large-scale violence, are those that put ethnic communities against each other. However, other forms of land-related conflict are very widespread, including community-level conflicts between farmers and large-scale concessionaires, between rural communities and mining companies, between pastoralists and farmers, and between national parks institutions and surrounding populations. While generally accompanied by low levels of violence, the grievances related to such conflicts often impact on the security and stability at the local level (Mathys & Vlassenroot, 2016).

The weakness of land legislation, associated with widespread corruption, led to a massive alienation of lands under the two existing land tenure systems, namely customary and statutory tenures. On the other hand, the Government has already signed a huge number of international agreements with multinational companies for large-scale land exploitation projects, mostly for mining and biofuel production (Landmatrix, 2017). These two causes brought to an incredibly difficult situation for the increasing population of the region who now is cornered in the less productive areas (Frankema & Buelens, 2013).

The situation is even more complicated by the huge number of refugees in the region. According to OCHA, some 430,000 refugees from the DRC are still living in neighbouring countries, including Burundi, Uganda, the United Republic of Tanzania and Rwanda (Externally Displaced Persons – EDP). The humanitarian profile of North Kivu, in particular, is alarming, with an estimated 863,400 internally displaced persons (IDP) between January 2009 and November 2014. All these people have the right to return to their home, as declared by several International Treaties concerning human rights in general and the refugee condition in particular (CIRGL, 2006).

For all these reasons, the agenda of international organizations dealing with peace seeking and keeping in the Eastern Congo are now focusing, among other issues, on drawing a clear sketch of land tenure and land ownership distribution in the region.

The project "Land Securisation in the Goma Dioceses"

The Department of Agricultural and Environmental Sciences (DISAA) of the University of Milan, is involved with Caritas Goma NGO in a three-years project called "Land Securisation in the Goma Dioceses" (LSGD), funded by the European Commission. The LSGD project aims, among other goals, at identifying reference pilot areas suitable for the re-settlement of Congolese refugees actually residing in Rwanda.

Identification of settlement sites is always a complex matter and, in such a region, it needs increased awareness of complex interactions among humans, environment, and potential land management decisions. This kind of complex decision making creates a demand for integrated multidisciplinary decision support tools within a spatial framework (Baker, Miller, & Paige, 2009).

On this assumption, the LSGD project is exploiting innovative methodologies, such as satellite remote sensing (RS) techniques, to provide new cartographic and thematic land use informative layers. In addition, the LSGD project is conducting an important data gathering effort over the target area (Diocese of Goma, 26223 km^2) in order to collect detailed information about existing agricultural resources, conflicts, and potentialities. Therefore, in the framework of the LSGD project the DISAA proposes the set up of a Spatial Decision Support System (SDSS) aimed at Multi Criteria Evaluation (MCE) for the identification of pilot zones.

Spatial Decision Support Systems and Remote Sensing

SDSSs are GIS-based models that “enhances a person or group's ability to make decisions” (Power, Sharda, & Burstein, 2015). As tools for improving evidence-based choices, SDSS are widely used in several sectors such as policy making, enterprise management, environmental studies and more recently sustainable development studies. As GIS-based systems, SDSSs are made of a geo-referenced database that is merged with a DSS which in turn is often related to some kind of Multi Criteria Analysis (MCA) (Chakhar & Mousseau, 2007).

Generally speaking, SDSS are widely used in order to tackle land development choices (Agatsiva & Oroda, 2002). Experiences in the East Africa region are reported bysevera authors (Baldyga, Miller, Driese, & Gichaba, 2008).

In the framework of International Cooperation for Development, and namely among the programs and projects funded by the EU, other experiences of SDSS development also exist (ITC, 2015; Janusz, 2016; Manakos & Braun, 2014; Refsgaard et al., 1998; Uyan, Cay, & Akcakaya, 2013). Satellite image has been used so far to classify and map land cover and land use changes with different techniques and data sets. Unsupervised and supervised approaches are the most commonly adopted for satellite images classification (Butt, Shabbir, Ahmad, & Aziz, 2015; Lu, Mausel, Brondizio, & Moran, 2004; Rundquist, Narumalani, & Narayanan, 2001; Zhang, Zhang, & Zhang, 2000).

The application of supervised approaches implies that the user or image analyst “supervises” the pixel classification process by specifying which pixels values or spectral signatures should be associated with each class according to known representative sample sites, called Training Sites. The “trained” algorithm is then able to classify the whole image. Precision of supervised classification depends heavily on the training sites, the skills of the expert who process the image, and the spectral distinctness of the classes.

A variety of supervised classification methods have been developed and applied to satellite images for land use mapping. Among these, some applications were specifically designed for land use monitoring in the DRC. Important examples are the contribution of Hansen et al., (Hansen et al., 2008) which focused on the use of Landsat images to map forest land-cover typologies exploiting unsupervised decision tree approach. They succeed in validating maps having 75% of overall accuracy. Duveiller et al., (Duveiller, Defourny, Desclée, & Mayaux, 2008) instead, focused on deforestation mapping in central Africa in the period 2000-2010 applying unsupervised object-based classification procedures to Landsat images. The overall accuracy estimated for their thematic products was 91%. Vancustem et al., (Vancutsem, Pekel, Evrard, Malaisse, & Defourny, 2009) proposed a semi-automatic classification of SPOT (Satellite Pour l' Observation de la Terre) temporal-spectral information, to produce a map discerning 18 vegetation types in the DRC.

An additional source of land-use information is census data, which has recently been explored for its relationship to remotely sensed imagery (Cardille & Foley, 2003). Land use/cover changes have been identified as a useful tool to aid the process of understanding human-environment interaction (Dale, Oneill, Pedlowski, & Southworth, 1993). Thematic and census land use descriptors can be integrated in a geographical information system (GIS) on the base of a given administrative level.

