GI_Forum 2017, Issue 1
Page: 228 - 243
Full Paper
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DOI: 10.1553/giscience2017_01_s228

Potential and Limitations of Radar Remote Sensing for Humanitarian Operations

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Abstract

Methods of earth observation deliver quick and reliable information covering large areas, which can be used for the management of natural disasters and humanitarian crises. However, optical sensors reach their limits in areas affected by cloud cover or atmospheric haze, while radar satellites are predominantly unaffected by atmospheric conditions. This paper discusses the application of radar imagery for the assistance of humanitarian operations. The opening section describes the need for complementary information gained from radar data as well as the challenges which arise when working with imaging systems. Subsequently, examples for the use of various sensors are given based on our own findings, and a literature review for various application domains. These include the monitoring of natural resources, the distribution of human settlements or dwellings, and the retrieval of hydrologic parameters. Against this background, limitations and how they were handled in selected studies are discussed. A summary reflects the findings in the light of new developments and discusses challenges for the future.

Keywords:

humanitarian relief; remote sensing; radar imagery; settlements; natural resources

1 Introduction

The contribution of geographical information systems (GIS) and remote sensing (RS) for humanitarian response has been discussed extensively during the last two decades (Kranz et al., 2016; Lang et al., 2015; Marx & Goward, 2013; Kaiser et al., 2003; Gentile et al., 1997). Many of the approaches based on earth observation (EO), however, report issues related to data availability or cloud cover (San-Miguel-Ayanz & Ravail, 2005; Song et al., 2001; Kogan, 1997). According to estimates by the US Department of Energy, on average about 52% of global land surfaces are covered by clouds (Warren et al., 1986). Regions within the intertropical convergence zone (ITC) are affected by seasonal or even year-round cloud cover. It is often within these areas of extreme climatic conditions that humanitarian aid is required (e.g. in cases of flooding, famines or the spread of vector-borne diseases).

This paper therefore discusses the application of synthetic aperture radar (SAR) imagery for humanitarian relief. It is based on work and experience gained in the research project

EO4HumEn+ (Extended EO-based Services for Dynamic Information needs in Humanitarian Action) funded by the Austrian Research Promotion Agency (FFG). The paper consists of a literature review enriched by the authors' own examples, as summarized in Table 1. The locations of the examples are shown in Figure 1, as are other selected locations investigated within EO4HumEn+.

Table 1: Overview of case studies. The Figure numbers refer to our Figures below.

	Setting (area)	Data
Figure 3: Speckle filter	Djabal refugee camp and the city of Goz Beïda, Eastern Chad	TerraSAR-X (Spotlight Mode), 07.03.2009
Figure 4: Biomass estimation	Border region between Chad and Sudan including refugee camps	ALOS PALSAR (ScanSAR Mode), 26.11.2010
Figure 5: Multi-temporal analysis	Minawao refugee camp, Northern Cameroon	TerraSAR-X (Staring Spotlight Mode), 12.07., 25.08. and 26.10.2015
Figure 6: Building detection	Dagahaley refugee camp, Eastern Kenya	TerraSAR-X (Staring Spotlight Mode), 10.03.2015
Figure 8: Surface geology	Settlement of Kidal, Eastern Mali	ALOS PALSAR-2 (SM1Mode), 31.12.2016; Sentinel-1 (IW Mode), 29.12.2016

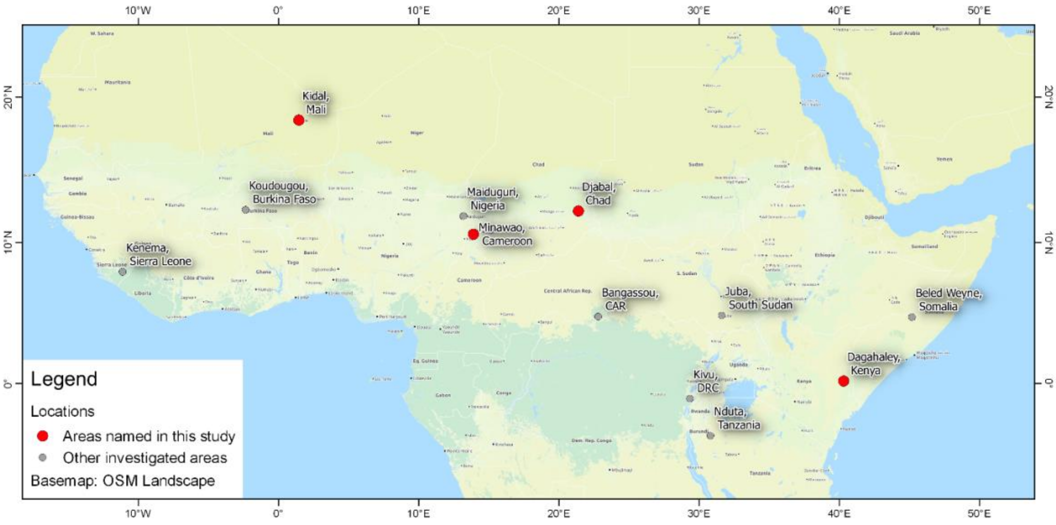

Figure 1: Map of the study areas used for this paper (red) and within the research project (grey).

2 Characteristics of SAR data

To overcome limitations described in section 1, satellites with synthetic aperture radar (SAR) were used. They operate at wavelengths of several centimetres, thus penetrating clouds. This makes them independent of atmospheric conditions and also capable of image acquisitions at night (Ulaby et al., 1981).

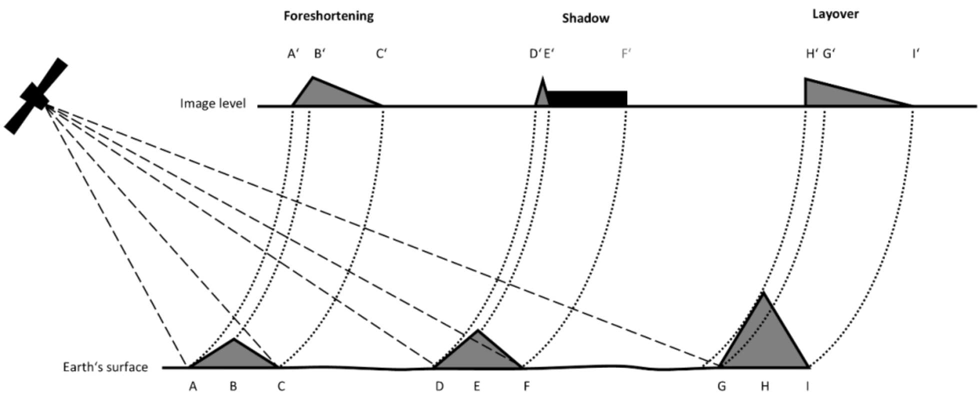

Figure 2: Topographic effects in SAR images. Note how A' and B' appear closer together in the SAR image, caused by the temporal shift of the signal (foreshortening). In cases of steeper slopes, some parts of the image are not reached by the signal at all (the location of F' is within the radar shadow). In cases of signal layover, the signal reaches the top of the hill before its slopes, leading to inversion of geometries (H' G').

