MODIS-based standing water detection for flood and large reservoir mapping: algorithm development and applications for the Australian continent

Juan P Guerschman, Garth Warren, Guy Byrne, Leo Lymburner, Norman Mueller and Albert Van Dijk

January 2011
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ABOUT THIS REPORT

Through the Water Information Research and Development Alliance, the Bureau of Meteorology and CSIRO are developing the Australian Water Resources Assessment or AWRA system. This report presents results from research aimed at developing the dynamic land cover information which will feed the AWRA system. This report in particular shows progress in developing a series of algorithms aimed at dynamically mapping the extent of standing water, mainly from floods and large reservoirs.
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EXECUTIVE SUMMARY

Accurate and timely monitoring of natural and man-made water bodies is a critical information input for water accounting, groundwater recharge estimation and flood response and forecasting. Remotely sensed information from satellites and airborne instruments can be used for estimating the extent and dynamics of standing water for large areas and complement in-situ observations.

Different uses of information on standing water extent lead to different requirements regarding spatial scale, data latency and temporal repetition these drive the selection of the most appropriate sensor/s and methods. For example, flood monitoring and warning systems need rapid access to processed data but optical imagery tends to be affected by cloud contamination. Retrospective analysis of flood recurrence, in contrast, does not require immediacy in the data supply and can rely on temporal compositing methods to overcome cloud contamination. Similarly daily data is not needed when monitoring water use in natural and human-made dams, but spatial resolution becomes critical particularly regarding the ability to detect water in small (subpixel) reservoirs.

This report presents a methodology for estimating standing water using the Moderate Resolution Imaging Spectroradiometer (MODIS), an optical sensor with a spatial resolution (pixel size) of 250 to 500 meters. The methodology was developed by investigating the spectral properties of standing water, particularly when it occupies a MODIS pixel only partially. The analysis was based on the use of a series of simultaneous classifications performed using higher resolution Landsat TM data using a image segmentation algorithm as described by Mueller and Lymburner (2010). Several empirical models using MODIS surface reflectance and ancillary variables derived from a Digital Elevation Model (DEM) were analysed. The model that had the best performance included surface reflectance from MODIS bands 6 (~1600 nm) and 7 (~2100 nm), the Normalised Difference Vegetation Index, the Normalised Difference Water Index and the Multi-resolution Valley Bottom Flatness index.

The MODIS sensor is mounted in two satellites which overpass daily in the morning (Terra, ~10.30 am) and in the afternoon (Aqua, ~1.30 pm). Using data from both satellites allows taking full advantage of the temporal repetition and provides the best chance of obtaining cloud-free data to monitor floods, particularly in near-real time applications. Analysing flood and reservoir dynamics for large areas (e.g. the Australian continent) and large periods of time (e.g. one decade) with sub-daily MODIS data represents a logistical problem as the data volumes involved would be large. To assess this issue a comparison was performed between the use of daily data (MODIS standard product MOD09GA), 8-day temporal composites using the “best pixel” selection technique (MOD09A1) and 16-day composites corrected by that model the bidirectional reflectance distribution function (MCD43A4). The results showed that in flood events part of the water is “missed” when temporal composites are used due to the incomplete use of all the cloud-free imagery (MOD09A1) or the “averaging” between dry and wet dates (MCD43A1). In the case of reservoirs, which water levels vary on weekly rather than daily steps, these issues tend to be less relevant. Despite this, using 8-day temporal composites from MOD09A1 (or MYD09A1) for retrospective analysis of floods and reservoir standing water recurrence is an acceptable approximation, although an underestimation of total area flooded, when large areas and long time-spans are required.

The algorithm developed was applied to 10 ½ years of MOD09A1 data for the Australian continent, to generate a description of flood recurrence at 500m pixel resolution. A classification scheme was adopted to characterise each 500m grid cell in the continent with respect to the recurrence of inundation and the fraction of the area affected. The classification results qualitatively agree with the general patterns of the hydrological network in Australia, and highlight some areas where the algorithm may need further refinement, particularly in the salt lakes and some areas of the New South Wales and Victorian alps.
The algorithm developed here is recommended for its implementation and testing within the Australian Water Resources Assessment system (AWRA), particularly for the dynamic estimation of surface water extent in the AWRA-L model which needs such information for the quantification of evaporative losses. It is also suggested that the algorithm is further validated and tested and improvements made in future versions as needed.

Future research should also focus on integrating this type of approach with passive or active microwave data (radar) which would allow the problems associated with cloud coverage to be overcome. It is also recommended that the derivation of water volume is explored by combining optical remote sensing with terrain modelling from DEMs and/or remote sensing-derived altimetry.
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1. INTRODUCTION

Accurate and timely monitoring of human and man-made water bodies is a critical information input for many applications which include water accounting, flood control and forecast, wetland ecology dynamics and groundwater recharge estimation.

The diversity of users of remotely-sensed standing water data makes the selection of the most appropriate method, sensor and spatial and temporal resolution highly application-dependent. For example, a wetland ecologist may be interested in the historic recurrence time and persistence of flooded area in the wetlands of a large basin. A flooding forecaster will be interested in the instantaneous volume of a particular flood currently occurring in a given stream. A district irrigation manager will be interested in the current and previous water volumes in dams and reservoirs even though those reservoirs may vary greatly in size. These three cases exemplify the variety of data requirements regarding latency (when the data becomes available), area of interest (extent), spatial resolution (pixel size), temporal resolution (revisit time), and the susceptibility to cloud contamination (sensor type).