Scope of the paper

This paper is focussed on the use of RS to collect data on the land cover/use, on the collection of the Census data on the ground, and on the potentiality of merging these two sources of information in order to support the multicriteria choice of pilot zones. Therefore, the final scope of this work is the set up a SDSS for the identification of pilot zones, based on the multicriteria evaluation (MCE) of land hosting capability. In order to indentify zones with “good” hosting capability, the LSDG project has defined several criteria. The principal criteria considered are presented in figure 1, where the scheme of the proposed SDSS is shown.

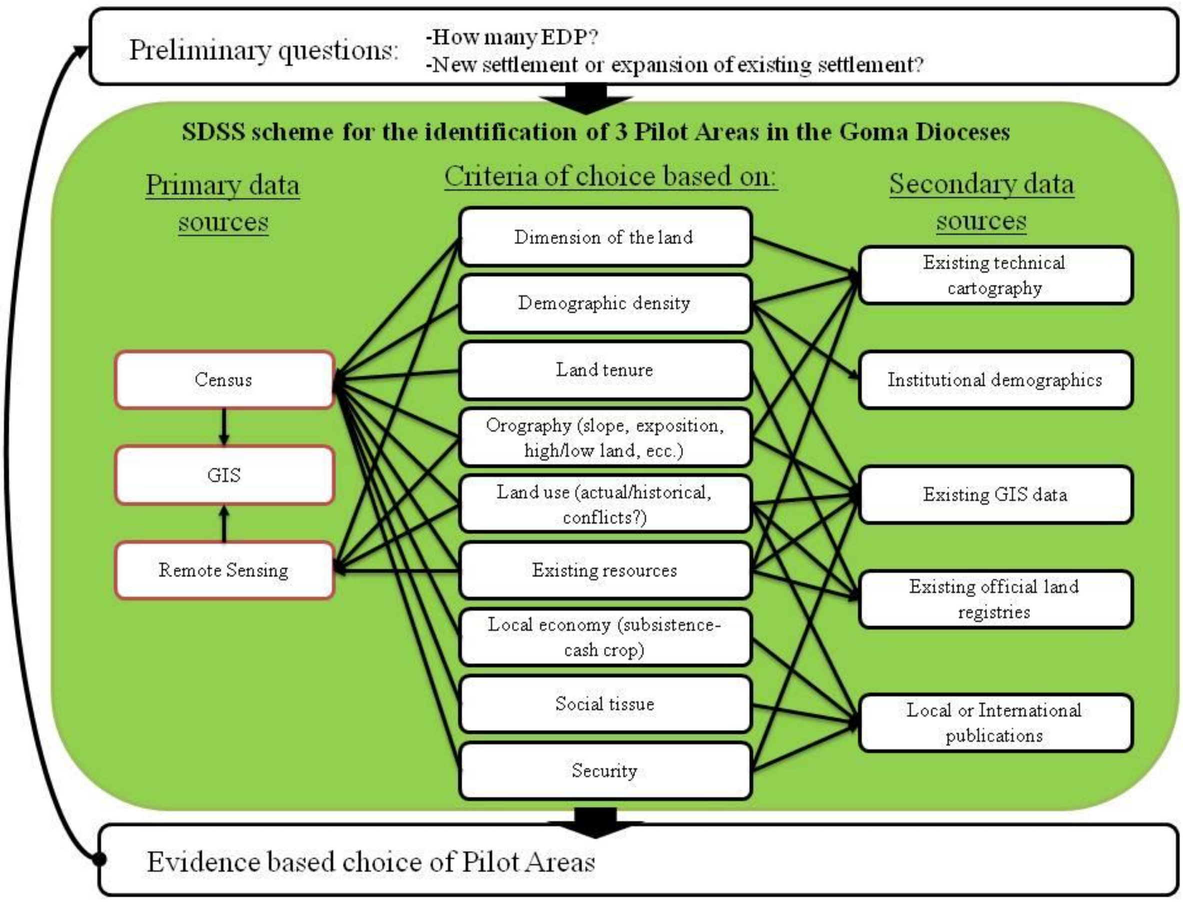

Figure 1- Scheme of the SDSS draft for the evidence based identification of LSGD project pilot zones, containing a list of the principal choice criteria which have been considered in this work.

It clearly appears how the choice of pilot areas depends on several criteria whose measurement relies on different data sources, both primary and secondary.

Three administrative units, named “collectives” of Wanyanga, Bakano and Bashali, placed in the study area of the Goma Dioceses (GD), have been selected on the base of the available Census results for this preliminary methodological test. The methodological approach concerns the integration in GIS environment of land use products derived by RS and detailed census data about existing agricultural resources, potentialities and existing conflicts. The generated land use knowledge is therefore used to build useful evidences for the identification of pilot zones and, generally speaking, to foster peace-seeking operations in the region.

Preliminary results highlight how the integration of different information sources lead to: (i) cross-validation between sources, (ii) identification of conflicting information between sources, and (iii) creation of emergent information stemming from the joining of the two sources.

Results, proposed in form of thematic maps and aggregations of census survey data, are discussed formulating new research perspectives in view of more detailed land hosting capability evaluation to be conducted in the project framework.

