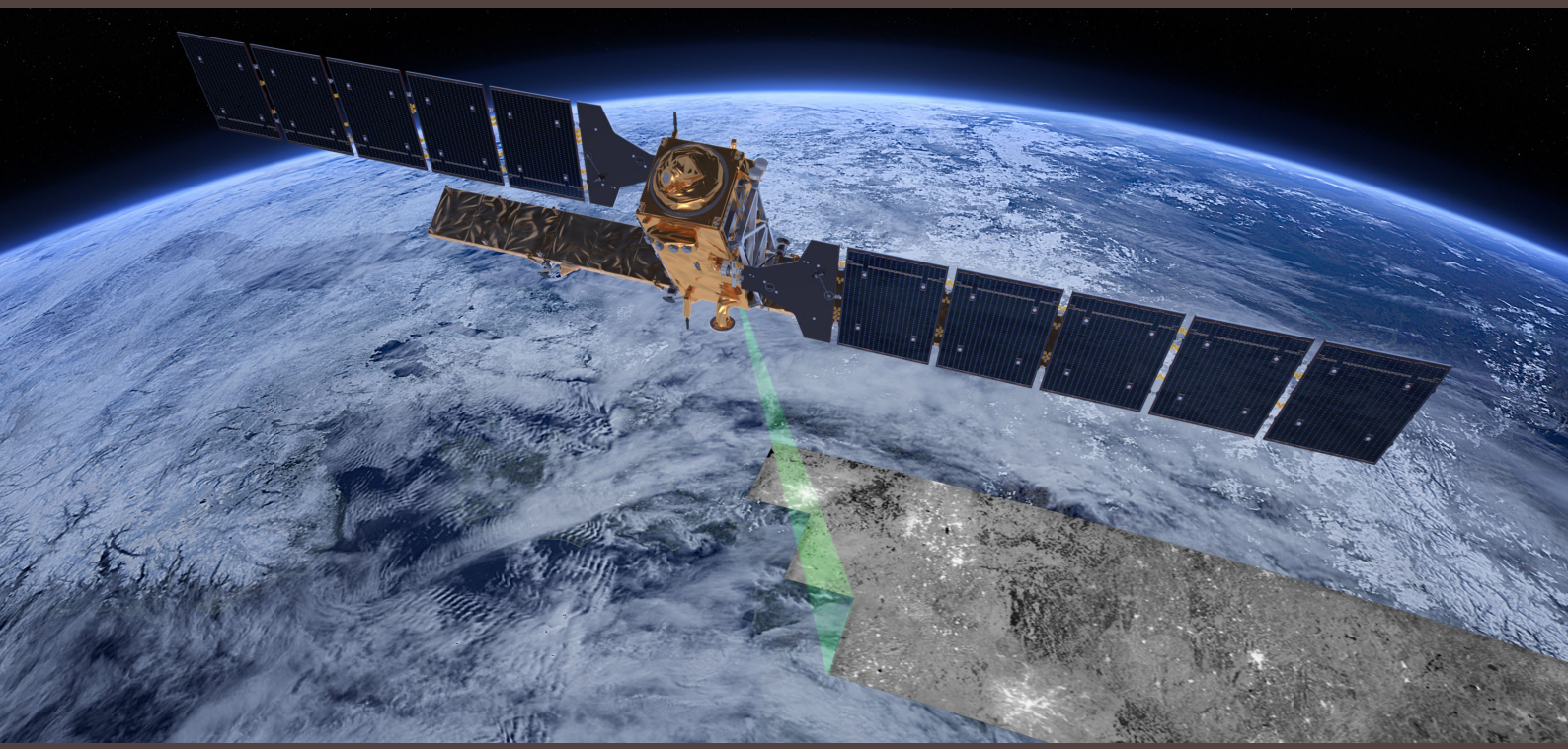
Northern Australia Environmental Resources Hub

National Environmental Science Programme



Evaluation of satellite remote sensing pathways for mapping and monitoring of gamba grass for the Savanna Fire Management Methodology

Report

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Cover photographs
Front cover: Sentinel-1 (ESA/ATG medialab)
Back cover: Example of high-resolution 3D ground-based LiDAR imagery (Shaun Levick)

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Acronyms

ALS..... Airborne Laser Scanning
BIOMASS..... Biomass Mission for Carbon Assessment
CFI..... Carbon Farming Initiative
CNN..... Convolutional Neural Network
DEA……. Digital Earth Australia
DLR ..... German Aerospace Centre
DoEE ..... Department of the Environment and Energy
EnMAP ..... Environmental Monitoring and Analysis Program
ERF..... Emissions Reduction Fund
ESA ..... European Space Agency
GEDI..... Global Ecosystem Dynamics Investigation
IFOV ..... Instantaneous Field of View
ISS..... International Space Station
LiDAR..... Light Detection and Ranging
MMU..... Minimum Mapping Unit
NASA ..... National Aeronautical Science Administration
NESP..... National Environmental Science Program
SAR ..... Synthetic Aperture Radar
TLS..... Terrestrial Laser Scanning
VHR ..... Very High Resolution

Executive summary

A core objective of NESP Project 2.3 '*Weed invasion, fire and ecosystem failure: catchment scale scenario modelling to improve planning and management*' is to work in consultation with the Australian Government's Department of the Environment and Energy to develop, if possible, a remote sensing approach at a scale, reliability, and cost suitable for mapping and monitoring gamba grass to meet the requirements of the Carbon Credits (Carbon Farming Initiative—Savanna Fire Management—Emissions Avoidance) Methodology Determination 2018.

This report has examined the suitability of a range of current remote sensing approaches to map and monitor gamba grass presence and density. This report covers an evaluation of current remote sensing missions and identifies important developments with relevance to gamba grass and other high-biomass grass mapping for the ERF. Our examination of the scale, reliability, and cost of the remote sensing methods has identified that a multi-scaled remote sensing approach that integrates optical and RADAR sensors (Section 4) is the most likely to achieve the mapping and monitoring aims of the Emissions Reduction Fund (ERF). Although a large range of sensors and satellites exist, each with their own strengths and weaknesses, our initial assessment is that research should focus on the fusion and time-series analysis of Sentinel-1 and Sentinel-2 data streams from the European Space Agency (ESA). Used in conjunction, these constellations provide both multi-spectral optical data and RADAR imagery at high spatial (10-20 m) and temporal (6-10 days) resolutions, facilitating mapping of both structural and spectral vegetation properties through different seasons. Both data streams are freely available under the Copernicus Programme and are readily accessible through multiple distributed storage and processing platforms.

A core objective of this research is to determine the scale and accuracy with which gamba grass can be mapped and monitored remotely. In order to calibrate and validate classifications derived from fused Sentinel data, higher resolution data that avoids mixed-pixels is required to provide robust endmembers. Airborne and ground-based LiDAR are well suited to generating endmember classes of vegetation 3D structure at plot scales (0.01–1,000 ha), and spectral classifications from Very High Resolution (VHR) optical imagery (Pleiades/WorldView-3/KOMPSAT-3/Planet) can fill this niche at landscape scales (1,000–10,000 ha). Hierarchically nesting plot and landscape scale classifications of gamba grass presence and density will enable explicit quantification of the accuracy and sources of error in classifications derived from coarser-scale Sentinel imagery.

