Chapter 2: Detecting humpback whales from high resolution satellite imagery

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1 Introduction

Humpback whales are distributed throughout the length of Kimberley coastal region, surveys are necessarily complicated by the size and remoteness of this region, platform logistics and observer biases. The costs of broad-scale surveys using planes or vessels (the traditional platforms to assess population size and distribution) are high, as is the time required by researchers to analyse the data. These issues are common to many studies and have led some researchers to trial high resolution satellite imagery to detect and count whales and other megafauna (Abileah 2001, Fretwell et al. 2014, McMahon et al. 2014, LaRue et al. 2017). For example, WorldView-2 (operated by Digital Globe) satellite imagery was used successfully to identify and count southern right whales (*Eubalaena australis*) breeding off the coast of Argentina (Fretwell et al. 2014). This satellite orbits at a height of 770 km above the earth and provides a maximum resolution of 1.6 m per pixel in the multispectral bands (includes two infrared bands) and 0.46 m in the panchromatic band (greyscale). The success of this earlier work led our study to trial WorldView-2 satellite imagery as a means to sample humpback whales. Images are now also available from WorldView-3, a newer version of the satellite, which orbits at 620 km above the earth and collects data at a resolution of 1.24 m per pixel in the multispectral bands and 0.31 m in the panchromatic band. The higher resolution of WorldView-3 was considered preferable for detecting whales, but as it was also more costly to source, we sought to first examine images from WorldView-2. The latter satellite also has a more extensive archive as it was launched in 2009, whereas the WorldView-3 satellite was launched in late 2014.

Here we used archived WorldView-2 images and tasked WorlView-3 images to assess whether humpback whales could be detected and counted using visual and automated methods.

2 Materials and methods

2.1 Image selection

We first set out to obtain a WorldView archived image that overlapped with the temporal and spatial extend of the humpback whales survey data (Table 1 in Chapter 1) and preferably obtained around the peak in humpback whale seasonal abundance in the Kimberley. To do this, all the survey data (Table 1 in Chapter 1) was collated into a single GIS dataset and used to define an area of interest (AOI) for the satellite images. The AOI was defined as the 95% kernel utilisation density of all sightings data combined (Fig. 1), which was then used to query Digital Globe's database for the WorldView Archival imagery. The query defined all pre-existing WorldView-2 and WorldView-3 imagery that intersected with the AOI and was downloaded as a shapefile of image footprints. We compared the temporal extent of the footprints to the survey data to search for images that were captured on or close to a corresponding survey date. No suitable WorldView-3 imagery was available that fulfilled these criteria, but three WorldView-2 Images were identified that were captured within a few hours of a survey completed on the 6th of August 2010 off James Price Point. We selected one image (Fig. 1) of the three available that appeared to have the best sea surface conditions (low swell, white caps and glare) based on the catalogue preview, and also overlapped with the survey that had the most observations of whales. We then acquired the 941 km², 8-band multispectral satellite image (10AUG06021738-M2AS-055137769010_01_P0011) on an evaluation license. The size of the image meant it was delivered as a tiled product with each tile provided as a geotiff or as a mosaic through the xml file. We followed a similar approach to that of (Fretwell et al. 2014), with an initial step of visually searching the image to identify some features that were likely to be whales based on size and shape that could then be used to train a supervised automated detection process using spectral image analysis of all bands and thresholding of the panchromatic band. The primary software package used in the analysis was ESRI's ArcGIS package and Exelis's ENVI.

