Better together: Integrating and fusing multispectral and radar satellite imagery to inform biodiversity monitoring, ecological research and conservation science

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Abstract

1. The availability and accessibility of multispectral and radar Satellite Remote Sensing (SRS) imagery are at an unprecedented high. These data have both become standard source of information for investigating species ecology and ecosystems structure, composition and function at large scales. Since they capture complementary aspects of the Earth's surface, synergies between these two types of imagery have the potential to greatly expand research and monitoring opportunities. However, despite the benefits of combining multispectral and radar SRS data, data fusion techniques, including image fusion, are not commonly used in biodiversity monitoring, ecology and conservation.

2. To help close this application gap, we provide for the first time an overview of the most common SRS data fusion techniques, discussing their benefits and drawbacks, and pull together case studies illustrating the added value for biodiversity research and monitoring.

3. Integrating and fusing multispectral and radar images can significantly improve our ability to assess the distribution as well as the horizontal and vertical structure of ecosystems. Additionally, SRS data fusion has the potential to increase opportunities for mapping species distribution and community composition, as well as for monitoring threats to biodiversity. Uptake of these techniques will benefit from more effective collaboration between remote sensing and biodiversity experts, making the reporting of methodologies more transparent, expanding SRS image processing capacity and promoting widespread open access to satellite imagery.

4. In the context of a global biodiversity crisis, being able to track subtle changes in the biosphere across adequate spatial and temporal extents and resolutions is crucial. By

making key parameter estimates derived from SRS data more accurate, SRS data fusion promises to become a powerful tool to help address current monitoring needs, and could support the development of Essential Biodiversity Variables.

Keywords: Image fusion, object-level fusion, pixel-level fusion, remote sensing of biodiversity, satellite data fusion

Introduction

Satellite Remote Sensing (SRS) data from both radar and multispectral sensors have become a standard source of information for investigating species' ecology and ecosystems distribution and dynamics at large spatial scales (Buchanan et al. 2009; Pettorelli et al. 2014a). These two types of sensors acquire information about the Earth's surface in fundamentally different ways: whilst multispectral sensors passively measure electromagnetic radiation reflected from the Earth's surface, radar sensors are active, meaning they emit electromagnetic radiation and then measure the returning signal. Multispectral sensors capture information on chemical properties of surfaces, such as nitrogen or carbon content and moisture (Asner 1998; Tempfli et al. 2009), whereas radar responds to the three-dimensional structure of objects, being sensitive to their orientation, volume and surface roughness (Treuhaft et al. 2004). Additionally, radar sensors penetrate atmospheric conditions that incapacitate multispectral sensors, such as clouds, haze and fog, and can (depending on wavelength) return information from below the canopy (Santoro et al. 2007) or even from subsurface layers (McCauley et al. 1982). However, even though multispectral and radar sensors detect complementary aspects of the Earth's surface (Lahat et al. 2015), the two types of data are so far not routinely combined in biodiversity monitoring and ecological research.

To capitalise on the complementary characteristics of multispectral and radar sensors, their data needs to be integrated systematically, in a process generally called data fusion (Wald 1999). SRS data fusion can occur at three levels of analysis (Pohl & van Genderen 1998; Fig. 1). First, imagery from different sensors can be used as separate predictors to estimate a parameter of interest. This includes using multispectral and radar imagery jointly in a classification algorithm (Haack et al. 2002; Naidoo et al. 2016) or a statistical model (van der Wal & Herman 2007; Hamdan et al. 2014; Poggio & Gimona 2017). This is commonly referred to as *decision-level fusion*. Second, multispectral and radar imagery can be fused to derive entirely new predictors. This type of fusion includes *object-level fusion*, in which a landscape is divided into multi-pixel objects based on information from different remote sensors (Blaschke 2010), and *pixel-level fusion*, where pixel values are combined to derive a fused image with new pixel values, either in the spatial (Zhang 2010) or the temporal (Reiche et al. 2015a) domain. Since both pixel- and object-level fusions result in a new image, we will here refer to them as image fusion. When referring to decision-level fusion of SRS imagery, we will use the term "SRS data integration", to emphasise that the SRS imagery remains separate. "SRS data fusion" refers to both SRS data integration and image fusion (Box 1).

The routine use of SRS data fusion in ecology and conservation science has been previously hampered by the need for intensive pre-processing, especially precise image co-registration (Pohl 1999). However, this obstacle has recently been removed with the launch of the ESA satellites Sentinel 1 and 2, which provide multispectral and radar imagery at high spatial and temporal resolutions, co-registered to sub-pixel accuracy, making these data suitable for direct use in SRS data fusion (Berger et al. 2012). As a result, there is now an unprecedented opportunity for ecologists and conservation scientists to capitalise on the opportunities associated with SRS data fusion. Whilst the benefits of data fusion for land cover and land use classification have recently been reviewed (Joshi et al. 2016), there is currently no overview detailing its potential applications in ecology and conservation. To address this literature gap, we here aim to (1) introduce relevant multispectral-radar SRS data fusion techniques, outlining their benefits and limitations, (2) illustrate situations where multispectral-radar SRS data fusion adds value over using a single source of data, and (3) outline existing limitations to the widespread use of SRS data fusion in ecology and conservation science, and discuss how these can be overcome. Because the application of multispectral-radar SRS data fusion in biodiversity monitoring is relatively new, we here aim to provide an overview over the variety of possible applications and opportunities arising from it, rather than present a systematic literature review.

Overview of multispectral-radar SRS data fusion techniques, their benefits and limitations

A wide variety of pixel- and object-level techniques for multispectral-radar SRS data fusion exists (Pohl & Yen 2014; Fig. 2), each with specific advantages and weaknesses.

Pixel- or observation-level fusion occurs when corresponding pixel values from multispectral and radar images are combined to produce a new pixel value (Zhang 2010; Fig. 2), which is then used in the subsequent analysis instead of the original multispectral and radar values. Pixel-level fusion reduces the amount of information available later on, meaning that relevant patterns could be lost (Zhang 2010), but further processing can be significantly sped up because data volume is reduced. One further issue with this type of fusion is that it can lead to the production of new variables that can be difficult to interpret and relate to ecologically meaningful entities.

There are three main classes of pixel-fusion techniques: Component substitution, multi-resolution analysis and arithmetic (or modulation-based) techniques (Zhang 2010).

(1) *Component substitution techniques* such as principal component analysis (PCA) (Yonghong 1998; Fu et al. 2017) and intensity-hue-saturation (IHS) transformation (Chen et al. 2003; Leung et al. 2014) are among the most widely used pixel-fusion techniques (Pohl & Yen 2014). During PCA fusion, the original pixel values extracted from the radar and multispectral images are used to define new axes along which data variability is maximised; the new, fused pixel values are essentially linear combinations of their position along these new axes (Amarsaikhan et al. 2012). PCA image fusion is the only pixel-level image fusion technique that cannot be applied to imagery with different spatial resolutions. It is also the only pixel-level fusion technique that allows a theoretically unlimited number of multispectral and radar images to be fused; others typically limit this number to four (Pohl & van Genderen 1998). IHS fusion represents another type of component substitution technique for pixel-level fusion, whereby three images with lower spatial resolution (typically multispectral data) are integrated with a single image with high spatial resolution (typically radar; Zhang 2010; Lu et al. 2011) to retain the radiometry but increase the spatial resolution of the former. Since the resulting images can be combined into a single RGB image, IHS fusion can facilitate visual interpretation (Zhang 2010). This process is similar to pansharpening, in which multispectral imagery with high spatial resolution is used to "sharpen" multispectral imagery with low spatial resolution, whilst maintaining the spectral information of the latter.

(2) *Multi-resolution analysis*, such as wavelet transformation (Zhang 2010; Lu et al. 2011; Wang et al. 2016), is another broad type of pixel-level fusion, which starts with the decomposition of multispectral and radar imagery into their respective low- and high-frequency components (Lu et al. 2011). The wavelet transform of an image with low spatial resolution (typically multispectral) is used to replace the low-frequency transform of imagery with a higher spatial resolution (typically radar) before the fused image is reconstituted from the combined transforms. Wavelet transformations typically require a lot of computational resources for processing (Pohl & Yen 2014), but tend to be better at preserving the radiometry of the imagery with the lower spatial resolution than component substitution techniques such as PCA and IHS (Lu et al. 2011; Pohl & Yen 2014).

(3) *Arithmetic fusion techniques* such as the Brovey transform algorithm (Zhang 2010) and high pass filtering (HPF; Zhang 2010; Lu et al 2011) are techniques occasionally used in pixel-level SRS image fusion (Pohl & Yen 2014). They involve combining the original pixel values of high and low spatial resolution imagery in a linear expression to "sharpen" imagery with low spatial resolution (Zhang 2010; Lu et al. 2011). Arithmetic fusion techniques do not deal well with imagery from different types of sensors, because they are based on the assumption that pixel values in the fused image are linear combinations of those in the original images (Zhang 2010), which may not be the case when combining multispectral and radar SRS data. Additionally, they do not typically perform well if there is a small or no difference in spatial resolution between the images to be fused (Zhang 2010). As a

result, arithmetic fusion techniques are unlikely to be appropriate for multispectral-radar SRS image fusion.

Object-or feature-level fusion means that objects such as lines, shapes or textures are extracted from radar and multispectral imagery, based on brightness and intensity values of each pixel, as well as its spatial context, which are then used in subsequent analyses (Zhang 2010). Under our definition of image fusion, this includes two techniques: First, multispectral and radar SRS images with the same spatial resolution can be fused via image segmentation, during which they are used jointly to split an area of interest into homogeneous, discrete and contiguous objects (Blaschke 2010; Fig. 2). This is the most commonly used object-based image analysis technique (Blaschke 2010). Second, objects can be extracted separately from multispectral and radar SRS data (of the same or different spatial resolution) and combined in a feature map, which is then used in subsequent analyses (Lisini et al. 2011). Object-based fusion reduces all multispectral and radar information into a single layer of discrete objects, which are often relatively easy to relate to ecological features. As a result, object-level fusion may facilitate the mapping of non-overlapping land cover classes because it reduces the number of objects that have to be classified. By contrast, pixel-based methods may be more suitable for mapping variables that vary significantly at spatial scales smaller than a given object, since they preserve the unique spectral and radar signal for each pixel.

Decision-level fusion, or SRS data *integration*, does not require an additional processing step; rather, SRS imagery from different sensors are combined as separate predictors in a quantitative decision-making framework – such as a regression, a quantitative model or a classification algorithm. Since SRS data integration is spatially explicit, it requires the same accurate co-registration and pre-processing as SRS image fusion techniques.

The SRS data fusion techniques detailed above are typically used separately (e.g. Lu et al. 2011); however, the development of hybrid techniques is an active research field, adding to the large choice of available techniques (Souza-Filho et al. 2009; Pohl & Yen 2014). The quality of information obtained through data fusion can vary significantly depending on the choice of the technique to be used (or combinations of techniques, e.g. Waske & Benediktsson 2007; Lisini et al. 2011; Lu et al. 2014; Wang et al. 2016). Since there is no coherent framework to choose the optimal technique given the large range of data types and applications, the current best practice is to test several different fusion methods on a representative subset of the area of interest, to gauge which approach may give the best results.

Benefits for ecology, biodiversity research and conservation science

Biodiversity is here defined as the structural, compositional and functional diversity of life, at different levels of organisation, including the genetic, species/population, and ecosystem levels (Noss 1990). Applications of multispectral-radar SRS data fusion (both image fusion and data integration) in biodiversity monitoring, ecology and conservation have the potential to improve the estimation of a wide range of key parameters, including 1) species distribution and community composition, 2) ecosystem distribution and structure, and 3) threats to biodiversity (Box 1; see Table 1A for case studies using image fusion, Table 1B for case studies for SRS data integration).