The large geographic spread and spatial size of properties enrolled in the Savanna Fire Management methodology in northern Australia will necessitate the use of distributed computing clusters, and ideally cloud-based platforms, for running processing chains and classification algorithms on rich time-series data. Machine Learning approaches to image analysis and classification show good potential on preliminary datasets and are a key research direction for successfully distinguishing gamba grass from other vegetation types.

1. Requirements for the mapping and monitoring of gamba grass in the Emission Reduction Fund

Regions of northern Australia are undergoing transformation by high-biomass grass invasion. Through their alteration of natural fire regimes, these weeds (particularly gamba grass – *Andropogon gayanus*) result in the loss of environmental, social and cultural assets (Setterfield et al. 2018). In particular, gamba grass alters the above-ground standing biomass and carbon stocks through altered fire regimes (Rossiter-Rachor 2003; Setterfield et al 2012).

The recently revised *Carbon Farming Initiative—Savanna Fire Management—Emissions Avoidance) Methodology Determination 2018* included formal requirements for project areas to exclude areas that contain a relevant weed species (14.2(a)), defined as weeds which materially impact on estimations of net abatement. The only species currently listed as a relevant weed species is *Andropogon gayanus* (gamba grass).

The DoEE Savanna Technical Guidance describes the mapping and monitoring instructions for relevant weed species (Section 8.1). Of particular relevance for this project is that:

- A project must submit a vegetation map, mapped at 250 x 250 m pixel scale
- The project area must not include an area of land that contains a relevant weed species. If a relevant weed species occurs in a project area, then the project is an ineligible offset project.
- Projects must be monitored for the presence of relevant weed species as required by the savanna fire management determinations.

A key consideration for developing a cost-effective remote sensing method for gamba grass mapping is the size the properties that require monitoring, and the diversity of vegetation types that will be assessed for gamba grass presence. Current ERF properties are spread across the NT, Qld and WA range in size from 300 to 30,000 km^2, with the largest being Kakadu National Park and WALFA (Figure 1). Accuracy of monitoring methods therefore need to be assessed across a broad range of vegetation types. The complexity of distinguishing gamba grass from other high biomass grasses which may be structurally and spectrally similar, such as *Megathyrsus maximus* (guinea grass), and *Cenchrus* species, also needs to be considered.

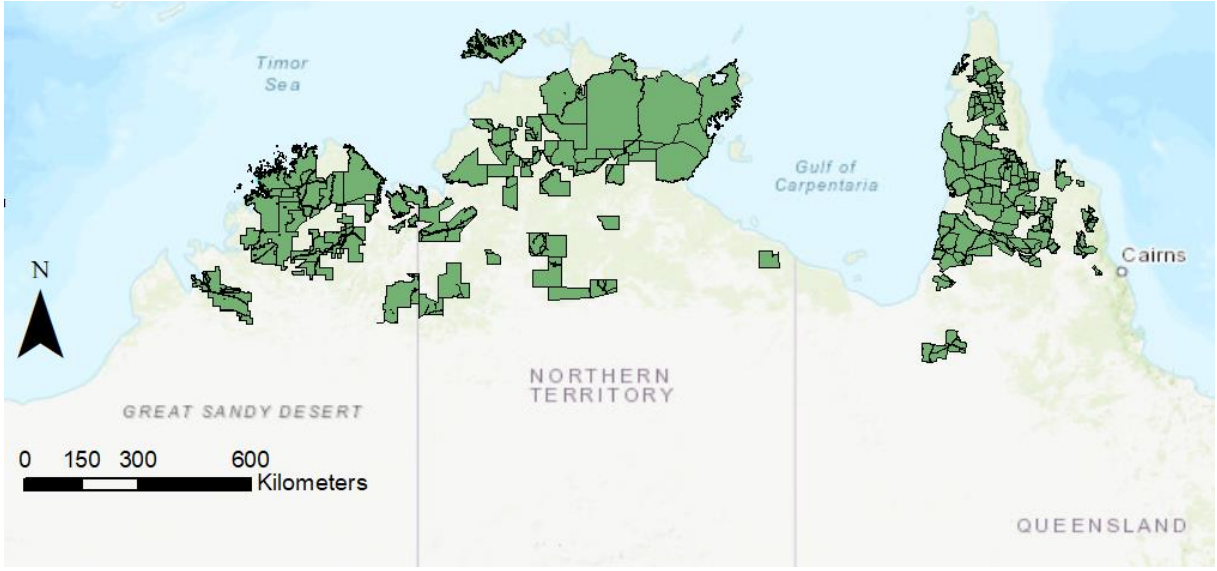

***Figure 1**. Map of properties enrolled in the Emissions Reduction Fund. Individual projects range in size from 300 to 30,000 km^2.*

***Figure 2**. Dense stand of gamba grass in the Batchelor region of the Northern Territory, Australia.*

2. Satellite remote sensing requirements for high-biomass grass mapping

Savanna grasses are notoriously difficult to map from space, due to their small individual plant size, co-occurrence with trees, and seasonally dynamic phenology (Skidmore et al. 2010, Ali et al. 2016). These issues are exacerbated in Australia's savannas by the regular presence of fires, often occurring in two out of every three years (Beringer et al. 2014). Objects without distinct structural or spectral properties are difficult to classify in remotely sensed imagery (Bradley 2013, Blaschke et al. 2014). However high-biomass grass invaders, like gamba grass are so structurally large (Figure 2) in comparison to most native grasses (Rossiter-Rachor et al. 2007, Setterfield et al. 2010), that detection from space within ERF project areas is potentially feasible. Furthermore, the phenology of gamba grass differs from many of its native neighbours - staying green (photosynthetically active) longer into to the dry season and curing later than native grasses (Rossiter et al. 2003). As such, there is potential to leverage spectral properties to distinguish gamba from native grasses, provided that imagery of a suitable resolution can be acquired at regular intervals at key times of the year, such as the start and end of the dry season.

We are fortunate to have a large range of satellite programs and sensors available for Earth Observation research, and the number of sensors has increased exponentially in recent years (Belward and Skøien 2015, Gorelick et al. 2017, Lewis et al. 2017). Each program has different objectives, so each sensor and satellite configuration differs in its core characteristics across a spectrum of spatial, temporal, spectral and radiometric domains. No one satellite can excel in all four of these dimensions, so trade-offs need to be made in selecting the sensor, or combination of sensors, most suitable to the mapping problem at hand.

2.1 Spatial, temporal, spectral and radiometric constraints

Spatial resolution refers to the pixel size of an image covering the Earth's surface, and is key to determining the size of the minimum mapping unit (MMU). Sensors offering higher spatial resolution have the advantage of being able to distinguish smaller features in landscapes, but often sacrifice temporal and radiometric resolution. Commercial satellites such a WorldView-3 and Pleiades, for example, offer spatial resolutions of < 0.5 m, but imagery needs to be tasked and in most cases only 1-2 images will be collected for a particular location per year.

Temporal resolution is also referred to as the revisit time, and denotes the frequency of image collections – how often each location on earth is imaged. Higher temporal frequencies are advantages in cloudy environment (by increasing the probability of attaining a cloud free image) and are useful in phenological studies aimed at identifying trends in photosynthetic activity. MODIS is an example of a satellite with a high temporal resolution, collecting image twice per day for a given location – the trade-off is its coarse spatial resolution (500 m).