For humanitarian response, SAR satellites offer gap-free images with a high degree of temporal flexibility. Their analysis does, however, present difficulties. As shown in Figure 2, images are distorted because of the side-looking geometry of the sensor, especially in areas with pronounced topography (Bayer et al., 1991). These distortions are of a geometric and radiometric nature and must either be reduced by the use of a digital elevation model, e.g. SRTM 1 ArcSec (Jarvis et al., 2008), or at least be considered in later steps of analysis. Additionally, the active nature of the signal causes positive and negative interference, which adds up to noise-like patterns within the data (Lee, 1981). This so-called speckle effect is shown in Figure 3 and reduces the sharpness of images. It, too, has to be dealt with by the user before reliable information can be retrieved.

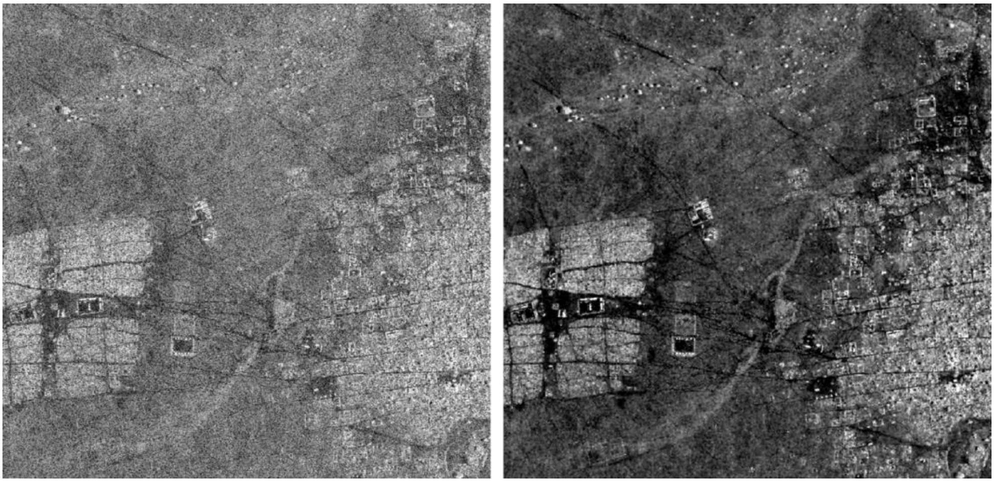

Figure 3: TerraSAR-X image (spatial resolution of 1m) of the Djabal refugee camp and the city of Goz Beïda, Eastern Chad. Left: Unfiltered. Right: After application of a speckle filter, which uses local statistics to reduce random noise-like structures while preserving actual edges.

3 Applications in the humanitarian domain

Natural resources

The use of SAR imagery at the landscape level dates back to the early 1990s when the first SAR satellites were launched, ERS-1 (European Space Agency) and JERS-1 (Japan Aerospace Exploration Agency) amongst others. Both delivered images of medium spatial resolution (20 to 30 metres) and comparably wide coverage (swathes of 75 to 100 kilometres). Surface characteristics such as roughness, texture, shape and moisture were enhanced by the wavelength of their signal, making them a valuable source of information complementary to the optical images of early Landsat missions (Kuplich et al., 2000; Solberg et al., 1994). The long wavelengths of ALOS PALSAR and JERS-1 (L-band) in particular were found to be effective for vegetation mapping because of their ability to penetrate canopies and their strong interaction with voluminous structures (Fransson, 1999; Paloscia et al., 1999).

For humanitarian action, information about the surrounding landscapes and the natural resources available is crucial (Haile, 2005; Bannon & Collier, 2003). Applications address the distribution of drinking water, firewood or building materials, as well as the management and monitoring of limited resources in terms of ecosystem capacities.

Mitchard et al. (2009) investigated the relationship between L-band backscatter intensity and above-ground biomass (AGB) and found a stable ratio based on samples collected within four different savannah landscapes. This finding was then used to quantify changes related to landscape degradation in Africa (Mitchard et al., 2011) and later extended to studies of carbon stocks in tropical regions across three continents (Saatchi et al., 2011). The work of Saatchi et al. can be considered a milestone as this was the first time that a calibrated model was transferred to other areas lacking sufficient ground measurements. Their findings were incorporated in numerous studies addressing the monitoring of natural resources in areas affected by deforestation and land degradation (Carreiras et al., 2012; Ryan et al., 2012; Englhart et al., 2011).

Besides the need for ground data used for validation, one of the main limitations of regression-based approaches is the issue of saturation (Imhoff, 1993). Above a certain level, often reported as being between 150 and 300 tons per hectare, SAR backscatter no longer increases accordingly. Estimations above this point are therefore considered to be increasingly inaccurate, as shown in Figure 4.

Long-term observations and monitoring of biomass were additionally limited by the failure of ALOS PALSAR in April 2011. ALOS-2 was launched in May 2014, leaving a temporal gap of three years without any L-band SAR satellite imagery available.

