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ENVIRONMENTAL ARMED CONFLICT ASSESSMENT USING SATELLITE IMAGERY

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Abstract

Armed conflicts not only affect human populations but can also cause considerable damage to the environment. Its consequences are as diverse as its causes, including; water pollution from oil spills, land degradation due to the destruction of infrastructure, poisoning of soils and fields, destruction of crops and forests, over-exploitation of natural resources and paradoxically and occasionally reforestation. In this way, the environment in the war can be approached as beneficiary, stage, victim or/and spoil of war.

Although there are few papers that assess the use of remote sensing methods in areas affected by warfare, we found a gap in these studies, being both outdated and lacking the correlation of remote sensing analysis with the causes-consequences, biome features and scale. Thus, this paper presents a methodical approach focused on the assessment of the existing datasets and the analysis of the connection between geographical conditions (biomes), drivers and the assessment using remote sensing methods in areas affected by armed conflicts. We aimed to find; weaknesses, tendencies, patterns, points of convergence and divergence. Then we consider variables such as biome, forest cover affectation, scale, and satellite imagery sensors to determine the relationship between warfare drivers with geographical location assessed by remote sensing methods. We collected data from 44 studies from international peer-reviewed journals from 1998 to 2019 that are indexed using scientific search engines. We found that 62% of the studies were focused on the analysis of torrid biomes as; Tropical Rainforest, Monsoon Forest / Dry Forest, Tree Savanna and Grass Savanna, using the 64% Moderate-resolution satellite imagery sensors as; Landsat 4-5 TM and Landsat 7 ETM+. Quantitative analysis of the trends identified within these areas contributes to an understanding of the reasons behind these conflicts.

Keywords: armed conflict, biomes, land use change, remote sensing, deforestation

INTRODUCTION

The complex relation between warfare and environment has been studied relatively little; one exception is the Report on the Protection of the Natural Environment in Armed Conflict made by the International Law and Policy Institute ILPI (2014). The report shows that war may generate large damage to the environment and populations that depend upon natural resources. Attacks produce direct harm on animals, vegetation, soil, and water systems, with consequent impacts on local or regional ecosystems. Vast defoliation campaigns are also utilized by combatants to realize strategic dominance. Meanwhile, serious contamination may incidentally result as an outcome from attacks on industrial sites, oil wells or other infrastructure (Gorsevski et al., 2012; Hanson et al., 2008; ILPI, 2014; Jha, 2014; Le Billon, 2001; Murad and Pearse, 2018; Potapov et al., 2012; Butsic et al., 2015). Secondary consequences such as displacement may in turn take tolls on the natural environment (Leiterer et al. 2018; Sanchez-Cuervo and Aide, 2013). In some cases, the environmental impacts of warfare extend over large regions and continue for years or perhaps decades after the conflict finishes.

The armed conflict is a less well-studied driver of deforestation (Machlis and Hanson, 2008; Butsic et al., 2015), which is unfortunately recurrent in tropical forests worldwide (Geist and Lambin, 2002; Gorsevski et al., 2012; Hecht and Saatchi, 2007). Empirical investigations as ILPI (2014) suggest a complex link between warfare and forest conservation (Armenteras et al., 2006; Draulans and Van Krunkelsven, 2002; Gorsevski et al., 2012; Rustad et al., 2008). Additionally, Machlis and Hanson (2008) and Butsic et al. (2015) have widely studied the direct effects of the conflict that includes road building, deforestation, and unsustainable use of natural resources. Indirect effects may include reduced economic activity during the wartime, which could reduce vegetation cover, and increase changes in land use (Jha, 2014; Stevens et al., 2011). It has been proven that these impacts remain in post-conflict times (Nackoney et al., 2014). Notwithstanding, experimental researches indicate that warfare may have both negative and positive results regarding wild forest conservancy (Rincon-Ruiz et al., 2013; Rustad et al., 2008) even in local areas (Gorsevski et al., 2013, Butsic et al., 2015). Additionally, the effectiveness of protected areas in times of hostilities also modifies over space and time (de Merode et al., 2007).

The appraisal of the implications of warfare on the environment is especially challenging due to the endogenous nature of vegetation cover loss and land-use changes. Warfare is also the outcome and/or the reason behind deforestation, implying a tight, unique, and particular relation. Neglecting this particularity in models of deforestation can produce biased coefficients and standard errors, thus constraining our ability to know the causal structure between warfare and deforestation in a statistical frame (Blackman, 2013; Butsic et al. 2015).

Ordway (2015) has demonstrated that wartime and post-conflict period may relate to land use and land cover activities to clout the alteration of the landscape and increase forest deterioration. Land use changes have promoted the devastating deterioration in biodiversity through habitat dissolution, modification and destruction, resulting in the decline of ecosystems and environmental services (Jha, 2014; Kwarteng, 1998; Ordway, 2015; Nackoney et al., 2014; Qamer 2012 et al., 2005). The increasing amount of literature framing various direct and indirect consequences of armed conflict on the environment has created diverse hypotheses (Black, 1994; Jarret, 2003; Machlis and Hanson, 2008; McNeely, 2003; Omar and Bath, 2009; Ordway, 2015). In fact, some assessments have shown that conflict and warfare can stimulate deforestation or promote vegetation cover recovery (Alvarez, 2003; Biswas and Tortajada-quiroz, 1996; Dávalos, 2001; Hecht and Saatchi, 2007; Lodhi et al., 1998; McNeely, 2003).

Armed conflict causes and effects on the environment

Direct causes are all activities that are physically associated with direct action of confrontation which generally appears within the immediate or short-term (bombings, direct armed confrontations, military infrastructure). While indirect causes are those that are frequently linked to several causes not necessarily military and only reveal themselves fully within the medium or long-term (Jha, 2014; Mendez and Valánszki, 2019; Partow, 2008; Solomon et al., 2018) (Fig. 1).

Some examples of direct effects encompass the intentional loss of natural resources, environmental pollution from the bombing of industrial areas, the military remains, and explosion wastes from military infrastructure. Furthermore, Solomon et al., (2018) affirms that indirect impacts include the ecological footprint of displaced communities (Hagenlocher et al., 2012), deforestation as a result of new expansion areas, the increase of illegal crops and illegal mining, the impossibility of the implementation of the

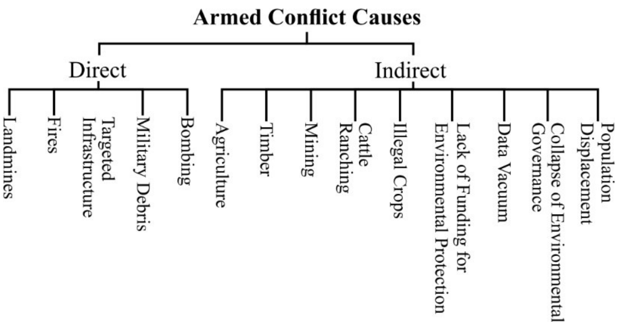

Fig. 1 Causes on environment based on Jha, 2014

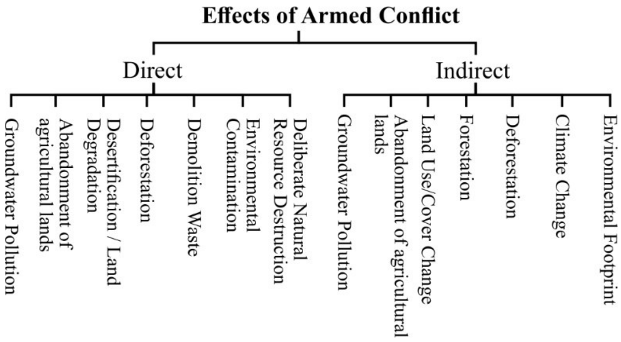

Fig. 2 Effects of conflict on environment based on Jha, 2014

environmental regulations, and also the information gaps, in addition to the lack of funds for environmental conservation. Another complementary problem is that any conflict destroys buildings and infrastructure that has to be rebuilt costing large resources and increasing emissions (Jha, 2014; Solomon et al., 2018) (Fig. 2).