A sensor's spectral resolution specifies the number of spectral bands, and the range of wavelengths, in which the sensor can collect reflected radiance. Radiometric resolution refers to the sensitivity of a sensor to the magnitude of the electromagnetic energy received. Trade-offs between these factors cannot be avoided when sensors are engineered (Turner et al. 2003). Sensors need to have a small instantaneous field-of-view (IFOV) to record images with

a high spatial resolution. However, as the pixel sizes become smaller, the amount of energy that can be detected also decreases as the area within the IFOV becomes smaller. Reduced energy means reduced radiometric resolution, and it becomes harder to detect small differences in reflectance (Jensen 2000). To increase the radiometric resolution without reducing the spatial resolution, it would be necessary to broaden the wavelength range for a particular channel/band – but this would have consequences for the spectral resolution. Coarser spatial resolution sensors allow for improved radiometric and spectral resolutions, and are often also associated with better temporal resolutions, as satellites with broader swaths can orbit the globe faster (Haldar 2013).

Recent developments in the European Space Agency's (ESA) Copernicus Programme have overcome some of these trade-offs by moving in the direction of satellite constellations (Torres et al. 2012). A good example of this is Sentinel-2, which is actually comprised of two satellites, Sentinel-2a and Sentinel-2b (Drusch et al. 2012). The two satellites travel the same track but are positioned opposite to each other in orbit. Sentinel-2a revisits a given location in northern Australia every 10 days, and so does Sentinel-2b, but since they sit opposite each other in orbit – that given location is actually imaged every 5–6 days. As such, the constellation approach allows for an increase in temporal resolution without sacrificing spatial, spectral or radiometric resolution.

3. Discussion

There are a large range of current satellite options that could potentially be used for mapping gamba grass in ERF properties (Table 1). However, preliminary investigations of available imagery and existing literature indicate that no single sensor will be able to provide the necessary information. Despite its physically large structure relative to native grasses, the presence of gamba amidst native trees and other grasses will be challenging to detect. As such, it will be necessary to leverage different types of sensors for the detection of subtle spectral and structural signals.

3.1 Sensor fusion and rich time-series analysis

Very high-spatial resolution (VHR) sensors (< 0.5 m) like WorldView-3 (Figure 3), Pleiades, and KOMPSAT-3 have the best chance of detection but are costly and are better suited to specific site studies than broad-scale property mapping. As such, while VHR imagery can contribute information at specific select sites, a more feasible option for the ERF property scale is the Sentinel program from the ESA – which encompasses high and medium resolution optical imagers (Sentinel-2 and Sentinel-3) and a C-band RADAR system (Sentinel-1)(Table 1). Incorporating the radar (Sentinel-1) is useful as it can penetrate the cloud layer which is prominent over northern Australia for most of the wet season, and its spatial resolution is closely matched to the 10 m sampling optical sampling of Sentinel-2 (Figure 4). Furthermore, by analysing the full time-series from these satellites (images every 6-10 days) it is possible to map features that are not evident in single time steps (Main et al. 2016). The Sentinel-1 and -2 constellations are powerful in their own right, but by fusing the two together it is possible to draw on their complementary strengths – cloud penetration, vertical structure sensitivity, spectral properties, and increased revisit time (Schmidt et al. 2017, Clerici et al. 2017). This concept could be taken a step further by introducing another independent sensor of similar spatial and spectral properties, such as NASA's Landsat 8, thereby creating a virtual constellation with even higher temporal resolution (Li and Roy 2017) (Figure 5), for key months at least – to target periods when native grasses are curing but gamba remains photosynthetically active.

Table 1. *Current satellite options with potential to provide information of vegetation structure and composition. *denotes missions that are not yet operational, **denotes missions experiencing extended delays. – denotes no cost to user*

	Agency	Platform	Type	Bands or polarisations	Spatial (m)	Revisit (days)	Cost
	NASA	MODIS	Multi-spectral	36 (620-14385 nm)	250, 500, 100	1	–
	NASA	Landsat 8	Multi-spectral	11 (435-12510 nm)	15, 30, 100	16	–
	ESA	Sentinel-1	RADAR	C-band (dual HH+HV or VV+VH)	5-100	5	–
	ESA	Sentinel-2	Multi-spectral	13 (443-2190 nm)	10, 20, 60	5	–
	ESA	Sentinel-3	Multi-spectral	11 (555-10850 nm)	500-1000	1-2	–
	ESA	Proba-V	Multi-spectral	4 (415-176 nm)	100	2	–
	Planet	RapidEye	Multi-spectral	5 (440-850 nm)	5	1-5	$
	Planet	PlanetScope	Multi-spectral	4 (440-850 nm)	3.125	1	$
	DigitalGlobe	WorldView-3	Multi-spectral	17 (450-2365 nm)	0.31, 1.24, 3.7	task	$$$
	JAXA	ALOS-2	RADAR	L-band (quad HH+HV+VH+VV)	10-100	14	$$
	DLR	TanDEM-X	RADAR	X-band (quad HH+HV+VH+VV)	1-18	11	$$
	AirBus	Pleiades	Multi-spectral	5 (470 – 940 nm)	0.5, 2	task	$$$
	KARI	KOMSAT-3	Multi-spectral	5 (450 – 900 nm)	0.7, 2.8	task	$$
	SurreySpace	NovaSAR	RADAR	S-band (tri HH, VV, HV or VH)	6-30	1-4	$
*	NASA	GEDI	LiDAR	HOMER – 1064 nm	25		–
*	CSA	RADARSAT constellation	RADAR	C-band (quad HH+HV+VH+VV)	1-100	4	$
*	ESA	BIOMASS	RADAR	P-band (quad HH+HV+VH+VV)	50 - 200	30	–
**	DLR	EnMAP	Hyper-spectral	230 (420 – 2450 nm)	30	1-27	–

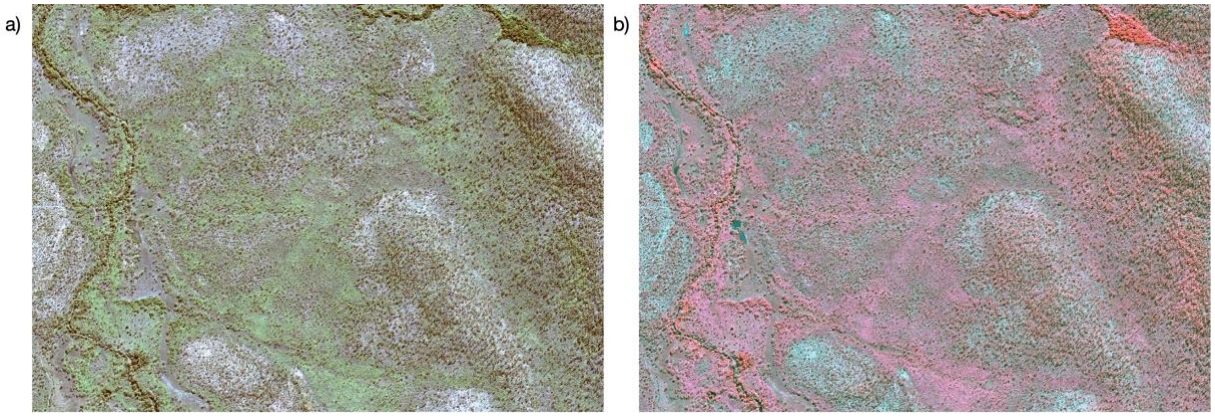

***Figure 3**. Examples of high-spatial resolution imagery obtained from WorldView-3, showing both (a) a true-colour composite and (b) a false colour composite. Very high-resolution imagery such as this has the advantage of being able to delineate individual trees and create reliable endmembers for calibration data and spectral unmixing of coarser resolution imagery.*