Materials

Study area

Our attention focused on the DRC (fig. 2A). Here, the administrative subdivision is as follows: the national territory is divided into Provinces, the province into Districts and Cities, the district into Territories, the territory into Local Communities (or collectives or collectivities), the local community into Groups, and the group into Villages (Comité Provincial-SRP du Nord-Kivu, 2005).
In addition we have to take in consideration a supplementary hierarchical subdivision of the national territory, namely the ecclesiastical administrative subdivision. In fact, in this paper, the administrative level of collectives is used in order to merge the data from the RS and the data from the Census which are instead collected at lower levels of the ecclesiastical subdivision (Shirika).
The study area corresponds to the rural area of the Dioceses of Goma (GD), which is part of the Ecclesiastical province of Bukavu and which is composed of 23 parishes. Each parish is composed of several branches. These branches, also called in Swahili "Kigigi", are not an exclusively ecclesial administrative units, because they correspond also to a pre-existing territorial division based on customary traditions. In each branch's territory, people are grouped in local ecclesial communities called Shirika. Kigigis in the GD are numbered at 105. Inside each collectivity, the project estimates an average number of Shirika equal to 305, but this number varies according to the fact that Shirika are dynamic groups of people and not once-for-all-defined territorial units.
Specifically, the target area of LSGD project, namely the GD (surface: 26 223 km^2), lays in the North Kivu Region and in a tiny strip of South Kivu Region, from Minova to Nyabibwe (fig. 2B). Inside the Dioceses there are 11 collectives appertaining to 5 territories (Goma, Rutshuru, Masisi, Walikale, Kalehe).
The present paper focuses on three collectives belonging to the GD: Bakano, Bashali and Wanyanga. These administrations cover respectively the 16.2% (4 251 km^2), the 4.4% (1 144 km^2) and the 39.9% (10 487 km^2) of the Dioceses (fig. 2C).

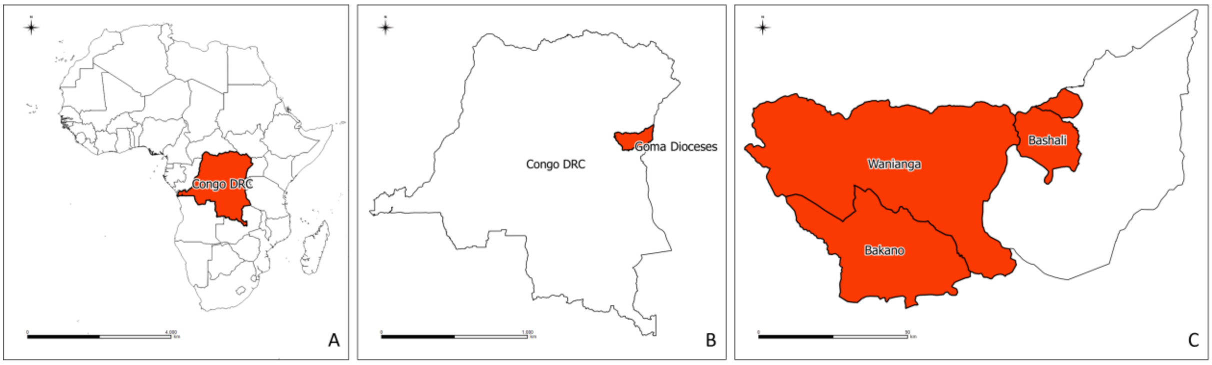

Figure 2 – Geographic positioning of the three collectives representing the investigated study sites. The DRC, Africa (A); the Goma Dioceses, in the Congo DRC' North Kivu region (B); the collectives of Wanyanga, Bakano and Bashali.

Ground reference data

In the Nord Kivu region, different land tenures correspond to different land use/cover patterns: while large concessions result in large, uniform territorial units typically covered by monoculture plantations or pastures, smallholders typically own small plots which result in fragmented, heterogeneous territorial units. This diversity in land use and ownership determines a meaningful land cover pattern in the region.

A data collection campaign was conducted in May 2017 in the GD with the purpose of collecting GPS points concerning different land use classes. A total of 110 polygons of surveyed areas were drown from the GPS point sample collection and successively used to train and test supervised classification algorithms. The polygons are representative for a total area of 904.3 ha. Table 1 summarizes the main information survey database features by listing the four land use classes as well as the number of polygons drown for each class and the respective area of concern.

Observed land use	**Available polygons**	**Total area [ha]**
Agriculture	39	343.4
Anthropic	25	131
Forest	12	20.6
Pasture	34	409.3
Total	110	904.3

Tab. 1 - Summary of the information collected in the geo-database produced through a field survey activity carried out in May 2017.

Satellite data

Eight Sentinel-2A satellite images, covering together the entire surface of GD were downloaded from the European Space agency (ESA) Copernicus open access hub archive (https://scihub.copernicus.eu/). In particular, we exploited level 1C (L1C) Sentinel images, provided as a set of tiles of 100 square kilometres. These products contain applied radiometric and geometric corrections (including orto-rectification and spatial registration). We selected the less cloud-contaminated acquisitions for each tile during the reference year 2017. Details on spatial resolution and the different spectral acquisition bands available in Sentinel-2A L1C images are shown in figure 3.

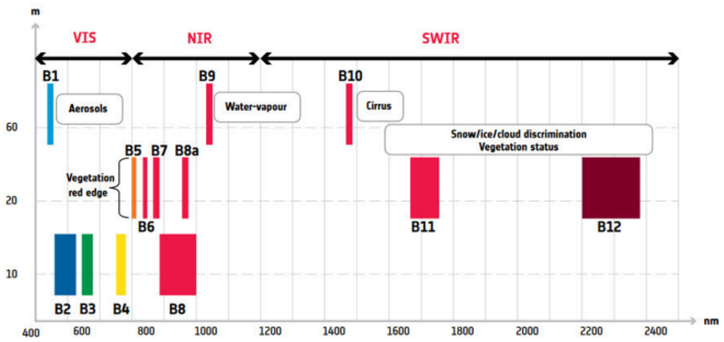

Figure 3 – Spatial resolution versus wavelength intervals of Sentinel-2A images. Sensor span of 13 spectral bands from the visible and the near-infrared to the short wave infrared at different spatial resolutions (pixel size) ranging from 10 to 60 m. (source http://esamultimedia.esa.int/docs/Earthobservation/Sentinel-2_ESA_Bulletin161.pdf)

A Digital Elevation Model (DEM) provided by the NASA Shuttle Radar Topographic Mission (SRTM - http://srtm.csi.cgiar.org) was used to gather information about altitude and slopes characterizing the area of study (Jarvis, H.I., Reuter, Nelson, & Guevara, 2016).

