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# Grand Challenges in Microwave Remote Sensing

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## INTRODUCTION

The last two decades have seen tremendous technological advances in the field of remote sensing, especially in sensor developments, such as considerable improvements in onboard processing, miniaturization of hardware and more efficient modes of communication and data connectivity. This significant technological progress has led to not only a proliferation of satellite Earth observation data, from both public missions and commercial missions operated by the private sector industry, but also a massive increase in big data acquired by airborne sensors, in particular onboard remotely piloted systems (unmanned aerial vehicles–UAVs or drones).

At the same time, compute processing power and computing infrastructure, especially online cloud computing, have greatly advanced, making high-performance computing now available at affordable and supported services to almost anyone connected to the internet. This development, coupled with the open data policies of many governments, organizations, and EO programs, has resulted in a quick and steady rise of research studies and downstream business applications that use remote sensing data at the core of their applications.

For remote sensing applications, particularly for satellite remote sensing, microwave sensors are of particular interest and growing rapidly in popularity for many applications. The reason for this is because, physically speaking, the microwave signals can easily penetrate clouds, are independent of daylight and remain largely unaffected by rain. However, many challenges related to different environments and applications remain, and just a few major ones are outlined hereafter.

## SENSOR TECHNOLOGY

Many applications still present a number of important technological and methodological challenges, such as soil moisture retrieval from (passive) radiometry or active synthetic aperture radar (SAR) or the generation of topographic datasets that are accurate enough for given application requirements. For example, Global Navigation Satellite Systems-Reflectometry (GNSS-R) is an emerging remote sensing technique that makes use of navigation signals to map global soil moisture fields and vegetation characteristics (Camps et al., 2016) and has even shown promise for tropical wetland mapping (Rodriguez-Alvarez et al., 2019) or potential for operational flood mapping (Chew et al., 2018). Despite these first demonstrations of success, the methods are far from ready to be used for developing robust downstream applications.

In addition, radar sensing technology developed for very specific applications, such as the Ka-band sensor onboard the upcoming Surface Water and Ocean Topography (SWOT) mission that will measure river width, slope, water level, and discharge measurements (Frasson et al., 2019) as well as

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fine-scale detail in the global ocean surface topography (Morrow et al., 2019), still need to be more fully investigated in terms of their accuracy and limitations for the target applications.

## APPLICATION ENVIRONMENTS

The most widely used radar frequencies on SAR sensors onboard civil satellites (C- and X-band) cannot fully penetrate vegetation cover, which for many applications, such as wetland conservation and ecological studies as well as flood mapping and monitoring water changes, would be highly desirable. In the case of SAR, vegetation typically causes diffusive and volume scattering and at short wavelengths (C- or X-band), most signals do not penetrate dense vegetation cover (Schumann and Moller, 2015). At longer radar wavelengths (e.g., L- or P-band), however, several successful approaches have been developed and been demonstrated [see for example, Hess et al. (1990) for an extensive review], although satellites carrying L-band sensors are fewer and images are currently not freely available. Even at shorter, more commonly used wavelengths, such as C- or X-band, approaches have been published (Pierdicca et al., 2017; Plank et al., 2017; El Hajj et al., 2019; Grimaldi et al., 2020) but their application has only seen limited success. Multi-satellite data, including passive microwave, have also been used successfully to map global wetland inundation dynamics (Prigent et al., 2012) and recent innovative approaches have looked at GNSS-R technology to improve the mapping of flooded forests (Rodriguez-Alvarez et al., 2019).