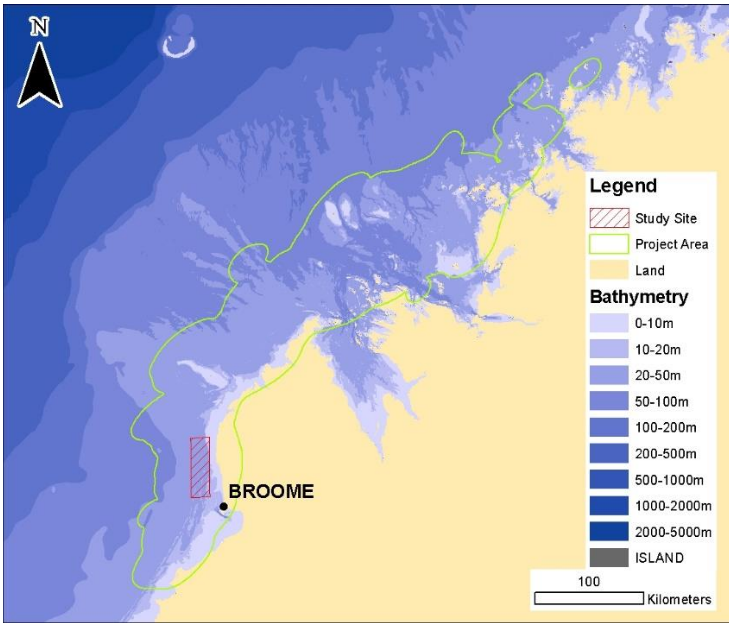

Figure 1. The study area showing the 95% kernel utilisation distribution from all the humpback whale survey data in green and the area where WorldView-2 archived image was captured in red square.

2.2 Spectral image analysis of WorldView-2 image

We classified all surface features found in the visual search including white caps, boats and whales and whale features (e.g. footprints) similar to the categories in Fretwell et al. (2014) in the panchromatic and multispectral bands. We then undertook a spectral analysis to determine whether pixels that contained whales had a different spectral signature to pixels of other non-whale surface features and the surrounding environment so that the spectral signature could potentially be used to automate the detection of whales in the satellite images.

Each visually feature was digitised as a polygon within ArcGIS and to provide the best shape definition and minimise inclusion of non-target cells, the panchromatic band was used, having the highest spatial resolution. To improve definition of the shape of objects a combination of the Dynamic Range Adjustment function and manual histogram stretching within the image analysis tools of ArcGIS were used to enhance their appearance. To provide comparison, additional features were digitised to capture deep water, shallow water, mid water, wave crest white water and boat wakes.

Each pixel's digital number value was extracted by loading the digitised feature polygons into ENVI to intersect with and sample the value ranges represented within each band and calculate the range and mean values for each of the surface feature categories (Fig. 2). For the multispectral bands we used the pan sharpened multispectral image resampled to 0.4m pixels in an attempt to reduce the sampling of non-target values (Fig. 3). We then used a supervised classification using the pixel values from each class to automatically classify the image. We also tried an unsupervised classification to classify surface objects in the image based only on information held within the image and using a clustering algorithm to determine the groupings. We also used an iterative process to formulate threshold pixel values to that maximised the signal of the 'whale' features and reduced the signal noise on non-whale surface features.

Following examination of the spectral profiles, separability tests were run using ENVI and the Gram Schmidt Pan Sharpened Multispectral image and all 8 bands. Jefferies-Matusita (JM) and Transformed Divergence (TD) scores were calculated from these tests, where values over 1.9 indicate the features are separable and values between 1.7 and 1.9 may be separable.

2.3 Tasking and analysis of WordView-3

Since there was no archived WorldView-3 data from our region, we tasked the WorldView-3 satellite to provide two images to be taken on two different days (early and mid-August) in 2016. The area over which the images were to be taken was based on the 25% kernel utilisation density area centred on Camden Sound (425 km^2 area). We then identified and counted the whales in the resulting images by eye. Each of three people counted the images independently and the results were cross checked for the final count. We also worked with Toyon Research Corporation to trial a semi-automated detection process using shape previously developed for detecting gray whales in remotely sensed imagery. We provided a subset of the grayscale, panchromatic WorldView-3 imagery that contained whales as input to this algorithm. Later, we provided the spatial locations of these whales in the imagery to validate their process. The algorithm ran a sliding window over the image and saved any image chips that met whale shape criteria. Then a human reviewed the chips generated by the algorithm and identified those that actually contained whales.