Species distribution and community composition

Species distribution and community composition are central topics in macroecology, biogeography, conservation science and environmental management (Myers et al. 2000; McDowall 2004; Keith et al. 2012). Species is here understood as a group of organisms sharing a unique, fixed set of heritable traits that allows them to be distinguished from other such groups (Cracraft 1987, Sangster 2014), whilst a community is defined a set of species co-occurring at a given time and place (McGill et al. 2006).

If a species of interest significantly affects the reflectance or backscatter signal received by a sensor, its distribution can be mapped directly from SRS (He et al. 2015). Whilst Light Detection and Ranging (LiDAR) and hyperspectral imagery (Box 1) is often recommended for mapping species directly, especially trees (e.g. Jones et al. 2010, Dalponte et al. 2012, Alonzo et al. 2014, Gosh et al. 2014), it is not possible (at present) to scale up these efforts to regional or continental scales, and systematically repeat them, since there are currently no active spaceborne LiDAR or hyperspectral missions. Due to the relatively coarse spatial resolution of most freely available multispectral and radar imagery (Fig. 3), direct species detection using this type of information has thus been mostly limited to mapping relatively large, homogenous stands of plants (e.g. Bradley & Mustard 2006, Gavier-Pizarro et al. 2012). In this context, multispectral-radar imagery fusion has the potential to improve mapping of sufficiently large stands of plants with subtly different growth forms or phenology. For instance, Hong and colleagues (2014) were able to map stands of alfalfa *Medicago sativa* in grasslands by fusing radar backscatter (from the RADARSAT-2 sensor) and multispectral radiance (from the MODIS sensor) via IHS transformation, essentially pan-sharpening the MODIS imagery before classification. This image fusion improved overall distribution mapping accuracy by 11% and 20% compared to using multispectral and radar data alone, respectively. The complementary strengths of multispectral and radar sensors can also be exploited by integrating them at the decision level to support species distribution mapping efforts. For instance, Ghulam et al. (2014) mapped three invasive plant species in a tropical forest by combining multispectral-derived information on vegetation type (from IKONOS and Geo-Eye-1) and radar-derived information on canopy structure (from ALOS PALSAR/RADARSAT-2) in a decision tree framework. The authors did not quantify how integrating these SRS data affected mapping accuracy compared to using a single data source, but they did report that the detection of one of the species was not possible based on multispectral SRS alone.

Indirect species mapping is based on the principle that remotely sensed variables reflect habitat conditions that in turn are related to species distribution (He et al. 2015). Usually, rather than fusing imagery, multispectral and radar SRS data are integrated as distinct predictor variables in species distribution models. For bird species in particular, vertical habitat structure is important (Bergen et al. 2009), and may be better captured by radar backscatter than more indirect parameters derived from multispectral SRS, such as forest cover (Buermann et al. 2008; Culbert et al. 2013). For instance, Bergen et al. (2007) found that integrating radar-derived biomass information with vegetation type derived from multispectral SRS data increased the accuracy with which the distribution of bird species could be predicted. A similar approach has been used to predict the distribution of trees species across South America, using the Leaf Area Index (LAI) and the Normalised Difference Vegetation Index (NDVI) data (both derived from multispectral SRS; Box 1) in combination with canopy moisture and roughness metrics derived from radar data (Prates-Clark et al. 2008). Notably, in some of the above examples, the size of the study area was several million square kilometres (Table 1), illustrating the potential offered by SRS data fusion for large-scale habitat mapping.

Compared to direct and indirect monitoring of species, SRS data fusion has rarely been applied to support the monitoring of communities. One exception to this pattern is the study by Wolter & Townsend (2011), who mapped the relative basal area of different tree species in a temperate forest after fusing multispectral and radar imagery (Landsat TM/SPOT-5 and RADARSAT-1/ALOS PALSAR respectively). In this particular situation, SRS image fusion improved the accuracy with which community composition was estimated, likely because the sensors had complementary strengths in detecting different tree species.

Ecosystem distribution and structure

Changes in ecosystem distribution and condition is at the heart of ecosystem accounting (UNSD SEEA-EEA 2013; Mace et al. 2015), and plays an important role in ecosystem risk assessments (Nicholson et al. 2009) such as the Red List of Ecosystems (Keith et al. 2013). Ecosystem here refers to a community, an associated abiotic environment, the interactions among and between them, and the physical space in which they interact (Tansley 1935; Pickett & Cadenasso 2002). SRS data fusion has been used to estimate a wide range of parameters informing the distribution of ecosystems, as well as parameters related to the horizontal and vertical structure of ecosystems (Table 1).

Ecosystem distribution

Multispectral-radar SRS data fusion generally increases land cover classification accuracy (Joshi et al. 2016), allowing the separation of subtly different land cover types. This is relevant for biodiversity monitoring where it allows distinguishing between different types of ecosystems, vegetation types or geomorphological structures. Integrating multispectral and radar data at the decision level has been shown to increase accuracy of forest type mapping. SRS data integration has been mainly applied in tropical rainforests (e.g. Laurin et al. 2013), though such efforts have also been successful in temperate regions (e.g. Hégart-Mascle et al. 1998, Polychronaki et al. 2014, Barrett et al. 2016). This is likely because multispectral and radar sensors respond to different characteristics of forest stands: whilst multispectral data picks up on differences in vegetation "greenness", radar backscatter contains information about canopy volume, and thus helps distinguish different stages of regrowth, or structurally distinct plantations from natural forests (e.g. Dong et al. 2013). This point is well illustrated by Rignot and colleagues' work (1997) in the Amazon, which combined forest maps derived from Landsat 5 TM and SIR-C radar imagery to distinguish primary from secondary forest, as well as several regrowth stages. The combined approach allowed distinguishing a higher number of forest categories at high accuracy than using either data type alone. In some cases, image fusion can have additional benefits over SRS data integration: Lu and colleagues (2014) for example argue that multispectral-radar SRS image fusion (Landsat TM and ALOS PALSAR L-band respectively) enables a better distinction between different stages of tropical forest succession than is achieved by integrating the same SRS data using a classification algorithm. Fusion of multispectral with longwave radar in particular facilitates mapping succession stages in tropical forests (Lu et al. 2011), potentially because it penetrates the canopy to a greater degree than shortwave radar (Baghdadi et al. 2009). Similarly, Morel et al. (2012) reported that effectively combining multispectral and radar at the *post-decision* stage (i.e. combining maps derived from each sensor separately) is less effective than SRS image fusion or data integration for improving forest detection accuracies.

In addition to forest mapping, wetland mapping efforts can benefit from multispectral-radar synergies, mostly via object-level image fusion (Table 1; but see Bwangoy et al. 2010 for an example of multispectral-radar SRS data integration applied to tropical wetlands). The rationale for combining multispectral and radar imagery for wetland monitoring is that radar imagery allows the mapping of surface water or wet soils, even beneath a canopy (Bourgeau-Chavez et al. 2009), whilst multispectral data responds to vegetation and wetness in open canopies. Multispectral-radar image fusion has been used to distinguish between geomorphological structures in wetlands (Hamilton et al. 2007, Souza-Filho et al. 2009), or different vegetation types (Bourgeau-Chavez et al. 2009, 2016). However, these studies did not compare mapping accuracy achieved after image fusion to that achieved by using a single type of sensor, so it is unclear what the added value of image fusion was in these cases. Some insights are provided by Fu et al. (2017), who found that fusing ALOS-PALSAR/RADARSAT-2 and multispectral imagery from GF-1 increased mapping accuracy of wetland vegetation types beyond that achieved by using these data on their own. Similarly, when multispectral and radar imagery (Landsat TM5 and ALOS PALSAR, respectively) were integrated in a classification tree modelling approach, misclassification of different types of wetland vegetation and the extent of standing water were significantly reduced (Ward et al. 2014). Nevertheless, benefits of multispectral-radar

SRS data fusion may vary by wetland class (Maillard et al. 2008; Robertson et al. 2015) or with patch size (Gala & Melesse 2012).

Horizontal structure

Apart from enabling a better assessment of ecosystem and vegetation type distributions, integrating multispectral and radar imagery can also support efforts to estimate continuous parameters that characterise horizontal ecosystem structure related to canopy or soil structure. Horizontal ecosystem structure is here understood as the horizontal arrangement of ecosystem components in space (Bergen et al. 2009). Naidoo et al. (2016) for example reported that woody canopy cover is more accurately estimated when adding ALOS PALSAR and Landsat TM to a Random Forest algorithm (instead of using ALOS PALSAR on its own). Similarly, Cartus et al. (2011) successfully mapped tree stem density across 1,5 mio km^2 of forest using on ERS-1 and 2 imagery and the MODIS Vegetation Continuous Field product. Multispectral-radar SRS data integration has also helped map sediment grain size in intertidal flats (van der Wal & Herman 2007), as well as soil properties such as moisture (Wang et al. 2004) and chemical or physical composition (Poggio & Gimona 2017).

Vertical structure

Estimating the vertical structure of ecosystems, which refers to the vertical arrangement of ecosystem components in space (Bergen et al. 2009), can be facilitated by SRS image fusion and data integration. So far, the focus has been on forest ecosystems and monitoring biomass, as demonstrated by Basuki and colleagues (2013) who used multispectral-radar image fusion to assess aboveground biomass in tropical forests. Others have derived biomass from integrating multispectral and radar data in quantitative (Wang & Qi 2008) or empirical (Hyde et al. 2006, Ismail et al. 2015) models. Hyde et al. (2006) found that whilst LiDAR does provide more accurate estimates of canopy height and biomass on its own, integrating multispectral and airborne (X-band) radar data could achieve comparable accuracies, much higher than that achieved by either sensor type alone. This result is echoed by Hamdan et al. (2014) and Attarchi & Gloaguen (2014), who both used spaceborne L-band radar to estimate biomass in tropical and temperate forests respectively. This suggests that integrating or fusing multispectral and radar imagery could provide an important opportunity to improve biomass monitoring in the absence of a spaceborne LiDAR sensor. Apart from estimating biomass, multispectral and radar imagery have been fused to monitor forest height (Walker et al. 2007; Kellndorfer et al. 2010) with moderate accuracy (R^2 between 0.7 and 0.9) when validated against forest inventory or LiDAR-derived samples of forest height. However, since these studies did not explicitly compare the accuracy of their models with and without data fusion, it is unclear to which extent combining the data types benefited them.

Threats to biodiversity

Being able to detect threats to biodiversity at all levels of biological and ecological organisation is necessary to prioritise areas for conservation (Joppa et al. 2016), plan conservation interventions (Pressey & Botrill 2008; Tulloch et al. 2015) and understand the processes that shape biodiversity across a landscape (Shea et al. 2004). So far, SRS data fusion has rarely been applied to detect threats to biodiversity, but some promising case studies have emerged, mainly mapping deforestation across medium-sized study areas (hundreds or thousands of square kilometres, Table 1). It's worth mentioning here that deforestation mapping has a different focus than forest distribution assessments: deforestation mapping aims to optimise the identification of areas where trees have been removed by humans, whereas forest mapping seeks to optimise the assessment of forest extent, often aiming to distinguish between different forest types (e.g. successional stages, Lu et al. 2011, 2014), and/or quantify forest condition.

Combining multispectral and radar imagery has been shown to improve deforestation monitoring and reduce the lag between a deforestation event and its detection in areas where multispectral SRS data have significant cloud gaps (Asner 2001; Lehmann et al. 2011; Reiche et al. 2015a,b). Reiche and colleagues (2015a) for example fused time series of multispectral and radar information at the pixel level, using the correlation between overlapping multispectral and radar time series to predict missing values in the former; this yielded a fused image for each time step, which was used to track deforestation. They reported that image fusion increased the overall accuracy with which deforestation was detected by 2.4% (compared to using only multispectral SRS data) under less cloudy conditions, but that, as cloud cover increased, this improvement in accuracy increased to ca. 40%. Additionally, the lag between deforestation events and their detection was significantly reduced, which makes these analyses more useful for informing responses on the ground.