Mid resolution optical sensors such as the Moderate Resolution Imaging Spectroradiometer (MODIS) are a convenient tool for monitoring standing water at the synoptic scale (hundreds of thousands of km² or more). MODIS provides roughly two observations per day for every point in the planet (although it depends on latitude) from the twin sensors mounted in the "morning" satellite (Terra) and the "afternoon" satellite (Aqua). The MODIS sensor has two bands in the red and near-infrared with a spatial resolution of 250m, and five bands, in the green, blue and the mid-infrared at 500m. Its ability to detect water bodies is in direct relationship with its spatial resolution. In principle it can potentially map water bodies equal or larger than a pixel although some techniques can be used for detecting pixels partially occupied with standing water.

The MODIS sensors have been in operation since 2000 (Terra) and 2002 (Aqua) and provide more than ten years of data. This already rich time-series can provide insights on flood occurrence and large reservoir water extent. In addition to retrospective analyses, MODIS can be used in near-real time applications because the data are available shortly after the satellite overpass.

A limitation of MODIS, or any other optical sensor, for detecting standing water is its susceptibility to cloud contamination. This is potentially problematic when standing water estimates are needed in near-real time, such as in flood monitoring for emergency services. Moreover, floods are usually associated with cloud borne rainfall events. While passive and active radar sensors are a good alternative in these situations, as these are mostly insensitive to clouds, microwave products are either too coarse (e.g. AMSR-E) or don’t have a revisit time frequent enough to daily monitor floods (ENVISAT). Merging optical and radar sensors is a very promising alternative (e.g. Ticehurst et al 2009).

1.1. Remote sensing of standing water using optical sensors

The reflective bands of optical sensors, defined as those with wavelengths from the visible to the mid-infrared (~400nm-2500nm), have been used for mapping standing water from the very early days of remote sensing. In general detecting water relies on the fact that water strongly absorbs incoming radiation in the near to mid-infrared wavelengths.

Methods developed include simple thresholding using an infrared band (Overton 2005; Powell et al 2008), combinations of two or more bands in indices, such as the normalised difference vegetation index (NDVI), the normalised difference water index (NDWI) (e.g. Brakenridge and Anderson 2006; Sakamoto et al 2007, Ezzy et al 2006, Stewardson et al 2009) and the inclusion of auxiliary variables related to relief and topography (e.g. Ordoyne and Friedl 2008).

There are several factors affecting the ability of remotely sensed data to distinguish between water and other land cover features. Water quality and depth affect the spectral response particularly in the visible portion of the spectrum. In fact, a great deal of research has been
devoted to methods for monitoring water quality and bathymetry using remote sensing (e.g. Brando et al. 2009; Dekker et al. 2005, Qin et al. 2007). Other factors which create challenges for mapping standing water are related to the mixed spectral response of pixels covered partially by water (also called mixed pixels or "mixels"). Mixed pixels occur at the boundaries of all homogeneous landcover patches, where pixels include portions of different cover types. This mixing might be simply a function of the landcover boundary or else it can be occurring at a scale below the pixel resolution for example in furrow irrigation or in flooded wetlands where vegetation is not completely submerged (Figure 1-1).

Figure 1-1: Mixing below the pixel scale

In this report we seek to develop an algorithm for quantifying the fraction of the MODIS pixel occupied with standing water and to test this algorithm for retrospective analysis of standing water across the Australian continent from 2000 to 2010.

1.2. The suite of MODIS reflectance products: implications for standing water mapping

As mentioned above, the MODIS sensors are mounted on two platforms which orbit the Earth in a sun-synchronous near polar orbit. This provides in principle two observations per day during daylight, at ~10:30 AM and ~1:30 pm local time. There are a suite of complimentary secondary products that can be used for deriving surface biophysical properties from the Terra and Aqua observations.

The MODIS standard products provide routine atmospheric corrections from which land surface reflectance can be obtained. The daily surface reflectance products from bands 1 to 7 at 500 meters from Terra and Aqua are called MOD09GA and MYD09GA respectively and the bands 1 and 2 are also provided at 250m (MOD09GQ and MYD09GQ from Terra and Aqua). These products appear a priori optimal for monitoring standing water on a regular basis. For retrospective analyses, however, dealing with bi-daily data for large areas can result in extremely large datasets difficult to process and manage. Alternative data sources are the composite reflectance products. These products are aimed primarily at minimising the problem of cloud contamination when weekly or biweekly repetition times can be offset by higher quality and or not cloud-affected data. There are two options of composited surface reflectance data from MODIS (Figure 1-2 and Table 1-1):

a) 8-day surface reflectance from Terra or Aqua (MOD/MYD09A1) and
b) 16-day nadir/BRDF adjusted surface reflectance (NBAR) from Terra and Aqua (MCD43A4).

Figure 1-2 shows a schematic of the two approaches used for generating the two composited surface reflectance products and Table 1-1 lists the advantages and disadvantages of each MODIS data source for standing water mapping. In general terms, the composited products can result in a summarised, easier analysis when large areas and long time-spans are of interest, but the trade-offs are in the possibility of “missing” water in rapid-changing events like floods. A careful analysis of such trade-offs is also one of the objectives of this report.