Witmer (2015) affirms that the impacts can be classified into four categories, arranged by time required for each consequence to be visible. For instance, physical harm generated by bomb or fire detonations is commonly an immediate effect, which appears in minutes or hours. Alternative impacts like environmental damage (hours to days), population forced and unforced displacement (days to months), and changes of land cover/use (months to years) take longer to emerge. Even though there is some overlap between various impacts of warfare between direct and indirect, this classification creates a convenient and methodical way of approaching research.

Satellite imagery and armed conflicts

Initially, Remote Sensing (RS) methods, including aerial photos, were used for analysis in conflict zones with warlike purposes. This is due to the military sector having for a long time been a source of technological innovation with enough financial resources to invest in RS research (Corson and Palka, 2004). Advances in photography, airplanes, and satellites have largely improved the efficacy of battleground monitoring, with many military helicopters, airplanes, and unmanned aircraft systems (UASs) now capable of grabs video evidence registering the effectiveness of air and ground attack missions. Improvements in RS technology and satellite imagery have increased the effectiveness of armies and the accuracy of military operations (Witmer, 2015).

The complicated access to a zone in wartime combined with a diffuse spatial and/or temporal definition makes a precise and timely evaluation of the effects highly demanding (Gorsevski et al., 2012; Uriarte et al., 2010; Butsic et al., 2015). Due to these restrictions, info acquired from satellite imagery can bring a wide vision of how confrontations affect directly the physical environment during wartime and post-conflict, and how indirect causes drive shifts in local communities, land-uses and land-covers (Hoffmann et al., 2018; Murad & Pearse, 2018). As a result of the cause-consequence complex interdependence generated by the warfare and the need for larger protection efforts, the link between conflict and ecosystem needs to be investigated more deeply (Ordway, 2015). Resolution is a major aspect of the usage of RS methods. Spatial, spectral, and temporal resolutions are perchance the most important but radiometric resolution also affects what can be perceived. Table 1 lists the sensors frequently used to detect the effects of armed conflict. The sensors are grouped by spatial resolution which are Very Fine ≤1 m, Fine >1-10 m, Moderate >10–120 m, and Coarse >250 m.

Aim

Although we found two studies that assess the use of RS analysis in areas impacted by armed conflicts (Solomon et al., 2018; Witmer, 2015), these studies present a gap in research because they do not cover many types of research related to conflicts and environment. Furthermore, these studies are outdated regarding the latest RS methods and satellite sensors. The diversity of methods, classifications, satellite imagery sensors, and approaches for RS calls for a systematic revision that addresses their relation to conflict features such as biome type and geographical location, conflict causes-consequences, and the study area scale. Our aim is the assessment of the existing studies to identify relationships and patterns (and, implicitly, differences) in order to methodically approach the warfare-environment issue within an accurate and integral view for each specific type of conflict in future investigations.

This study seeks to offer an overview of the most important tendencies in the usage of RS as a tool for environmental damage assessment in warfare areas. Our aim is to demonstrate the specific correlation between armed conflicts (causes) and environment (consequences) using state-of-the-art RS technology to provide conditioned geospatial environmental information. More exactly, this paper presents an integrative and transferable approach for the quantification, systematic comparison, and evaluation of the RS studies used in zones affected by armed conflicts.

The impacts outlined in this paper, such as deforestation or land-use/land-cover changes, were quantified systematically and in exclusive regard to their RS analysis. This means that results here provided are considered applicable and relevant for the analysis of RS studies and are not necessarily applicable nor usually considered accurate for armed conflicts in general. Other scopes will be considered in future investigations.

Table 1 Characteristics of commonly used sensors

Sensor	Spatial resolution [m]	Swath width [km]	Spectral bands	Operating period	Active	Domain	Origin
Very fine spatial resolution (≤1m)							
GeoEye	0.46	10	Pan	09-2008 - Currently	Yes	Pr	US
World View II	0.46	18	Pan	10-2009 - Currently	Yes	Pr	US
QuickBird II (Pan)	0.6	30	Pan	10-2001 to 12-2014	No	Pr	US
IKONOS (Pan)	0.82 - 1	11	Pan	09-1999 to 03-2015	No	Pr	US
Fine spatial resolution (>1–10m)							
GeoEye	1.84	10	4	09-2008 - Currently	Yes	Pr	US
QuickBird II (MS)	2.4	30	4	10-2001 to 12-2014	No	Pr	US
ALOS	2.5		Pan	01-2006 to 05-2011	No	Pu	JP
SPOT-5	2.5, 5, 10	60	Pan	05-2002 to 03-2015	No	Pu	FR
CBERS-2B	2.7	27	Pan	09-2007 to 06-2010	No	Pu	CN-BR
IKONOS (MS)	3.28 – 4	11	4	09-1999 to 03-2015	No	Pr	US
KVR-1000 (MS)	3.3	40	4	1994 - N.D.	No	Pu	RU
Rapid Eye	5	77	5	02-2009 to 03-2020	No	Pr	DE-UK
Google Earth VHR	5, 10	N.A.	Pan	N.A.	Yes	Pr	US
IRS 1C LISS III	6	70	Pan	12-1995 - 09-2007	No	Pu	IN
Moderate spatial resolution (>10–120m)							
Sentinel 2	10, 20, 60	290	13	06-2015 - Currently	Yes	Pu	EU
ASTER	15, 30, 90	60	14	02-2000 - Currently	Yes	Pu	US-JP
Landsat 8 OLI	15, 30	185	11	02-2013 - Currently	Yes	Pu	US
Landsat 6-7 ETM +	15, 30	185	8	10-1993 - Currently	Yes	Pu	US
IRS 1C LISS III	23, 50	142	4	12-1995 to 09-2007	No	Pu	IN
Landsat 4-5 TM	30	185	7	07-1982 to 06-2013	No	Pu	US
Landsat 1-3 MSS	60, 120	N.D.	4	07-1972 to 01-1983	No	Pu	US
Coarse spatial resolution (>250 m)							
MODIS	250, 500, 1000	2330	36	1999 to 2005	No	Pu	US
VIIRS	375, 750	3060	22	10-2011 - Currently	Yes	Pr	US
AVHRR	1100, 4400	2500	5, 6	03-2004 - Currently	Yes	Pu	US-EU
Radar Data - No Category							
LIDAR	1	N.A.	N.A.	N.A.	Yes	Pr	N.A.
Aerial Photos		N.A.	N.A.	N.A.	N.A.	Pr / Pu	N.A.