Given the high cost of tasking the WorldView satellites, we also conducted a cost-benefit analysis for the use of this technology to monitor humpback whales in the Kimberley region and compared costs to traditional surveys to achieve the same goals.

3 Results

3.1 WorldView-2

From the visual search of the WorldView-2 image a total of 59 surface features related to whales were identified including possible submerged whales, surfaced or partially-surfaced whales and footprints from tail beats or landing marks of breaches (Table 1). Additionally, 6 vessels where identified ranging from only a few meters to 35 m in length. We were not able to reproduce these images here as the image was obtained using an evaluation licence, however they were of similar to poorer quality to those shown in Fretwell et al. (2014). Only one of the surface features was able to be classified as 'whale certain'. For the actual vessel survey that coincided with the day of image capture there were 66 whales observed over the entire 941 km^2 footprint of the image or 7 whales per 100 km^2, however sufficient information was not available to determine whether the survey was representative of the entire footprint.

Table 1. Results of the visual search of WorldView-2 image.

Classification	Feature	Count
Certain	Whale	1
	Boat	6
	Total	7
Probable	Whale	3
	Footprints etc	4
	Submerged whale	12
	Total	19
Possible	Whale	21
	Footprints etc	10
	Submerged whale	2
	Total	33
	Grand total	59

Examination of the spectral signals on the panchromatic band (Fig. 2) shows that minimum values are relatively common and is most likely because all features have water in common which is difficult to completely exclude from the pixels. Within the maximum values there are spikes, with Boats having the highest maximum values followed by, Boat-Wakes, then Whale-Certain and Whale-Related features. Boats also have the highest mean values followed by Boat-Wakes, Whale-Related features and Whales-Certain. However, with the exception of the Whale-Related features, mean values for whale categories are not significantly higher than mean values for water features, with Whales-Certain having a mean value of 153 compared with 145 for Water-Shallow.

When whale features were re-examined using the pixel inspector tool we were able to tighten the range of the pixel values to 200-810 and boat features to 300-1978. Although the maximum value of boats allowed them to be selected and removed, there was still overlap with whale features and boat wake (which was found to vary greatly), and shallow water (Fig. 2).

Surface disturbance believed to have been caused by whales was difficult to isolate from white water and sun glint with thresholding alone, and a significant amount of noise and false targets remained. It was noted that white water and sun glint both associated with swell had a distinct orientation which possibly could allow it to be filtered out from target features. Shape of whale related surface disturbance varied but could be of use in further separating surface features. In addition to overlaps with other surface features, shallow waters with seemingly reflective sea floor returned high values that overlapped with whales, whale related features and whitecaps making it difficult to rely on thresholding alone to extract whale features.

Submerged whales had no overlap with other features but had varying values, presumably based on varying depth and could not be distinguished from deep water areas. While other bands may help distinguish submerged whales from deeper waters, low resolution of other bands and poor distinction of submerged features prevents this from being a suitable option for thresholding alone.

We tried reclassifying based on threshold values of 200 and greater than 810, however this did still not allow discrimination of whale related features from boat waked and neither did the use of minimum bounding geometry calculated along with the geometry attributes and a filter applied to exclude all features with a length of less than 4m and a length of greater than 18 m leading us to conclude that thresholding in the panchromatic even with the use of basic geometry measures to filter was not adequate. However, the process did successfully filter out the boats, water and the majority of the white water.

We found similar results with the spectral analysis of the multispectral bands, with whale features not being able to be distinguished from the surrounding water (Fig. 3). The primary draw back of the multispectral bands is they have a maximum resolution of 1.6 m or 2.56m², this represents 16 of the 0.4 m pixels in the panchromatic band, and larger pixels result in more overlap with non-target features such as water, providing a mixed signal which when identifying relatively small features makes it difficult.