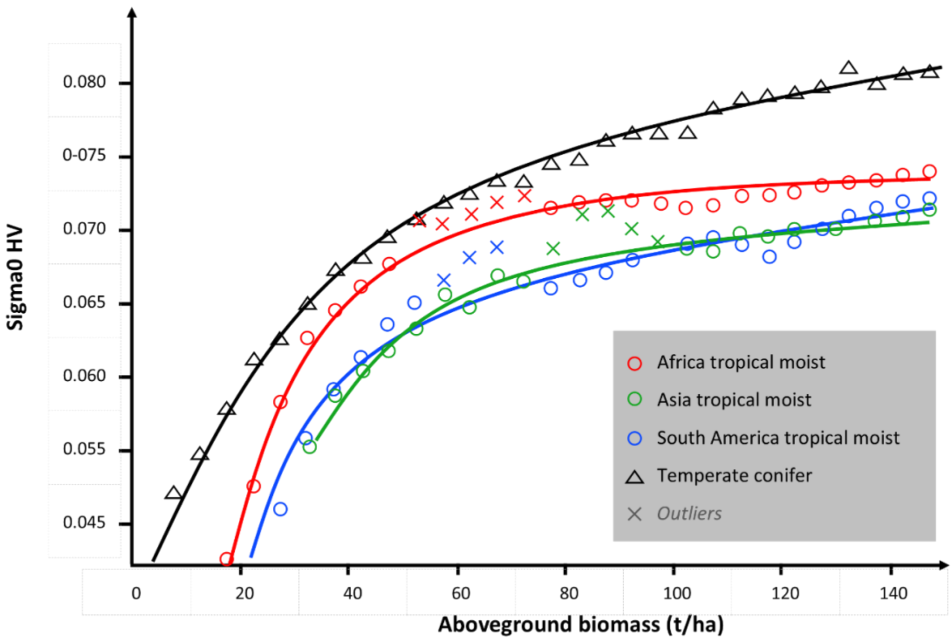

Figure 4: Saturation of SAR backscatter intensities for biomass estimation, adapted from Yu and Saatchi (2016). The chart shows backscatter coefficients plotted against field measurements conducted in six different forests. Note the flattening of the curves and increasing uncertainty with biomass values larger than 100 t/ha.

The example given in Figure 5 shows how the calibrated models of Mitchard et al. (2009) can be applied to similar savannah ecosystems along the Sahel border. Although this approach may not deliver precise estimates and lacks ground validation, seasonal abundancies of biomass can be quickly assessed for large areas. Linking this information to locations of refugee camps can then assist collection of firewood and resource management.

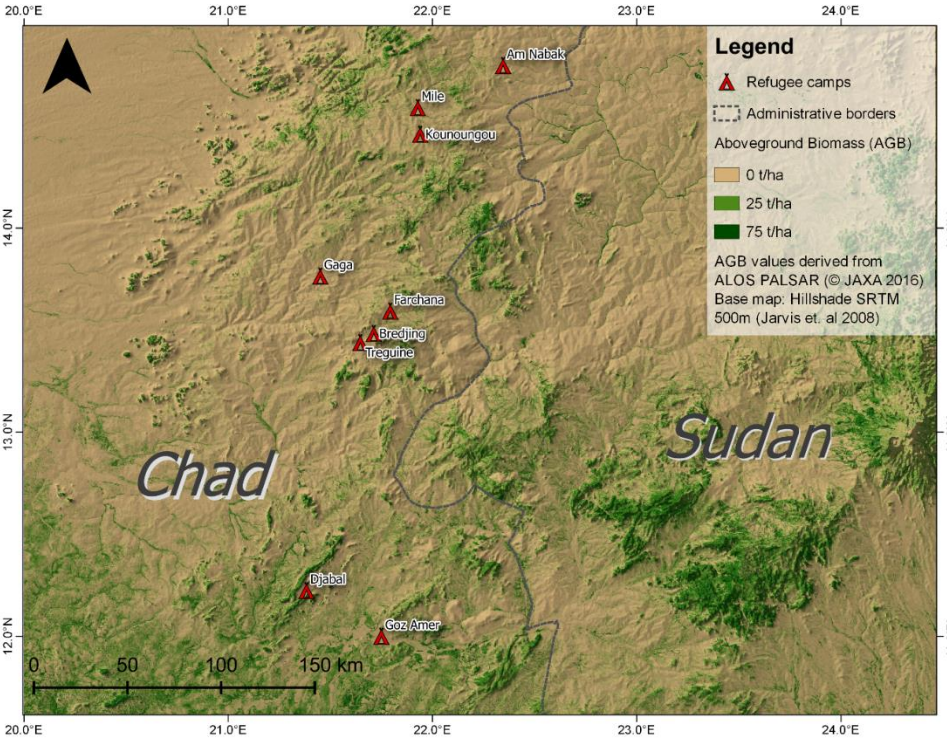

Figure 5: Continuous biomass estimates along the Chad–Sudan border based on ALOS PALSAR.

Settlements

One of the most important pieces of information retrieved by EO techniques can help to identify the distribution of people in impassable or insecure areas, or in emergencies of unclear situation. In the humanitarian sector, this applies mostly in the detection of urban growth, the discrimination of districts, and the classification and counting of building types. While approaches based on VHR optical data are already highly developed (Kemper & Heinzel, 2014; Spröhnle et al., 2014; Voigt et al., 2014; Ergünay et al., 2013), SAR applications in urban emergency situations are rare.

One main limitation of SAR in urban areas is spatial resolution: the discrimination of dwelling types requires spatial resolutions down to 1 metre. To achieve this, special modes of image acquisition are applied which are currently provided by only a few radar satellites, as shown in Table 2. However, the area which can be covered with such modes is limited. Obtaining complete images of large cities or regions in a single overflight is nearly impossible. Additionally, these modes compete with the regular imaging modes and have to be tasked specifically. This results in only small amounts of data actually being acquired and archived.

Table 2: Very high resolution SAR satellites

Satellite (operator)	Imaging mode (spatial resolution)	Maximum area covered	Time of operation
TerraSAR-X (DLR)	Staring Spotlight (0.6m)	4 x 3.7km	2013 – today
COSMO SkyMed (ASI)	Spotlight-2 (0.8m)	10 x 10km	2007 – today
HRWS (DLR)	StripMap (1m)	70 x 70km	expected 2019
TerraSAR-X (DLR)	Spotlight (1m)	10 x 10km	2007 – today
Radarsat-2 (CSA)	Spotlight (1m)	8 x 18km	2007 - today
Radarsat-2 (CSA)	UltraFine (3m)	20 x 20km	2007 – today
ALOS PALSAR-2 (JAXA)	Spotlight (3m)	25 x 25km	2014 – today
RISAT-1 (ISRO)	FR Stripmap (3m)	25 x 25km	2012 – today
Sentinel-1	StripMap (5m)	80 x 80km	2014 – today

Urban areas often show high radar backscatter because of so-called double-bounce effects. These can be observed when the incoming signal is reflected by rectangular structures (e.g. buildings) and returns directly to the sensor. This leads to over-saturation in images of densely built-up areas. In turn, this type of corner reflexion has also been exploited for the detection of buildings (Balz & Liao, 2010; Brunner et al., 2009; Guillaso et al., 2005)