![Flowchart showing the different available MODIS reflectance products and their relationship. MOD= Terra (morning), MYD= Aqua (afternoon), MCD= Terra/Aqua combined, GA/QA are the daily reflectances at 500 and 250 meters, A1 and Q1 are the 8-day composites at 500 and 250 meters. MCD43A4 is the 16-day NBAR reflectance at 500m.](image-url)
### Table 1-1: List of MODIS reflectance products with their advantages and disadvantages for mapping standing water

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<td>Subject to cloud contamination. Only 500m resolution. Large data volumes if long-term time series desired.</td>
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<td>“best pixel” compositing may miss rapid flood events, but subject to chance.</td>
</tr>
<tr>
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<td>MCD43A4</td>
<td>Nadir Bidirectional Reflectance Distribution Function-Adjusted reflectance (‘NBAR’). 16-day composite using both Terra (morning) and Aqua (afternoon).</td>
<td>Cloud contamination minimised by compositing method. (16 days and both Terra and Aqua). Useful for time-series analyses.</td>
<td>Reflectance ‘averaged’ over 16 days and with outlier rejection. Likely to miss rapid flood events. Only 500m resolution available</td>
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Figure 1-3: MOD09A1 (8-day surface reflectance) showing the effect of the compositing method. The image in the left is a false colour with MODIS bands 7,2,1 in RGB. The image on the right shows the day within the compositing window (from 1 to 8) for which surface reflectance was used in each pixel.
1.3. Objectives of this report

The objectives of this report are:

1. To develop and test a generic algorithm for quantifying water fractions based on MODIS and ancillary data sources
2. To analyse the effects of using different MODIS products for standing water estimation, particularly of flood events and large reservoirs
3. To apply the best model obtained to MODIS composited data to generate a time-series of standing water for the Australian continent from 2000 to the present
4. From the time series above, derive secondary products such as flood recurrence and flood persistence
2. METHODS

2.1. Overview

A generic description of the steps taken for developing and testing the standing water algorithm is shown in Figure 2-1.

Three Landsat images covering a flood cycle from mid November to late December 2004 were initially used for mapping presence or absence of standing water. The images include parts of the Gwydir, Namoi, and Border Rivers catchments in northern NSW. The catchments include large floodplains subjected to seasonal and regular floods. During those events water may be harvested in man-made reservoirs and then used for irrigation, but those reservoirs can also be filled through pumping surface or ground water independently of flood events. The images also include rangelands used for cattle grazing and eucalyptus forests, most notably the Pilliga forests.

The three Landsat images were classified into water/non water classes and were then used as "ground truth" for estimating the fractions of standing water in the corresponding MODIS 500m pixels. Such "observed" fractions were empirically linked to MODIS reflectance and ancillary variables through non-linear regression models. The best performing model was then applied to all daily Terra and Aqua data in the area as well as to the 8 and 16 days composites. The effects of using composited data were compared to the results obtained when all the daily available data were used. The potential for using MODIS data at 250m was also assessed. Finally, the best performing model was applied to the whole archive of MODIS 8-day composites (from Terra) to create a time series of ~10 years of standing water data for the whole Australian continent.
Figure 2-1: Flowchart showing a schematic of the processes done in this report.

### 2.2. Description Landsat TM and MODIS sensors

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Table 2-1: Wavelengths and names of reflectance bands in MODIS and Landsat
2.3. Object-oriented open water classification using Landsat

2.3.1. Data and Pre-processing

Landsat 5 Thematic Mapper (LTM) data were used to create maps of standing water using a ‘seed and growth’ object oriented classification technique. The open water maps were later used to validate the MODIS open water mapping products.

Three LTM scenes were used; 26 November 2004, 12 December 2004, and 28 December 2004 (Figure 2-2). These scenes were chosen because they each contain distinct flood events, most notably the large rainfall event that occurred between 4 to 10 December, and the minor rainfall event between 23 and 27 December.

Figure 2-2: Landsat 5 TM images; A = 26 Nov, B = 12 Dec, and C = 28 Dec

The imagery was provided by Geoscience Australia and has been corrected using an atmospheric and Nadir BRDF Reflectance (NBAR) function following the methodology described by Li et al. (2010). In order to illustrate the results of the various mapping products five full resolution ‘test areas’ were selected, the location these are shown in Figure 2-3. These areas encompass a range of floodplain, rangeland, land use and elevation components.

Figure 2-3: Landsat 5 TM images 26/11 with five high resolution study areas defined
Figure 2-4: Daily rainfall totals in the three catchments included in the study area. The arrows show the dates of the three Landsat TM images used.

### 2.3.2. Algorithm description

The advantage of spatially coherent remotely sensed data in environmental monitoring is the complete coverage it provides. However this data density often produces very large datasets that usually have high levels of spatial autocorrelation. Analysing these data traditionally involves testing each pixel against particular search and classification criteria - which for large data sets is invariably slow. Object oriented image analysis exploits patterns of spatial and spectral correlation and allows pixels to be grouped into ‘like’ segments or objects. The size of these objects is related to the innate image data resolution, the resolvable landscape features and the interpretive model being applied by the application at hand.

The LTM data have been classified for standing water using a ‘seed and grow’ object oriented classification technique (Mueller and Lymburner, 2010). This semi automated technique greatly reduces the need for operator input and provides an opportunity for the rapid generation of specific image products in response to particular emergency situations – such as flood and fire.

This classification model is driven by ‘seed values’ derived from the analysis of a time series of Landsat NBAR data. In this case, a stack of eleven scenes of the Moree floodplain imaged through 2004 is used. The seed value for the water class is based on the minimum water reflectance in Band 5 (1.55-1.75 um), which was found by analysing the overall reflectance histogram and isolating the data peak that describes pure water.

Image segmentation tools are used to partition individual LTM scenes into a smaller number of image objects which are then tested against the seed value. Objects that have pixel values in band 5 at, or below, the initial threshold value are disaggregated back to the individual pixel resolution. Those pixels that meet the band 5 seed criteria are tested against the fuzzy water cover classes.

The algorithm then updates the water variables based on the statistics of the newly populated water classes. These new feature values are then used to retest the remaining unclassified pixels against updated fuzzy class feature descriptors. This loop is then repeated using the updated seed values.

Figure 2-5 shows a simplified model of the algorithm
Apart from mapping deep standing pure water pixels this technique can also apportion pixels to mixed water classes, primarily water and soil and water and vegetation, however in the context of this study only the deep pure water classes were used as the spatial resolution of the MODIS data is much coarser than the LTM data.