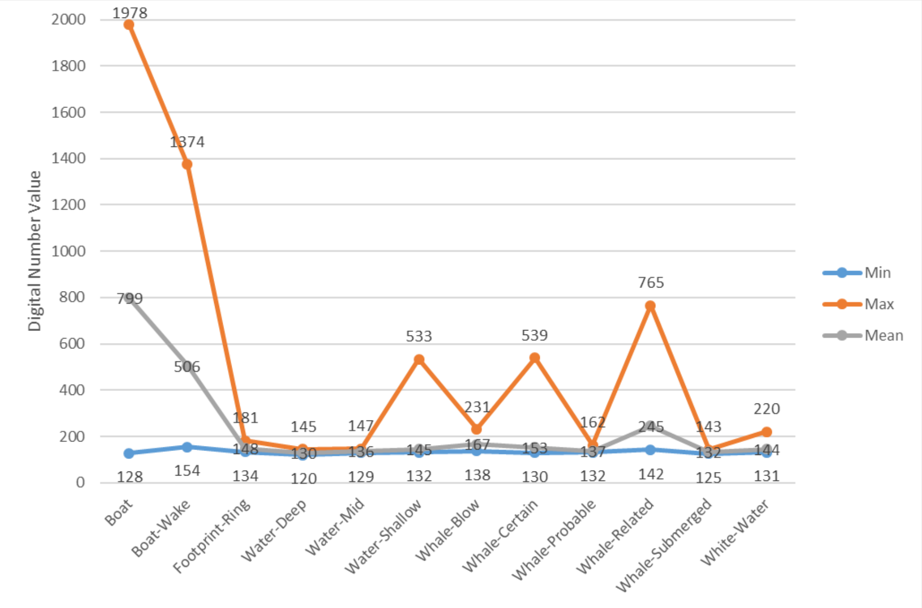

Figure 2. The minimum, maximum and mean values within the panchromatic band for each of the identified surface features and the surrounding environment.

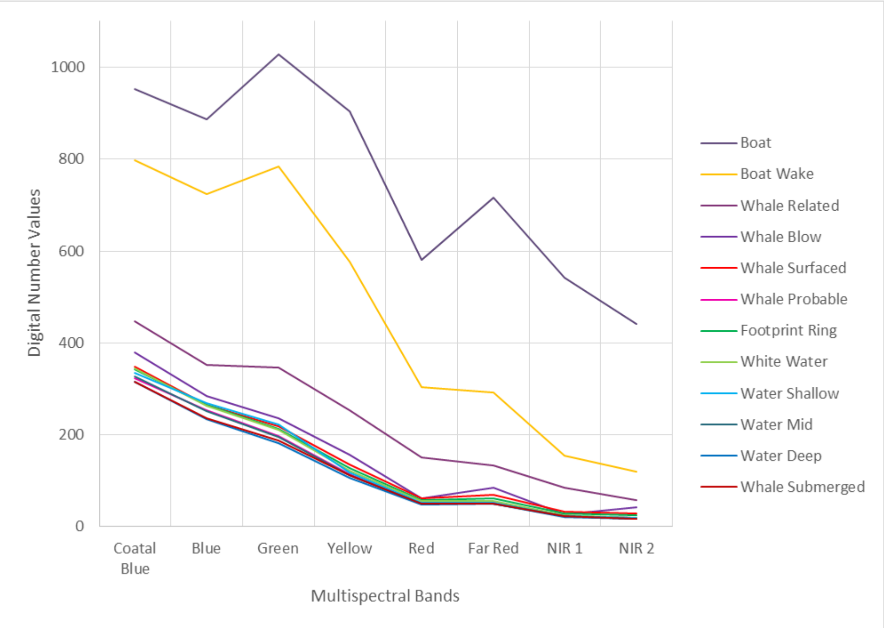

Figure 3. Mean values within the multispectral bands (from sampling a pan sharpened multispectral image) for each of the identified surface features and the surrounding environment.