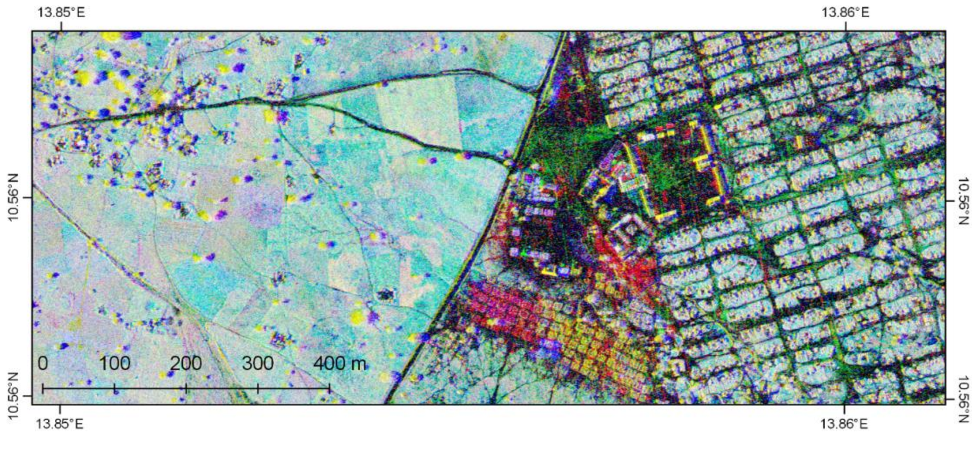

Figure 6: RGB colour composite of TerraSAR-X scenes for the Minawao refugee camp, Cameroon. Red: 12.07.2015, Green: 25.08.2015, Blue: 26.10.2015. Note that the blue image was acquired from a different direction, leading to shadow-like structures next to the trees.

In the humanitarian context, VHR SAR data can be used for monitoring developments within refugee camps. Figure 6 shows a colour composite of three TerraSAR-X scenes, where red and yellow indicate that buildings have already been removed and buildings shown in blue were built before the acquisition of the last image. Camp structures like administrative buildings or neighbourhoods of simple tents can be identified clearly.

However, the detection of single dwellings is constrained by the density and orientation of dwellings, as well as by vegetation cover. Figure 7 clearly demonstrates the advantages and limits of SAR data: clouds hinder the analysis of the optical image but white buildings can be clearly delimited. The SAR image is not affected by atmospheric constraints, but the presence of many shrubs and hedges separating the single households causes volume scattering to such an extent that the footprint of the dwellings nearly vanishes. So even if the buildings stand on flat terrain and the area is only sparsely built, detection of dwellings can be difficult.

These issues can be addressed in various ways. Possible solutions include the aggregation of buildings to urban structure types (Reigber et al., 2007), combinations with optical information (Wegner et al., 2011; Sportouche et al., 2009), or the use of SAR images acquired from different angles (Thiele et al., 2007; Simonetto et al., 2005).

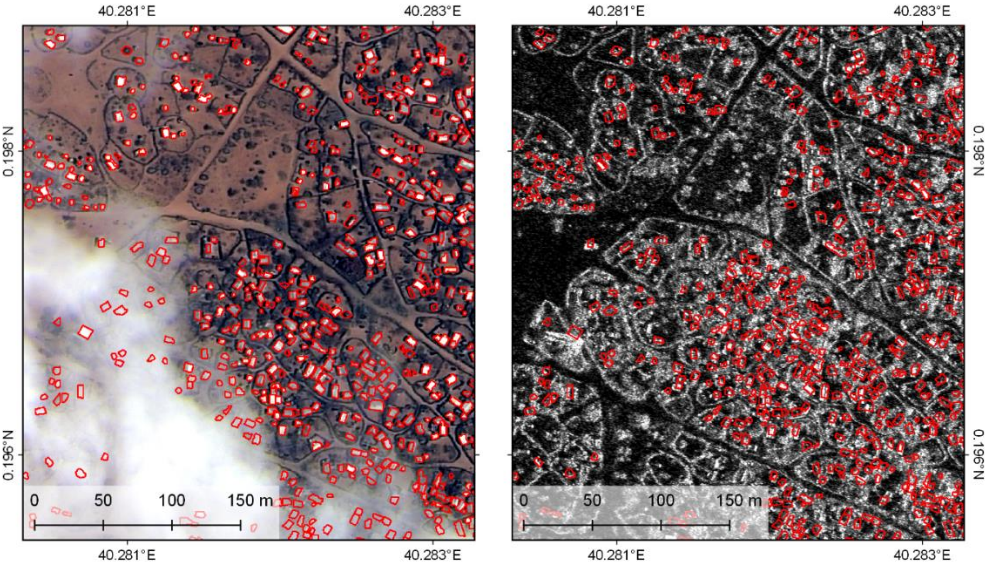

Figure 7: Detection of dwellings in Dagahaley refugee camp, Kenya. Comparison between WordView-3 (left) and TerraSAR-X (Staring Spotlight mode, right). The red polygons indicate detected houses based on WorldView-3 by Tiede et al. (2013).

Hydrology

Radar imagery has often been used to detect variations of moisture at the earth's surface (Baghdadi et al., 2012; Engman & Chauhan, 1995; Dubois et al., 1995). This information can efficiently assist the provision of drinking water, especially in arid regions (Wendt et al., 2015). However, as indicated by Figure 8, microwaves are sensitive not only to dielectricity (as the main proxy for soil moisture), but also to surface characteristics and the local incidence angle (Mason et al., 2016; Shi et al., 1997). The direct relationship of backscatter intensity and soil moisture cannot therefore be exploited based on single images or for wide areas covering different types of land-use at high resolutions. Additionally, every model needs field measurements for calibration purposes, which are not given in cases of emergencies. At the global scale, systems such as SMOS (Soil Moisture and Ocean Salinity, satellite operated by ESA), SMAP (Soil Moisture Active Passive, satellite operated by NASA) or ASCAT (Advanced Scatterometer, instrument on the MetOp-A weather satellite) deliver radiometer-based soil moisture estimates at an operational level, but at spatial resolutions of several kilometres (Al-Yaari et al., 2014).