Integrating multispectral and radar SRS data acquired at (roughly) the same time can help simultaneously reduce data gaps from cloud cover (for multispectral SRS) and layover (for radar SRS, Reiche et al. 2013), as well as improve the ability to distinguish forest from other land cover classes (Lehmann et al. 2011), both of which facilitates deforestation detection. By contrast, integrating subsequent multispectral and radar images in a Bayesian decision-framework has given mixed results: Whilst Lehmann et al. (2015) report that switching between SRS data types (here: from Landsat to PALSAR) increases erroneous detection of deforestation, Reiche et al. (2015b) found higher deforestation detection accuracy, and a reduction in detection lag, when integrating these SRS data sets. Forest degradation is another key threat to forest biodiversity which could benefit from fusing multispectral and radar SRS data. Forest degradation can either be detected through changes in forest structure, composition and function; it is also possible in some instances to map discrete degradation categories. For instance, integrating backscatter from ALOS PALSAR and tasselled cap-transformed Landsat 5 TM imagery in a Random Forest classification framework helped distinguish different stages of palm swamp degradation (Hergoualc'h et al. 2017).

Compared to species- and ecosystem-level biodiversity monitoring multispectral-radar SRS data fusion has been applied to a relatively small range of biodiversity threats (Table 1), but four potential further avenues are worth mentioning. First, SRS data fusion has been shown to improve the accuracy with which indicators of eutrophication – such as Secchi depth – can be estimated across large areas (Zhang et al. 2002, Liu et al. 2014). This suggests that SRS data fusion could be a useful tool for monitoring threats to freshwater and marine ecosystems which are under pressure from anthropogenic eutrophication, such as coastal areas (e.g. Kemp et al. 2005). Second, Stroppiana and colleagues (2015) reported that integrating radar imagery from Envisat ASAR and multispectral imagery from Landsat 5 TM in a fuzzy decision framework improved burned area mapping. Though it is not possible to distinguish anthropogenic and wildfires from space, this suggests that SRS data fusion could support monitoring changes in fire dynamics, which threaten biodiversity in many ecosystems (Enright et al. 2015). Third, the detection of infrastructure associated with anthropogenic threats to biodiversity, such as roads, may benefit from SRS data fusion. Integrating LiDAR information about three-dimensional structure of landscapes with multispectral imagery has been shown to improve road detection over using multispectral imagery alone (Hu et al. 2004). Given the current lack of a satellite-based LiDAR mission, however, radar imagery could be used to provide similar information about the vertical structure of surfaces, and could be fused with multispectral imagery to facilitate road mapping (Lisini et al. 2011). Fourth, multispectral-radar synergies could help improve the mapping of invasive plant species, which may differ from native species in spectral characteristics (reflected in spectral reflectance), as well as growth and volume patterns (reflected in radar backscatter; Ghulam et al. 2014). Whether and to which degree data fusion can improve the detection of these anthropogenic threats however remains to be tested.

What currently limits wider use of data fusion techniques?

Multispectral-radar SRS data fusion can have significant added value over using multispectral and radar SRS data alone, but there are currently four challenges that could prevent its routine use.

First, there is a lack of understanding of the contexts in which multispectral-radar SRS data fusion likely improves estimates, which makes it difficult for scientists to decide where to invest time and energy in additional processing and analysis. There are indeed contexts in which multispectral-radar SRS data fusion does not improve accuracy over using a single type of SRS data, or in which the benefits of fusion depend on the type of multispectral and radar data used (Ban 2003), the fusion technique (Lisini et al. 2011; Basuki et al. 2013; Hong et al. 2014; Wang et al. 2016) or (in the case of classifications) which land cover class and/or which time period is considered (Polychronaki et al. 2014; Robertson et al. 2015; Carreiras et al. 2017). Collaboration between the ecology/biodiversity and the remote sensing communities, via platforms like the Group on Earth Observations Biodiversity Observation Network, will be crucial in identifying which biodiversity parameters could benefit most from SRS data fusion approaches, and which datasets and processing techniques are most appropriate (Pettorelli et al. 2014b).

Second, multispectral-radar image fusion is often used without reporting a reason for data selection or fusion techniques, so it is hard to learn from experience. Additionally, it is often difficult to report all data analysis steps to a reproducible level of detail. A key step towards improving the transparency of SRS data fusion is making the code used in such analyses accessible, e.g. by using open-source software (Fig. 2). Scientific workflow systems, such as

Kepler (Ludäscher et al. 2009), could also help make SRS fusion methods more transparent, and aid quick identification and uptake of useful approaches (Michener & Jones 2012).

Third, data fusion requires the capacity, both in terms of hardware and analysis skills, to source and process two very different types of SRS data. Barriers to more widespread use of SRS data by ecologists in general – such as unfamiliar data formats, pre-processing requirements, or lack of appropriate hardware (Kuenzer et al. 2014) – are multiplied when using two different types of data. Even among ecologists and biodiversity researchers which routinely use SRS data, self-reported data handling proficiency tends to be lower for active sensors such as radar (Palumbo et al. 2017). The added value of multispectral-radar SRS data fusion may well outweigh these technical drawbacks in many cases, but will clearly present an obstacle for widespread adoption in a scientific community that is still in the process of embracing big data (Michener & Jones, 2012). However, the emergence of cloud computing (e.g. in the Google Earth Engine), and growing coding literacy amongst ecologists could help minimise the impact of this obstacle (Marvin et al. 2016). Moreover, many open-source software platforms already have tools supporting common data fusion techniques, reducing the entry barrier to a more widespread uptake (Fig. 1).

Fourth, data accessibility can remain a significant obstacle to multi-sensor SRS data fusion. Whilst multispectral SRS data, notably from the Landsat mission, have been freely available for almost a decade (Wulder et al. 2012), open access radar data has been more restricted, although ESA's Sentinel missions are likely to alleviate this data accessibility problem (Turner et al. 2015; Fig. 3). To fully take advantage of multispectral-radar data fusion opportunities, especially for time series analysis, accessibility to past acquisitions is necessary. As a result, promoting open-access data policies for current and future missions as well as data archives remains important (Turner et al. 2015).

Conclusion

SRS data fusion allows taking advantage of the complementary information captured by different sensors (Lu et al. 2014; Joshi et al. 2016), and has the potential to increase the quality of SRS-derived parameters for ecology and conservation. The case studies presented here are entry points for more structured efforts to benefit from the growing availability of multi-satellite data. There are currently many SRS missions with an open-access policy providing global and repeated coverage of the Earth's surface, both for multispectral and radar data (Fig. 3). This offers the unique opportunity to scale up SRS image fusion and integration to large spatial scales, and support global biodiversity monitoring efforts. These efforts are currently centred on the concept of Essential Biodiversity Variables (EBVs) (Pereira et al. 2013), which are variables that allow quantification of the rate and direction of change in one aspect of the state of biodiversity over time and across space (Pettorelli et al. 2016). SRS variables have been identified as a key resource to produce EBVs (so-called SRS-EBVs; Pettorelli et al. 2016), mainly for variables relating to ecosystem structure and function (Geijzendorfer et al. 2016, Pettorelli et al. 2017). So far, however, development of SRS-EBVs and other variables for large-scale biodiversity monitoring has been largely focused on using SRS data from a single sensor (e.g. Pasher et al. 2013, Vihervaara et al. 2017). Whilst multispectral and radar SRS data fusion has mainly been applied to structural or compositional aspects of biodiversity, it could also benefit monitoring of functional aspects. For instance, mapping wetland inundation extent (e.g. Ward et al. 2014), forest succession stage (e.g. Lu et al. 2011), or burned areas (Stroppiana et al. 2015), and monitoring water quality (Zhang et al. 2002, Liu et al. 2014), have all been shown to benefit from multispectral-radar synergies, allowing more accurate characterisation of related ecosystem processes and functions (such as water and disturbance regulation and primary productivity). Identifying how SRS data fusion could support global biodiversity monitoring efforts through SRS-EBVs requires collaboration between remote sensing scientists and biodiversity/ecology scientists (Fig. 4). Each community's expertise and experience will be required to match monitoring requirements to remote sensing capability, so that SRS-EBVs are relevant, cost-effective and their production feasible (Pettorelli et al. 2016). This process will be particularly important for exploring the as-yet untapped opportunities arising from SRS data fusion to expand our biodiversity monitoring options from space. Much remains to be discovered about how best to capitalise on recent technological developments and changes in SRS data availability; we hope this contribution, by providing a solid introduction to SRS data fusion and its benefits for ecology and conservation, paves a way for this.

References

Amarsaikhan, D., Saandar, M., Ganzorig, M., Blotevogel, H. H., Egshiglen, E., Gantuyal, R., Nergui, B. & Enkhjargal, D. (2012), Comparison of multisource image fusion methods and land cover classification. *International Journal of Remote Sensing*, **33**, 2532-2550.

Asner, G. P. (1998), Biophysical and biochemical sources of variability in canopy reflectance. *Remote sensing of Environment*, **64**, 234-253.

Asner, G. P. (2001), Cloud cover in Landsat observations of the Brazilian Amazon. *International Journal of Remote Sensing*, **22**, 3855-3862.

Attarchi, S., & Gloaguen, R. (2014). Improving the estimation of above ground biomass using dual polarimetric PALSAR and ETM+ data in the Hyrcanian mountain forest (Iran). *Remote sensing*, **6**, 3693-3715.

Baghdadi, N., Boyer, N., Todoroff, P., El Hajj, M., & Bégué, A. (2009). Potential of SAR sensors TerraSAR-X, ASAR/ENVISAT and PALSAR/ALOS for monitoring sugarcane crops on Reunion Island. *Remote Sensing of Environment*, **113**, 1724-1738.

Ban, Y. (2003), Synergy of multitemporal ERS-1 SAR and Landsat TM data for classification of agricultural crops. *Canadian Journal of Remote Sensing*, **29**, 518-526.

Barrett, B., Raab, C., Cawkwell, F., & Green, S. (2016), Upland vegetation mapping using Random Forests with optical and radar satellite data. *Remote Sensing in Ecology and Conservation*, **2**, 212-231.

Basuki, T. M., Skidmore, A. K., Hussin, Y. A., & Van Duren, I. (2013). Estimating tropical forest biomass more accurately by integrating ALOS PALSAR and Landsat-7 ETM+ data. *International journal of remote sensing*, **34**, 4871-4888.

Bergen, K. M., Gilboy, A. M., & Brown, D. G. (2007). Multi-dimensional vegetation structure in modeling avian habitat. *Ecological Informatics*, **2**, 9-22.

Bergen, K. M., Goetz, S. J., Dubayah, R. O., Henebry, G. M., Hunsaker, C. T., Imhoff, M. L., ... & Radeloff, V. C. (2009). Remote sensing of vegetation 3-D structure for biodiversity and habitat: Review and implications for lidar and radar spaceborne missions. *Journal of Geophysical Research: Biogeosciences*, **114**.

Berger, M., Moreno, J., Johannessen, J. A., Levelt, P. F., & Hanssen, R. F. (2012), ESA's sentinel missions in support of Earth system science. *Remote Sensing of Environment*, **120**, 84-90.

Blaschke, T. (2010), Object based image analysis for remote sensing. *ISPRS journal of photogrammetry and remote sensing*, **65**, 2-16.