2.4. Fractional cover mapping of standing water using mid-resolution sensors.

2.4.1. Algorithm development

In general, remote sensing data with medium and low spatial resolution are less suited to segmentation-based analysis. Imagery at small spatial scales typically has low spectral variability (highly autocorrelated); because of this, pixels belonging to subtly different land cover types could be grouped into the same object as only the large spectral textural variants are visible in the data.

Traditionally a number of non-object based techniques have been used to map land cover types using remote sensing data. Most commonly, a range of statistically based supervised, unsupervised, and hybrid image classification approaches are used to group image pixels into thematic classes. Alternatively, the image data can be used as input to mathematical models that estimate the extent and form of different the land cover types.

With respect to standing water most techniques exploit the unique spectral characteristic of water, namely the strong absorption of near and middle infra-red (NIR, MIR) radiation (Figure 2-6). The strength of the absorption of NIR radiation is influenced by variables including water depth, the amount of organic material in the water column and turbidity (Kirk 1994). In addition, the visibility of open water to an orbiting sensor is influenced by the amount of vegetation cover and the soil background colour (Sims and Thoms 2002).
Figure 2-6: Typical reflectance characteristics of green vegetation, dry vegetation, soils, and open water of different quality.

In this study, a statistical modelling approach using multiple remote sensing variables, in a nonlinear regression framework was used to develop an estimator of the fraction of standing water.

This project investigates the use of two types of remotely sensed data to map standing water: optical surface reflectance (Landsat and MODIS) and the Shuttle Radar Topography Mission (SRTM) 3 second Digital Elevation Model (DEM).

The sensitivity of a range of water detection models were investigated using the LTM imagery, and subsequently translated to the MODIS data. The LTM images were used to allow direct pixel-to-pixel comparison of the segmentation-based classification (section 2.3) and the pixel-based algorithm.

The Landsat imagery and the segmentation-based classification of open water were aggregated to 250 and 500 meters. The aggregate data were calculated by dividing the count of Landsat-scale water cells, per MODIS scale pixel, by the total number of Landsat-scale cells (water and non-water) that make up each MODIS scale pixel. The result is a fraction of standing water, where an aggregate cell value of 1.0 (100%) indicates that all composite 30m cells were classified as open water. Figure 2-7 shows the object-oriented classification of open water at 30m and 500m.
Figure 2-7: The object-oriented classification of open water for a subset of the study area. The original 30m classification (a); the 30m classification aggregated to 500m (b).

Nadir BRDF-Adjusted Reflectance (NBAR) Landsat 5 Thematic Mapper (TM) data were acquired for the three classification dates (see section 2.3). Landsat TM Band 5 (middle infrared 1; 1.55 – 1.75 μm), Landsat TM Band 7 (middle infrared 2; 2.08 – 2.35 μm), and the Normalised Difference Water Index (NDWI) and Normalised Difference Vegetation Index (NDVI) were explored as possible predictors of open water.

The Normalised Difference Water Index and the Normalised Difference Vegetation Index are calculated as:

$$NDWI = \frac{\rho_{NIR} - \rho_{MIR}}{\rho_{NIR} + \rho_{MIR}} \quad \text{Equation 2-1}$$

$$NDVI = \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + \rho_{RED}} \quad \text{Equation 2-2}$$

The 3 second (approximately 90m) DEM is derived from the 1 second SRTM product using the mean value of the intersecting pixel neighbourhood. To add spatial context to the digital elevation model the terrain metrics: MrVBF, percent of slope and degree of slope were calculated. The Multi-resolution index of Valley Bottom Flatness (MrVBF) of Gallant and Dowling (2003) identifies areas that are low and flat relative to the surrounding topography. Large MrVBF values indicate broad and flat valley bottoms where the maximum value represents the broadest and flattest area in the landscape. Typically, values below 0.5 identify areas either too steep or too high to be valley bottoms (Gallant and Dowling 2003). Slope identifies the maximum rate of change in elevation between each cell and its neighbours. Large slope values indicate steep terrain. Slope can be measured using the angle of the slope in degrees (degree of slope), or by the rise over run (percent of slope).

It is beyond the scope of this report to examine each of the models and the selected predictor variables as it would introduce significant detail and repetition. However, the report does provide a valuable treatment of the potential of surface reflectance and topography to identify standing water by examining a subset of the modelling results, and summarising the remainder.

Figure 2-8 shows a scatter plot of the fraction of standing water and NDWI. There is a clear positive relationship between standing water and NDWI. In comparison, the relationship between standing water and NDVI (see Figure 2-9) is strongly negative. In each case the
relationship is visibly sigmoidal (logistic). There is little or no change in the observed fraction of standing water for low NDWI values, followed by rapid S-shaped changes occurring between 0.0 to 0.6 NDWI, and finally a levelling off of open water at NDWI values greater than 0.6.

Figure 2-8: Scatter plot showing the relationship between the observed fraction of standing water (aggregated object-based classification) and NDWI. The plot shows the local density around each sample point. High density is shown in red and low density is shown in blue and purple.

Figure 2-9: Scatter plot showing the relationship between the observed fraction of open water (aggregated object-based classification) and NDVI. The plot shows the local density around each sample point. High density is shown in red and low density is shown in blue and purple.
Although less pronounced than the previous examples, standing water and middle infrared radiation also feature a sigmoidal relationship (see Figure 2-10). Typically, high MIR-reflectance corresponds to a low fraction of standing water, while low MIR reflectance corresponds to a high fraction of standing water. This is expected given the strong absorption of middle infrared radiation by water.

Figure 2-10: Scatter plot showing the relationship between the observed fraction of standing water (object-based classification) and Landsat TM band 5 (a) and band 7 (b). The plot shows the local density around each sample point. High density is shown in red and low density is shown in blue and purple.