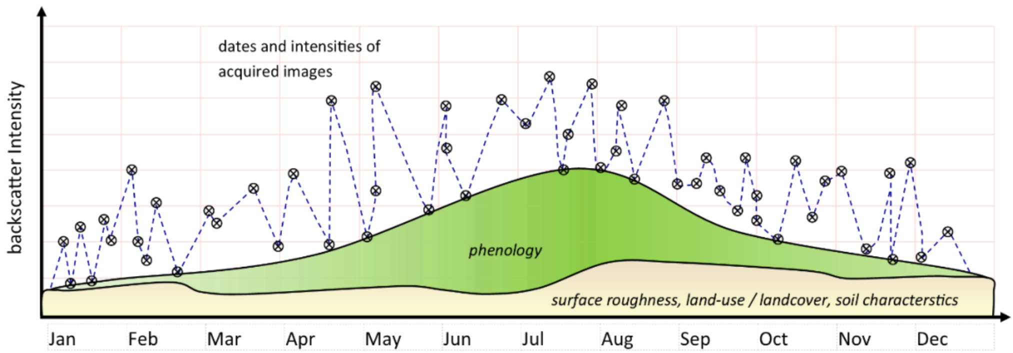

Figure 8: Influence of surface characteristics, vegetation cover and soil moisture on radar backscatter. While backscatter intensity caused by surface roughness and landcover (light area) is mostly stable during the year, phonologic variations are highly dynamic and contribute to the overall signal (green area). Changes in moisture of surfaces additionally enhance/attenuate the signal fluctuations (blue dashed line).

To overcome these limitations, different solutions have been proposed. Moran et al. (2000) used the variation of SAR values for the SAR images from the rainy and dry seasons in order to minimize the effect of surface roughness. A similar approach was proposed by Srivastava et al. (2003), who used SAR data of different incidence angles to overcome geometric variations. Upsampling techniques applied on global soil moisture data sets, such as those provided by SMOS or ASCAT, are used in other studies that are based on SAR images of finer resolution (Pierdicca et al., 2014; Gruber et al., 2013). These approaches manage to increase the spatial resolution to the kilometre scale, but are still limited to specific parts of the earth or require field measurements for calibration. They are first steps towards fine-scaled operational services but cannot as yet fulfil the needs of humanitarian organizations for near real-time information.

For the provision of drinking water, other approaches seem more promising. Quesney et al. (2000) propose a SAR-based index for soil moisture over different types of land-use. Although few absolute estimates are given, the approach incorporates seasonal fluctuations and the influence of vegetation cover. In the context of food security and agricultural yield, Brisco and Brown (2015) investigated SAR data as predictors for drought stress for various crop types.

In arid regions, investigation of subsurface geology allows the detection of groundwater flows and recommendations on drilling activities (Paillou et al., 2010; Verjee & Gachet, 2007; Dabbagh et al., 1997). Many approaches use the penetration of microwaves into dry surfaces, which can reveal buried structures. Importantly, the combination of SAR sensors of different wavelengths can lead to new insights into geomorphologic and hydrologic features, because systems of higher wavelength have higher penetration capabilities than shorter ones.

Figure 9 demonstrates the information content of different wavelengths compared to optical images, using the example of Kidal, Eastern Mali. While in arid regions most of the surface is covered by sand, rock or shrub vegetation, waves of different penetration depths help to define subsurface structures, such as smaller wadis and buried river channels, which often contain usable drinking water. As demonstrated, only large geologic structures are shown as darker patterns in the optical image, while a combination of SAR images of different wavelengths provides detailed insights regarding surface geology (blue granites), wadi channels (red lines), and lineaments and ridges around the city of Kidal (light lines on green and yellow background).

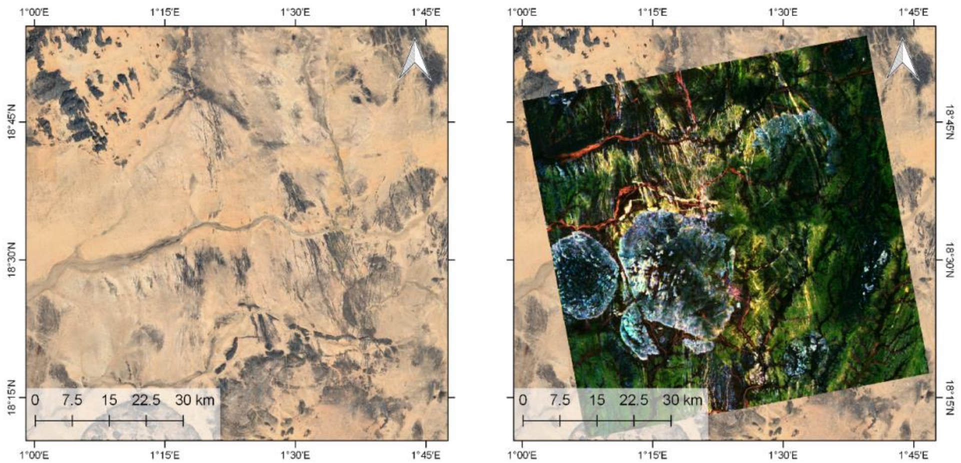

Figure 9: Area around settlement of Kidal, Mali during the dry season. Left: Optical information from Sentinel-2. Right: SAR composite of L-band (red, ALOS PALSAR-2, HH), L-band (green, ALOS PALSAR-2, HV) and C-band (blue, Sentinel-1, VV).

4 Discussion and Outlook

The examples presented are just a few of the many possible applications of SAR imagery in the humanitarian sector. Besides resources, settlements and hydrology, solutions for the following domains have already been proposed: image classification for the analysis of changes or ecosystem capacity (Braun et al., 2016; Mitchard et al., 2011); damage assessment after earthquakes or tsunamis (Plank, 2014; Chen & Sato, 2013); ground subsidence resulting from water extraction or mining (Engelbrecht & Inggs, 2011; Tomás et al., 2005); the detection of flood-prone areas (Schlaffer et al., 2015; Long et al., 2014).

Two factors have been largely responsible for promoting the use of radar data during the last decade:

a) Availability of data: With the launch of Sentinel-1 A and B within the Copernicus programme, data is collected systematically according to acquisition plans and freely available for scientific, commercial and civilian use. This service will be complemented by Sentinel-1 C and D, creating an unprecedented constellation of SAR data-acquisition of both high temporal and high spatial coverage. Furthermore, more and more data of former radar missions, such as ENVISAT, ALOS or ERS, is becoming publicly available through the provision of access to the long-term archives.
b) Software: for a long time, SAR processing was mainly restricted to engineers or research facilities, and only a few specialized software packages existed. Triggered by multidisciplinary discourse and collaborative software development, an increasing number of open-source tools are now available. While many of them are command line-based and highly specialized (StaMPS, GIAnT or GMTSAR), others address more basic tasks and provide graphical user interfaces, allowing less-experienced users to enter the field of radar data (MapReady by the ASF, SNAP by the ESA, or PolSARpro by the IETR). Consequently, a larger user community will further boost the development of new methods and applications.