Abbreviations: (N.D) No Date, (N.A.) Not Applicable, (PAN) Panchromatic, (Pr) Private, (Pu) Public

The questions motivating this paper are:

- What is the relationship between remote sensing sensors and the geographical / biome location of the study area?
- How are the remote sensing sensors and the scale of the study area related?
- What is the relationship between causes generated by the armed conflict (indirect and direct drivers) and the study area type of biome?
- What is the relationship between armed conflict consequences and the study area type of biome?

MATERIALS AND METHODS

RS assessment has been used at least in 21 countries across 4 continents as an approach to armed conflict and their environmental effects. For the data collection and the analysis of methods, we looked for articles and data sets through scientific search engines using the following keywords: "Remote sensing + Armed Conflict", "Biomes + Armed Conflict" and "Deforestation + Armed Conflict". Then we made a filtered search based on the indicators (satellite sensor, resolution, scale, cause, consequence, biome, location, imagery preprocessing, etc.). We collected and analyzed 116 studies. After a second and deeper revision, we chose 44, documents that fulfilled all or almost all the parameters required for the assessment. These are listed in Table 2. The documents were read, evaluated, synthesized, and tabulated for their processing. Although the studies analyzed were carried out from 1998 to 2019, they do not necessarily correspond to the time when the armed conflicts occurred. The majority of the studied armed conflicts occurred between 1980 and the present.

In order to evaluate the datasets from 44 studies that used satellite imagery and aerial photos, we framed the assessment seeking the following parameters: study area size, armed conflict causes and consequences, types of causes (direct or indirect), affectation of forest cover (increase or decrease), time-lapse, satellite imagery sensor, spatial resolution, conflict period, imagery preprocessing, imagery classification, geographical location, and type of biome. Quantitative analysis of the parameters identified within these studies contributed to an understanding of the reasons behind these consequences. Their correlations can be useful for future research suggestions and can work as a guideline of RS assessment in areas affected by conflict. Besides the assessment of satellite resolution, we analyzed the micro and macro-level consequences that can be drawn in the resulting inventory mapping of comprises statistics charts, patterns, trends, and findings on RS and its relationship with the armed conflict. This was done in the context of a comprehensive review, processing, tabulating, appraising, and synthesis of collected data.

Table 2 Features of remote sensing studies of armed conflict repercussions in the environment

Country	Scale (km^2)	Causes	Consequences	Sensor	Reference
Kuwait	Re	Bo	LU, LC	LS4-5	Abuelgasim et al. 1999
N. Macedonia, Palestine	Re	N.D.	N.D.	IKONOS	Al-Khudhairy et al. 2005
Colombia	Re 42000	Ag, CR, Ti	Df	LS1-3, LS4-5, LS6-7	Armenteras et al. 2006
Colombia	Na 1,142,000	NFM, IC, Ag, CR, Ti, Fi	Df	LS4-5, LS6-7	Armenteras et al. 2013
Thailand	Lo	FM	LU	KVR-1000	Bjorgo 2000
Sierra Leona	Re 71740	Bo, DC, MI	Df	LS4-5, LS6-7	Burgess et al. 2015
Colombia	Na 1,142,000	Mn, Ag, CR	Df, LU	LS6-7, LS8, ASTER, Se, CBERS, RE	Cabrera et al. 2019
Colombia	Re	IC	Df	LS6-7	Chadid et al. 2015
Liberia	La 1639	DC, MI, FM, Ms, Ag	Df, Ds, LU, LC	LS4-5, LS6-7, LS8	Enaruvbe et al. 2019
Colombia	Re 25000	FM, CR	Df, LU, LC	ASTER	Garcia-Corrales et al. 2019
Sierra Leona	Lo 557	FM, NFM, Ag	Df, LU, LC	SPOT-5, LS1-3, LS4-5, LS6-7	Gbanie et al. 2018
Belgium	La 2500	Bo	MI	AP, ALS	Gheyle et al. 2018
Colombia	Lo 935	Mn	Df, LU	LS6-7	Gómez-Rodríguez et al. 2017
S. Sudan, Uganda	La 8375	FM	Df, Fo, Ds, AAL	LS4-5, LS6-7, MODIS, AP	Gorsevski et al. 2012
South Sudan	La 1032	FM	Df	SPOT-5	Gorsevski et al. 2013
South Sudan	La	FM	Df, Ds, LD, Gw	QB	Hagenlocher et al. 2012
El Salvador	Re 21000	FM	Df	LS4-5, MODIS, AVHRR	Hecht and Saatchi 2007
Afghanistan	La	IC, Ag, CR	Df, LU, LC, AAL	GE, LS4-5	Ingalls and Mansfield 2017
Kuwait	La	Bo, DC, MI	LU	LS4-5	Kwarteng 1998
Colombia	Na 1,142,000	DC, MI, FM	Df, LU, LC	N.D.	Landholm et al. 2019
South Sudan	La	FM	Df, LC	LS4-5, LS6-7, LS8, WV2	Leiterer et al. 2018
Arab Countries	Na	Bo, DC, MI	AAL	VIIRS	Levin et al. 2018

Country	Scale (km^2)	Causes	Consequences	Sensor	Reference
Pakistan	Lo 618	FM	Df	LS1-3, LS4-5	Lodhi et al. 1998
Cambodia	Lo 50	Bo, DC, MI	Df	LS6-7	Loucks et al. 2009
Colombia	La 3927	Mn, Ag	LC	LS6-7, LS-8	Monroy and Armenteras 2017
Colombia	Re	IC, Ag, CR	Df, LU, LC	LS6-7, LS-8	Murad and Pearse 2018
R.D. Congo	La 1510	FM	Df, LU, LC	LS4-5, LS6-7	Nackoney et al. 2014
Colombia	Na 1,142,000	DC, MI, IC	Df	N.D.	Negret et al. 2019
Belgium	Lo 142,5	Bo	MC	AP	Note et al. 2018
Rwanda	La 271	FM, NFM, Ag, Ti	Df	LS4-5, LS6-7, ASTER	Ordway 2015
R.D. Congo	La	FM, NFM	LU, LC	LS4-5, LS6-7, LS8, GE-VHR, WV2	Pech and Lakes 2017
Zambia	Lo 217	N.D.	Df, LU	SPOT-5	Petit et al. 2001
R.D. Congo	Na 2,345,409	FM, NFM, Mn	Df	QB, LS6-7	Potapov et al. 2012
Pakistan	La 4109	FM, Ag, CR	Df, LU	SPOT-5, LS4-5, LS6-7, ASTER	Qamer et al. 2012
Colombia	Na 1,142,000	N.D.	Df, LU, LC	QB, GE-VHR, MODIS	Sánchez-Cuervo and Aide 2013
South Sudan	Re 23000	FM	LU, LC	MODIS	Sosnowski et al. 2016
Nicaragua	La 1600	FM	Df	LS1-3, LS4-5	Stevens et al. 2011
Belgium	La 1560	Bo	MC	AP, ALS	Stichelbaut et al. 2016
Sri Lanka	La 1125	DC, MI, Lm, FM, Ti	Df, LU, MI	LS4-5, IRS	Suthakar and Bui 2008
Myanmar	Na 236342	IC	Df, LU, LC	SPOT-5, QB, IKONOS, ALOS, ASTER	Tian et al. 2011
R.D. Congo	Na 2,345,409	DC, MI, Mn	Df, LU, LC, MI, AAL	LS4-5, LS6-7	Van Butsic et al. 2015
Turkey	La 7600	Bo, DC, MI	Df, LU, LC	LS4-5	Van Etten et al. 2008
Sierra Leone	La 5397	N.D.	Df, LU, LC	LS4-5	Wilson and Wilson 2013
Bosnia & Herzegov.	Re 3887	Bo, Lm, FM	LU, LC	LS4-5, LS6-7, QB	Witmer 2008