The logistic regression model is:

\[ f_w = \frac{1}{1 + \exp(-z)} \]  

where,

\[ z \]  

Equation 2-3
\[ z = \beta_0 + \sum \beta_i \cdot x_i \] 

Equation 2-4

In the equation above \( x_i \) are the independent variables, \( \beta \) are parameters fitted empirically, and \( f_w \) is the “observed” fraction of standing water, that is, the aggregated segmentation-based classification as described previously.

IDL and the MPFIT routine of Markwardt (2008) were used to fit the non linear logistic function of the fraction of standing water. Table 2-2 summarises the model results. The summary table is critical as it provides a synopsis of the selected weighting factors and the performance of each independent variable as a predictor of open water.

For each model the Root Mean Square Error (RMSE) and \( r^2 \) were calculated. The model number (model ID), the weighting factor, the explanatory variables used, and the date of the training data are listed. The four weighting schemes used are described below. The models selected for further analysis are highlighted.

**Table 2-2: Nonlinear logistic regression results. The table lists the fitted parameters for each variable per model. The RMSE and \( r^2 \) for each model is shown. Models 31 and 35 are highlighted because those were later selected and compared.**

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<td>-----</td>
<td>------------</td>
</tr>
<tr>
<td></td>
<td>25</td>
<td>-1.4395</td>
<td>-0.0035</td>
<td>0.0057</td>
<td>11.9406</td>
<td>-2.4925</td>
<td>0.0280</td>
<td>-</td>
<td>-</td>
<td>A</td>
<td>0.0381</td>
<td>0.8145</td>
<td>28/12/2004</td>
</tr>
<tr>
<td></td>
<td>26</td>
<td>-1.3633</td>
<td>-0.0051</td>
<td>0.0072</td>
<td>14.4423</td>
<td>-3.0104</td>
<td>0.0536</td>
<td>-</td>
<td>-</td>
<td>B</td>
<td>0.0392</td>
<td>0.8025</td>
<td>28/12/2004</td>
</tr>
<tr>
<td></td>
<td>27</td>
<td>-1.4863</td>
<td>-0.0043</td>
<td>0.0067</td>
<td>14.0125</td>
<td>-2.8788</td>
<td>0.0366</td>
<td>-</td>
<td>-</td>
<td>C</td>
<td>0.0390</td>
<td>0.8012</td>
<td>28/12/2004</td>
</tr>
<tr>
<td></td>
<td>28</td>
<td>-1.4881</td>
<td>-0.0043</td>
<td>0.0063</td>
<td>18.6338</td>
<td>-4.5765</td>
<td>0.0907</td>
<td>-</td>
<td>-</td>
<td>D</td>
<td>0.0433</td>
<td>0.7605</td>
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<tr>
<td></td>
<td>29</td>
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<td>-0.0002</td>
<td>0.0030</td>
<td>10.4502</td>
<td>-0.1439</td>
<td>-0.0866</td>
<td>-</td>
<td>-</td>
<td>A</td>
<td>0.0549</td>
<td>0.9056</td>
<td>28/12/2004</td>
</tr>
<tr>
<td></td>
<td>30</td>
<td>-3.4500</td>
<td>0.0014</td>
<td>0.0014</td>
<td>9.6095</td>
<td>0.0139</td>
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<td>-</td>
<td>-</td>
<td>B</td>
<td>0.0578</td>
<td>0.9012</td>
<td>28/12/2004</td>
</tr>
<tr>
<td></td>
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<td>-3.4138</td>
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<td>0.0042</td>
<td>14.1928</td>
<td>-0.4304</td>
<td>-0.0961</td>
<td>-</td>
<td>-</td>
<td>C</td>
<td>0.0574</td>
<td>0.8970</td>
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<tr>
<td></td>
<td>32</td>
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<td>0.0060</td>
<td>26.2493</td>
<td>-1.2142</td>
<td>-0.1388</td>
<td>-</td>
<td>-</td>
<td>D</td>
<td>0.0706</td>
<td>0.8529</td>
<td>28/12/2004</td>
</tr>
<tr>
<td></td>
<td>33</td>
<td>1.2013</td>
<td>-</td>
<td>-</td>
<td>10.7714</td>
<td>-6.0214</td>
<td>-0.2322</td>
<td>-</td>
<td>-</td>
<td>A</td>
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<td>28/12/2004</td>
</tr>
<tr>
<td></td>
<td>34</td>
<td>1.1721</td>
<td>-</td>
<td>-</td>
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<td>-6.4318</td>
<td>-0.3204</td>
<td>-</td>
<td>-</td>
<td>B</td>
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<td>0.8620</td>
<td>28/12/2004</td>
</tr>
<tr>
<td></td>
<td>35</td>
<td>1.1320</td>
<td>-</td>
<td>-</td>
<td>14.6610</td>
<td>-6.9952</td>
<td>-0.2835</td>
<td>-</td>
<td>-</td>
<td>C</td>
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<td>28/12/2004</td>
</tr>
<tr>
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<td>36</td>
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<td>-</td>
<td>-</td>
<td>33.0813</td>
<td>-9.5826</td>
<td>-0.3864</td>
<td>-</td>
<td>-</td>
<td>D</td>
<td>0.0829</td>
<td>0.8019</td>
<td>28/12/2004</td>
</tr>
</tbody>
</table>

Linear and non-linear regression assumes that the distribution of values around the fitted curve is approximately normal, or Gaussian. Figure 2-11 shows a plot of the residuals against the fitted values for model 29 (see Table 2-2). Although the plot does not suggest any extreme departure from the model assumption, some non-consistency of the error variance is visible. The residuals depart from 0 in a systematic manner; values less than 0.5 are predominantly negative, while for fitted values greater than 0.5 the residuals are predominantly positive. Note the dense band of positive values in (a) and negative values in (b). This represents areas of over-prediction and under-prediction respectively, and can be seen in the plot of the observed values against the fitted values (see Figure 2-12).