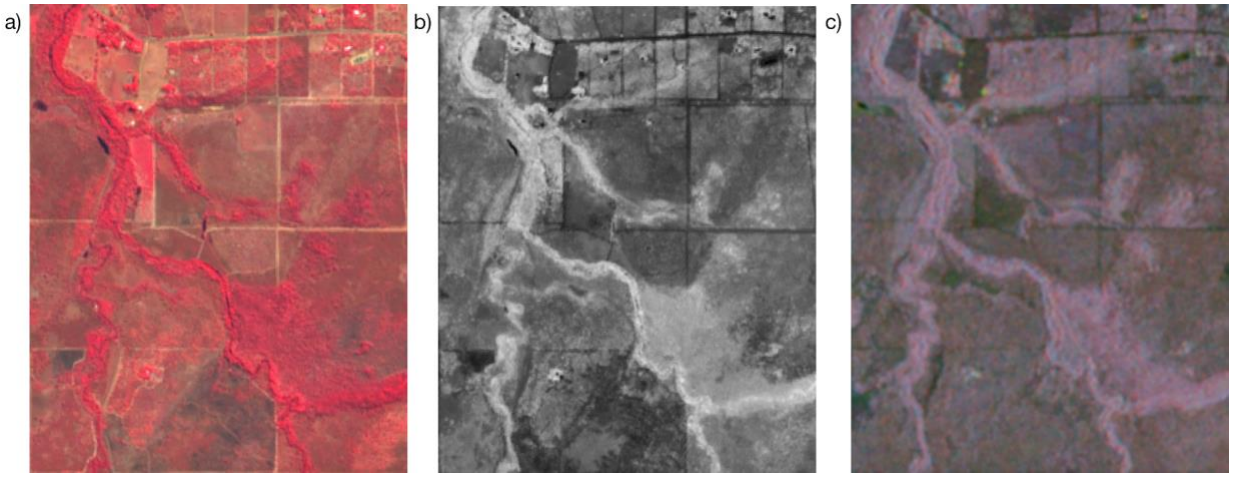

***Figure 4.** Recent imagery collected over the Batchelor area, NT Australia, from the ESA Sentinel constellations – (a) false colour composite from Sentinel-2, (b) NDV-derived from Sentinel-2, and (c) a RADAR backscatter composite from Sentinel-1.*

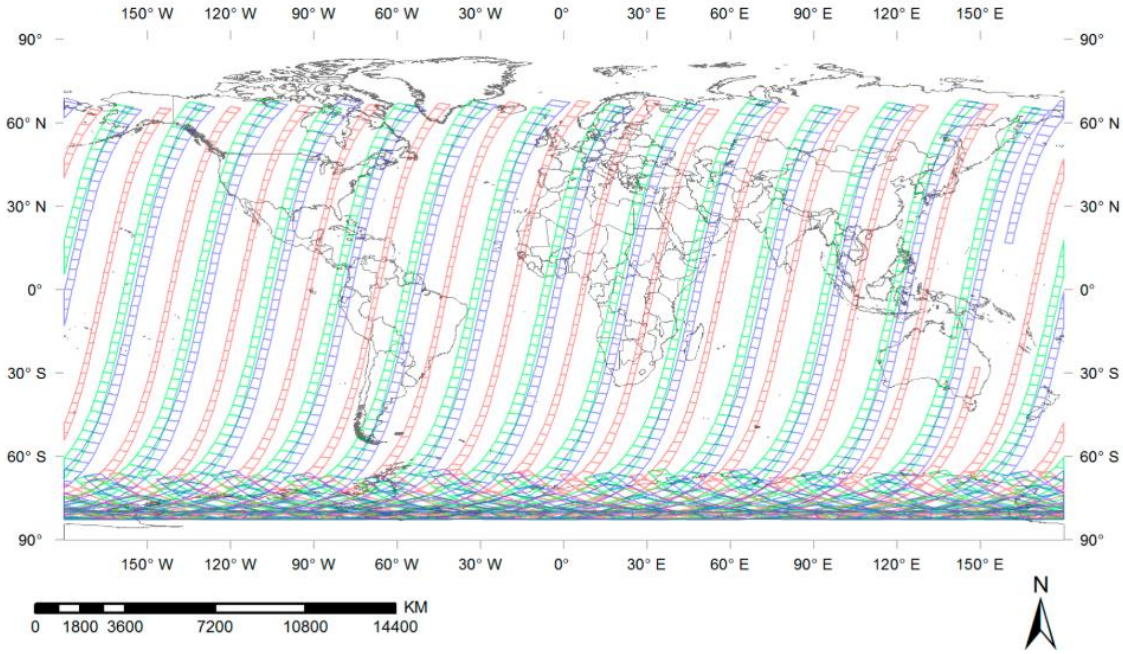

***Figure 5**. Example of the virtual constellation concept. A single day's daytime swaths for Landsat 8 (red), Sentinel-2a (green) and Sentinel-2b (blue). This virtual constellation enables near weekly cloud-free medium resolution surface observations with global coverage (Li et al 2017).*

3.2 Legacy satellite missions

The lifespan of satellite programs is difficult to predict, but recent missions have been very successful and there is a large degree of redundancy built into current global Earth monitoring programs. A number of older sensors could still add value to the gamba grass mapping challenge, but their longevity is questionable. NASA's MODIS (Moderate Resolution Imaging Spectroradiometer), for example, has been a cornerstone of Earth Observation since its launch in 2000 (Pettorelli et al. 2005). It has greatly exceeded its design life of 6 years and continues to provide imagery twice daily across the globe. Although MODIS is still widely used by the fire community in Australia for its burned area products (Hill et al. 2006, Maier 2010), we would not recommend developing new mapping initiatives based upon its lifespan. If very high temporal (daily) and greater spectral resolution is required over large areas, then emphasis should shift to Sentinel-3 (Table 1) which largely fills this niche in the years ahead (Donlon et al. 2012, Wooster et al. 2012).

For exploration of historical land cover and land cover change, the Landsat program is unparalleled (Wulder et al. 2018). Landsat imagery dating back to the 1972 provides valuable insight into how ecosystem structure has changed over time (Cohen and Goward 2004), and is widely used across the globe for forest and water resource monitoring (Hansen and Loveland 2012, Pflugmacher et al. 2012, Hansen et al. 2013). In the context of high-biomass grass mapping in northern Australia, imagery from Landsat 5 and Landsat 7 provide monthly time-series of land surface reflectance at 30 m spatial resolution. Although this archive provides useful background information on historic trends in land cover, from roughly the same period when gamba grass was trialled as pasture grass in the Northern Territory, we don't consider analysis of longer term historical dynamics to be essential for the current mapping challenge

4. Multi-scaled mapping with rigorous calibration and validation

Mapping high-biomass grasses in ERF properties will require the classification of gamba presence at the satellite pixel level based on spectral and structural features. The vast majority of land cover classification approaches from remotely sensed imagery are supervised procedures and require calibration (training) data composed of reference data of known status (Wulder et al. 2018). Suitable training data could be contributed for classification training purposes using LiDAR technology. Recent research in the Northern Territory has shown that the distinctive structure of gamba grass is readily detectable from airborne LiDAR (Figure 6, Levick et al. 2015) and preliminary terrestrial LiDAR scanning in the region has shown good potential for characterising gamba grass stands of variable densities (Figure 7). The ability to acquire robust 3D representations of gamba infested sites in conjunction with field vegetation surveys will provide excellent calibration and validation data for use in satellite-based analyses – providing a pathway for determining mapping accuracy and confidence limits at different scales.