The Jefferies-Matusita (JM) and Transformed Divergence (TD) scores resulting from the separability tests indicated that white water and whale footprints cannot be spectrally separated with a JM score of 1.333 and a TD score of 1.543. The TD Test suggested all other features were separable while the JM tests suggested a number of features were either not separable or not well separable. Submerged whales were one of these showing poor separability from Mid Waters with a score of 1.656 and surprisingly poor separability from White Water at 1.694, while possibly being separable from Deep Water with a score of 1.79. Whale related surface features were not separable from Boat Wake in the JM test with a score of 1.668. Surfaced whales where highly separable from most features but less separable from Footprint Rings with a JM score of 1.865 and White Water with a JM score of 1.848, though these scores are sufficiently high enough to suggest separation can still be achieved.

Despite promising results from the separability tests, the supervised classification of the pan sharpened multispectral image did not provide adequate separation with identified classes having significant overlap in feature identification.

3.2 WorldView-3

For the WorldView-3 tasked images captured at higher resolution we manually counted 33 adult whales, and eight calves on Aug 06, 2016 and 23 adult whales and seven calves on Aug 12, 2016 (Table 3). Unlike with WorldView-2 (Table 1), the majority of these were in the ‘certain’ category (Table 3). Figure 4 shows a selection of these images and one of a boat, demonstrating that WV3 had sufficient spatial resolution to discern size differences in humpback whales and to thus identify some calves (potentially not all). For the semi-automated detection algorithm using shape, 100% detection rate was achieved (Table 2). There were a high number of false identifications of whales (max of 128) at times, and these took a total of 20 mins to resolve visually by an observer. Two of the positive identifications obtained from visual searches were not whales. Visual searching with three replicates (three people searching independently) of one 425 km^2 image set took 24 person-hours (eight hours per person).

Table 2. Results of the semi-automated detection algorithm of a selection of the WorldView-3 images of Camden Sound.

Image name	**Whale ID**	**Detected?**	**No. False positives**	**Algorithm time (mins)**	**Chip review time (mins)**
16AUG12022217-P2AS_R1C4-055488310050_01_P002.TIF	1	Yes	14	7	<1
	2	Yes			
	3*	No			
16AUG06022458-P2AS_R5C3-055488310050_01_P001.TIF	4	Yes	128	20	2
	5	Yes			
16AUG12022217-P2AS_R2C2-055488310050_01_P002.TIF	6	Yes	0	7	<1
	7	Yes			
	8*	No			

Note: Whale IDs 3 and 8 were confirmed not to be whales

Table 3. Results of the visual search of WorldView-3 image.

Classification	**Feature**	**6 August**	**12 August**
Certain	Adult whale	18	11
	Calf	5	2
	Total	23	13
Probable	Adult whale	6	6
	Calf	2	3
	Total	8	9
Possible	Adult whale	9	6
	Calf	1	2
	Total	10	8
	Grand total	33A + 8C = 41	23A + 7C = 30