![Figure 2-11: The residual plot for model 29.](image-url)
Figure 2-12: Scatter plot of the observed fraction of standing water against the fitted fraction of standing water from model 29.

Several weighting factors were explored to make the variances of the error term more nearly equal. Data were weighted to adjust for the uneven distribution of observed fraction of standing water values, namely the high proportion of values at, or near, 0.0 and 1.0. The weightings explored are as follows:

A. Equal weight is applied to all points
B. Points with 100% fraction of standing water are weighted 10 times more than points with less than 100% standing water
C. Points with 0% and 100% fraction of standing water are weighted 10 times more than points with less than 100% standing water, or greater than 0% standing water.
D. Points with 0% and 100% fraction of standing water are weighted 100 times more than points with less than 100% standing water, or greater than 0% standing water.
Figure 2-13: Scatter plot and residual plot for model 30 (a) and (c), and 32 (b) and (d).

The effects of the weighting schemes are compared by examining the differences between models 29 to 32.

Figure 2-13 shows the effect of weighting factors B and D. Note the effect of weighting factor D on model 32 (Figure 2-13b & Figure 2-13d). The over-prediction of the observed fraction of standing water at, or close to, 0.0 is largely eliminated. However there is an increase in the under prediction of water at the same location. Note the clustering of fitted values at 0.0 and 1.0; the proportion of estimated values between 0.0 and 1.0 is significantly lower than that for Figure 2-12 and Figure 2-13c. Of the four weighing methods D produced the highest RMSE and lowest r-squared value. The $r^2$ for model 32 (0.85) is significantly lower than that for model 29 (0.91). This pattern is repeated for each model set.

The scatter and residual plots of model 29 and 30 are visually similar. Figure 2-13a and Figure 2-13c show an increase in the proportion of fitted values between 0.2 and 1.0. This is due to the greater weighting assigned to observed values at, or close to, 1.0. The RMSE and $r^2$ show only a marginal difference between models 29 and 30. In most cases the models that employ equal weightings (weighting factor A) show a slight improvement in fit compared to those that apply a greater weight to standing water values of 1.0 (100%).

Figure 2-14 shows the residual plot of model 31. The vertical distribution of values close to the horizontal zero line and between 0.2 and 1.0 (x) is approximately similar for models 29, 30 and 31. Note the cluster of positive values shown in Figure 2-13 (a), and the cluster of negative values shown in Figure 2-13 (b) is significantly less dense in model 31.
Further, the variation in fitted values at, or close to, 0.0 and 1.0 for model 31 is smaller compared to models 29 and 30. Figure 2-15 shows a scatter plot of the observed values against fitted values for model 31. Over prediction of very small (less than 10%) fraction of standing water is reduced. Note the horizontal size of the cluster of values close to 0.0 in Figure 2-15 is significantly smaller than that in Figure 2-12.

In each model above there is a noticeable under-prediction of standing water for observed values less than 0.25. There is only a marginal difference (< 1%) in the RMSE and $r^2$ value for models 29, 30 and 31. Model 31 was selected for further analysis because the distribution of the fit more closely approximates the observed at values close to 0.0 and 1.0. The accuracy of the model for very low or very high fractions of standing water is of comparatively high importance due to the large proportion of observed values at these locations.
A comparison of the RMSE and $r$-squared value of each model set (see Table 2-2) indicates the most suitable predictors of the observed fraction of standing water.

The models shown above use NDVI, NDWI, MrVBF, and both middle infrared bands as predictors of standing water.

Model sets 9-12, 13-16, and 17-20 show the relative significance of each terrain metric. The Multi-resolution index of Valley Bottom Flatness (MrVBF) displays the greatest apparent relationship with standing water. For each weighting pair in the three model sets mentioned the model using MrVBF produced the highest $r$-squared and lowest RMSE. As the three metrics are highly correlated it is not surprising that the difference in RMSE and $r^2$ for each model were marginal. Further, there was no improvement in fit for the models that used all three terrain metrics compared to those that used only MrVBF.

A comparison of model sets 17-20 and 21-24, and model sets 29-32 and 33-36 show that the inclusion of the middle infrared bands improves model fit. The mean $r^2$ for model set 17-20 is 0.916 compared to 0.878 for model set 21-24 which uses only NDVI, NDWI, and MrVBF. Similarly the five variable models 29-32 show a mean increase in $r^2$ of 0.046 compared to the three variable models 33-36. Figure 2-16 shows the scatter plot of the observed fraction of standing water against the fitted fraction of standing water for models 33 – 36.

Figure 2-15: Scatter plot of the observed fraction of standing water against the fitted fraction of standing water from model 31.
Figure 2-16: Scatter plot of the observed fraction of standing water against the fitted fraction of standing water from models 33 (a), 34 (b), 35 (c), and 36 (d).

The models developed using data taken on the 12th December exclusively, produced the best fit. However, it should be noted that the final model parameters were trained using reflectance data from a side-by-side mosaic of the three study dates. As shown in section 2.3, a large flood event occurred between the first two image dates, and a smaller flood event occurred some time before the final image data. As a result the 12 December image has a high proportion of large fraction of standing water values relative to the 26 November image and the 28 December image. A combination of the three dates was used to provide a more balanced proportion of dry to wet areas. The assumption is that the fitted model would be better able to map the fraction of standing water in a variety of landscapes.

Based on the analyses described above, models 31 and 35 provide the best fit between observed and estimated fraction of standing water using 5 or 3 independent variables respectively. In the following section these two models were applied to a time series of MODIS data to assess the dynamics of standing water and flooding.