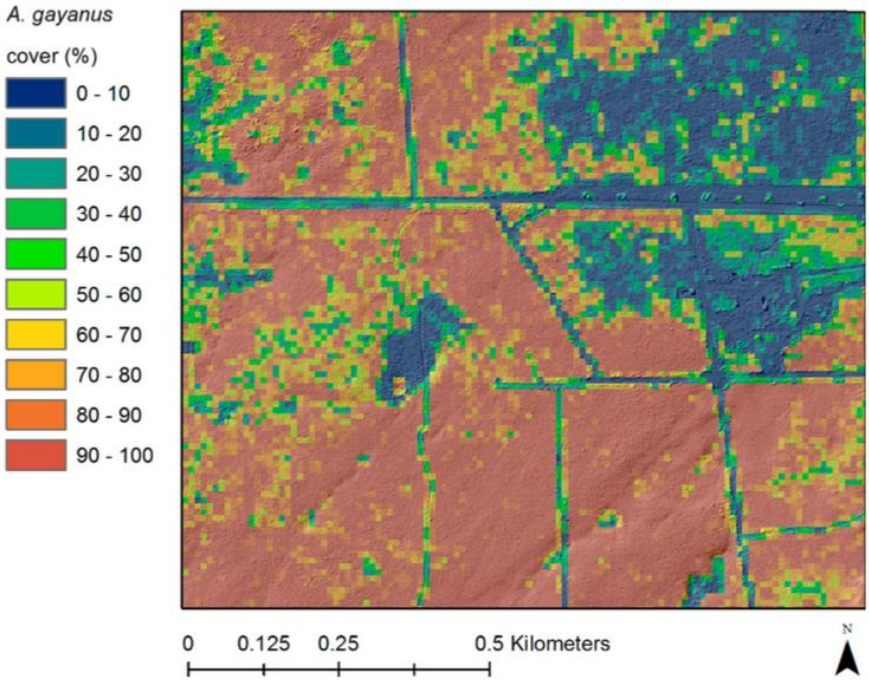

***Figure 6**. Airborne LiDAR-based classification of gamba grass cover at 10 m scale (Levick et al. 2015).*

In our opinion, the strongest potential for gamba grass mapping lies in a multi-scaled remote sensing approach that employs a combination of new generation active and passive spaceborne sensors at broad scales, and uses high-resolution data at local scales for calibration and validation (Figure 8). Broad-scale Sentinel-1 and -2 satellite imagery can be trained and validated through the targeted collection of ecosystem 3D structural data from airborne LiDAR and terrestrial laser scanning (0.01 – 1,000 ha). Additional validation in remote areas, and potential future auditing steps at a project level, can be conducted with commercial VHR satellites such as WorldView-3/ KOMPSAT-3/Pleiades or Planet data (1,000 – 10,000 ha).

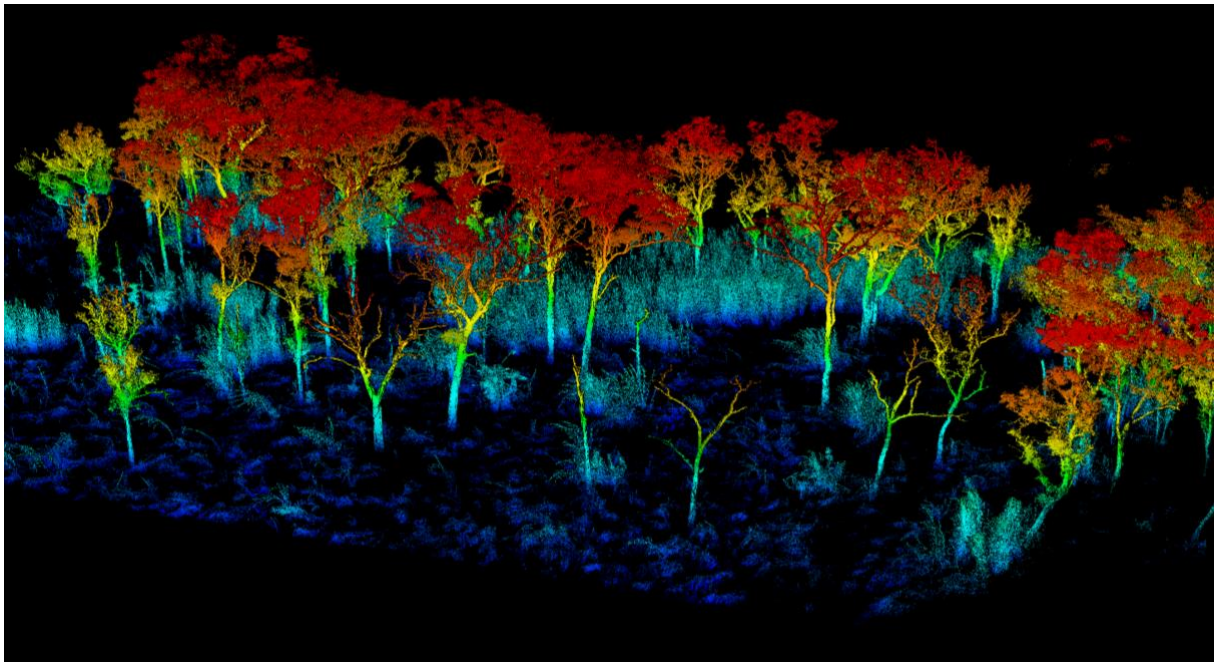

***Figure 7**. High-resolution 3D ground-based LiDAR mapping of ecosystem structure for satellite calibration and validation. Rigorous baselines of ecosystem structure are an integral component of the upscaling process.*