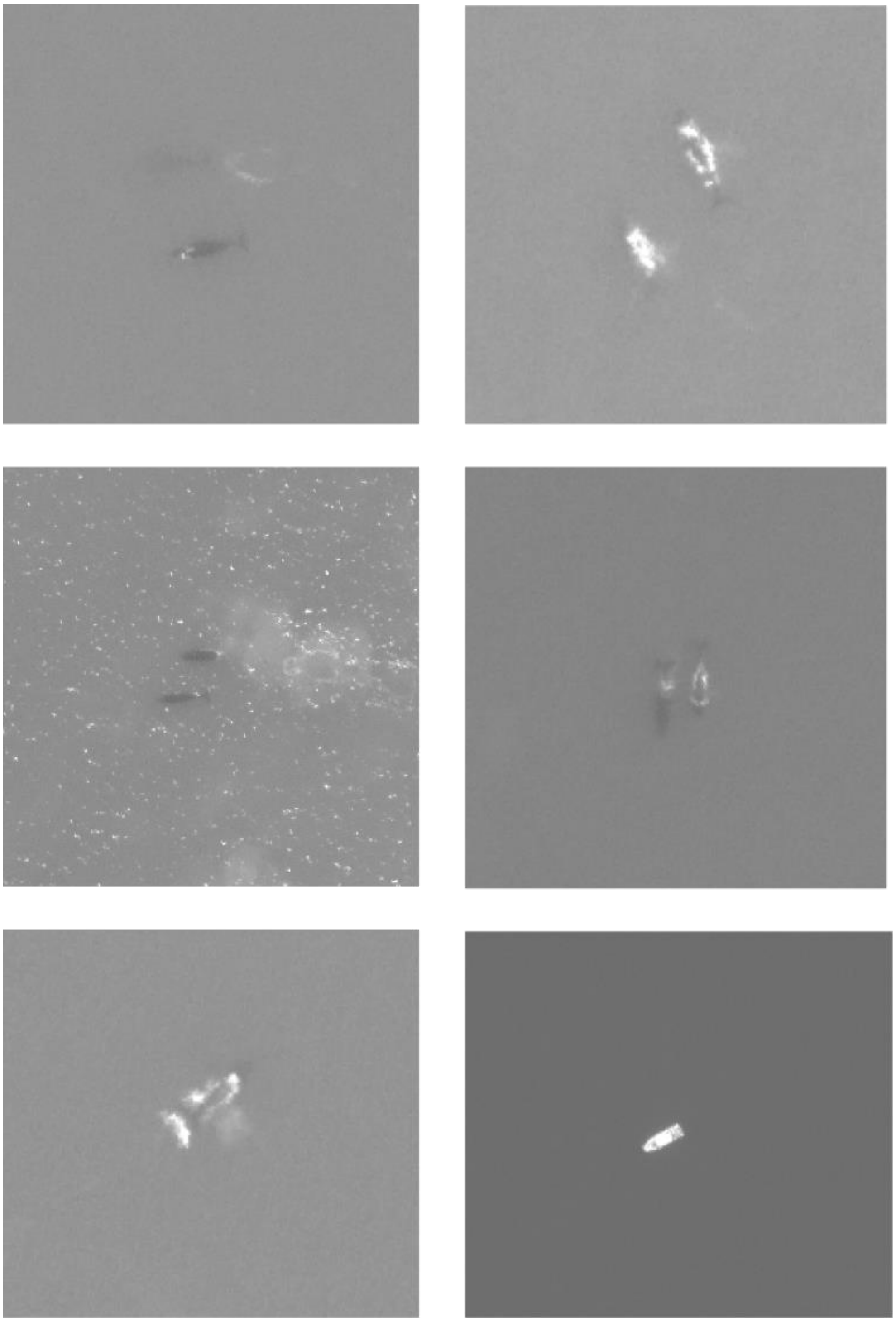

Figure 4. Humpback whales and boat (bottom right) captured in WorldView-3 satellite imagery.

4 Discussion

We have shown that it is possible to visually detect humpback whales in images collected by the WorldView satellites but that the higher spatial resolution of WorldView-3 is needed to provide more confidence around whale identification and thus have robust input information for successful automatic classification algorithms.

Analysis of the WorldView-2 spectral signatures found that there was no clear distinction between whale related features and surrounding water but that boats could be distinguished from whales. To detect whales successfully, a strong contrast between the whale and the surrounding environment is needed (LaRue et al. 2017). This was challenging for the WorldView-2 imagery as whales were always partly submerged and thus it was difficult to completely exclude water from the 'whale pixels'. In addition, although the image acquired was selected considering minimal swell, this assessment was based on examination of the quick look image on the catalogue website, however when the image was delivered there was significant swell across the image. This meant there was a significant number of whitecaps and few clearly distinguishable whales could be identified on the surface visually. In addition to the surface swell, examination of the acquired image showed bright areas which coincided with shallow bathymetry and other variations that appeared to be related to turbid water. Bright areas decrease the contrast between the background environment and the target features. As a result, when using unsupervised classification techniques these bright areas tend to fall in the same classes as whale features. This problem meant that only approximately 70% of the image could be classified with the remaining area having to be excluded due to background noise.