Abbreviations: (N.D) No Date, (N.A.) Not Applicable
Scale: (Lo) Local 0-999 km^2, (La) Landscape 1000-9999 km^2, (Re) Regional 10000-99999 km^2, (Na) National/Global ≥100,000 km^2
Causes: (Ag) Agriculture, (Bo) Bombing, (CR) Cattle Ranching, (DC) Direct Confrontation, (Fi) Fires, (FM) Forced Migration, (IC) Illegal Crops, (Lm) Landmines, (MI) Military Infrastructure, (Mn) Mining, (NFM) Non-Forced Migration, (Ti) Timber
Consequences: (AAL) Abandonment of Agricultural Lands, (Df) Deforestation, (Ds) Desertification, (Fo) Forestation, (Gw) Groundwater Pollution, (LC) Land Cover Changes, (LD) Land Degradation, (LU) Land Use Changes, (MC) Mine Craters, (MI) Military Infrastructure.
Sensor: (ALOS) Advanced Land Observation Satellite, (ALS) Lidar - Airborne Laser Scanning, (AP) Aerial Photo, (ASTER) Advanced Spaceborne Thermal Emission and Reflection Radiometer, (AVHRR) Advanced Very-High-Resolution Radiometer, (CBERS-2B) China–Brazil Earth Resources Satellite, (GE-VHR) Google Earth Very High Resolution, (GE) GeoEye, IKONOS, (IRS) IRS-1C LISS-III Indian Remote-Sensing Satellite, KVR-1000, (LS1-3) Landsat 1-3 MSS, (LS4-5) Landsat 4-5 TM, (LS6-7) Landsat 6-7 ETM+, (LS8) Landsat 8 OLI, (MODIS) Moderate Resolution Imaging Spectroradiometer, (QB) QuickBird II,(RE) Rapid Eye, (Se) Sentinel 2, (SPOT-5) Satellite Pour l'Observation de la Terre, (VIIRS) Visible Infrared Imaging Radiometer Suite, (WV2) WorldView-2

RESULTS

Armed conflict & remote sensing assessment by biomes

Unlike countries' borders, biomes' physical limits are rarely clear or defined. As a result, several studies may cover two or more biomes. Within the 44 investigations assessed, we found the use of RS in the study of 13 general types of biomes and the assessment in 92 different cases. This means that each study could have used more than one sensor to assess two or more biomes, depending on the area, complexity, and the availability of satellite imagery data set. The analysis outcome regarding the number of studies by biome indicates that high biodiversity spots near the equatorial line such as tropical rainforest (23), monsoon forest/dry forest (17), tree savanna (7) and grass savanna (6) cover the biggest number of studies. Furthermore, we found a considerable number of studies located in subtropical areas, a diverse number of biomes as a montane forest (13) temperate broadleaf forest (5), semi-arid desert (4), alpine tundra (4), subtropical dry forest (4) and subtropical rainforest (1). Finally, we identified few studies performed in the temperate biomes; Mediterranean vegetation (3), dry steppe (2), and xeric shrubland (1) (Fig. 3 & 4).

Relationship between satellite imagery sensors and biomes

Regarding the satellite sensors used, we observed that two-thirds (64%) of the biomes were analyzed by sensors with moderate resolution (10-120 m) where Landsat 4-5 TM and Landsat 7 ETM+ stand out (e.g., Armenteras et al., 2013; Butsic. et al., 2015; Gorsevski et al., 2012; Leiterer et al., 2018; Murad and Pearse, 2018). We found that Very fine (≤1m) and Fine (1-10m) resolution sensors covered 23% of the biomes, with SPOT-5 and QuickBird II sensors slightly standing out (e.g., Petit et al., 2001; Qamer et al., 2012).

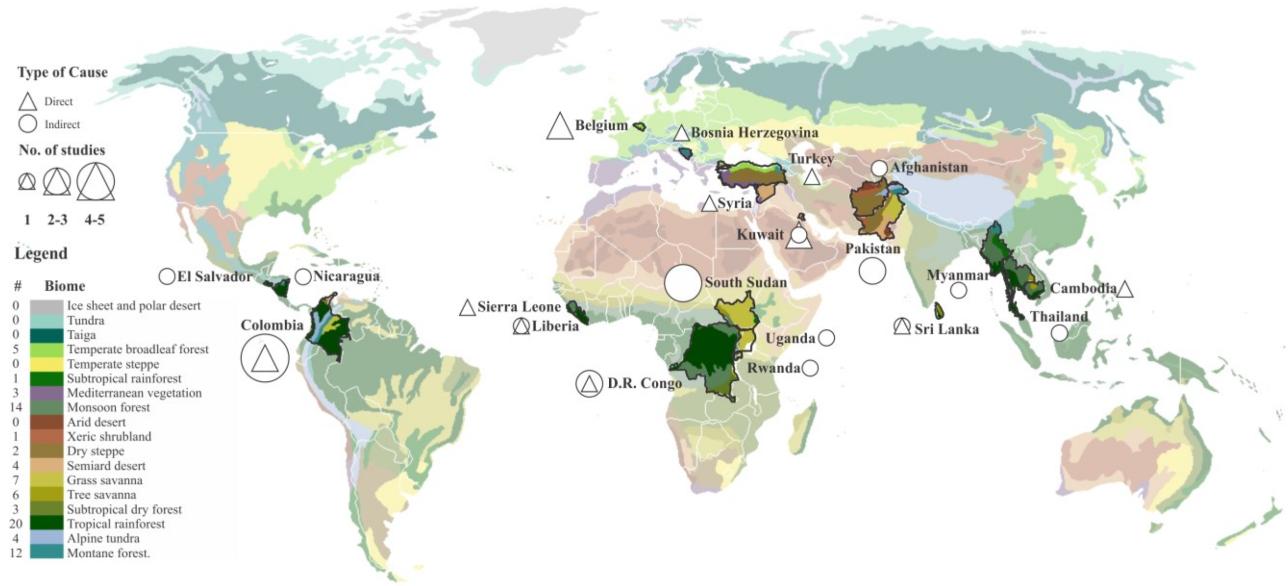

Fig. 3 Armed conflict causes analyzed using remote sensing by biomes and countries

Uncategorized sensors covered 7% of the biomes, aerial photographs, and Lidar ALS sensor stands out within this segment (e.g., Note et al., 2018). Finally, coarse sensors (>250 m) covered 6% of the biomes in which MODIS sensor was the most outstanding (e.g., Gorsevski et al., 2012; Hecht and Saatchi, 2007; Sánchez-Cuervo and Aide, 2013; Sosnowski et al., 2016) (Fig. 5).