Bourgeau-Chavez, L.L., Riordan, K., Powell, R.B., Miller, N. & Nowels, M. (2009) Improving Wetland Characterization with Multi-Sensor, Multi-Temporal SAR and Optical/Infrared Data Fusion. In: *Advances in Geoscience and Remote Sensing*, Gary Jedlovec (Ed.), InTech, DOI: 10.5772/8327.

Bourgeau-Chavez, L. L., Endres, S., Powell, R., Battaglia, M. J., Benscoter, B., Turetsky, M., ... & Banda, E. (2016). Mapping boreal peatland ecosystem types from multitemporal radar and optical satellite imagery. *Canadian Journal of Forest Research*, **47**, 545-559.

Bradley, B. A., & Mustard, J. F. (2006). Characterizing the landscape dynamics of an invasive plant and risk of invasion using remote sensing. *Ecological Applications*, **16**, 1132-1147.

Buchanan, G. M., Nelson, A., Mayaux, P., Hartley, A., & Donald, P. F. (2009), Delivering a global, terrestrial, biodiversity observation system through remote sensing. *Conservation Biology*, **23**, 499-502.

Buermann, W., Saatchi, S., Smith, T. B., Zutta, B. R., Chaves, J. A., Milá, B., & Graham, C. H. (2008). Predicting species distributions across the Amazonian and Andean regions using remote sensing data. *Journal of Biogeography*, **35**, 1160-1176.

Bwangoy, J. R. B., Hansen, M. C., Roy, D. P., De Grandi, G., & Justice, C. O. (2010). Wetland mapping in the Congo Basin using optical and radar remotely sensed data and derived topographical indices. *Remote Sensing of Environment*, **114**, 73-86.

Carreiras, J. M., Jones, J., Lucas, R. M., & Shimabukuro, Y. E. (2017), Mapping major land cover types and retrieving the age of secondary forests in the Brazilian Amazon by combining single-date optical and radar remote sensing data. *Remote Sensing of Environment*, **194**, 16-32.

Chen, C. M., Hepner, G. F., & Forster, R. R. (2003), Fusion of hyperspectral and radar data using the IHS transformation to enhance urban surface features. *ISPRS Journal of photogrammetry and Remote Sensing*, **58**, 19-30.

Cartus, O., Santoro, M., Schmullius, C., & Li, Z. (2011). Large area forest stem volume mapping in the boreal zone using synergy of ERS-1/2 tandem coherence and MODIS vegetation continuous fields. *Remote Sensing of Environment*, **115**, 931-943.

Cracraft, J. (1987). Species concepts and the ontology of evolution. *Biology and philosophy*, **2**, 329-346.

Culbert, P. D., Radeloff, V. C., Flather, C. H., Kellndorfer, J. M., Rittenhouse, C. D., & Pidgeon, A. M. (2013). The influence of vertical and horizontal habitat structure on nationwide patterns of avian biodiversity. *The Auk*, **130,** 656-665.

Dong, J., Xiao, X., Chen, B., Torbick, N., Jin, C., Zhang, G., & Biradar, C. (2013). Mapping deciduous rubber plantations through integration of PALSAR and multi-temporal Landsat imagery. *Remote Sensing of Environment*, **134**, 392-402.

Enright, N. J., Fontaine, J. B., Bowman, D. M., Bradstock, R. A., & Williams, R. J. (2015). Interval squeeze: altered fire regimes and demographic responses interact to threaten woody species persistence as climate changes. *Frontiers in Ecology and the Environment*, **13**, 265-272.

Fitzpatrick, B. M., Ryan, M. E., Johnson, J. R., Corush, J., & Carter, E. T. (2015). Hybridization and the species problem in conservation. *Current Zoology*, **61**, 206-216.

Fu, B., Wang, Y., Campbell, A., Li, Y., Zhang, B., Yin, S., Xing, Z., & Jin, X. (2017), Comparison of object-based and pixel-based Random Forest algorithm for wetland vegetation mapping using high spatial resolution GF-1 and SAR data. *Ecological Indicators*, **73**, 105-117.

Gala, T. S., & Melesse, A. M. (2012). Monitoring prairie wet area with an integrated LANDSAT ETM+, RADARSAT-1 SAR and ancillary data from LIDAR. *Catena*, **95**, 12-23.

Gavier-Pizarro, G. I., Kuemmerle, T., Hoyos, L. E., Stewart, S. I., Huebner, C. D., Keuler, N. S., & Radeloff, V. C. (2012). Monitoring the invasion of an exotic tree (Ligustrum lucidum) from 1983 to 2006 with Landsat TM/ETM+ satellite data and Support Vector Machines in Córdoba, Argentina. *Remote Sensing of Environment*, **122**, 134-145.

Geijzendorffer, I. R., Regan, E. C., Pereira, H. M., Brotons, L., Brummitt, N., Gavish, Y., ... & Schmeller, D. S. (2016). Bridging the gap between biodiversity data and policy reporting needs: An Essential Biodiversity Variables perspective. *Journal of Applied Ecology*, **53**, 1341-1350.

Ghulam, A., Porton, I., & Freeman, K. (2014), Detecting subcanopy invasive plant species in tropical rainforest by integrating optical and microwave (InSAR/PolInSAR) remote sensing data, and a decision tree algorithm. *ISPRS Journal of Photogrammetry and Remote Sensing*, **88**, 174-192.

Goetz, A. F. H., Vane, G., Solomon, J., & Rock, B. (1985). Imaging spectrometry for earth remote sensing. *Science*, **228**, 1147-1152.

Haack, B. N., Solomon, E. K., Bechdol, M. A., & Herold, N. D. (2002), Radar and optical data comparison/integration for urban delineation: a case study. *Photogrammetric Engineering and Remote Sensing*, **68**, 1289-1296.

Hamdan, O., Hasmadi, I. M., & Aziz, H. K. (2014), Combination of SPOT-5 and ALOS PALSAR images in estimating aboveground biomass of lowland Dipterocarp forest. *IOP Conference Series: Earth and Environmental Science*, **18**, 012016.

Hamilton, S. K., Kellndorfer, J., Lehner, B., & Tobler, M. (2007). Remote sensing of floodplain geomorphology as a surrogate for biodiversity in a tropical river system (Madre de Dios, Peru). *Geomorphology*, **89**, 23-38.

He, K. S., Bradley, B. A., Cord, A. F., Rocchini, D., Tuanmu, M. N., Schmidtlein, S., Turner, W., Wegmann, M. & Pettorelli, N. (2015), Will remote sensing shape the next generation of species distribution models? *Remote Sensing in Ecology and Conservation*, **1**, 4-18.

Hégarat-Mascle, S., Bloch, I., & Vidal-Madjar, D. (1998). Introduction of neighborhood information in evidence theory and application to data fusion of radar and optical images with partial cloud cover. *Pattern recognition*, **31**, 1811-1823.

Hergoualc'h, K., Gutiérrez-Vélez, V. H., Menton, M., & Verchot, L. V. (2017). Characterizing degradation of palm swamp peatlands from space and on the ground: An exploratory study in the Peruvian Amazon. *Forest Ecology and Management*, **393**, 63-73.

Hong, G., Zhang, Y., & Mercer, B. (2009), A wavelet and IHS integration method to fuse high resolution SAR with moderate resolution multispectral images. *Photogrammetric Engineering & Remote Sensing*, **75**, 1213-1223.

Hong, G., Zhang, A., Zhou, F., & Brisco, B. (2014), Integration of optical and synthetic aperture radar (SAR) images to differentiate grassland and alfalfa in Prairie area. *International Journal of Applied Earth observation and geoinformation*, **28**, 12-19.

Hu, X., Tao, C. V., & Hu, Y. (2004), Automatic road extraction from dense urban area by integrated processing of high resolution imagery and lidar data. *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, **35**, B3.

Hyde, P., Dubayah, R., Walker, W., Blair, J. B., Hofton, M., & Hunsaker, C. (2006). Mapping forest structure for wildlife habitat analysis using multi-sensor (LiDAR, SAR/InSAR, ETM+, Quickbird) synergy. *Remote Sensing of Environment*, **102**, 63-73.

Ismail, R., Kassier, H., Chauke, M., Holecz, F., & Hattingh, N. (2015). Assessing the utility of ALOS PALSAR and SPOT 4 to predict timber volumes in even-aged Eucalyptus plantations located in Zululand, South Africa. *Southern Forests: a Journal of Forest Science*, **77**, 203-211.

Joppa, L. N., O'Connor, B., Visconti, P., Smith, C., Geldmann, J., Hoffmann, M., … & Burgess, N. D. (2016), Filling in biodiversity threat gaps. *Science*, **352**, 416-418.

Joshi, N., Baumann, M., Ehammer, A., Fensholt, R., Grogan, K., Hostert, P., ... & Waske, B. (2016), A review of the application of optical and radar remote sensing data fusion to land use mapping and monitoring. *Remote Sensing*, **8**, 70.

Keith, S. A., Webb, T. J., Böhning-Gaese, K., Connolly, S. R., Dulvy, N. K., Eigenbrod, F., … & Isaac, N. J. (2012) What is macroecology? Biology Letters, DOI:10.1098.

Keith, D. A., Rodríguez, J. P., Rodríguez-Clark, K. M., Nicholson, E., Aapala, K., Alonso, A., … & Zambrano-Martínez, S. (2013), Scientific foundations for an IUCN Red List of Ecosystems. *PLOS one*, **8**, e62111.

Kellndorfer, J. M., Walker, W. S., LaPoint, E., Kirsch, K., Bishop, J., & Fiske, G. (2010), Statistical fusion of Lidar, InSAR, and optical remote sensing data for forest stand height characterization: A regional-scale method based on LVIS, SRTM, Landsat ETM+, and ancillary data sets. *Journal of Geophysical Research*, **115**, G00E08.

Kemp, W. M., Boynton, W. R., Adolf, J. E., Boesch, D. F., Boicourt, W. C., Brush, G., ... & Harding, L. W. (2005). Eutrophication of Chesapeake Bay: historical trends and ecological interactions. *Marine Ecology Progress Series*, **303**, 1-29.

Kuenzer, C., Ottinger, M., Wegmann, M., Guo, H., Wang, C., Zhang, J., Dech, S. & Wikelski, M. (2014), Earth observation satellite sensors for biodiversity monitoring: potentials and bottlenecks. *International Journal of Remote Sensing*, **35**, 6599-6647.

Lahat, D., Adali, T., & Jutten, C. (2015), Multimodal data fusion: an overview of methods, challenges, and prospects. *Proceedings of the IEEE*, **103**, 1449-1477.

Laurin, G. V., Liesenberg, V., Chen, Q., Guerriero, L., Del Frate, F., Bartolini, A., ... & Valentini, R. (2013). Optical and SAR sensor synergies for forest and land cover mapping in a tropical site in West Africa. *International Journal of Applied Earth Observation and Geoinformation*, **21**, 7-16.

Lehmann, E. A., Caccetta, P. A., Zhou, Z. S., McNeill, S. J., Wu, X., & Mitchell, A. L. (2011), Joint processing of Landsat and ALOS-PALSAR data for forest mapping and monitoring. *IEEE Transactions on Geoscience and Remote Sensing*, **50**, 55-67.

Lehmann, E. A., Caccetta, P., Lowell, K., Mitchell, A., Zhou, Z. S., Held, A., Milne, T. & Tapley, I. (2015), SAR and optical remote sensing: Assessment of complementarity and interoperability in the context of a large-scale operational forest monitoring system. *Remote Sensing of Environment*, **156**, 335-348.

Leung, Y., Liu, J., & Zhang, J. (2014), An improved adaptive intensity–hue–saturation method for the fusion of remote sensing images. *IEEE Geoscience and Remote Sensing Letters*, **11**, 985-989.

Leutner, B. & Horning, N. (2016), RStoolbox: Tools for Remote Sensing Data Analysis. R package version 0.1.4. Available at: https://CRAN.R-project.org/package=RStoolbox, retrieved 10/04/2016.