The lack of contrast might have also been related to the behaviour of the whales, i.e. that they might not always be positioned parallel to the sea surface where visibility would be highest. Such body position is likely more indicative of travelling rather than when resident on the breeding grounds as was likely the case here. In addition, the resolution of WorldView-2 likely contributed to the problem of obtaining pure whale pixels and resulting lack of spectral separation. It made visual detection difficult with only one whale identified as 'certain' and majority of whale related features classified as 'possible'. The supervised classification of right whales from WoldView-2 imagery also showed no meaningful results, however their unsupervised classification gave reasonable results as did simple thresholding of the panchromatic and band 5 (Fretwell et al. 2014). This might be due to right whales having a larger surface presence than humpback whales. However the WorldView-2 images in Fretwell et al. (2014) show similar poor resolution as found here.

Although we could have tried object oriented feature extraction using the shape of the surface objects to detect whales in WorldView-2, the issues we highlight above meant that the observed features lacked clear shape definition suggesting object orientated classification would have a low chance of success. Whereas, the higher resolution of imagery captured by the WorldView-3 satellite allowed humpback whales to be easily detected by eye and also by the semi-automated, shape-based detection algorithm. The algorithm made the detection of whales in the image very efficient, with an average review time for researchers of three minutes for each of the three images, compared to two days for the visual (by-eye) search of the entire area. We thus recommend WorldView-3 over WorldView-2 for the remote sensing of humpback whales and the use of shape/object oriented analysis rather than pixel based analysis in automated classification algorithms. In addition, unsupervised classification is preferable as it does not require prior visual identification of the image. Although the time taken for visual detection of an image is relatively low for small images (as we had here), this might not be efficient and cost effective with larger images.

At present the high cost of WorldView-3 means that it would be prohibitive as a tool to monitor the entire distribution (as shown in Fig. 1), which we estimate at a cost of Approx. $4M. and this is only for one snapshot in time, whereas given the annual variability in the peak season (Jenner et al. 2001), more than one capture would be needed over the season. Although projections infer that costs are rapidly reducing over time, it is still likely to be five years or more before this would be reduced to an affordable level to management agencies. This means that it is only affordable to monitor small, targeted areas such as hotspots like Camden Sound and Pender Bay.

The counts made using satellite telemetry have bias, similar to traditional methods such as availability bias (whales not able to be counted as they are underwater), however would not be subject to observer bias (whales on the surface but missed by the observer). Thus while traditional methods extrapolate from counts made along line transects to the larger area they are representative of, by correcting for these and other biases, counts made from a satellite image of an area require no extrapolation (as the whole area has been counted), just correction for availability bias. But more work needs to be done to understand bias (such as how deep whales can be detected) and whether counts from images can be used as a reliable index of population size (Fretwell et al. 2014). Our rough calculations of how many whales were counted on a vessel survey that overlapped with the area of the WorldView-2 image turned up a higher number of whales. We suggest that this is related the fact that the image is taken by the satellite instantaneously, whereas during a vessel survey, the observers have greater time to make their observations.

Even if costs are reduced in the future to be able to survey the entire Kimberley area with very high resolution satellite imagery, we still suggest there would be some drawbacks including: 1. Limited opportunities for successful capture, 2. Low chance of ideal conditions across entire area, 3. Limited chance of capture in same day and 3. Greater difficulty in detection in low density whale areas especially with swell.

We thus recommend the use of high resolution satellite imagery for the targeted monitoring of smaller areas where whale density is high. In these areas higher densities of whales facilitate easier detection and can be processed in a shorter time period. Smaller targeted areas provide more flexibility in finding a suitable window that meets time, satellite position and environmental conditions and where unavoidable, manually analysing imagery captured in adverse environmental conditions becomes more manageable.

We also recommend investigating the capture of high spatial resolution but lower spectral resolution imagery from an aircraft platform. Use of an aircraft would not only allow the capture of higher resolution imagery but would also increase the level of control over the capture time and environmental conditions accepted. In this case panchromatic resolution of 10 or 20 cm may be sufficient but the capture of Red, Green, Blue and Near Infra-red should also be considered.

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Humpback whale use of the Kimberley: understanding and monitoring spatial distribution

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