Table 3 was obtained after crossing the data between the study area type of biome and the satellite imagery sensors used for RS. The outcome indicates that the most common satellite imagery sensors used was the moderate resolution sensors (10-120 m) with 61% of the total, mainly Landsat 4-5 TM and Landsat 7 ETM+ in the analysis of biomes such as tropical rainforest, monsoon forest/dry forest, montane forest, and tree savanna. The Very fine (≤1 m) and Fine (1-10 m), resolution sensors were used in 27% of the studies per biomes; Spot 5, QuickBird, and Google Earth VHR have been used noticeably more in the study of biomes such as tropical rainforest, monsoon forest/dry forest, montane forest, tree savanna, and grass savanna. GeoEye sensor was used once each in non-common biomes as xeric shrubland, dry steppe, and alpine tundra. Sensors with coarse resolution (>250 m) were utilized in the 8% of the total and highlight the use of MODIS for several types of biomes. Uncategorized sensors were used rarely (4% of the total). Aerial photos and LIDAR ALS were used mainly in the temperate broadleaf forest.

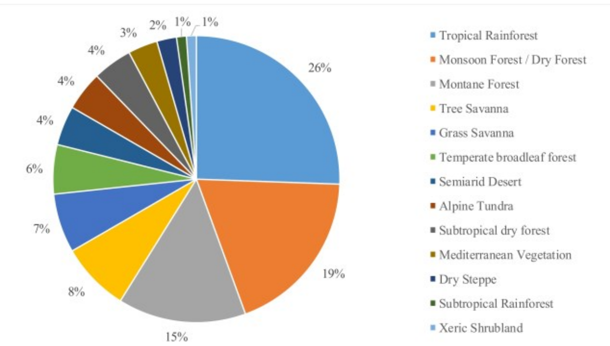

Fig. 4 Biomes analyzed for occurrence in the studies

Relationship between satellite imagery sensors and study area scale

To analyze and study the relationship between the use of satellite image sensors and the scale of the area affected by armed conflict, we first categorized the scale sizes into four types: Local (0-999 km^2), Landscape (1000-9999 km^2), Regional (10,000-99,999 km^2) and National/Global (≥100,000 km^2). Then, we checked, crossed the data and created a correlation table to identify trends and patterns of repetition. We obtained the following results: moderate resolution (10-120 m) sensors such as Landsat 4-5 TM, Landsat 7 ETM+ and to a lesser extent Landsat 8 OLI are the most widely used sensors in all scales, is noticeable a clear trend in the use of these sensors mainly in studies of medium to large small such as Landscape (e.g., Gorsevski et al., 2012; Gorsevski et al., 2013; Leiterer et al., 2018; Monroy and Armenteras, 2017; van Etten, 2008), and Regional (e.g., Armenteras et al., 2006; Burgess et al., 2015; Hecht and Saatchi, 2007; Witmer, 2008).

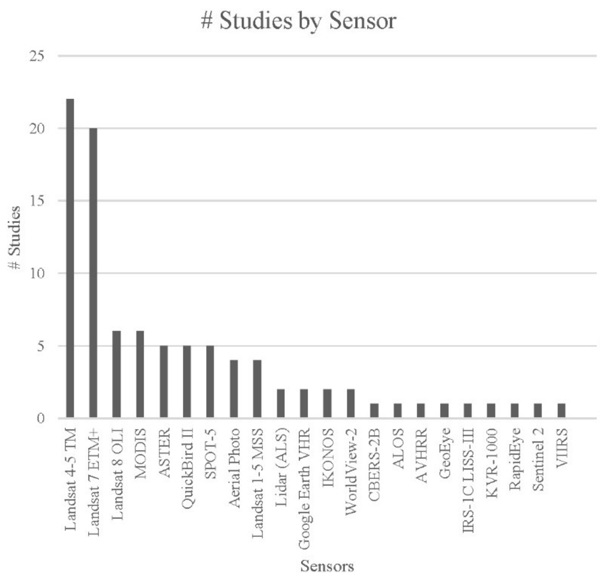

Fig. 5 Distribution by satellite sensor

In addition, we observed that high (1-10m) and very high-resolution (≤1m) satellite image sensors such as QuickBird, IKONOS, RapidEye, and CBERS were barely used in studies that analyzed sites with small scales such as Regional (10,000-99,999 km^2) and National/Global (≥100,000 km^2) excepting SPOT-5 and KVR-1000 that were used mainly in smaller scales. Concerning coarse (>250 m) sensors, the use was very low with the MODIS sensor standing out slightly on the regional scale. The aerial photos and ALS sensors were used primarily in researches that use Landscape scale. Several studies used more than one sensor to fulfil the gaps of information that the use of a single sensor can offer. This produces that each study can use the satellite images from more than one sensor mainly when Landsat data does not provide sufficient cloud-free coverage imagery or the availability does not cover the required period (Table 4).

Preprocessing of satellite imagery sensors

Preprocessing involves geometric (orthorectification) and radiometric calibration. Geometric calibration corrects for the angle of sight of the satellite sensor, the relief of the ground, and lens distortions in order that images from different sensors at different times may be compared with the same way as maps made using the identical projection and scale (Warner et al., 2009). Radiometric calibration is recommended due to the appearance of the identical image varies with the angle of view and radiance conditions. Of the 44 studies analyzed, 18% mentioned explicitly the utilization of satellite imagery preprocessing methods. For the reflectance calibration and image normalization, top-of-atmosphere (TOA) data was used 15 times in five studies (e.g., Cabrera et al. 2019; Enaruvbe et al. 2019; Potapov et al. 2012; Stevens et al. 2011; Wilson and Wilson 2013). In the case of top of canopy (TOC) reflectance data sets were performed just in one study (Potapov et al. 2012) with two satellite imagery sensors. Finally, the cloud presence was removed through atmospheric corrections using the Atmospheric & Topographic Correction - ATCOR-2 for haze removal in two studies with three Landsat sensors (e.g., Kwarteng 1998; Murad and Pearse 2018) (Table 5).

Table 3 Relationship between satellite imagery sensors and biomes

	Sensor vs Biome	Temperate broadleaf forest	Subtropical Rainforest	Mediterranean Vegetation	Monsoon Forest / Dry Forest	Xeric Shrubland	Dry Steppe	Semiarid Desert	Grass Savanna	Tree Savanna	Subtropical dry forest	Tropical Rainforest	Alpine Tundra	Montane Forest	**Total**
Very fine (≤1m) and Fine (1 - 10m)	SPOT-5		**1**		**2**				**1**	**1**	**1**	**2**	**1**	**1**	10
	QuickBird II			**1**	**2**				**2**	**1**		**3**	**1**	**2**	12
	IKONOS	**1**		**1**	**1**			**1**				**1**			5
	WorldView-2								**1**	**1**		**1**			3
	GeoEye					**1**	**1**						**1**		3
	ALOS				**1**							**1**			2
	CBERS-2B											**1**		**1**	2
	KVR-1000 (MS)				**1**							**1**			2
	Rapid Eye											**1**		**1**	2
	Google Earth VHR				**1**				**1**	**1**		**2**	**1**	**1**	7
Moderate (10–120 m)	Landsat 1-3 MSS				**1**							**3**		**1**	5
	Landsat 4-5 TM	**1**		**1**	**8**	**1**	**2**	**2**	**1**	**3**		**12**	**2**	**6**	39
	Landsat 6-7 ETM+			**1**	**10**				**1**	**2**	**1**	**14**	**1**	**9**	39
	Landsat 8 OLI				**1**				**1**	**1**	**1**	**4**		**2**	10
	ASTER				**3**					**1**	**1**	**4**	**1**	**3**	13
	Sentinel 2											**1**		**1**	2
	IRS-1C LISS-III									**1**		**1**			2
Coarse (>250 m)	MODIS				**2**				**2**	**2**	**1**	**4**	**1**	**3**	15
	VIIRS			**1**			**1**								2
	AVHRR											**1**			1
No Category	Aerial Photo	**3**			**1**					**1**				**1**	6
	Lidar – ALS	**2**													2
	Total	7	1	5	34	2	4	3	10	15	5	57	9	32	**181**