Lisini, G., Gamba, P., Dell'Acqua, F., & Holecz, F. (2011), First results on road network extraction and fusion on optical and SAR images using a multi-scale adaptive approach. *International Journal of Image and Data Fusion*, ***2***, 363-375.

Liu, M., Liu, X., Li, J., Ding, C., & Jiang, J. (2014). Evaluating total inorganic nitrogen in coastal waters through fusion of multi-temporal RADARSAT-2 and optical imagery using random forest algorithm. *International Journal of Applied Earth Observation and Geoinformation*, **33**, 192-202.

Lu, D., Li, G., Moran, E., Dutra, L., & Batistella, M. (2011), A comparison of multisensor integration methods for land cover classification in the Brazilian Amazon. *GIScience & Remote Sensing*, **48**, 345-370.

Lu, D., Li, G., Moran, E., & Kuang, W. (2014), A comparative analysis of approaches for successional vegetation classification in the Brazilian Amazon. *GIScience & Remote Sensing*, **51**, 695-709.

Lucas, R. M., Clewley, D., Accad, A., Butler, D., Armston, J., Bowen, … & Seabrook, L. (2014), Mapping forest growth and degradation stage in the Brigalow Belt Bioregion of Australia through integration of ALOS PALSAR and Landsat-derived foliage projective cover data. *Remote Sensing of Environment*, **155**, 42-57.

Ludäscher, B., Altintas, I., Bowers, S., Cummings, J., Critchlow, T., Deelman, E., ... & Klasky, S. (2009). Scientific process automation and workflow management. *Scientific Data Management: Challenges, Existing Technology, and Deployment, Computational Science Series*, *230*, 476-508.

Mace, G. M., Hails, R. S., Cryle, P., Harlow, J., & Clarke, S. J. (2015), Review: towards a risk register for natural capital. *Journal of Applied Ecology*, **52**, 641-653.

Maillard, P., Alencar-Silva, T., & Clausi, D. A. (2008). An evaluation of Radarsat-1 and ASTER data for mapping veredas (palm swamps). *Sensors*, **8**, 6055-6076.

Marvin, D. C., Koh, L. P., Lynam, A. J., Wich, S., Davies, A. B., Krishnamurthy, R., Stokes, E., Starkey, R. & Asner, G. P. (2016), Integrating technologies for scalable ecology and conservation. *Global Ecology and Conservation*, **7**, 262-275.

McCauley, J. F., Schaber, G. G., Breed, C. S., Grolier, M. J., Haynes, C. V., Issawi, B., Elachi, C. & Blom, R. (1982), Subsurface valleys and geoarcheology of the eastern Sahara revealed by shuttle radar. *Science*, **218**, 1004-1020.

McGill, B. J., Enquist, B. J., Weiher, E., & Westoby, M. (2006). Rebuilding community ecology from functional traits. *Trends in ecology & evolution*, **21**, 178-185.

McDowall, R. M. (2004), What biogeography is: a place for process. *Journal of Biogeography*, **31**, 345-351.

Michener, W. K., & Jones, M. B. (2012), Ecoinformatics: supporting ecology as a data-intensive science. *Trends in ecology & evolution*, **27**, 85-93.

Morel, A. C., Fisher, J. B., & Malhi, Y. (2012). Evaluating the potential to monitor aboveground biomass in forest and oil palm in Sabah, Malaysia, for 2000–2008 with Landsat ETM+ and ALOS-PALSAR. *International Journal of Remote Sensing*, **33**, 3614-3639.

Myneni, R. B., Ramakrishna, R., Nemani, R., & Running, S. W. (1997). Estimation of global leaf area index and absorbed PAR using radiative transfer models. *IEEE Transactions on Geoscience and remote sensing*, **35**, 1380-1393.

Myers, N., Mittermeier, R. A., Mittermeier, C. G., Da Fonseca, G. A., & Kent, J. (2000). Biodiversity hotspots for conservation priorities. *Nature*, **403**, 853.

Naidoo, L., Mathieu, R., Main, R., Wessels, K., & Asner, G. P. (2016), L-band Synthetic Aperture Radar imagery performs better than optical datasets at retrieving woody fractional cover in deciduous, dry savannahs. *International Journal of Applied Earth Observation and Geoinformation*, **52**, 54-64.

Nicholson, E., Keith, D. A., & Wilcove, D. S. (2009), Assessing the threat status of ecological communities. *Conservation Biology*, **23**, 259-274.

Noss, R. F. (1990). Indicators for monitoring biodiversity: a hierarchical approach. *Conservation biology*, **4**, 355-364.

Pajares, G., & De La Cruz, J. M. (2004), A wavelet-based image fusion tutorial. *Pattern recognition*, **37**, 1855-1872.

Palumbo, I., Rose, R. A., Headley, R. M., Nackoney, J., Vodacek, A., & Wegmann, M. (2017), Building capacity in remote sensing for conservation: present and future challenges. *Remote Sensing in Ecology and Conservation*, **3**, 21-29.

Pasher, J., Smith, P. A., Forbes, M. R., & Duffe, J. (2013). Terrestrial ecosystem monitoring in Canada and the greater role for integrated earth observation. *Environmental Reviews*, **22**, 179-187.

Pereira, H. M., Ferrier, S., Walters, M., Geller, G. N., Jongman, R. H. G., Scholes, R. J., ... & Coops, N. C. (2013). Essential biodiversity variables. *Science*, **339**, 277-278.

Pettorelli, N., Vik, J. O., Mysterud, A., Gaillard, J. M., Tucker, C. J., & Stenseth, N. C. (2005). Using the satellite-derived NDVI to assess ecological responses to environmental change. *Trends in ecology & evolution*, **20**, 503-510.

Pettorelli, N., Laurance, W. F., O'Brien, T. G., Wegmann, M., Nagendra, H., & Turner, W. (2014a), Satellite remote sensing for applied ecologists: opportunities and challenges. *Journal of Applied Ecology*, **51**, 839-848.

Pettorelli, N., Safi, K., & Turner, W. (2014b). Satellite remote sensing, biodiversity research and conservation of the future. *Phil Trans Royal Soc B*, 369: 20130190.

Pettorelli, N., Wegmann, M., Skidmore, A., Mücher, S., Dawson, T. P., Fernandez, M., ... & Jongman, R. H. (2016). Framing the concept of satellite remote sensing essential biodiversity variables: challenges and future directions. *Remote Sensing in Ecology and Conservation*, **2**, 122-131.

Pettorelli, N., Schulte to Bühne, H., Tulloch, A., Dubois, G., Macinnis-Ng, C., Queirós, A. M., ... & Sonnenschein, R. (2017). Satellite remote sensing of ecosystem functions: opportunities, challenges and way forward. *Remote Sensing in Ecology and Conservation*. In press.

Pickett, S. T., & Cadenasso, M. L. (2002). The ecosystem as a multidimensional concept: meaning, model, and metaphor. *Ecosystems*, **5**, 1-10.

Poggio, L., & Gimona, A. (2017), Assimilation of optical and radar remote sensing data in 3D mapping of soil properties over large areas. *Science of The Total Environment*, **579**, 1094-1110.

Pohl, C. (1999), Tools and methods for fusion of images of different spatial resolution. *International Archives of Photogrammetry and Remote Sensing*, **32**, part 7-4-3 W6.

Pohl, C., & Van Genderen, J. L. (1998), Review article multisensor image fusion in remote sensing: concepts, methods and applications. *International journal of remote sensing*, **19**, 823-854.

Pohl, C., & Yen, T. L. (2014) Compilation of a remote sensing image fusion atlas. *35th Asian Conference of Remote Sensing (ACRS)*, 1-6.

Polychronaki, A., Gitas, I. Z., & Minchella, A. (2014), Monitoring post-fire vegetation recovery in the Mediterranean using SPOT and ERS imagery. *International Journal of Wildland Fire*, **23**, 631-642.

Prates-Clark, C. D. C., Saatchi, S. S., & Agosti, D. (2008). Predicting geographical distribution models of high-value timber trees in the Amazon Basin using remotely sensed data. *Ecological Modelling*, **211**, 309-323.

Pressey, R. L., & Bottrill, M. C. (2008), Opportunism, threats, and the evolution of systematic conservation planning. *Conservation Biology*, **22**, 1340-1345.

Reiche, J., Souza, C. M., Hoekman, D. H., Verbesselt, J., Persaud, H., & Herold, M. (2013). Feature level fusion of multi-temporal ALOS PALSAR and Landsat data for mapping and monitoring of tropical deforestation and forest degradation. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, **6**, 2159-2173.

Reiche, J., Verbesselt, J., Hoekman, D., & Herold, M. (2015a), Fusing Landsat and SAR time series to detect deforestation in the tropics. *Remote Sensing of Environment*, **156**, 276-293.

Reiche, J., de Bruin, S., Hoekman, D., Verbesselt, J., & Herold, M. (2015b), A Bayesian approach to combine Landsat and ALOS PALSAR time series for near real-time deforestation detection. *Remote Sensing*, **7**, 4973-4996.

Rignot, E., Salas, W. A., & Skole, D. L. (1997). Mapping deforestation and secondary growth in Rondônia, Brazil, using imaging radar and Thematic Mapper data. *Remote Sensing of Environment*, **59**, 167-179.

Robertson, B. P., Gardner, J. P., & Savage, C. (2015), Macrobenthic–mud relations strengthen the foundation for benthic index development: a case study from shallow, temperate New Zealand estuaries. *Ecological Indicators*, **58**, 161-174.

Sangster, G. (2014). The application of species criteria in avian taxonomy and its implications for the debate over species concepts. *Biological Reviews*, *89*(1), 199-214.

Santoro, M., Shvidenko, A., McCallum, I., Askne, J., & Schmullius, C. (2007), Properties of ERS-1/2 coherence in the Siberian boreal forest and implications for stem volume retrieval. *Remote sensing of environment*, **106**, 154-172.

Shea, K., Roxburgh, S. H., & Rauschert, E. S. (2004), Moving from pattern to process: coexistence mechanisms under intermediate disturbance regimes. *Ecology letters*, **7**, 491-508.

Souza-Filho, P. W. M., Goncalves, F. D., Rodrigues, S. W. P., Costa, F. R., & Miranda, F. P. (2009), Multi-sensor data fusion for geomorphological and environmental sensitivity index mapping in the Amazonian mangrove coast, Brazil. *Journal of Coastal Research*, **56**, 1592-1596.

Stroppiana, D., Azar, R., Calò, F., Pepe, A., Imperatore, P., Boschetti, M., ... & Lanari, R. (2015). Integration of optical and SAR data for burned area mapping in Mediterranean Regions. *Remote Sensing*, **7**, 1320-1345.

Tansley, A. G. (1935). The use and abuse of vegetational concepts and terms. *Ecology*, **16**, 284-307.

Tempfli, K., Kerle, N., Huurneman, G. C., & Janssen, L. L. (2009), Principles of remote sensing. *The International Institute for Geo-Information Science and Earth Observation (ITC). Enschede, Netherlands*.

Treuhaft, R. N., Law, B. E., & Asner, G. P. (2004), Forest attributes from radar interferometric structure and its fusion with optical remote sensing. *BioScience*, **54**, 561-571.

Tulloch, V. J., Tulloch, A. I., Visconti, P., Halpern, B. S., Watson, J. E., Evans, M. C., … & Possingham, H.P. (2015), Why do we map threats? Linking threat mapping with actions to make better conservation decisions. *Frontiers in Ecology and the Environment*, **13**, 91-99.

Turner, W., Rondinini, C., Pettorelli, N., Mora, B., Leidner, A. K., Szantoi, Z., …& Woodcock, C. (2015), Free and open-access satellite data are key to biodiversity conservation. *Biological Conservation*, **182**, 173-176.