Census information

The LSGD project has a strong preliminary component related to sensitization about land tenure issues in front of EDP/IDP return. In the framework of these activities aimed at building a positive environment for the implementation the whole project, a survey in the GD was carried out by 8 field supervisors of Caritas Goma NGO. The structure of the survey form is resumed in table 2 while collected information is resumed in table 5. The survey aimed at collecting at least one interview per each Shirika in the GD, which are estimated to be about 305 per collectivity. The survey was scheduled between May 2016 and December 2017. This paper reports the results of the first 73 interviews that were dispensed between May and August 2016 in 73 Shirika laying in three collectives, as reported in table 3.

Tab. 2 - Structure and contents of the Survey form used for gathering information about existing agricultural resources, conflicts, and potentialities

Topics	**Questions**	**Description**
General information on the Shirika	4	Features of the Shirika (with a focus on co-existing ethnic groups).
Land ownership and land use	2	Land uses and land owners.
Soil erosion	9	Soil erosion: its presence and its intensity
Agricultural land use	2	Agriculture: crops, depending on the type of land owner.
Information about land tenure in owned/vacant lands	3	Land tenure on owned/vacant lands.
Existing value chains (production-marketing)	5	Local production/consumption chain.
Other activities	5	Other peculiar activities eventually existing in the Shirika
Externally displaced people and land	8	Willingness of resident population to manage the re-settlement of externally displaced people.
Internally displaced people and land	8	Willingness of resident population to manage the re-settlement of internally displaced people.

Tab. 3- Number of interviews per Shirika in each target collectivity-territory-province.

Province	**Territory**	**Collectivity**	**Interviewed chiefs of Shirika**
Nord Kivu	Walikale	Bakano	29
Nord Kivu	Masisi	Bashali	167
Nord Kivu	Walikale	Wanyanga	143
Total			339

Method

The applied methodology involved an independent processing of two different data sources and their successive integration in GIS environment. From one hand, remote sensed satellite images were analyzed with the aim to produce land use maps of the three communities of interest. On the other hand, census data were gathered, organized in a database and finally summarized at collectivity level. Once retrieved at the same spatial level, data sources were integrated by overlapping them in a GIS environment and were used to build a SDSS based on MCE of land hosting capability towards the return of Congolese EDP. Figure 4 proposes a flow chart of the main methodological steps followed in the proposed methodology.

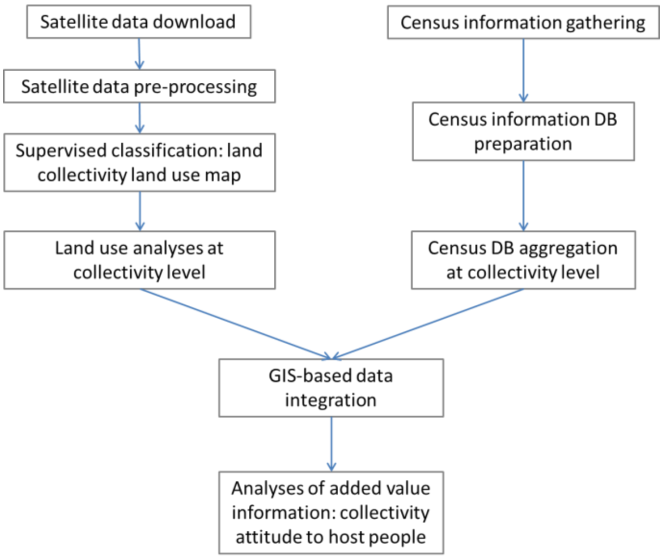

Figure 4 - Flow-chart summarizing the main phases of the designed methodology.

Analyses of Satellite data

A selection and download of the best available cloud free Sentinel-2 images were conducted on the ESA web catalog (January-June 2017 time window). Eight images entirely covering the GD were chosen.

A preliminary image pre-processing phase was carried out on selected images by resampling all the images spectral bands components at a 10-m resolution and subsequently by creating a composite mosaic as cloud-free as possible of the GD.

The mosaic was then classified using a Spectral Angle Mapper (SAM) supervised classifier (Kruse et al., 1993). All the Sentinel-2A bands with native spatial resolution of 10 -m and 20-m were used as independent input variables in the classification procedure.

We used 50% of the data to train the algorithm (calibration) and the other 50% for testing the land use map (validation) produced by the supervised classification. Four target classes were formalized to be automatically mapped by the SAM algorithm. The classes were: (a) pastoral land use, (b) forest, (c) agricultural land use and (d) anthropic land use areas.

A thematic land use map of the GD represented the output of the classification phase. A pixel-to-pixel comparison between the validation dataset (reference data) and the land use map (estimated data) was then conducted using the error matrix methodology (Brivio, Lechi, & Zilioli, 2006; Congalton, 1991). After the validation, three map resizes were made in correspondence of Wanyanga, Bakano and Bashali communities and statistics related to the percentage distribution of the estimated land use classes were compiled.

Analyses of Census data

Data from the first 73 paper questionnaires were preliminarily analyzed through participative approach: one *ad hoc* focus group was organized in collaboration with the whole survey staff in Caritas Goma headquarter during May 2017. This first participatory analysis of the data served as a first-glance assessment of the integrity and internal consistency of the survey data. This step made it possible to highlight some critical issue in the survey form and in the data flow toward sources integration. The 73 questionnaires were manually digitalized and recorded in an electronic database. Among the possible aggregation levels, determined by the existing administrative units and related GIS reference data, the collectivity (or collective) level was chosen as a good compromise between clarity of the exposition and ease in the overlay of the data from satellite and census. After the creation of this preliminary database and the choice of a consistent aggregation level, data were analyzed with the software Stata (StataCorp. 2015. Stata Statistical Software: Release 14. College Station, TX: StataCorp LP.).

Integration of remote sensed and census data

The integration of data form Census and RS was approached in two steps:

Firstly, a simple synoptic table, as show in the Results section (figure 7), was built and analysed in ad hoc participatory sessions with the aim of systematically identifying important relations between data from the two sources.