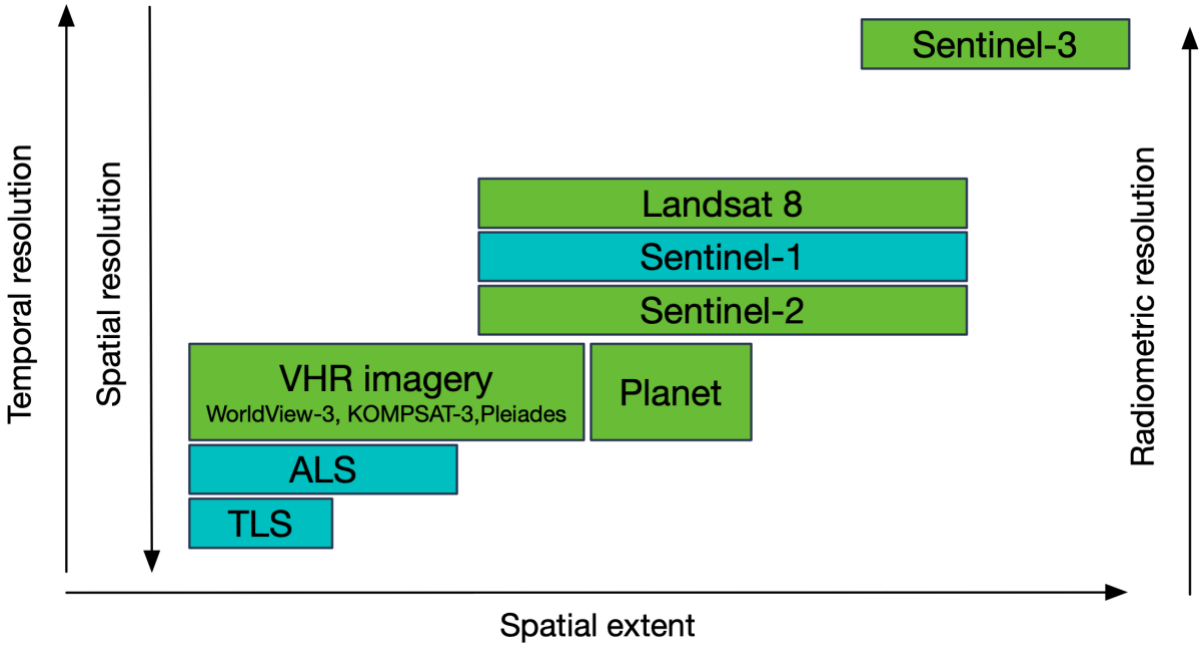

***Figure 8**. Schematic representation of scaled integration of sensors for gamba grass mapping in northern Australia. Blue boxes indicate active sensors targeted at grass structure. Green boxes indicate optical sensors targeting grass spectral characteristics.*

5. Accessibility and processing of remote sensing data

A key factor in establishing a feasible remote sensing method for mapping and monitoring gamba grass on ERF properties is the accessibility and cost of the required data and processing requirements.

5.1 Accessibility and cost

The vast majority of current Earth Observation programs from national agencies support free use and open access of imagery for research purposes. This trend was first established by the USGS, who changed policy in 2008 to provide all Landsat data for free over the internet (Wulder et al. 2012). This policy shift was pivotal, and opening up the archive has had substantial downstream effects by growing the user base and leading to more efficient processing tools and analysis algorithms (Turner et al. 2015). Landsat 8 data remains freely available (Table 1).

The ESA Copernicus Programme has adopted a similar model in making all Sentinel products accessible to the public (Table 1). This is a significant factor in prioritising their use in gamba grass monitoring for the ERF.

Open access to national space agency imagery is commendable, but these agencies cannot cover all bases and niche markets exist for commercial providers to meet specialist requirements. The primary commercial satellite of benefit for gamba grass mapping is Digital Globe's WorldView-3, the tasking of which costs approximately **$4,000** for a minimum order size of 100 km^2. Similar specification (multi-spectral, 0.5m spatial resolution) options can also be acquired from KOMPSAT-3 and Pleiades for **$ 2,000–$3,000** per 100 km^2 depending on the timeliness of the dataset (Table 1). These VHR commercial satellites have the additional advantage of flexible tasking times to align with particular periods of the year that are of phenological interest. Given the property-scale size of 300–30,000 km^2 (Section 1), these satellites may be cost prohibitive for monitoring, but we will undertake further assessment for their accuracy and cost to meet the ERF requirements.

5.2 Machine Learning and advanced processing techniques

With a surge of new imaging satellites being launched providing more frequent and repetitive coverage over large areas, there is an ever-increasing need for accurate and transferable algorithms for automated classification**.** For similar classification problems, a variety of supervised learning techniques (e.g. random forest, support vector machines, etc.) have been previously employed, with convolutional neural network (CNN) based approaches commonly showing the most accurate results (Hung et al. 2014). CNN is a class of artificial neural networks in the field of Deep Learning. CNN-based classification is particularly relevant for this project as it has been proven to be generalisable across continents and satellites (Nogueira et al. 2017, Shendryk et al. 2018) – and transferability across different environments of northern Australia is important in the ERF context. Therefore, the potential of CNN-based classification algorithms to upscale LiDAR generated gamba grass extent maps to the larger areas through VHR imagery (WorldView-3, KOMPSAT-3, Pleiades) and Sentinel data is a promising research direction. Preliminary results have shown good potential for upscaling gamba grass extent of

variable densities from airborne LiDAR scans to VHR satellite imagery (Figure 9) (Rist et al. 2018).

It was previously noted that time-series imagery provides enhanced ability to predict current ecosystem state as compared to that of single date imagery (Pflugmacher et al. 2012). Given the prohibitive cost of VHR satellite imagery to generate dense time-series, it will be important to explore the potential of medium resolution satellite imagery to detect areas of high biomass grass invasions. Machine Learning models can be implemented on time-series of Sentinel-1 SAR imagery, providing detailed information on gamba grass structure, with time-series of Sentinel-2 imagery providing information on spectral characteristics of gamba grass, specifically targeting the beginning and end of the dry season.

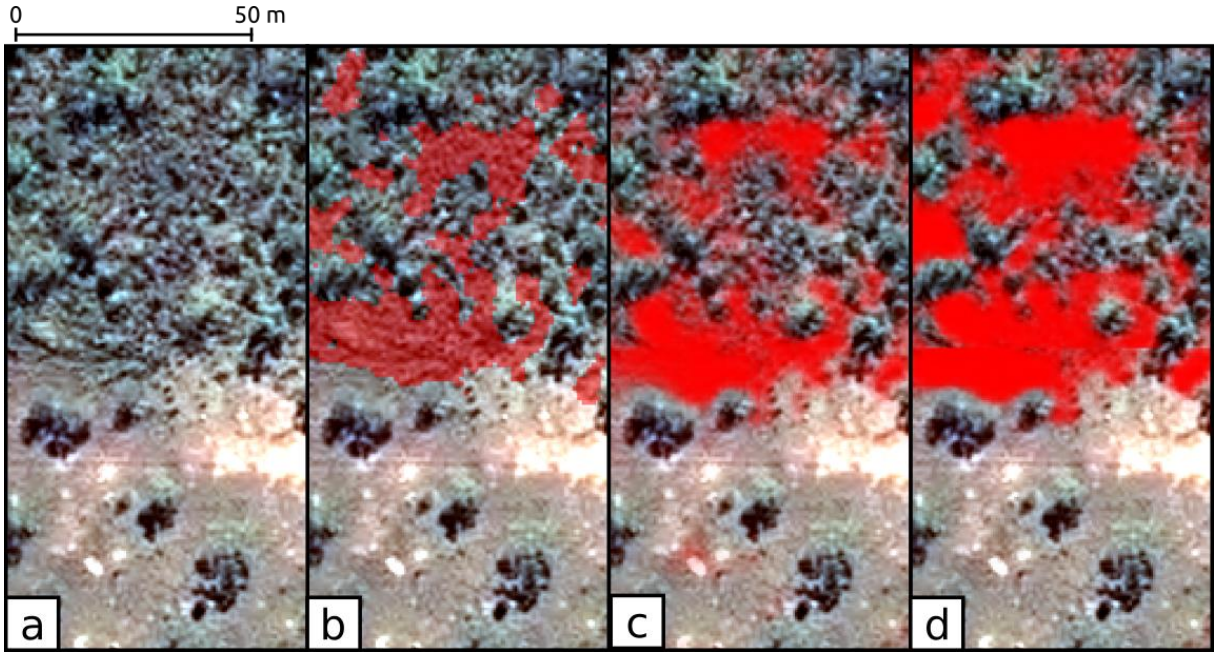

Figure 9. *(a) A portion of a high-resolution Pleiades satellite scene overlaid with (b) airborne LiDAR-derived ground gamba grass extent mask, compared to confidence scores of CNN-based classification using (c) a 256×256 pixels sliding window and (d) a 128×128 pixels window. The colour scale for confidence in (c) and (d) is linear from transparent to opaque red.*