Despite the emergent use of SAR data in many fields of study, their intensive exploitation in humanitarian action seems still to come. As limitations of a technical nature, such as speckle, terrain effects or spatial resolution, become less important in the future, the focus will shift towards the delivery of automatic and reliable services. Most of the existing studies are of a scientific nature and achieve results of high quality based on intensive research. But emergency scenarios require a short response time, precluding lengthy periods of research. In addition, many scientific approaches produce results with high producer accuracies, while user's accuracy is insufficiently low for humanitarian-response purposes. Currently, therefore, there is still a trade-off between quality, speed, transferability, and the degree of automation. Both scientists and users need to collaborate in order to minimize these limitations. It is the scientists' task to develop robust methods based on both data and software which will be part of operational workflows. In turn, users of these services will have to specify their needs and contribute to calibration and validation in order to improve the methods and products.

While optical approaches are considerably closer to becoming operational (Drusch et al., 2012; Eisen & Lozano-Fuentes, 2009; San-Miguel-Ayanz & Ravail, 2005; Hielkema & Snijders, 1994), awareness of the potential and limitations of SAR data is needed to close this gap, as are people working with confidence with radar imagery. The increasing amounts of available data and a growing community contributing to open software development are ideal conditions for this.

Acknowledgements

This work was funded by the Austrian Research Promotion Agency (FFG) under the Austrian Space Applications Programme (ASAP 12, 854041). TerraSAR-X imagery was provided by the German Aerospace Center / DLR. ALOS imagery was provided by JAXA. Sentinel-1, ERS and ENVISAT imagery was provided by the European Space Agency.

References

Al-Yaari, A., Wigneron, J.-P., Ducharne, A., Kerr, Y., Wagner, W., De Lannoy, G., Reichle, R., Al Bitar, A., Dorigo, W., Richaume, P., & Mialon, A. (2014). Global-scale comparison of passive (SMOS) and active (ASCAT) satellite based microwave soil moisture retrievals with soil moisture simulations (MERRA-Land). Remote Sensing of Environment, 152, 614–626. doi:10.1016/j.rse.2014.07.013

Baghdadi, N., Aubert, M., & Zribi, M. (2012). Use of TerraSAR-X data to retrieve soil moisture over bare soil agricultural fields. IEEE Geoscience and Remote Sensing Letters, 9(3), 512–516.

Balz, T., & Liao, M. (2010). Building-damage detection using post-seismic high-resolution SAR satellite data. International Journal of Remote Sensing, 31(13), 3369–3391.

Bannon, I., & Collier, P. (2003). Natural resources and violent conflict: Options and actions: World Bank publications.

Bayer, T., Winter, R., & Schreier, G. (1991). Terrain influences in SAR backscatter and attempts to their correction. IEEE Transactions on Geoscience and Remote Sensing, 29(3), 451–462.

Braun, A., Lang, S., & Hochschild, V. (2016). Impact of Refugee Camps on Their Environment A Case Study Using Multi-Temporal SAR Data. Journal of Geography, Environment and Earth Science International, 4(2), 1–17. doi:10.9734/JGEESI/2016/22392

Brisco, B., & Brown, R. J. (2015). Drought Stress Evaluation in Agricultural Crops Using C-HH SAR Data. Canadian Journal of Remote Sensing, 16(3), 39–44. doi:10.1080/07038992.1990.11487623

Brunner, D., Bruzzone, L., Ferro, A., & Lemoine, G. (2009). Analysis of the reliability of the double bounce scattering mechanism for detecting buildings in VHR SAR images. In 2009 IEEE Radar Conference (pp. 1–6). doi:10.1109/RADAR.2009.4976983

Carreiras, J. M. B., Vasconcelos, M. J., & Lucas, R. M. (2012). Understanding the relationship between aboveground biomass and ALOS PALSAR data in the forests of Guinea-Bissau (West Africa). Remote Sensing of Environment, 121, 426–442.

Chen, S.-W., & Sato, M. (2013). Tsunami damage investigation of built-up areas using multitemporal spaceborne full polarimetric SAR images. IEEE Transactions on Geoscience and Remote Sensing, 51(4), 1985–1997.

Dabbagh, A. E., Al-Hinai, K. G., & Khan, M. A. (1997). Detection of sand-covered geologic features in the Arabian Peninsula using SIR-C/X-SAR data. Remote Sensing of Environment, 59(2), 375–382.

Drusch, M., Del Bello, U., Carlier, S., Colin, O., Fernandez, V., Gancon, F., Hoersch, B., Isola, C., Laberinti, P., Martimort, P., Maygret, A., Spoto, F., Sy, O., Marchese, F., & Bargellini, P. (2012). Sentinel-2: ESA's Optical High-Resolution Mission for GMES Operational Services. The Sentinel Missions - New Opportunities for Science, 120, 25–36. doi:10.1016/j.rse.2011.11.026

Dubois, P. C., van Zyl, J., & Engman, T. (1995). Measuring soil moisture with imaging radars. IEEE Transactions on Geoscience and Remote Sensing, 33(4), 915–926. doi:10.1109/36.406677

Eisen, L., & Lozano-Fuentes, S. (2009). Use of Mapping and Spatial and Space-Time Modeling Approaches in Operational Control of Aedes aegypti and Dengue. PLOS Neglected Tropical Diseases, 3(4), 1–7. doi:10.1371/journal.pntd.0000411

Engelbrecht, J., & Inggs, M. R. (2011). Detection and monitoring of surface subsidence associated with mining activities in the Witbank Coalfields, South Africa. In Geoscience and Remote Sensing Symposium (IGARSS), 2011 IEEE International (pp. 1596–1599). doi:10.1109/IGARSS.2011.6049452

Englhart, S., Keuck, V., & Siegert, F. (2011). Aboveground biomass retrieval in tropical forests—The potential of combined X-and L-band SAR data use. Remote Sensing of Environment, 115(5), 1260–1271.

Engman, E. T., & Chauhan, N. (1995). Status of microwave soil moisture measurements with remote sensing. Remote Sensing of Environment, 51(1), 189–198.

Ergünay, S. K., Kahraman, F., & Ates, H. F. (2013). Automated detection of refugee/IDP tents from satellite imagery using two-level graph cut segmentation. In Imaging and Mapping for Disaster Management.