Secondly, on the base of emerged relations and themes, data were merged in a GIS environment by using the collectivity aggregation level in order to produce thematic maps.

Results:

Collective-level land use maps

Figure 5 shows Sentinel-2A reflectance average response to four land use classes of interest in Goma as depicted in the calibration database. Pastoral land use (figure 5A) showed the higher spectral signature response (i.e. the most reflective land use typology, figure 5E), the signature was similar to the forest and agricultural land uses, but with higher magnitude. Forest spectral signature (figure 5B) behalf similarly to the agriculture land use (figure 5C), with differences mainly marked in the Short Wave Infra-Red region (SWIR) between 1200 nm to 2200 nm and corresponding to Sentinel-2 bands b11 and b12. For this portion of the spectra, forest land covers were more reflective than the agricultural one (figure 5E). Anthropic areas showed the lower spectral signature (i.e. the less reflective, figure 5E), with the lover differences between the Red (around 650 nm, Sentinel-2 band b4) and NIR (around 850 nm, Sentinel-2 band b8) regions due to the absence of photosynthetic activity and having almost the same reflectance values from 800 nm to 2200 nm (figure 5D). All the spectral signatures presented reflectance maximum values in the NIR region (Sentinel-2 band b8).

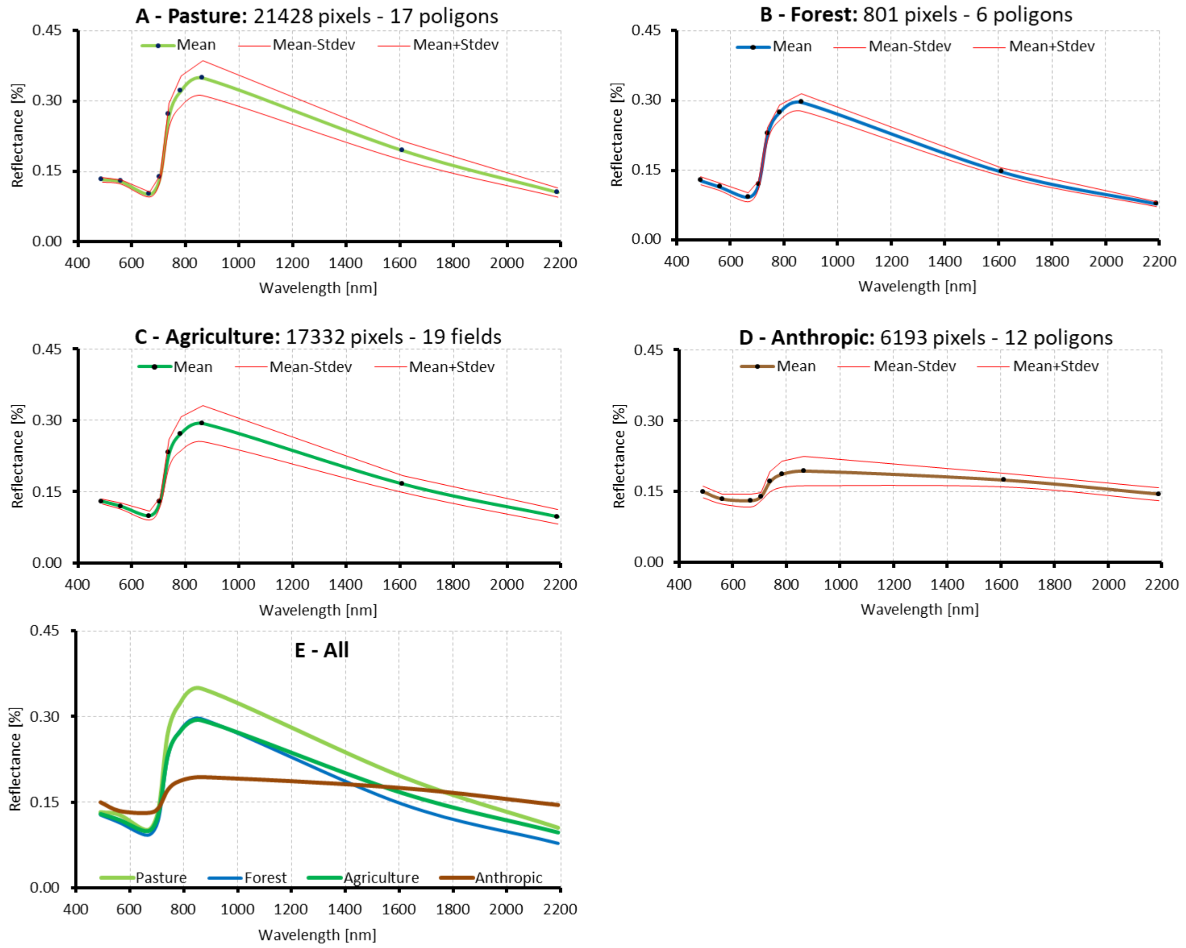

Figure 5 – Training dataset. Average Sentinel-2 reflectance responses and standard deviations for four land use classes. (a) Pastoral land use, (b) forest land use, (c) agricultural land use, (d) anthropic land use, (e) all the target classes together.

Table 4 shows the validation results of the retrieved land use map for the study area of the Goma. This classification result has to be considered a preliminary methodological exercise, mainly devoted to set-up the broad project's methodological framework rather than maximize its single component performances. Given this, the classification reached an overall accuracy of 66% meaning 66/100 cases of agreement between field data and RS classification. The anthropic and pasture land use classes, were mapped with acceptable levels of omission and commission errors, lower or equal to 29%. Further improvements are needed with reference to both agricultural and forest land use estimations, which was conservatively classified in view of decreasing mutual misclassification.