Table 4 Relationship between satellite imagery sensors and study area scale

	Sensor vs Scale	Local (0-999 km^2)	Landscape (1000-9999 km^2)	Regional (10,000-99,999 km^2)	National/global (≥100,000 km^2)	**Total**
Very fine (≤1m) and Fine (1 - 10m)	SPOT-5	**2**	**2**		**1**	5
	QuickBird II		**1**	**1**	**3**	5
	IKONOS			**1**	**1**	2
	WorldView-2		**2**			2
	GeoEye		**1**			1
	ALOS				**1**	1
	CBERS-2B				**1**	1
	KVR-1000 (MS)	**1**				1
	Rapid Eye				**1**	1
	Google Earth VHR		**1**		**1**	2
Moderate (10–120 m)	Landsat 1-3 MSS	**2**	**1**	**1**		4
	Landsat 4-5 TM	**2**	**13**	**5**	**2**	22
	Landsat 6-7 ETM+	**3**	**8**	**5**	**4**	20
	Landsat 8 OLI		**4**	**1**	**1**	6
	ASTER		**2**	**1**	**2**	5
	Sentinel 2				**1**	1
	IRS-1C LISS-III		**1**			1
Coarse (>250 m)	MODIS		**1**	**2**	**3**	6
	VIIRS				**1**	1
	AVHRR			**1**		1
No Category	Aerial Photo	**1**	**3**			4
	Lidar – ALS		**2**			2
	Total	11	42	18	23	**92**

Table 5 Relationship between satellite imagery sensors and preprocessing methods

	Sensor vs Preprocessing	TOA	TOC	ATCOR	IDOS	**Total**
Very fine (≤1m) and Fine (1–10m)	SPOT-5					0
	QuickBird II	**1**	**1**			2
	IKONOS					0
	WorldView-2					0
	GeoEye					0
	ALOS					0
	CBERS-2B	**1**				1
	KVR-1000 (MS)					0
	Rapid Eye	**1**				1
	Google Earth VHR					0
Moderate (10–120 m)	Landsat 1-3 MSS	**1**			**1**	2
	Landsat 4-5 TM	**3**		**1**	**1**	5
	Landsat 6-7 ETM+	**3**	**1**	**1**	**1**	6
	Landsat 8 OLI	**2**		**1**		3
	ASTER	**1**				1
	Sentinel 2	**1**				1
	IRS-1C LISS-III					0
Coarse (>250 m)	MODIS	**1**	**1**			2
	VIIRS					0
	AVHRR					0
	Total	15	3	3	3	**24**

Abbreviations: (TOA) Top of Atmosphere, (TOC) Top of Canopy, (ATCOR) Atmospheric & Topographic Correction, (IDOS) Improved Dark Object Subtraction

Satellite imagery sensors and imagery classification

The classifiers used for satellite image classification are split into two categories: statistical and machine learning approaches, the performance of which relies on the information distribution. The statistical learning approaches support some mathematical theories which cope with finding a relationship between classes to predict some substantial outcome (e.g., Borra et al., 2019). Maximum Likelihood Classifier was used in at least 25% of the studies. Object-based Image Analysis (OBIA) classifier was utilized in just 5% of the research. The fully automated Multivariate Alteration Detection (MAD) method was used once (2%).

Regarding indexed classification, 25% of the assessed studies, indicated explicitly the use of Normalized Difference Vegetation Index (NDVI) as a graphical indicator to analyze RS measurements. 43% of the studies used some type of Land-Cover Land-Use classification (LULC). Additionally, 36% of the studies stated the utilization of some type of Forest Cover Classification (FCC). Other multispectral vegetation indices as Enhanced Vegetation Index (EVI) and Modified Soil-Adjusted Vegetation Index (MSAVI) were performed in just one study each (Table 6).

Relationship between biomes and causes generated by armed conflicts.

In the table of crossed data between the causes generated by armed conflicts and the types of biomes, we found that the utilization of RS was used three times more in the analysis of indirect causes (74%) than in the analysis of direct causes (26%). Regarding direct causes as bombing (10%) (e.g., Burgess et al., 2015; Kwarteng, 1998; Note et al., 2018; Witmer, 2008; van Etten et al., 2008) were studied mainly at the temperate broadleaf forest, dry forest, and semiarid desert biomes. Direct confrontation and military infrastructure (14%) (e.g., Kwarteng, 1998; Suthakar and Bui, 2008; van Etten et al., 2008) were assessed principally at monsoon forest / dry forest and tropical rainforest biomes. On the another hand, in the case of indirect causes analyzed by RS, we found that forced migration mostly affected biomes (23%) (e.g., Enaruvbe, et al., 2019; Hecht and Saatchi, 2007; Hagenlocher et al., 2012; Leiterer et al., 2018; Lodhi et al., 1998; Suthakar and Bui, 2008), mainly; tropical rainforest, the monsoon forest / dry forest, montane forest, grass savanna, and tree savanna. Other relevant causes studied were agriculture (12%) (Armenteras et al., 2006; Murad and Pearse, 2018; Qamer et al., 2012), illegal crops (10%) (e.g., Armenteras et al., 2013; Murad and Pearse, 2018; Rincón Ruiz et al., 2013), cattle ranching (10%) (e.g., Murad and Pearse, 2018), mining (7%) (e.g., Monroy and Armenteras, 2017; Potapov et al., 2012) and non-forced migration (6%) (e.g., Armenteras et al., 2013), affecting mainly the tropical rainforest followed in decreased order by the montane forest, monsoon forest / dry forest, tree savanna, alpine tundra, and grass savanna (Table 7).