Another challenging environment for SAR is in urban areas. For example, most people and valuable assets at risk from flooding are located in urban areas, so it is obviously desirable to map flooding in those areas. However, urban areas in flood present important challenges: inadequate spatial resolution; high building density obstructing street view; many different building types and a large variety of other man-made features which cause a lot of signal distortion; obstruction by cloud cover; and mixing of many different land cover types that are flooded and non-flooded. In fact due to these challenges, at present, accurate remote sensing of urban flooding seems restricted either to aerial photography (Yu and Lane, 2006), dGPS-generated wrack marks (McMillan and Brasington, 2007; Neal et al., 2009) or the use of high resolution LiDAR intensity data (Hoefle et al., 2009). Some successes have been shown using space-borne fine resolution SAR particularly sensors like TerraSAR-X or COSMO-SkyMed (Mason et al., 2010; Chini et al., 2012; Giustarini et al., 2013). However, more fundamental research is required into understanding the complex interactions between building structure and SAR signal processing as well as noise reduction and shadow/layover effects. Parts of those complex issues can be solved by employing a theoretical scattering model (Franceschetti et al., 2003) as demonstrated by Mason et al. (2014) or by making use of complementary SAR signal information contained in signal polarization modes or signal coherence (Chini et al., 2016; Chaabani et al., 2018), which has been shown recently to hold most promise for reliable operational urban flood mapping (Chini et al., 2019).

## PROCESSING ALGORITHMS

Within the application environments challenges described above, there are some pitfalls that can significantly limit the success for solutions or indeed make robust and reliable solutions difficult to develop. For instance, the rapidly and constantly changing nature of urban landscapes and vegetation dynamics over different spatial and temporal scales poses a difficult problem to addressing the challenge of mapping inundation below vegetation canopy and in urban areas. Although characterizing and simulating or predicting the various signal interactions in these complex and dynamic environments is possible and the theoretical basis of doing so is known and robust [see for example, Pulvirenti et al. (2011)], practical application of the mathematical models that need to be part of the solution requires expert SAR signal knowledge. Therefore, at least for the moment, promising operational solutions that have been proposed, for example, for flood mapping from SAR under different types of vegetation or urban areas are limited to only a few papers as outlined in the previous section. This is particularly true for urban flood mapping that received only recently the attention it deserves using complex SAR signal coherence processing (Chini et al., 2019; Li et al., 2019a; Li et al., 2019b).

More recently, machine learning algorithms have gained hugely in popularity and have seen much progress, despite their application to satellite images dating back at least 25 years, even for SAR imagery (Chen et al., 1996; Kubat et al., 1998). Recent applications of machine learning models to SAR imagery include methods to map oil spills (Chen et al., 2017) and sea ice (Lee et al., 2016), detect ships (Schwegmann et al., 2016), and monitor floods in urban areas (Li et al., 2019a), just to name a few. However, one of the main challenges that needs to be urgently addressed with respect to machine learning and SAR in particular, is that of open-access image archives being relatively short in record length but image volumes are prohibitively large, thus making open data sharing across online cloud compute platforms running machine learning algorithms rather difficult and, consequently, progress may be slower than expected. Moreover, microwave data are complex and images are not easily interpretable, compared to optical imagery which the human eye is much more accustomed to. Nevertheless, there have been some notable efforts in the past year to prepare SAR datasets specifically for machine learning applications and make them as well as labels easily available (Wang et al., 2019; Bonafilia et al., 2020).

## OUTLOOK

Microwave remote sensing, whether passive or active sensors onboard satellite or airborne platforms, has kept its promise to be an inviting alternative to optical and thermal remote sensing for many applications, especially to measure and monitor Earth surface and even sub-surface processes when those are obscured by clouds or vegetation. With the proliferation of current and planned satellite missions, including commercial satellites, carrying microwave sensors and providing high-repeat big data, there is a growing need to overcome existing technological challenges, improve methods and facilitate data sharing and compute processing, so that data can be turned into actionable information more seamlessly and become available to end-users at an adequate operational readiness level. It is clear that, to achieve this, many challenges still need to be addressed, of which many are related to the development of robust, sharable and interoperable operational algorithms that are independent of satellite and image type and can be applied in a variety of environments (Schumann and Moller, 2015).

## AUTHOR CONTRIBUTIONS

I confirm that I have written all of this article myself and it only expresses my opinion and views.

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