UNSD SEEA-EEA (2013), System of Environmental-Economic Accounting 2012: Experimental Ecosystem Accounting. Accessible at http://unstats.un.org/unsd/envaccounting/eea_white_cover.pdf, retrieved on 10/04/2017.

van der Wal, D., & Herman, P. M. (2007), Regression-based synergy of optical, shortwave infrared and microwave remote sensing for monitoring the grain-size of intertidal sediments. *Remote Sensing of Environment*, **111**, 89-106.

Vihervaara, P., Auvinen, A. P., Mononen, L., Törmä, M., Ahlroth, P., Anttila, S., ... & Koskelainen, M. (2017). How Essential Biodiversity Variables and remote sensing can help national biodiversity monitoring. *Global Ecology and Conservation*, **10**, 43-59.

Vivone, G., Alparone, L., Chanussot, J., Dalla Mura, M., Garzelli, A., Licciardi, G. A., ... & Wald, L. (2015). A critical comparison among pansharpening algorithms. *IEEE Transactions on Geoscience and Remote Sensing*, **53**, 2565-2586.

Wald, L. (1999), Some terms of reference in data fusion. *IEEE Transactions on geoscience and remote sensing*, **37**, 1190-1193.

Walker, W. S., Kellndorfer, J. M., LaPoint, E., Hoppus, M., & Westfall, J. (2007), An empirical InSAR-optical fusion approach to mapping vegetation canopy height. *Remote Sensing of Environment*, **109**, 482-499.

Wang, C., Qi, J., Moran, S., & Marsett, R. (2004). Soil moisture estimation in a semiarid rangeland using ERS-2 and TM imagery. *Remote Sensing of Environment*, **90**, 178-189.

Wang, C., & Qi, J. (2008). Biophysical estimation in tropical forests using JERS-1 SAR and VNIR imagery. II. Aboveground woody biomass. *International Journal of Remote Sensing*, **29**, 6827-6849.

Wang, X. Y., Guo, Y. G., He, J., & Du, L. T. (2016), Fusion of HJ1B and ALOS PALSAR data for land cover classification using machine learning methods. *International Journal of Applied Earth Observation and Geoinformation*, **52**, 192-203.

Ward, D. P., Petty, A., Setterfield, S. A., Douglas, M. M., Ferdinands, K., Hamilton, S. K., & Phinn, S. (2014). Floodplain inundation and vegetation dynamics in the Alligator Rivers region (Kakadu) of northern Australia assessed using optical and radar remote sensing. *Remote Sensing of Environment*, **147**, 43-55.

Waske, B., & Benediktsson, J. A. (2007), Fusion of support vector machines for classification of multisensor data. *IEEE Transactions on Geoscience and Remote Sensing*, **45**, 3858-3866.

Wegmann, M. & Leutner, B. (2016) Introduction to Remote Sensing and GIS. In: M. Wegmann, B. Leutner, S. Dech (eds) *Remote Sensing and GIS for Ecologists*. Pelagic Publishing, Exeter, UK.

Wolter, P. T., & Townsend, P. A. (2011), Multi-sensor data fusion for estimating forest species composition and abundance in northern Minnesota. *Remote Sensing of Environment*, **115**, 671-691.

Wulder, M. A., Masek, J. G., Cohen, W. B., Loveland, T. R., & Woodcock, C. E. (2012), Opening the archive: How free data has enabled the science and monitoring promise of Landsat. *Remote Sensing of Environment*, **122**, 2-10.

Yonghong, J. (1998), Fusion of Landsat TM and SAR image based on principal component analysis. *Remote Sensing Technology and Application*, **13**, 46-49.

Zhang, Y., Pulliainen, J., Koponen, S., & Hallikainen, M. (2002). Application of an empirical neural network to surface water quality estimation in the Gulf of Finland using combined optical data and microwave data. *Remote sensing of environment*, **81**, 327-336.

Zhang, J. (2010), Multi-source remote sensing data fusion: status and trends. *International Journal of Image and Data Fusion*, **1**, 5-24.

Figures and Tables

Box 1: Definitions of key terms relating to remote sensing and data fusion.

Table 1 Overview of current applications of multispectral-radar SRS data fusion for species and ecosystem monitoring , as well as biodiversity threat detection via (A) image fusion (P= pixel-based fusion; O=object-based fusion) or (B) decision-level data fusion (integration). (*) identifies studies that explicitly compare multispectral-radar image fusion/data integration to approaches which use either data alone.

Figure 1: Schematic overview of multispectral-radar SRS data fusion techniques. The parameter of interest can be a categorical variable, like land cover, or a continuous variable, like species richness. In pixel-level fusion, the original pixel values of radar and multispectral imagery are combined to yield new, derived pixel values. Object-based fusion refers to 1) using radar and multispectral imagery is input into an object-based image segmentation algorithm, or 2) segmenting each type of imagery separately before combining them. Finally, decision-level fusion corresponds to the process of quantitatively combining multispectral and radar imagery to derive the parameter of interest (by e.g. combining them in a regression model, or classification algorithm).

Figure 2: Overview of the advantages and drawbacks of the most common multispectral-radar SRS image fusion techniques, as well as examples for open-source software to implement them.

Figure 3: Spatial resolution and launch date of freely available SRS data with global coverage from active, long-term missions. Included are only missions which are currently

active. The relative lack of radar missions is due to the fact that most missions with open-access data policies are not active (e.g. JERS-1, ALOS PALSAR, ERS-1/2) whilst imagery from active radar missions is often behind a paywall (ALOS-2, RADARSAT-1/2, TerraSAR-X).

Figure 4: Roadmap for identifying and generating Essential Biodiversity Variables based on SRS (SRS-EBVs) supported by data fusion. The ecology/conservation science community and the remote sensing community each contribute their intradisciplinary expertise to a collaborative, interdisciplinary process in which biodiversity monitoring requirements are matched with appropriate SRS data and analysis techniques. The outcome of this process is a consensus about which SRS-EBVs will benefit from data fusion approaches, as well as the SRS data required and recommendations for data fusion techniques. This then feeds into the operationalisation stage, which involves the two science communities as well as policy-makers, to enable the production and use of SRS-EBVs, and which includes validation, endorsement, repeated generation, storage, dissemination of SR_EBVs.

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Box 1: Definitions of key terms relating to satellite remote sensing and data fusion

Band: Defined section in the visible and near-infrared part of the electromagnetic spectrum (Wegmann & Leutner 2016).

Data fusion: A formal framework in which data from different sources (and hence, sensors) is combined ("'alliance des données") to obtain information of greater quality (Wald 1999).

Hyperspectral remote sensing: Type of remote sensing which records radiance in a high number of sections of the electromagnetic spectrum (typically 100s of bands), allowing the reconstruction of a contiguous reflectance profile (Goetz et al. 1985).

Image fusion: A type of data fusion, in which images from different sources are combined into a new image. The aim is to create an image that retains salient information whilst minimizing artefacts or distortion.

Integration: We use "integration" to refer to decision-level data fusion, emphasising that whilst no new imagery is produced, the SRS data is systematically combined in a quantitative framework.

Leaf Area Index (LAI): One-sided green leaf area per unit ground area (Myneni et al. 1997).

Light Detection and Ranging (LiDAR): A type of active remote sensor which emits pulses of light and measures the proportion of the signal which is reflected; based on this information, the three-dimensional location of the object that reflected the light can be reconstructed.

Multispectral remote sensing: Measuring the amount of electromagnetic radiation in a limited number of bands (typically less than 10) in the visible and infrared part of the spectrum. Widely used spaceborne multispectral sensors include the Landsat and MODIS missions. Different from hyperspectral remote sensing (see above).

Normalised Difference Vegetation index (NDVI): A common vegetation index based on reflectance in the red and the near-infrared part of the spectrum, sensitive to the amount of photosynthetically active vegetation in a given area (Pettorelli et al. 2005).

Pan-sharpening: Fusing multispectral imagery with a panchromatic image of higher spatial resolution to increase the spatial resolution of the former whilst preserving its spectral information ("colour") (Vivone et al. 2015).

Radar remote sensing: Emitting a signal of electromagnetic radiation with a defined wavelength in the microwave spectrum and measuring the intensity and wavephase of the returning signal. Widely used spaceborne radar sensors include ALOS PALSAR and RADARSAT-2.

Table 1

(A)

	Variable	**Proxy**	**Multispectral sensor (spatial resolution)**	**Radar sensor (wavelength; spatial resolution)**	**Spatial scale**	**Reference**	**Type of data fusion**
Species-level biodiversity	Species distribution	Distribution of alfalfa stands (*Medicago salvatica*)	MODIS (250m)	RADARSAT-2 (C-band; 50m)	50,000 km²	Hong et al. 2014*	P
	Community composition	Relative basal area of 10 tree species and 2 tree genera	Landsat 5 TM (30m), SPOT 5 (10m)	Radarsat-1 (C-band, ca. 27m), ALOS PALSAR (L-band, ca. 12.5m)	360 km²	Wolter & Townsend 2011*	P
Ecosystem-level biodiversity	Ecosystem distribution	Distribution of different forest types, including different successional stages	Landsat 5 TM (30m)	RADARSAT-2 (C-band, 8m), ALOS PALSAR (L-band, 12.5m)	3,100 km²	Lu et al. 2011*	P
			Landsat 5 TM (30m)	ALOS PALSAR (L-band, 12.5m)	3,000 km²	Lu et al. 2014*	P
			Landsat 5 TM and Landsat 7 ETM+ (30m)	ALOS PALSAR (25m)	ca. 370,000 km²	Lucas et al. 2014	O
		Distribution of vegetation and/or geomorphology types in a wetland ecosystem	Landsat 7 ETM+(15m and 30m)	JERS-1 (L-band, 100m), SRTM (C-band, ca. 90m)	31,000 km²	Hamilton et al. 2007	O
			Landsat 5 TM (30m)	RADARSAT-1 (C-band, 33x27 m)	1,600 km²	Souza-Filho et al. 2009	P
			Landsat 5 TM (30m)	ALOS PALSAR (L-band, 20m), ERS-1/2 (C-band, 30m)	250 km²/34,000 km² respectively	Bourgeau-Chavez et al. 2009, 2016	0
			GF-1 (2m and 8m)	ALOS PALSAR (L-band, 14m)	250 km²	Fu et al. 2017*	P/O

				RADARSAT-2 (C-band, 6.3m x 5.2m)			
	Vertical ecosystem structure	Canopy height	Landsat 5 TM and Landsat 7 ETM+ (30m)	SRTM (C-band, ca. 30m)	62,000 km²	Walker et al. 2007*	O
			Landsat 7 ETM+ (30m)	SRTM (C-band, ca. 30m)	110,000 km²	Kellndorfer et al. 2010	O
		Aboveground biomass	Landsat 7 ETM+ (30m)	ALOS PALSAR (L-band, 16m resampled)	31, 000 km²	Basuki et al. 2013	P
Threats to biodiversity	Deforestation	Historic deforestation events	Landsat 7 ETM+ (30m)	ALOS PALSAR (L-band, 25m)	30 km²	Reiche et al. 2015a*	P