2.4.2. Application to MODIS reflectance products

All model runs performed for this report were done using the set of parameter estimates described in section 2.4.1. ENVI and the IDL scripting language were used to implement model 31 (five variable model) and model 35 (three variable model) (see Table 2-2) as a spatial layer for each MODIS product and date. Developing the time-series of standing water
was a multi-step process. Automation of the process via IDL was important due to the large volume of data and the large number of reflectance products included in the study.

Daily and composite MODIS optical reflectance data were collated for multiple dates in October-December 2004, and January 2005. The products used were MOD09GA (500m, daily surface reflectance) and MOD09A1 (500m, 8-day composited surface reflectance), in both cases from the Terra (morning) sensor. The image tiles were mosaicked and rectified to a common geographical projection using the MODIS re-projection tool (https://lpdaac.usgs.gov/lpdaac/tools/modis_reprojection_tool). Further, a spatial subset was applied to the image data using IDL. An ENVI spatial re-sampling routine run from the IDL programming environment was applied to the MrVBF data. Aggregate 250m and 500m MrVBF data layers were produced and used as input in model 31 and 35 for the native 250m and 500m MODIS products respectively. Subsequently, the fraction of standing water (from model 31 and 35) was calculated for each product and date of imagery between 31 October 2004 and 2 January 2005. The remote sensing variables NDVI and NDWI were calculated on-the-fly; that is, the indices were calculated automatically in IDL using the selected MODIS reflectance data for each model run and stored in virtual memory.

An objective of this study was to show the implications of mapping the fraction of standing water at different spatial resolutions, and when using composite data. To enable direct pixel-to-pixel comparison of the 500 and 250 meter MODIS reflectance products the 500m estimates of standing water were oversampled to 250m. Similarly, the maximum daily MOD09GA and MYD09GA fraction of standing water value for each 8 day and 16 day period were calculated to allow a comparison of the daily and composite Aqua and Terra products and the combined 16 day product (MCD43A4).

2.4.3. Generation of a time series of standing water for the Australian continent

The fraction of standing water was calculated for the whole of Australia using the full time series of MOD09A1 collection 5 data for the Australian continent from 2000 to early 2010.

Due to an increase in data volume the fraction of standing water estimates for the Australian continent were processed using an ad-hoc tiling method in IDL. This programming feature allows the continental scale estimates to be calculated on a standard desk-top computer.
3. RESULTS AND DISCUSSION

3.1. Landsat-derived standing water

Figure 3-1 shows the results of the object-oriented classification of the Landsat 5 TM images. It can be observed the high amount of flooded area in the image corresponding to the 12 of December, which follows a large rainfall event occurred from December 4th to 10th (Figure 2-4). Sixteen days later, on the 28th of December, most of that water has disappeared from the image, likely being infiltrated, flowed downstream, harvested in dams of evaporated. A detailed area is shown in Figure 3-2 where some dams have been filled after the flood event.

Figure 3-1: False colour images of the Landsat TM in the study area (above) and result of the object-oriented classification of standing water, in red (below). Bands showed in R-G-B are Landsat 7-4-3.
3.2. Derivation of an algorithm for mapping standing water fractions using MODIS

3.2.1. Overview

The aim of this section of the report is to compare model estimates at different temporal and spatial scales and to quantify and discuss the differences encountered. Model estimates and independent observations were compared to provide an objective assessment of the different mapping scales. The same model parameterisation was used in all cases; see section 2.4.1, model 31.

Confusion matrices were used to provide an objective quantification of the model estimates. Confusion matrices, also known as contingency tables, compare the prediction of interest against some estimate of the truth. In this report the aggregated object-oriented classification of standing water was used as the assumed truth. A number of techniques are available to assess classification accuracy using confusion matrices. This study uses a point-based approach where each corresponding cell, or pixel, in the modelled and observed spatial data layers are compared and categorised according to the following criteria:

- Modelled cells predicted to be inundated and were inundated in the observation (Predicted + and Actual +);
- Modelled cells predicted to be inundated but were not inundated in the observation (Predicted + and Actual -);
- Modelled cells predicted to be not inundated but were inundated in the observation (Predicted - and Actual +);
- Modelled cells predicted to be not inundated and were not inundated in the observation (Predicted - and Actual -).

The performance of the model estimates can be assessed using the above criteria to populate the theoretical confusion matrix shown in Table 3-1 (after Fielding and Bell 1997). A
range of statistical measures of classification accuracy can be calculated using the tabulated information.

Table 3-2: Confusion matrix.

<table>
<thead>
<tr>
<th></th>
<th>Actual +</th>
<th>Actual -</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predicted +</td>
<td>A</td>
<td>B</td>
</tr>
<tr>
<td>Predicted -</td>
<td>C</td>
<td>D</td>
</tr>
</tbody>
</table>

The confusion matrix approach described above is primarily used to assess the classification accuracy of binary, presence or absence, maps of land cover. To convert the modelled fraction of standing water to a binary classification of, water and non-water, the model estimates were grouped into threshold categories. Multiple binary value spatial layers were produced for each standing water prediction according to the following statements:

Standing water fraction greater than, or equal to 0.1 (10%);
Standing water fraction greater than, or equal to 0.2 (20%);
Standing water fraction greater than, or equal to 0.3 (30%);
Standing water fraction greater than, or equal to 0.4 (40%);
Standing water fraction greater than, or equal to 0.5 (50%);
Standing water fraction greater than, or equal to 0.6 (60%);
Standing water fraction greater than, or equal to 0.7 (70%);
Standing water fraction greater than, or equal to 0.8 (80%);
Standing water fraction greater than, or equal to 0.9 (90%);
Standing water fraction greater than 0.0 (0%), and less than 0.1 (10%);
Standing water fraction greater than 0.0 (0%), and less than 0.2 (20%).