Table 6 Relationship between satellite imagery sensors and imagery classification

	Sensor vs Imagery Classification	NVDI	LULC	FCC	OBIA	MODIS-EVI	MLC	MAD	MSAVI	**Total**
Very fine (≤1m) and Fine (1 - 10m)	SPOT-5	1	3	3			2			9
	QuickBird II	3	2	2	1	1		1		10
	IKONOS			1	1					2
	WorldView-2	1	2	1						4
	GeoEye			1						1
	ALOS			1						1
	CBERS-2B			1						1
	KVR-1000 (MS)									0
	Rapid Eye			1						1
	Google Earth VHR		2			1				3
Moderate (10–120 m)	Landsat 1-3 MSS		2	3			1			6
	Landsat 4-5 TM	6	11	11			7	1	1	37
	Landsat 6-7 ETM+	7	12	11			5	1		36
	Landsat 8 OLI	1	4	2			3			10
	ASTER		2	3						5
	Sentinel 2			1						1
	IRS-1C LISS-III		1				1			2
Coarse	MODIS	3	2	3		1	1		1	11
	VIIRS									0
	AVHRR						1		1	2
	Total	22	43	45	2	3	21	3	3	**142**

Relationship between biomes and consequences of the armed conflicts

Based on the analysis of the consequences of armed conflicts on the environment with the affected biomes, we found that the use of RS is strongly focused on the analysis of deforestation (46%) (e.g., Armenteras et al., 2006; Gorsevski et al., 2012; Hagenlocher et al., 2012; Murad and Pearse, 2018; Nackoney et al., 2014; Ordway, 2015; Potapov et al., 2012; Rincón Ruiz et al., 2013; Stevens et al., 2011) and on changes of land use and land cover (36%), mainly in the biomes of tropical rainforest, the monsoon forest / dry forest, montane forest, and tree savanna (e.g., Bjorgo, 1999; Enaruvbe, 2019; Murad and Pearse, 2018; Petit et al., 2001; Rincón Ruiz et al., 2013; Sánchez-Cuervo and Aide, 2013). The analysis of abandonment of agricultural lands (8%) (e.g., Gorsevski et al., 2012; Hagenlocher et al., 2012; Witmer, 2008) is noticeable in the biomes of mediterranean vegetation, the monsoon forest / dry forest, dry steppe, and montane forest (Table 8).

DISCUSSION

Concerning the relationship between RS analysis and geographical location of areas affected by armed conflicts, we can infer that the distribution of the RS articles is mainly located near equatorial line in tropical and monsoon forest areas. This is not because, in general, in these areas, there have been more conflicts, since it is not entirely true, indeed many armed conflicts have occurred in temperate, or desert areas such as the Caucasus, the Balkans, Syria, Yemen, Iraq, Turkey, and Afghanistan, where the use of RS to assess the impact on the environment has been considerably less. Comparing Figure 3 to any armed conflict map in the world will show that the pattern is not the same.

We can consider that the high number of investigations that use RS methods in equatorial zones compared to other biomes is mainly due to a set of factors. The reasons that we infer are, the long duration average of conflicts in these areas, the type of armed conflict, many of them guerrilla wars and internal conflicts on a smaller intensity of bombings and direct confrontations, but with a greater generation of displaced persons and fatalities. Furthermore, the fragility and vulnerability of tropical ecosystems and the high forest density makes land-use and land-cover changes and deforestation more evident. As well in the tropical rainforest, there is a considerable number of collateral affectations such as illicit crops, illegal logging and, illegal mining. Additionally, there is a higher presence of population forced to migrate and settle in refugee camps, the limited attention to this population, which in turn generates higher demand for natural resources and greater environmental damage. The difficulty of physically approaching in situ evaluation to these areas makes the use of RS methods more frequently in tropical biomes.

Table 7 Relationship between biomes and causes generated by armed conflict

	Cause vs Biome	Temperate broadleaf forest	Subtropical Rainforest	Mediterranean Vegetation	Monsoon Forest / Dry Forest	Xeric Shrubland	Dry Steppe	Semiarid Desert	Grass Savanna	Tree Savanna	Subtropical dry forest	Tropical Rainforest	Alpine Tundra	Montane Forest	**Total**
Direct	Bombing	4		2	3		1	3				2		1	16
	Direct Confrontation / Militar Infrastructure	1		1	5		1	2	1	2		7	1	2	23
	Landmines			1						1		1		1	4
Indirect	Forced Migration (Camp Refugees)		1	1	6				4	5	2	12	1	5	37
	Non-Forced Migration (Colonization)				2							5		2	9
	Mining				3						1	5		2	11
	Illegal Crops				3	1	1		1	1		4	2	4	17
	Agriculture				3	1	1				1	7	2	5	20
	Cattle Ranching				1	1	1			1	1	5	2	4	16
	Timber				1					1		4		2	8
	Fires											1		1	2
	Total	5	1	5	27	3	5	5	6	11	5	53	8	29	**163**

Table 8 Relationship between biomes and consequences of the armed conflict

Consequence vs Biome	Temperate broadleaf forest	Subtropical Rainforest	Mediterranean Vegetation	Monsoon Forest / Dry Forest	Xeric Shrubland	Dry Steppe	Semiarid Desert	Grass Savanna	Tree Savanna	Subtropical dry forest	Tropical Rainforest	Alpine Tundra	Montane Forest	**Total**
Deforestation	2	1		14	1	2		5	7	2	20	4	11	69
Forestation				1					1				1	3
Desertification / Land Degradation				1				1	1		1		1	5
Land Use / Land Cover Changes	2		2	10	1	2	3	3	4	4	13	3	7	54
Mine Craters	2													2
Militar Infrastructure	1			1					1		2			5
Abandonment of agricultural lands			2	2	1	2			1		1	1	2	12
Groundwater Pollution							1	1						2
Total	7	1	4	29	3	6	4	10	15	6	37	8	22	**152**

We found that 64% of the documents analyzed used more than one sensor as a source of satellite imagery. This is because in many cases; it is required to complement the information required for the analysis, the use of more than one sensor. The main reasons are the gaps in temporal availability, availability of high-resolution images, availability of cloud-free imagery and, the availability of specialized satellite imagery data in a particular sector, especially for multivariate RS analysis.

The most significant findings of the use of satellite imagery sensors are concentrated in the use of moderate resolution sensors (10-120 m). Mainly Landsat 4-5 TM and Landsat 7 ETM+ were the used to study affectations in the biomes of tropical rainforest, montane forest,