Tab.4 – Error matrix showing a pixel-by-pixel comparison between the validation dataset (reference dada) and the thematic classification map (estimated data). CE: commission error, OE: omission error, OA: overall accuracy.

	validation data				*accuracy indicators*		
	Agriculture	Anthropic	Forest	Pasture	CE	OE	OA
Land use map:	[px]	[px]	[px]	[px]	[%]	[%]	[%]
Agriculture	17802	2079	528	4337	28	42	66
Anthropic	51	7565	0	0	1	29	-
Forest	9615	652	1350	551	89	28	-
Pasture	3472	351	8	14647	21	25	-

The SAM classifier allowed the production of a land use map of the study area. This map was resized for target collectives: Wanyanga (figure 6A), Bashali (figure 6B) and Bakano (figure 6C).
With reference to the whole GD (map not reported), the classification mapped a relevant presence of forest that counts for 74% of the study area (around 19 405 km^2). The agricultural land use were instead identified on 20% of the map surface (5 244 km^2) and were mainly concentrated near rivers and streets. Pastoral and anthropic land uses were mapped in low percentages, with 5% (1 311 Km^2) and 1% (262 km^2) respectively. For the collectivity of Wanyanga (figure 6A) a higher presence of forest (+13%) and a lower presence of agricultural land use (-8%) were found in comparison with the entire dioceses. In the Eastern part of the collectivity, a higher presence of agricultural land use was mapped. In the central part instead, it is possible to note some cloud and cloud shadow noises. These represent for our purposes an unavoidable loss of land use information. Figure 6B shows the land use map of Bashali, this collectivity has land use proportions in line with the Goma study area. Although a marked presence of cloud contamination, it is possible to note a predominant presence of forests in the Western side as well as a predominant presence of agricultural land use on the Eastern side. In the Northeastern part of Bashali the algorithm identified the presence of pastoral land use and in the Southeastern the presence of three main water bodies. These latter, are presumably volcanic lakes. The land use map of Bakano (figure 6C) reported a strong presence of forest (15% more than the entire GD) and a minor presence (-9%) of agricultural land use. This was mainly concentrated in the central part of the map, along the East to West direction, and in the South.

In addition to the land use information, we also obtained data concerning average (AVG) elevation and slope for the study area of Goma and for the three collectives we focused on. The SRTM dataset showed for Goma AVG elevation of 1299 m and 3.33% AVG slope. Weather for the three collectivities: 1026 with 2.59% (Wanyanga), 1626 with 4,53% (Bashali) and 1056 with 2.44% (Bakano) for the AVG elevation and the AVG slope respectively.

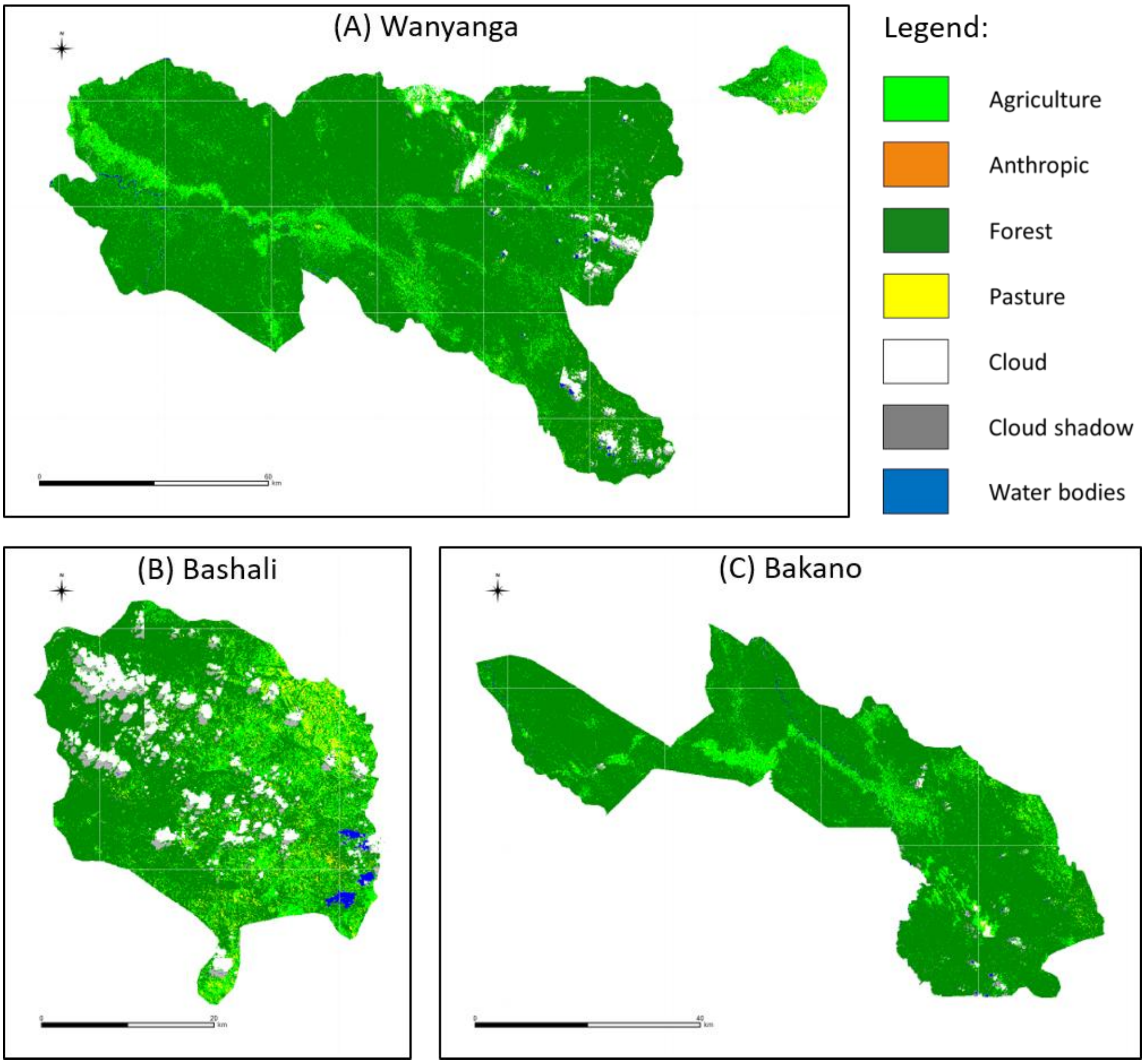

Figure 6 – Resize of the land use map of GD for the three collectives object of this study: (A) Wanyanga, (B) Bakano and (C) Bashali. The legend reports four target land uses (agricultural, anthropic, forest and pastoral), map sources of noise (cloud and cloud shadow) and water bodies.