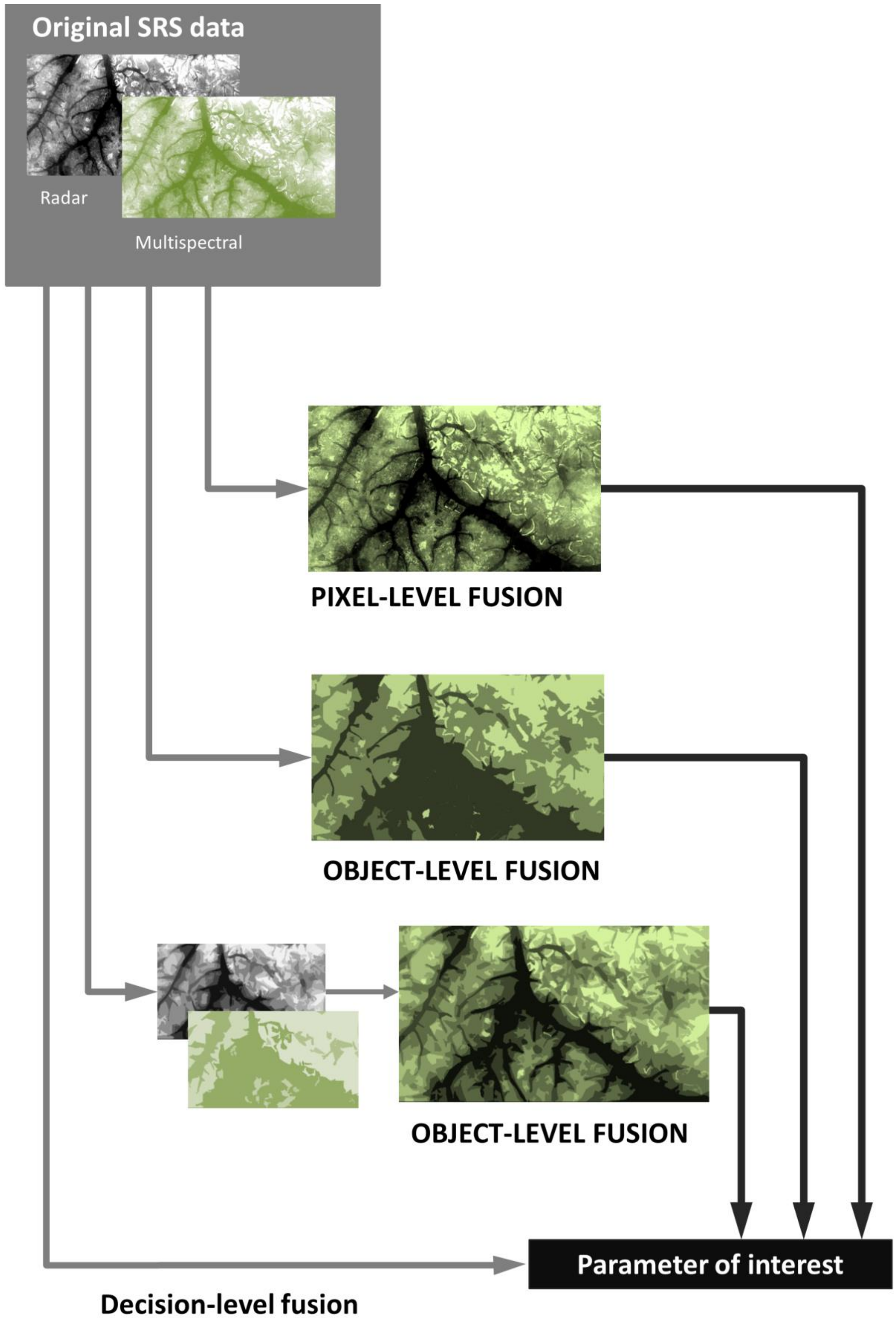
(B)

	Variable	**Proxy**	**Multispectral sensor (spatial resolution)**	**Radar sensor (wavelength; spatial resolution)**	**Spatial scale**	**Reference**	**Type of data fusion**
Species-level biodiversity	Species distribution	Bird species	NLCD (from Landsat TM; 30m)	SIR-C (both L and C band, 25m)	ca. 1,200 km²	Bergen et al. 2007*	Genetic Algorithm For Rule Set Production
			MODIS–derived LAI and Vegetation Continuous Fields (500m)	QuickScat (X-band, 1km)	17.8 million km²	Buermann et al. 2008	Species Distribution Model
		Subcanopy plant species	Landsat 5 TM and 7 ETM+ (30m), GeoEye-1 (1.64m), IKONOS (4m)	RADARSAT-2 (L-band, 8m), ALOS PALSAR (L-band, 12.5m)	22.3 km²	Ghulam et al. 2014	Decision tree algorithm
		Tropical tree species	MODIS-derived NDVI, LAI, Vegetation continuous fields (500m)	QuickScat (X-band, 1km)	ca. 7.5 million km²	Prates-Clark et al. 2008	Species Distribution Model
			MODIS –derived LAI and Vegetation Continuous Fields	QuickScat (X-band, 2.25km), SRTM (C-band, ca. 30m)	17.8 million km²	Buermann et al. 2008	Species Distribution Model

			(500m)				
Ecosystem-level biodiversity	Ecosystem distribution	Wetland vegetation types	Landsat TM and ETM+ (57m)	JERS-1 (L-band, 100m), SRTM (C-band, 30m)	1.2 million km²	Bwangoy et al. 2010	Classification trees
			GF-1 (2m and 8m)	ALOS PALSAR (L-band, 14m) RADARSAT-2 (C-band, 6.3m x 5.2m)	250 km²	Fu et al. 2017*	Random forest
		Forest types	Landsat TM (30m), AVNIR-2 (10m)	ALOS PALSAR (L-band, 15m)	7,750 km²	Laurin et al. 2013	Maximum Likelihood & Neural Networks Classifiers
			SPOT 1 or 2 (20m)	ERS (C-band, 12.6m)	Not reported	Hégart-Mascle et al. 1998	Dempster-Shafner fusion
			Landsat TM (30m)	SIR-C (C and L-band, 12.5m)	ca. 520 km²	Rignot et al. 1997*	Rule-based classification
	Horizontal ecosystem structure	Forest stem density	MODIS vegetation continuous field product (500m)	ERS1-2 (C-band, 25 m or 50m depending on location)	1.5 million km²	Cartus et al. 2011	Exponential SIBERIA model, semi-empirical Interferometric Water Cloud Model
		Woody canopy cover	Landsat TM (30m)	ALOS PALSAR (L-band, 12.5m)	ca. 31,000 km²	Naidoo et al. 2016*	Random Forest
		Sediment grain size	Landsat TM (30m)	ERS-1 and 2 (C-band, 12.5m)	ca. 100 km²	van der Wal & Herman 2007*	Multiple least-squares regression
		Soil density, composition	Sentinel-2, Landsat, MODIS (rescaled to 100m)	Sentinel-1 (C-band, rescaled to 100m)	ca. 78,000 km²	Poggio & Gimona 2017*	Generalised additive model
		Soil moisture	Landsat 5 TM (30m)	ERS-2 (C-band, not reported)	400 km²	Wang et al. 2004	Quantitative modelling
	Vertical ecosystem structure	Biomass	JERS VNIR (18m)	JERS-1 SAR (L-band, 60m)	6700 km²	Wang & Qi 2008	Quantitative modelling
			Landsat 7 ETM+ (30m)	ALOS PALSAR (L-band, resampled to 30m)	107 km²	Attarchi & Gloaguen 2014*	Linear regression
			SPOT-5 (5m)	ALOS PALSAR (L-band, 25m)	1,090 km²	Hamdan et al. 2014*	Linear regression
		Timber volume	SPOT-4 (resampled to 100m)	ALOS PALSAR (L-band, resampled to 100m)	ca. 360 km²	Ismail et al. 2015	Linear regression

	Ecosystem function	Fire dynamics extent of burned areas	Landsat 5 TM (30m)	Envisat ASAR (C-band, 60m x 80m)	ca. 90,000 km^2	Stroppiana et al. 2015*	Fuzzy decision algorithm
		Wetland inundation dynamics	Landsat 5TM (30m)	ALOS PALSAR (L-band, 100m)	ca. 3,400 km^2	Ward et al. 2014*	Classification tree modelling
			Landsat 7 ETM+ (30m)	RADARSAT-1 (C-band, 12.5m)	ca. 15 km^2	Gala & Melesse 2012	Post-classification combination
Threats to biodiversity	Eutrophication	Chlorophyll-α, Secchi disk depth, suspended sediment concentration, turbidity	Landsat 5 TM (30m)	ERS-2 (C-band, 12.5m)	ca. 29,600 km^2	Zhang et al. 2002*	Artificial neural networks
		Inorganic nitrogen concentration	HJ-1 (30m)	RADARSAT-2 (C-band, 12 x 8m)	ca. 2,500 km^2	Liu et al. 2014*	Random Forest
	Forest degradation	Degradation of palm swamp	Landsat 5 TM (30m)	ALOS PALSAR (L-band, 12.5m)	3,500 km^2	Hergoualc'h et al. 2017	Random Forest
	Deforestation	Plantation expansion	Landsat TM and ETM+ (30m)	ALOS PALSAR (L-band, 50m)	3,400 km^2	Dong et al. 2013	Post-classification combination
		Deforestation events	Landsat TM (30m)	SIR-C (L and C-band, 12.5m), JERS-1 (L-band, 12.5 m)	ca. 520 km^2	Rignot et al. 1997*	Rule-based classification
			Landsat 5 and 7 (30m)	ALOS PALSAR (L-band, 25m)	ca. 7,800 km^2	Reiche et al. 2013*	Rule-based classification
			Landsat 7 ETM+ (30m)	ALOS PALSAR (L-band, 25m)	ca. 96 km^2	Reiche et al. 2015b*	Bayesian time series modeling
			Landsat MSS/TM/ETM+ (30m)	ALOS PALSAR (L-band; 25m)	3,300 km^2	Lehmann et al. 2011*	Bayesian time series modeling

Figure 1



Original SRS data
Radar
Multispectral
PIXEL-LEVEL FUSION
OBJECT-LEVEL FUSION
OBJECT-LEVEL FUSION
Parameter of interest
Decision-level fusion