5.3 Data cubes and cloud-based distributed processing

A further consideration for mapping and monitoring of gamba grass for the ERF methodology is the data storage and processing requirements. Local storage and processing of imagery is inefficient and unfeasible for mapping tasks of large spatial extent and with rich time-series data. Given the huge volumes of satellite data collected daily, and the large spatial area of properties in northern Australia - a mapping campaign aimed at characterising high-biomass grasses will need to utilise high-performance storage and computing clusters. Fortunately, computing power and access to servers is no longer a restriction nor major limiting expense (Wulder et al. 2018). Cloud-based distributed storage and processing platforms like Google Earth Engine have made access and processing of image archives accessible, transparent and standardised (Gorelick et al. 2017). Within the Australian context, the development of Digital Earth Australia (DEA) is facilitating the analysis of continental scale time-series of

satellite data through an implementation of the Open Data Cube, and implements geometric and spectral corrections for comparability of measurements across the time-series (Lewis et al. 2017). While Sentinel-2 imagery is available as analysis-ready datasets through DEA, the provision of analysis-ready Sentinel-1 data is planned for the year ahead. Therefore, future analysis will utilise CSIRO high-performance computing facilities, with a planned migration to the data cube. Cloud-based distributed processing is the most feasible route for operationalising mapping of gamba grass from Sentinel data on larger scales. Development of training data and algorithm development can still take place locally, but applying the algorithms to the full time-series of data will require higher performance computing.

6. Future developments in Earth Observation

Earth Observation from space is a rapidly expanding frontier, and multiple space-agencies around globe have new satellites in development for launch in the coming years. There are numerous missions on the horizon that could be of benefit to gamba grass mapping and should be kept in mind when developing the gamba grass mapping and monitoring strategy for the ERF purposes.

The NASA GEDI (Global Ecosystem Dynamics Investigation) mission is set to launch in December 2018. GEDI is a spaceborne LiDAR mission that will conduct high resolution laser ranging of Earth's forests and topography from the International Space Station (ISS**).** The footprint of the laser beam will be 25 m wide – and by examining the shape of the retuning pulse it will be possible to derive height and canopy layering information from vegetation that it interacts with (Qi and Dubayah 2016). Good opportunity exists to link the shape of the GEDI waveforms with terrestrial LiDAR collected across different densities of gamba grass invasion.

In September this year we saw the successful launch of NovaSAR, an S-band SAR satellite developed by SurreySat in the United Kingdom. The S-band wavelength will likely hold some advantages over the C-band used in Sentinel-1 in terms of vegetation canopy penetration, and its potential to assist in gamba mapping should be explored. The CSIRO has an agreement in place with SurreySat for 10% of the NovaSAR tasking time – meaning that the CSIRO will be able to direct the satellite to collect imagery over Australian areas of interest from early 2019.

The ESA will increase its vegetation mapping capability with the launch of BIOMASS in 2021. This P-band SAR mission will provide monthly information on vegetation height, biomass and disturbance across the globe (Heliere et al. 2009). Two further exciting missions are currently under development at the German Aerospace Centre (DLR) - the Environmental Mapping and Analysis Program (EnMAP) and Tandem-L. EnMAP is a hyperspectral satellite mission that aims at monitoring and characterising the Earth's environment on a global scale. EnMAP will measure and model key dynamic processes of the Earth's ecosystems by extracting geochemical, biochemical and biophysical parameters, which provide information on the status and evolution of various terrestrial and aquatic ecosystems (Guanter et al. 2015), and is scheduled to launch in the next few years. Tandem-L, an L-band SAR constellation, is still in planning and development stages (Moreira et al. 2015), but is expected to make a large contribution to vegetation mapping in 2022. The L-band wavelength is particularly well suited to vegetation biomass mapping, and it will provide complementary information to Sentinel-1, BIOMASS and NovaSAR.

The next decade will therefore continue to be very exciting from an Earth Observation perspective. However, irrespective of the developments that take place in terms of sensor and satellite technologies, reliable mapping and quantification of accuracies and confidence limits will ultimately hinge on robust calibration and validation data from the field and/or from proximal remote sensing. As such, the reference endmembers and classification results produced in the next few years will hold great value for calibration of future space missions.

7. Next steps for developing the mapping strategy

This report has examined a range of remote sensing approaches for mapping and monitoring gamba grass to meet the requirements of the ERF. Our examination of the scale, reliability, and cost of the mapping methods has identified that a multi-scaled remote sensing approach that utilises both optical and RADAR imagery (Section 4) is the most likely to achieve the mapping and monitoring aims of the ERF. We recommend that the proposed multi-scaled remote sensing approach be trialled in three different regions of northern Australia to test its suitability to meet the requirements of the ERF. We have identified three case study regions (Batchelor, Kakadu and Cape York) that encompass a range of vegetation and climatic conditions within the tropical savanna zone. Under Phase 2 of this project, we will explicitly determine the scale, accuracy and cost with which gamba grass can be mapped from space in these different environments.

The analysis workflow (Figure 10) will link field-based estimates of gamba presence and density (obtained from field vegetation surveys and terrestrial/UAV LiDAR) with very high-resolution satellite imagery (WorldView-3, KOMPSAT-3, Pleiades, Planet) tasked over the three case study regions. A convolutional neutral network (CNN) classification will be developed for the VHR imagery using the field data as training and validation data. The VHR classification will in turn be used as training and validation data for upscaling to Sentinel-1 and -2 data streams.

- Ground-based field data will be collected by the CDU, UWA and CSIRO field teams.
- Terrestrial LiDAR and UAV LiDAR will be acquired by CSIRO.
- WorldView-3 imagery will be tasked commercially through DigitalGlobe (3 x $4,000)
- KOMPSAT-3 will provide 2 free taskings over our case study regions by prior agreement
- Planet will provide free access to 10,000 km^2 of imagery per month for 2019 under an established research agreement
- Sentinel-1 and Sentinel-2 data are open access through the European Space Agency's Copernicus program