Aggregation of census data at the collectivity level

In table 5 some results of the census are shown for the three target collectivities, together with some results of the GIS and Remote Sensing analysis.

In relation to its surface, Bashali is the most densely populated community and respondents mention few erosion problems, seasonal water scarcity, few conflicts over the land and apparently no land appertaining to EDP/IDP. Moreover, according to respondents, Bashali shows the lowest propensity to the return of EDP/IDP even if vacant lands seem to be available.

The Collectivity of Bakano is characterized by the lowest population density, low level of conflict even if vacant lands are not available, seasonal water scarcity, no presence of lands appertaining to EDP/IDP and no will for them to settle back.

The collectivity of Wanyanga shows 13,8 inhabitants for square kilometre, diffused erosion phenomenon, seasonal water scarcity, presence of conflicts over the lands even if vacant lands seem to be available. Similarly to the other two other collectivities Wanyanga's respondents are not willing to accept the return of EDP/IDP.

Tab.5- Census results aggregated for the three target collectivities.

	Bakano		**Bashali**		**Wanyanga**		**Total**	
Surface (Sq.km)	4251		1144		10487		15882	
Population (Inhab.)	16584		17292		145024		178900	
Pop. density (Inhab./Sq.km)	3,9		15,1		13,8		11,3	
Number of interviews	**Bakano**		**Bashali**		**Wanyanga**		**Totale**	
	Count	**%**	**Count**	**%**	**Count**	**%**	**Count**	**%**
	29	9%	167	49%	143	42%	339	100%
Question	**Answers**							
1. Is soil erosion a problem in the area?	**Count**	**%**	**Count**	**%**	**Count**	**%**	**Count**	**%**
N	13	45%	58	35%	108	76%	179	53%
Y	16	55%	109	65%	35	24%	160	47%
Tot.	29	100%	167	100%	143	100%	339	100%
2. Is there water yearly-round (as flow or well) ?	**Count**	**%**	**Count**	**%**	**Count**	**%**	**Count**	**%**
N	1	3%	6	4%	4	3%	11	3%
Y	28	97%	158	96%	139	97%	325	97%
Tot.	29	100%	164	100%	143	100%	336	100%
3. Are there vacant lands?	**Count**	**%**	**Count**	**%**	**Count**	**%**	**Count**	**%**

N	10	34%	153	92%	121	85%	284	84%
Y	19	66%	14	8%	22	15%	55	16%
Tot.	29	100%	167	100%	143	100%	339	100%
4. Do conflicts over land exist in the area?	**Count**	**%**	**Count**	**%**	**Count**	**%**	**Count**	**%**
N	5	17%	76	46%	97	68%	178	53%
Y	24	83%	89	54%	45	32%	158	47%
Tot.	29	100%	165	100%	142	100%	336	100%
5. Are there any land appertaining to EDP/IDP in the area?	**Count**	**%**	**Count**	**%**	**Count**	**%**	**Count**	**%**
N	0	0%	8	6%	0	0%	8	4%
Y	15	100%	134	94%	70	100%	219	96%
Tot.	15	100%	142	100%	70	100%	227	100%
6. Is the resident population willing to accept the return of EDP/IDP?	**Count**	**%**	**Count**	**%**	**Count**	**%**	**Count**	**%**
N	9	38%	16	11%	57	42%	82	27%
Y	15	63%	133	89%	79	58%	227	73%
Tot.	24	100%	149	100%	136	100%	309	100%

Data integration

The data coming from the two sources (Census and Remote Sensing) were firstly integrated in a synoptic table (Table 13), and successively through the ARCGIS software by using the smallest administrative unit available on GIS maps (MONUSCO, 2016), namely the "collectivity" administrative unit.