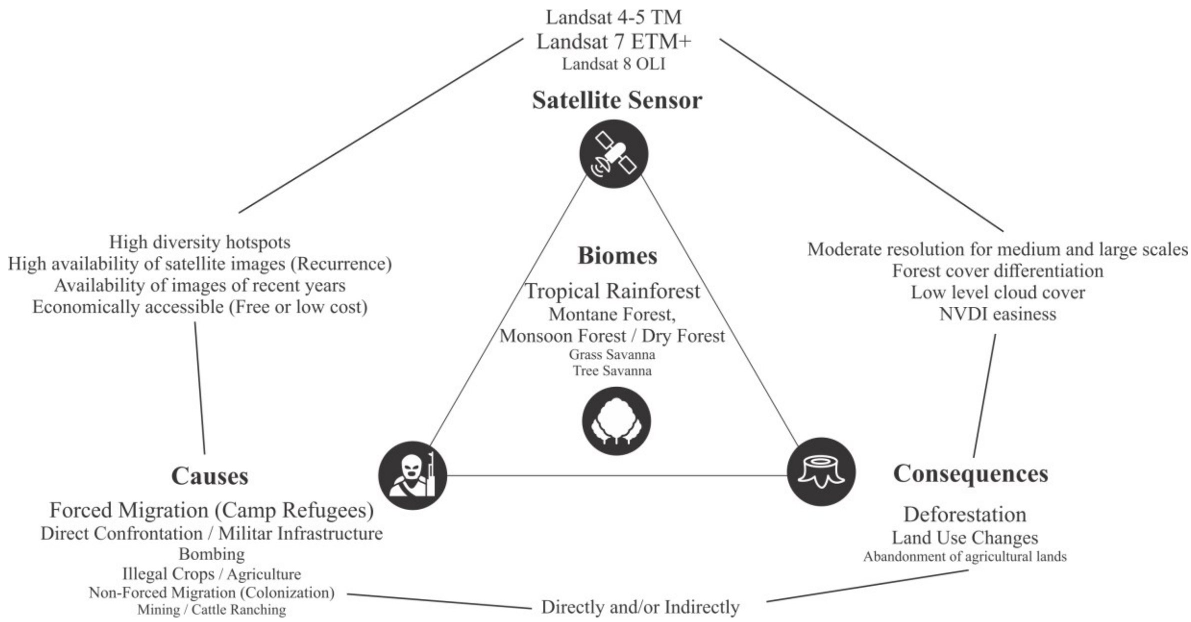

Fig. 6 Relationship between satellite sensor, causes, consequences and biome

monsoon forest/dry forest and to a lesser extent in the biomes of grass savanna and tree savanna. They cover principally the medium-scale (1000-9999 km^2) and the small scale (10,000-99,999 km^2). This is due not only to a single cause but to a set of reasons, such as the higher temporary availability of recurrent and high-quality satellite images. Furthermore, due to the possibility of finding a larger quantity of images with a low level of cloud cover. Another possible cause closely related to the analysis of the consequences is because, for the analysis of vegetation cover of these types of biomes, the size of the scale used does not require a very high level of resolution. Finally, another reason is the ease of acquiring this imagery data set due to the public domain character of these sensors (Fig. 6 and Table 4).

Imagery preprocessing is a mandatory step in the RS analysis. In the case of tropical biomes, the availability of cloud-free cover images is more difficult to acquire because mostly, these biomes present long rainy seasons throughout the year. It means that the use of calibration correctors and haze removals techniques such as TOA, TOC, and ATCOR-2, gain importance as an imperative process, especially in deforestation, land-use, and land cover changes analysis. Nevertheless, just a few studies mentioned explicitly the utilization of which type of preprocessing methods used. Unfortunately, the acquired data is not enough representative to produce significant conclusions.

NDVI can be inferred as the most common method used to classify covers. Mainly because of a series of factors such as high compatibility with several types of satellite sensors (mainly Landsat), the simplicity of the algorithm, and its capacity to distinguish vegetated areas from other surface types. This is especially noticeable in biomes with a large presence of perennial vegetation as the tropical rainforest. NDVI also has the utility of reducing the size of the data to be managed by a factor 2 (or more), since it changes the two spectral bands by a single new.

A relevant finding is a notable relationship between indirect causes and to a lesser extent direct causes with the use of RS in biomes such as tropical rainforests and monsoon forests. Indirect causes such as forced migration generate large refugee camps and to a lesser amount, no-forced migration generates processes of colonization of previously virgin areas and in rare cases, the conflict generates protected lands (forestation). Mining, agriculture, logging, and livestock have also been studied to a certain degree in tropical biomes by RS methods. Direct confrontation and military infrastructure also have a significant but not superlative impact on tropical forests. Illicit crops, forced migration, and agriculture heavily affect mountain forests. The monsoon forest/dry forest has been most affected by military infrastructure, direct confrontation, and bombing. The main cause of the damage to the tree savanna and grass savanna in sub-Saharan Africa is forced migration, generating large refugee camps and changes in land use. Regarding the findings of analyzed consequences in the environment, deforestation and secondly the land-use changes are the most analyzed impacts, mainly in the following high biodiversity biomes; tropical forests, mountain forests, monsoon forest/dry forest, and less studied in tree savanna and grass savanna biomes (Fig. 6).

Some barriers and boundaries that we had during the research were, that despite finding a considerable amount of studies that address the issue of conflict and environment, there is not a very large number of documents that have addressed this problem using RS methods. In those that used RS, it was not easy to identify the type of biome analyzed since they often focus more on country boundaries than on biomes, and these are considered mostly in general rather than specific. Likewise, biome boundaries are not only different from country boundaries but are much more difficult to delimit since in most cases, there are biological transition zones between one biome and another, which is why it is very common to find that each armed conflict affects more than one type of biome (Uriarte et al., 2010). This is especially noticeable in Colombia, since, due to its particular geographical conditions, in a relatively small area, six different biomes can be differentiated. Some works used RS to assess ecological and wildlife consequences or to identify human populations at risk, but these lines of research are beyond the scope of this analysis and therefore were not considered for this investigation.

We would like to highlight that the scope of this paper is to frame the state of the art on the relationship between armed conflicts, the environment, and their study methods. In order to, from this first step, lay the foundations for more exhaustive research that will allow a better understanding of the complex relationship between armed conflicts and their impact on the environment. This will allow subsequent researches to create more precise and complete methods of evaluation, diagnosis, and possible restoration of the damaged environment. Given the recent and current peace processes, it would be especially interesting to continue tracking deforestation, land-use changes, and other consequences in those countries by adding more data and study parameters. Tracking of year-to-year changes using high-resolution data would be notably useful for correlating specific economic and political conditions with landscape, land use, and deforestation rates and distributions.

CONCLUSION

The observations and results presented here are considered applicable and relevant for the analysis of RS data related to studying the issue between armed conflict and environment, which is not applicable nor considered generally true for armed conflicts itself. The impacts of warfare on environments are diverse and complex; increase mainly deforestation and land-use changes. Over 79% of the RS studies of major armed conflicts between 1980 and 2019 occurred within the torrid area, biomes located near the equatorial line; more than 64% took place directly within high biodiversity hotspot areas. Less than one-third of the 34 recognized hotspots escaped from significant conflict during this period and most suffered repeated episodes of violence. This pattern has been remarkably consistent over these 3 decades.

The most affected studied biome is tropical rainforest; this biome may be found in Southeast Asia, Central Africa, and Amazonia, covering about 12% of Earth's land surface (excluding ice-covered areas such as Antarctica). The largest impact studied using RS in the biomes is deforestation with 45% of the studies, and secondly the land-use change with one-third of the studies. The greatest cause of affectation is indirect causes (70%) such as forced and unforced migration, illicit crops, mining, agriculture, and cattle ranching. This can be explained because migrant populations are larger in these zones, demanding large resources for movement as well as settlement. In the case of Colombia and Afghanistan, illicit crops are a major factor in deforestation and land-use change. Consequences of armed conflicts such as deforestation and land-use change are the most predominant effects in tropical biomes (tropical rainforest, montane forest, monsoon forest/dry forest).

The present research could be useful as a base for future investigations in specific areas in order to analyze armed conflicts and their effect on the landscape. Moreover, it could work as a guideline to make decisions regarding which RS methods and satellite sensors might be used, based on biomes, scales, causes, and consequences. Indeed, the present document provides a background and a starting point that allows for a more extensive analysis of the warfare-environment affair. In the future, we will study the case of the National Parks of Colombia affected by the internal armed conflict, taking as a sample area the "Sumapaz NP".

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