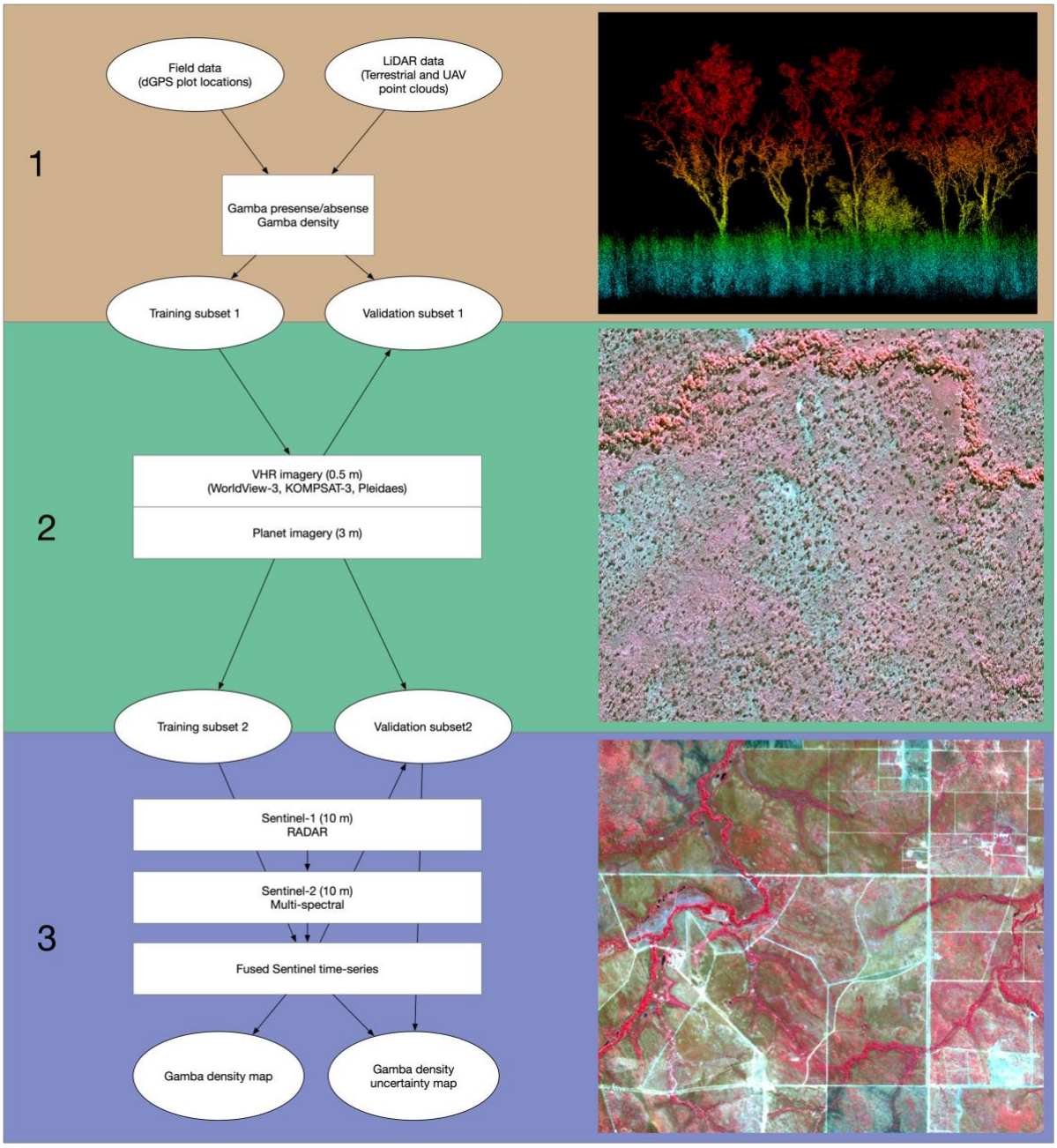

***Figure 10**. Phase 2 workflow schematic showing how field and ground-based LiDAR data will be used to train a classification of VHR imagery, which will in turn be used for training and validation of fused Sentinel-1/-2 time-series.*

8. Conclusions

The combination of Sentinel-1 and Sentinel-2 data streams present a compelling avenue for large area mapping at ecologically useful spatial (10-20 m) and temporal resolutions (6-10 days) across northern Australia. The fusion of optical data from Sentinel-2 with RADAR backscatter and polarimetry data from Sentinel-1 (which penetrates cloud cover) will provide a rich data cube of structural and spectral properties that is freely available and readily accessible from cloud-based distributed computing platforms. Robust calibration and validation is critical to the success of the mapping challenge, and should rely upon rigorous fine scale habitat characterisation from LiDAR and VHR imagery (e.g. WorldView-3/KOMPSAT-3/Pleiades/Planet). Machine Learning approaches to image and time-series classification are likely to yield the best classification results and will help distinguish subtle signatures in heterogeneous landscapes. Case studies currently being established will provide quantitative estimates of classification accuracies and confidence limits in Phase 2 of the project.

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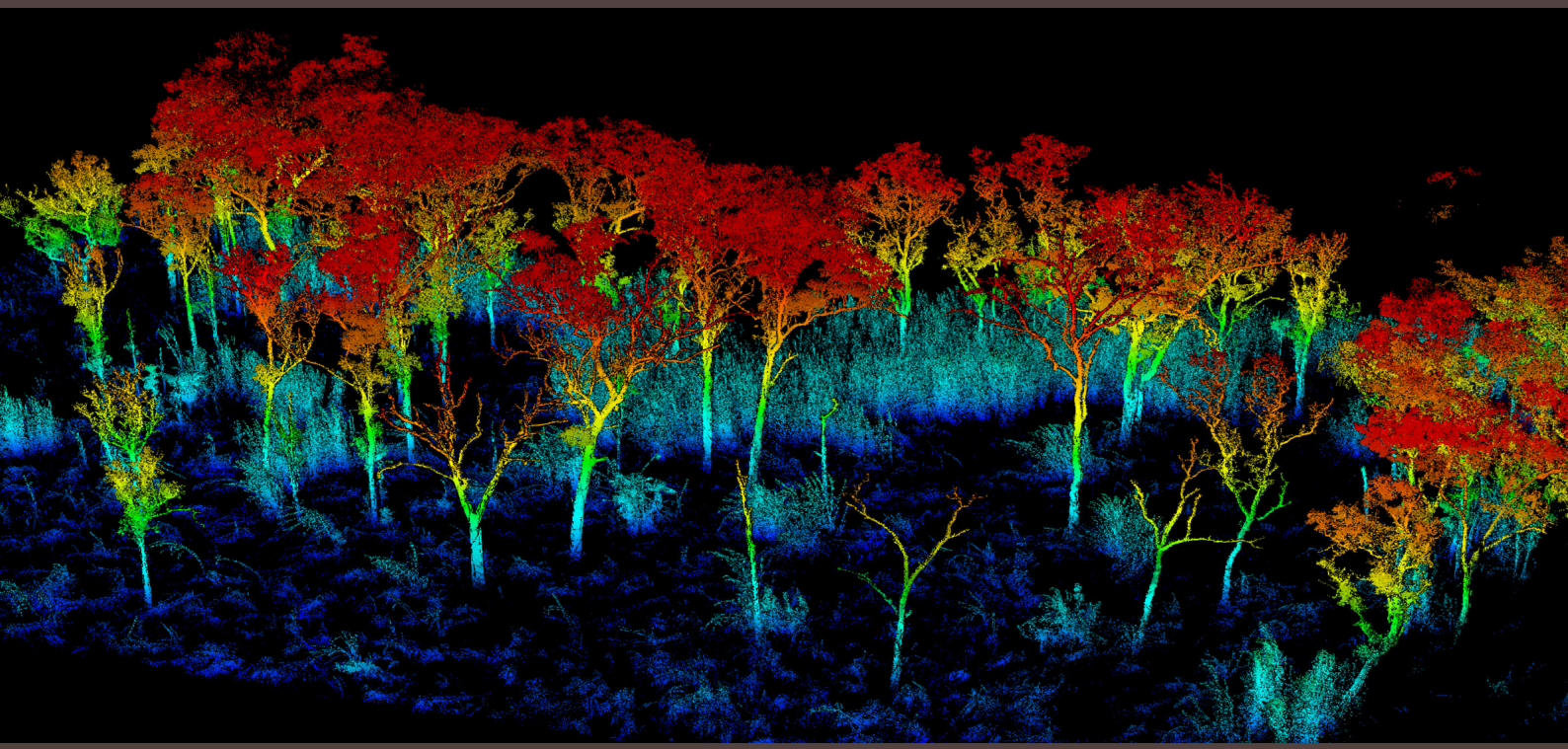

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