Fransson, J. E. (1999). Estimation of stem volume in boreal forests using ERS-1 C-and JERS-1 L-band SAR data. International Journal of Remote Sensing, 20(1), 123–137.

Gentile, J., Gustafson, G., C., Kimsey, M., Kraenzle, H., Wilson, J., & Wright, S. (1997). Use of imagery and GIS for humanitarian demining management. In W. G. Fishell (Ed.): SPIE Proceedings, Optical Science, Engineering and Instrumentation '97 (pp. 104–109). SPIE. doi:10.1117/12.283928

Gruber, A., Wagner, W., Hegyiova, A., Greifeneder, F., & Schlaffer, S. (2013). Potential of Sentinel-1 for high-resolution soil moisture monitoring. In IGARSS 2013 - 2013 IEEE International Geoscience and Remote Sensing Symposium (pp. 4030–4033). doi:10.1109/IGARSS.2013.6723717

Guillaso, S., Ferro-Famil, L., Reigber, A., & Pottier, E. (2005). Building characterization using L-band polarimetric interferometric SAR data. IEEE Geoscience and Remote Sensing Letters, 2(3), 347–351.

Haile, M. (2005). Weather patterns, food security and humanitarian response in sub-Saharan Africa. Philosophical Transactions of the Royal Society B: Biological Sciences, 360(1463), 2169–2182.

Hielkema, J. U., & Snijders, F. L. (1994). Operational use of environmental satellite remote sensing and satellite communications technology for global food security and locust control by FAO: The ARTEMIS and DIANA systems. Acta Astronautica, 32(9), 603–616. doi:10.1016/0094-5765(94)90071-X

Imhoff, M. L. (1993). Radar backscatter/biomass saturation: Observations and implications for global biomass assessment. In Better Understanding of Earth Environment (Vol. 1, pp. 43–45). doi:10.1109/IGARSS.1993.322465

Jarvis, A., Reuter, H. I., Nelson, A., & Guevara, E. (2008). Hole-filled SRTM for the globe Version 4, available from the CGIAR-CSI SRTM 90m Database: Version 4.

Kaiser, R., Spiegel, P. B., Henderson, A. K., & Gerber, M. L. (2003). The Application of Geographic Information Systems and Global Positioning Systems in Humanitarian Emergencies: Lessons Learned, Programme Implications and Future Research. Disasters, 27(2), 127–140. doi:10.1111/1467-7717.00224

Kemper, T., & Heinzel, J. (2014). Mapping and Monitoring of Refugees and Internally Displaced People Using EO Data. Global Urban Monitoring and Assessment through Earth Observation, 195.

Kogan, F. N. (1997). Global Drought Watch from Space. Bulletin of the American Meteorological Society, 78(4), 621–636. doi:10.1175/1520-0477(1997)078

Kranz, O., Schoepfer, E., Sproehnle, K., & Lang, S. (2016). Earth observation for conflict mitigation and peacekeeping – from humanitarian relief to supporting peace and conflict studies.

Kuplich, T. M., Freitas, C. d. C., & Soares, J. V. (2000). The study of ERS-1 SAR and Landsat TM synergism for land use classification. International Journal of Remote Sensing, 21(10), 2101–2111.

Lang, S., Füreder, P., Kranz, O., & Papp, A. (2015). Humanitarian Emergencies: Causes, Traits, and Impacts as Observed by Remote Sensing. In Remote Sensing Handbook. Remote Sensing of Water Resources, Disasters, and Urban Studies (pp. 483–511). CRC Press. doi:10.120/b19321-29

Lee, J.-S. (1981). Speckle analysis and smoothing of synthetic aperture radar images. Computer graphics and image processing, 17(1), 24–32.

Long, S., Fatoyinbo, T. E., & Policelli, F. (2014). Flood extent mapping for Namibia using change detection and thresholding with SAR. Environmental Research Letters, 9(3), 35002.

Marx, A., & Goward, S. (2013). Remote Sensing In Human Rights And International Humanitarian Law Monitoring: Concepts And Methods. Geographical Review, 103(1), 100–111. doi:10.1111/j.1931-0846.2013.00188.x

Mason, D. C., Garcia-Pintado, J., Cloke, H. L., & Dance, S. L. (2016). Evidence of a topographic signal in surface soil moisture derived from ENVISAT ASAR wide swath data. International Journal of Applied Earth Observation and Geoinformation, 45, 178–186. doi:10.1016/j.jag.2015.02.004

Mitchard, E. T. A., Saatchi, S. S., Lewis, S. L., Feldpausch, T. R., Woodhouse, I. H., Sonké, B., Rowland, P., & Meir, P. (2011). Measuring biomass changes due to woody encroachment and deforestation/degradation in a forest–savanna boundary region of central Africa using multi-temporal L-band radar backscatter. Remote Sensing of Environment, 115(11), 2861–2873.

Mitchard, E. T. A., Saatchi, S. S., Woodhouse, I. H., Nangendo, G., Ribeiro, N.S., Williams, M., Ryan, C. M., Lewis, S. L., Feldpausch, T. R., & Meir, P. (2009). Using satellite radar backscatter to predict above- ground woody biomass: A consistent relationship across four different African landscapes. Geophysical Research Letters, 36(23).

Moran, M. S., Hymer, D. C., Qi, J., & Sano, E. E. (2000). Soil moisture evaluation using multi-temporal synthetic aperture radar (SAR) in semiarid rangeland. Agricultural and Forest Meteorology, 105(1), 69–80.

Paillou, P., Lopez, S., Farr, T., & Rosenqvist, A. (2010). Mapping subsurface geology in Sahara using L-Band SAR: First results from the ALOS/PALSAR imaging radar. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 3(4), 632–636.

Paloscia, S., Macelloni, G., Pampaloni, P., & Sigismondi, S. (1999). The potential of C-and L-band SAR in estimating vegetation biomass: the ERS-1 and JERS-1 experiments. IEEE Transactions on Geoscience and Remote Sensing, 37(4), 2107–2110.

Pierdicca, N., Pulvirenti, L., & Pace, G. (2014). A Prototype Software Package to Retrieve Soil Moisture From Sentinel-1 Data by Using a Bayesian Multitemporal Algorithm. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 7(1), 153–166. doi:10.1109/JSTARS.2013.2257698

Plank, S. (2014). Rapid damage assessment by means of multi-temporal SAR: A comprehensive review and outlook to Sentinel-1. Remote Sensing, 6(6), 4870–4906.