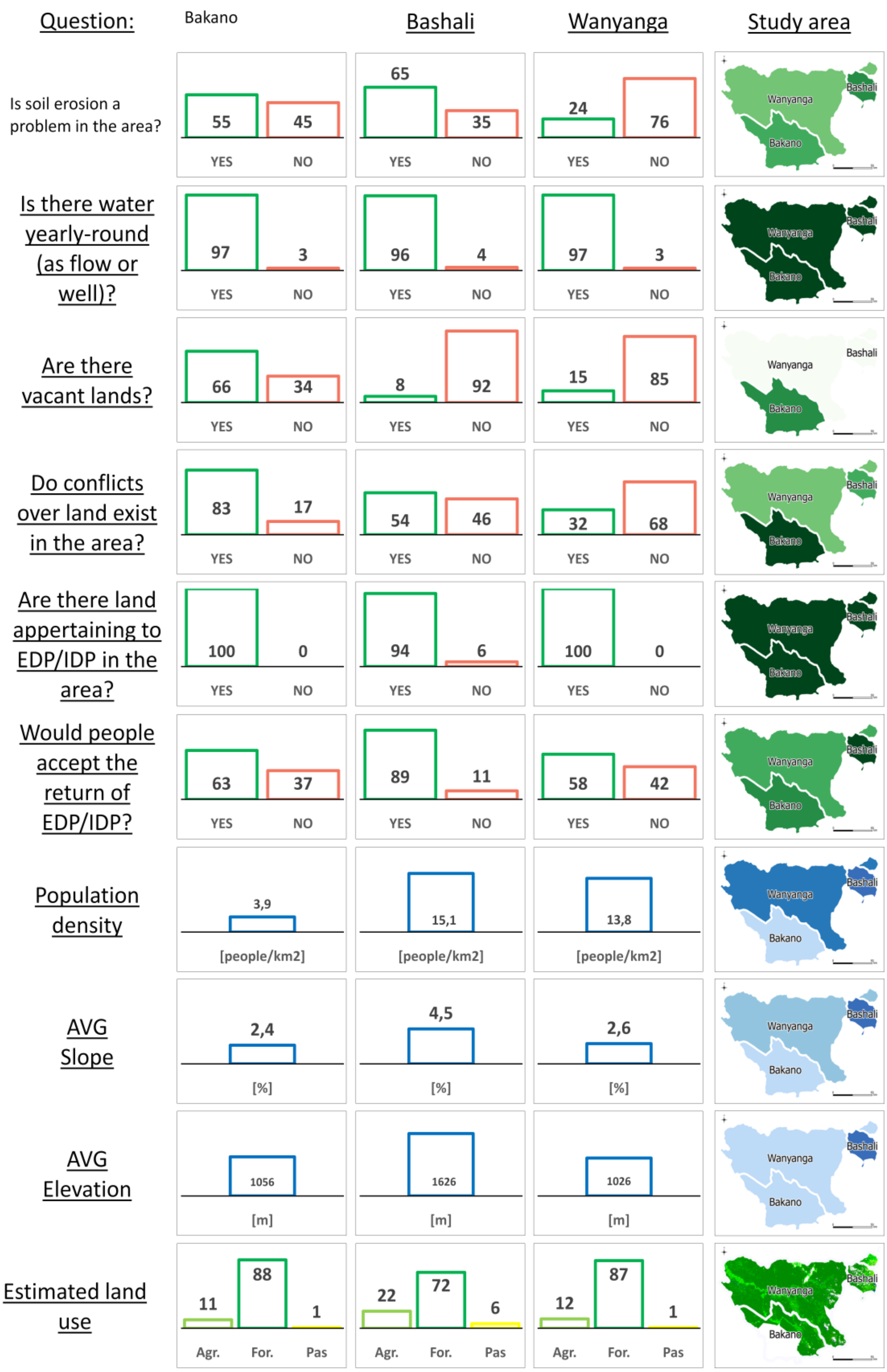

Figure7 - Data integration for the two sources, presented as histograms of different features and corresponding colored layers of the three target collectives (Bakano, Bashali and Wanyanga).

Discussions and conclusions:

Through the implementation of the proposed methodology, we obtained the integration of different sources of information, respectively based on remotely-sensed images and on the field survey.

The proposed methodology, even in this preliminary phase, is able to overlay different data sources and therefore allows multicriteria evidence-based considerations.

In fact, the overlay of information provided by the two sources produced "added" information that is useful to support the MCE of land hosting capacities and the identification of potentially suitable pilot areas.

It is interesting to remark that the coupling of the two information sources is able to support the process, as a SDSS, in different ways and at different degrees. In fact, the overlay of the two sources produces results that can be classified according to the following three cases.

1. Case of mutual confirmation: the two sources confirm each other and therefore bring to a stronger knowledge base.
2. Case of contradiction: the two sources contradict each other. This case underlines critical issues in the project' knowledge base or in the proposed methodology for data integration.
3. Case of "added value": it represents the main goal of the methodological approach. The two sources of information allow the creation of additional information "over the simple sum of the parts", which leads to more complex evaluations.

As an example of this third case, which is strongly desirable in the study, we can make the case of Bashali collective. The proposed methodology works as a SDSS tool by integrating the data related to all the proposed criteria (table 1). In particular, if we only consider the oral knowledge collected during field visits, Bashali is the richest collectivity among the three target collectivities and therefore is one of the sound zones where to propose a pilot and where the "suitable conditions for the refugees' return may already exist". If we take in consideration the results of RS analyses, at first glance, the Bashali collectivity has a higher presence of agricultural and pastoral land, and could therefore be confirmed as the best collectivity where to propose a pilot. On the contrary, coupling the information from RS with census data, it clearly appears that Bashali is also the most densely populated collectivity, the one with more lands appertaining to missing EDP/IDP and the one that shows the lowest presence of vacant lands. Even if most of the respondents in Bashali show a positive attitude toward the return of refugees, the composite information we can draw from the overlay of sources may explain the medium-high presence of conflicts over land use. Then, if we

also take in consideration the average slope of the collectivity, we can add another item to the reflexion and therefore resize our interest on this collectivity to be the host of one of the pilots.
This evidence based, “added knowledge” about Bashali is possible only if projects like the LSGD adopts a SDSS based on MCE, as the one drafted in the present paper.
Further research will be conducted in the framework of the LSDG project, and more detailed information to support the choice of pilot zones will be produced. A next step will be the use of a multi-temporal analysis approach in the analysis of satellite images. As a matter of fact, agricultural and pastoral land extensions in Bashali are higher than in other collectives (as can be observed by RS). As we know from literature and as we confirmed with our census, Bashali collectivity, and Masisi territory as a whole, suffers from chronic disputes over land tenure, because all the lands are already exploited. Land conflict in Masisi are often generated by the dichotomy farmers-pastoralists where farmers are in majority smallholders while pastoralist areas are dominated by huge, under-exploited, concessions. The RS methodology implemented in this first step-methodological approach is still not able to produce land cover classes on the base of the difference between landscape patterns, but this results will be obtained with multi-temporal analysis in the second phase of the project. The information obtained, joined with information collected by census about vacant lands and existence/features of large concessions will allow to strengthen the proposed SDSS.
However, it is crucial to stress that, in a complex situation as the Nord Kivu’s one, any decision about the re-settlement of IDP/EDP should be preceded by a strong consultation process with local people and institutions, and in this sense the SDSS results can constitute only a discussion base for supporting these operations.

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