Figure 2

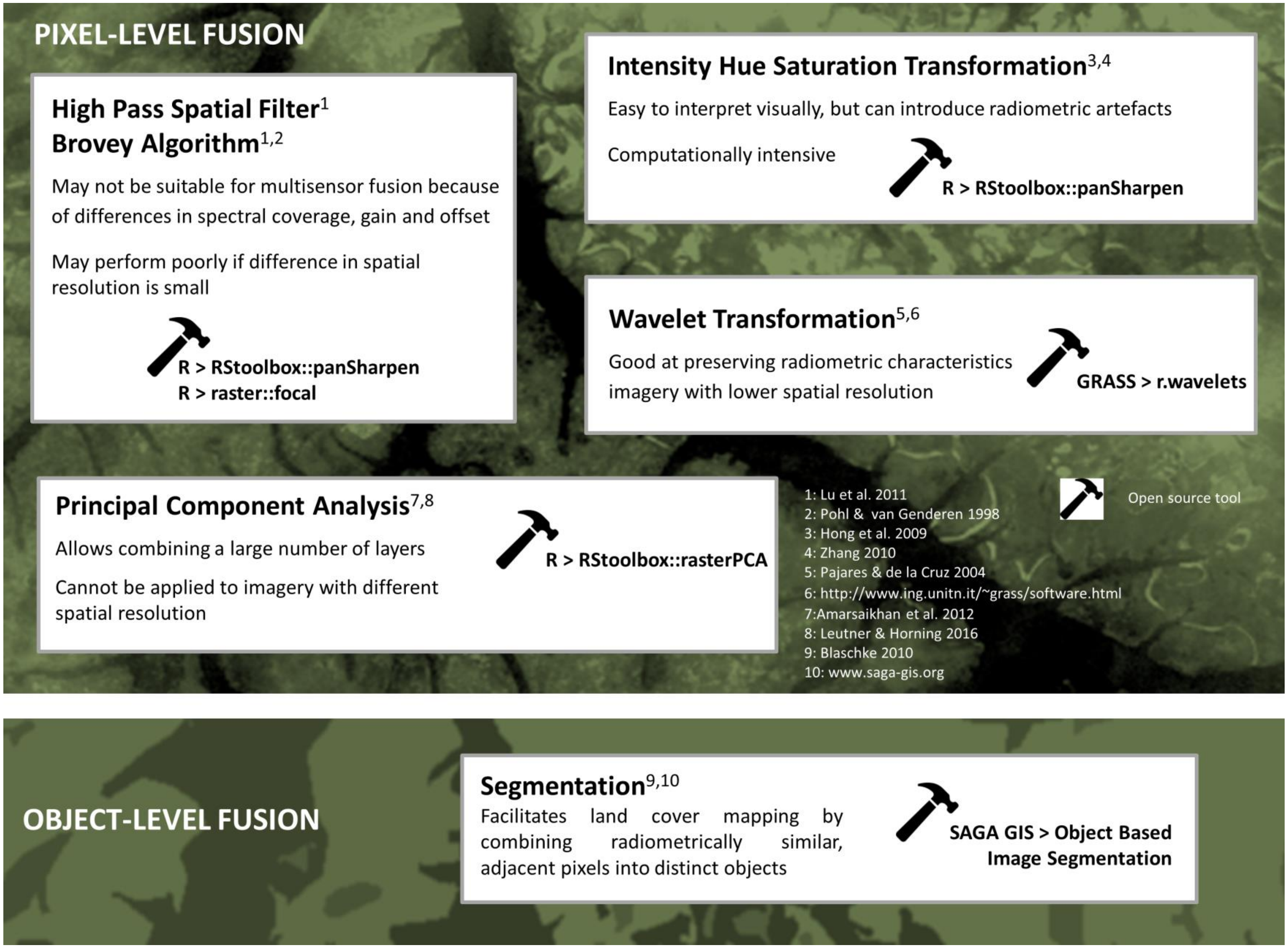
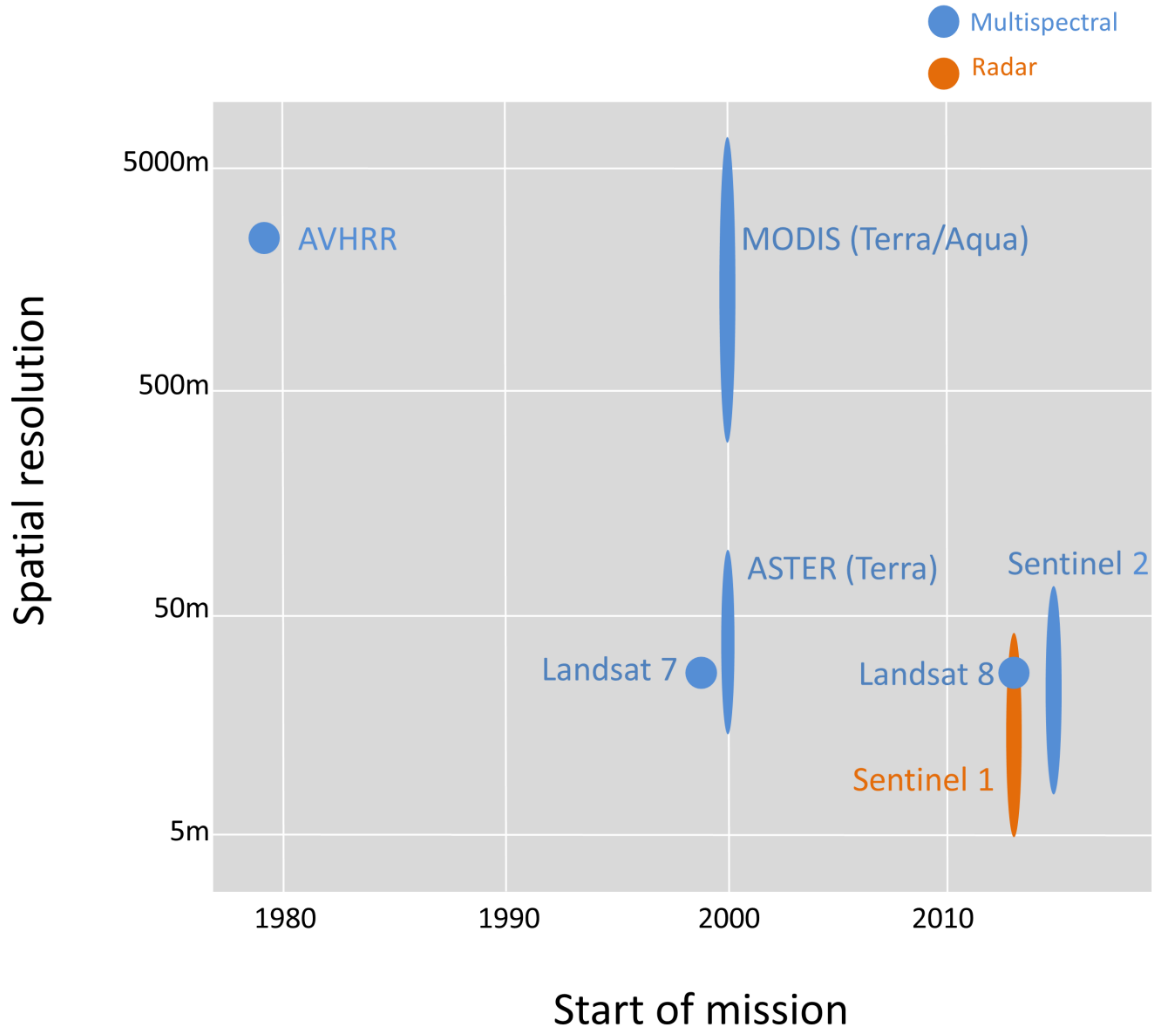
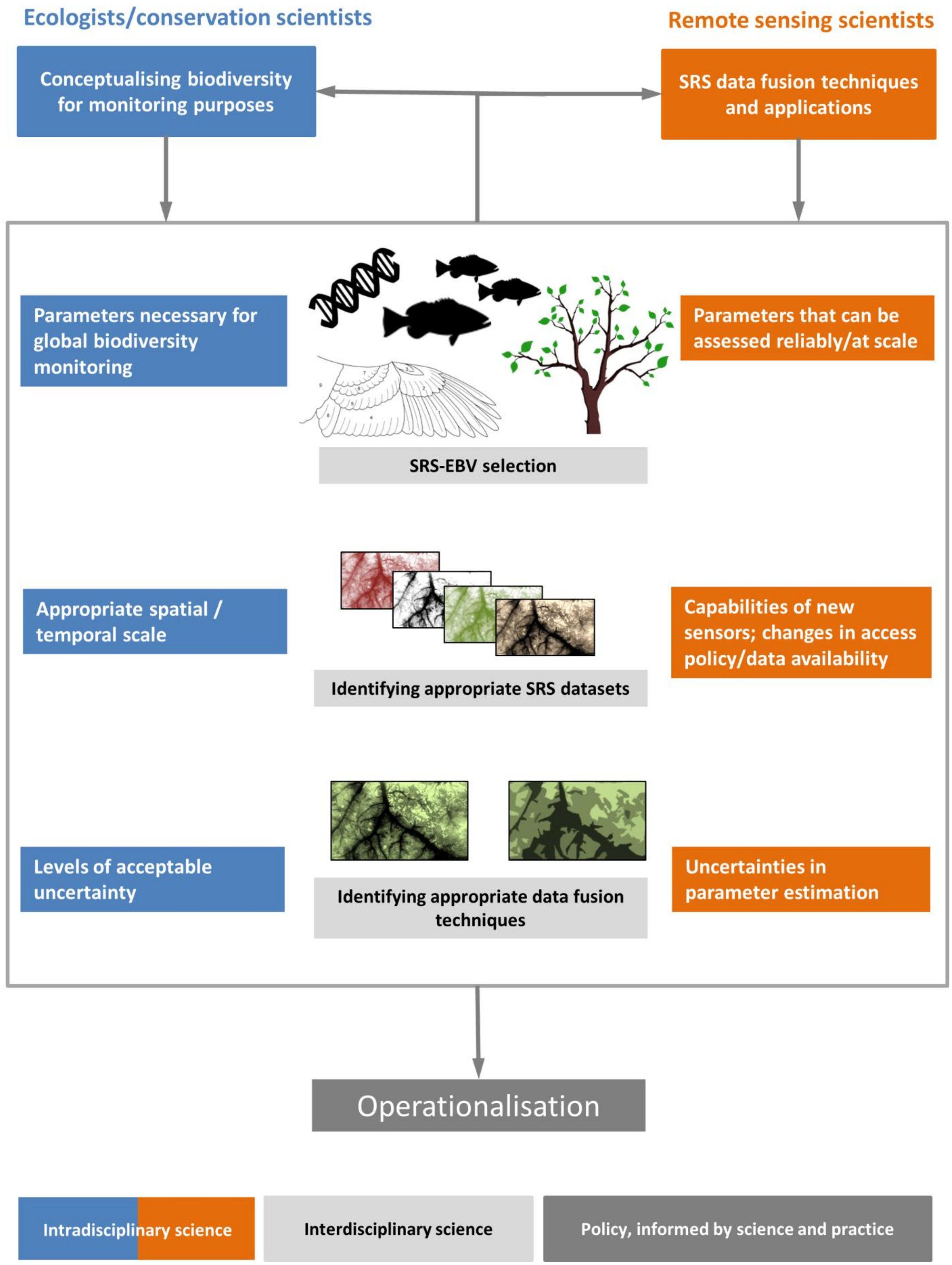

PIXEL-LEVEL FUSION
High Pass Spatial Filter[1]
Brovey Algorithm[1,2]
May not be suitable for multisensor fusion because of differences in spectral coverage, gain and offset
May perform poorly if difference in spatial resolution is small
R > RStoolbox::panSharpen
R > raster::focal
Intensity Hue Saturation Transformation[3,4]
Easy to interpret visually, but can introduce radiometric artefacts
Computationally intensive
R > RStoolbox::panSharpen
Wavelet Transformation[5,6]
Good at preserving radiometric characteristics imagery with lower spatial resolution
GRASS > r.wavelets
Principal Component Analysis[7,8]
Allows combining a large number of layers
Cannot be applied to imagery with different spatial resolution
R > RStoolbox::rasterPCA
1: Lu et al. 2011
2: Pohl & van Genderen 1998
3: Hong et al. 2009
4: Zhang 2010
5: Pajares & de la Cruz 2004
6: http://www.ing.unitn.it/~grass/software.html
7:Amarsaikhan et al. 2012
8: Leutner & Horning 2016
9: Blaschke 2010
10: www.saga-gis.org
Open source tool
OBJECT-LEVEL FUSION
Segmentation[9,10]
Facilitates land cover mapping by combining radiometrically similar, adjacent pixels into distinct objects
SAGA GIS > Object Based Image Segmentation

Figure 3



Multispectral
Radar
5000m
500m
50m
5m
AVHRR
MODIS (Terra/Aqua)
ASTER (Terra)
Sentinel 2
Landsat 7
Landsat 8
Sentinel 1
1980
1990
2000
2010
Spatial resolution
Start of mission

Figure 4


Ecologists/conservation scientists
Remote sensing scientists
Conceptualising biodiversity for monitoring purposes
SRS data fusion techniques and applications
Parameters necessary for global biodiversity monitoring
Parameters that can be assessed reliably/at scale
SRS-EBV selection
Appropriate spatial / temporal scale
Capabilities of new sensors; changes in access policy/data availability
Identifying appropriate SRS datasets
Levels of acceptable uncertainty
Uncertainties in parameter estimation
Identifying appropriate data fusion techniques
Operationalisation
Intradisciplinary science
Interdisciplinary science
Policy, informed by science and practice