Quesney, A., Le Hégarat-Mascle, S., Taconet, O., Vidal-Madjar, D., Wigneron, J. P., Loumagne, M., & Normand, M. (2000). Estimation of watershed soil moisture index from ERS/SAR data. Remote Sensing of Environment, 72(3), 290–303.

Reigber, A., Jager, M., He, W., Ferro-Famil, L., & Hellwich, O. (2007). Detection and classification of urban structures based on high-resolution SAR imagery. In 2007 Urban Remote Sensing Joint Event (pp. 1–6). doi:10.1109/URS.2007.371819

Ryan, C. M., Hill, T., Woollen, E., Ghee, C., Mitchard, E., Cassells, G., Grace, J., Woodhouse, I.H., & Williams, M. (2012). Quantifying small- scale deforestation and forest degradation in African woodlands using radar imagery. Global Change Biology, 18(1), 243–257.

Saatchi, S. S., Harris, N. L., Brown, S., Lefsky, M., Mitchard, E.T., Salas, W., Zutta, B.R., Buermann, W., Lewis, S.L., Hagen, S., Petrova, S., White, L., Silman, M., & Morel, A. (2011). Benchmark map of forest carbon stocks in tropical regions across three continents. Proceedings of the National Academy of Sciences, 108(24), 9899–9904.

San-Miguel-Ayanz, J., & Ravail, N. (2005). Active Fire Detection for Fire Emergency Management: Potential and Limitations for the Operational Use of Remote Sensing. Natural Hazards, 35(3), 361–376. doi:10.1007/s11069-004-1797-2

Schlaffer, S., Matgen, P., Hollaus, M., & Wagner, W. (2015). Flood detection from multi-temporal SAR data using harmonic analysis and change detection. International Journal of Applied Earth Observation and Geoinformation, 38, 15–24.

Shi, J., Wang, J., Hsu, A. Y., O'Neill, P.E., & Engman, E. T. (1997). Estimation of bare surface soil moisture and surface roughness parameter using L-band SAR image data. IEEE Transactions on Geoscience and Remote Sensing, 35(5), 1254–1266. doi:10.1109/36.628792

Simonetto, E., Oriot, H., & Garello, R. (2005). Rectangular building extraction from stereoscopic airborne Radar images. IEEE Transactions on Geoscience and Remote Sensing, 43(10), 2386–2395. doi:10.1109/TGRS.2005.853570

Solberg, A. H. S., Jain, A. K., & Taxt, T. (1994). Multisource classification of remotely sensed data: fusion of Landsat TM and SAR images. IEEE Transactions on Geoscience and Remote Sensing, 32(4), 768–778.

Song, C., Woodcock, C. E., Seto, K. C., Lenney, M. P., & Macomber, S. A. (2001). Classification and Change Detection Using Landsat TM Data: When and How to Correct Atmospheric Effects? Remote Sensing of Environment, 75(2), 230–244. doi:10.1016/S0034-4257(00)00169-3

Sportouche, H., Tupin, F., & Denise, L. (2009). Building extraction and 3D reconstruction in urban areas from high-resolution optical and SAR imagery. In 2009 Joint Urban Remote Sensing Event (pp. 1–11). doi:10.1109/URS.2009.5137746

Spröhnle, K., Tiede, D., Schoepfer, E., Füreder, P., Svanberg, A., & Rost, T. (2014). Earth Observation-Based Dwelling Detection Approaches in a Highly Complex Refugee Camp Environment: A Comparative Study. Remote Sensing, 6(10), 9277–9297.

Srivastava, H. S., Patel, P., Manchanda, M. L., & Adiga, S. (2003). Use of multiincidence angle RADARSAT-1 SAR data to incorporate the effect of surface roughness in soil moisture estimation. IEEE Transactions on Geoscience and Remote Sensing, 41(7), 1638–1640.

Thiele, A., Cadario, E., Schulz, K., Thönnessen U., & Soergel, U. (2007). Building Recognition From Multi-Aspect High-Resolution InSAR Data in Urban Areas. IEEE Transactions on Geoscience and Remote Sensing, 45(11), 3583–3593. doi:10.1109/TGRS.2007.898440

Tiede, D., Füreder, P., Lang, S., Hölbling, D., & Zeil, P. (2013). Automated Analysis of Satellite Imagery to provide Information Products for Humanitarian Relief Operations in Refugee Camps. Photogrammetrie-Fernerkundung-Geoinformation, 2013(3), 185–195.

Tomás, R., Márquez, Y., Lopez-Sanchez, J. M., Delgado, J., Blanco, P., Mallorqui, J. J., Martinez, M., Herrera, G., & Mulas, J. (2005). Mapping ground subsidence induced by aquifer overexploitation using advanced Differential SAR Interferometry. Remote Sensing of Environment, 98(2), 269–283.

Ulaby, F. T., Moore, R. K., & Fung, A. K. (1981). Microwave remote sensing: Active and passive. volume 1-microwave remote sensing fundamentals and radiometry.

Verjee, F., & Gachet, A. (2007). Mapping Water Potential: The Use of WATEX to Support UNHCR Refugee Camp Operations in Eastern Chad. Perspectives on Social Vulnerability, 94.

Voigt, S., Schoepfer, E., Fourie, C., & Mager, A. (Eds.) 2014. Towards semi-automated satellite mapping for humanitarian situational awareness: IEEE.

Warren, S. G., Hahn, C. J., London, J., Chervin, R. M., & Jenne, R. L. (1986). Global distribution of total cloud cover and cloud type amounts over land. NCAR Tech. Note TN-273+STR. URL: http://opensky.ucar.edu/islandora/object/technotes%3A444/datastream/PDF/download/citation.pdf

Wegner, J. D., Hansch, R., Thiele, A., & Soergel, U. (2011). Building Detection From One Orthophoto and High-Resolution InSAR Data Using Conditional Random Fields. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 4(1), 83–91. doi:10.1109/JSTARS.2010.2053521

Wendt, L., Robl, J., Hilberg, S., Braun, A., Rogenhofer, E., Dirnberger, D., Strasser, T., Füreder, P., & Lang, S. (2015). Assisting Groundwater Exploration for Refugee/IDP Camps by Remote Sensing and GIS. In EGU General Assembly Conference Abstracts (Vol. 17, p. 2912).

Yu, Y., & Saatchi, S. (2016). Sensitivity of L-Band SAR Backscatter to Aboveground Biomass of Global Forests. Remote Sensing, 8(6), 522. doi:10.3390/rs8060522