For each estimate of standing water fraction; grid cells that conform to the selected threshold were given a value of 1 in the output layer, while grid cells that did not conform were given a value of 0.
To provide a visual synopsis of model performance five 100,000 hectare (approximately 1000 km²) validation regions were selected. Figure 3-3 shows the location of the validation sites. The five regions describe the major variations that occur within the local landscape. Figure 3-4 shows a close up of each validation region.
3.2.2. Performance of the two alternative models

Further to the objectives outlined in section 3.2.1 above, models 31 (five variable model) and 35 (three variable model) were compared to highlight the additional predictive accuracy gained by using the two middle infrared channels as separate independent variables. The fraction of standing water from models 31 and 35 were calculated using MOD09GA reflectance data taken on the three study dates. For each date, the three and five variable models were compared to the aggregate LTM object-based classification using the methods described in section 3.2.1.

Table 3-3 to Table 3-8 show twelve confusion matrices produced for each data and model. Consideration of the amount and distribution of standing water for each of the three study dates is needed to supplement the statistical summary. Note the proportion of negative counts (observed non standing water) far exceeds the count of positive cases.

Table 3-3: Confusion matrices of models 31 and 35 for 26 November 2004. Grid cells were classified as inundated if the modelled standing water fraction was greater than, or equal to 0.5.
### Table 3-4: Confusion matrices of models 31 and 35 for 26 November 2004. Grid cells were classified as inundated if the modelled standing water fraction was greater than, or equal to 0.8.

**Model 31: Standing water fraction ≥ 0.8**

<table>
<thead>
<tr>
<th></th>
<th>Actual +</th>
<th>Actual -</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predicted +</td>
<td>0.1%</td>
<td>0.1%</td>
</tr>
<tr>
<td>Predicted -</td>
<td>0.5%</td>
<td>99.3%</td>
</tr>
<tr>
<td></td>
<td>0.6%</td>
<td>99.4%</td>
</tr>
</tbody>
</table>

**Model 35: Standing water fraction ≥ 0.8**

<table>
<thead>
<tr>
<th></th>
<th>Actual +</th>
<th>Actual -</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predicted +</td>
<td>0.2%</td>
<td>0.2%</td>
</tr>
<tr>
<td>Predicted -</td>
<td>0.4%</td>
<td>99.2%</td>
</tr>
<tr>
<td></td>
<td>0.6%</td>
<td>99.4%</td>
</tr>
</tbody>
</table>

### Table 3-5: Confusion matrices of models 31 and 35 for 12 December 2004. Grid cells were classified as inundated if the modelled standing water fraction was greater than, or equal to 0.5.

**Model 31: Standing water fraction ≥ 0.5**

<table>
<thead>
<tr>
<th></th>
<th>Actual +</th>
<th>Actual -</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predicted +</td>
<td>8.1%</td>
<td>4.4%</td>
</tr>
<tr>
<td>Predicted -</td>
<td>3.0%</td>
<td>84.5%</td>
</tr>
<tr>
<td></td>
<td>11.0%</td>
<td>89.0%</td>
</tr>
</tbody>
</table>

**Model 35: Standing water fraction ≥ 0.5**

<table>
<thead>
<tr>
<th></th>
<th>Actual +</th>
<th>Actual -</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predicted +</td>
<td>7.4%</td>
<td>3.5%</td>
</tr>
<tr>
<td>Predicted -</td>
<td>3.7%</td>
<td>85.5%</td>
</tr>
<tr>
<td></td>
<td>11.0%</td>
<td>89.0%</td>
</tr>
</tbody>
</table>

### Table 3-6: Confusion matrices of models 31 and 35 for 12 December 2004. Grid cells were classified as inundated if the modelled standing water fraction was greater than, or equal to 0.8.

**Model 31: Standing water fraction ≥ 0.8**

<table>
<thead>
<tr>
<th></th>
<th>Actual +</th>
<th>Actual -</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predicted +</td>
<td>6.2%</td>
<td>1.8%</td>
</tr>
<tr>
<td>Predicted -</td>
<td>4.8%</td>
<td>87.1%</td>
</tr>
<tr>
<td></td>
<td>11.0%</td>
<td>89.0%</td>
</tr>
</tbody>
</table>

**Model 35: Standing water fraction ≥ 0.8**

<table>
<thead>
<tr>
<th></th>
<th>Actual +</th>
<th>Actual -</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predicted +</td>
<td>5.9%</td>
<td>1.7%</td>
</tr>
<tr>
<td>Predicted -</td>
<td>5.1%</td>
<td>87.2%</td>
</tr>
<tr>
<td></td>
<td>11.0%</td>
<td>89.0%</td>
</tr>
</tbody>
</table>
Table 3-7: Confusion matrices of models 31 and 35 for 28 December 2004. Grid cells were classified as inundated if the modelled standing water fraction was greater than, or equal to 0.5.

<table>
<thead>
<tr>
<th>Model 31: Standing water fraction ≥ 0.5</th>
<th>Model 35: Standing water fraction ≥ 0.5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual +</td>
<td>Actual -</td>
</tr>
<tr>
<td>0.4%</td>
<td>0.3%</td>
</tr>
<tr>
<td>0.6%</td>
<td>98.7%</td>
</tr>
<tr>
<td>1.0%</td>
<td>99.0%</td>
</tr>
</tbody>
</table>

Table 3-8: Confusion matrices of models 31 and 35 for 28 December 2004. Grid cells were classified as inundated if the modelled standing water fraction was greater than, or equal to 0.8.

<table>
<thead>
<tr>
<th>Model 31: Standing water fraction ≥ 0.5</th>
<th>Model 35: Standing water fraction ≥ 0.8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual +</td>
<td>Actual -</td>
</tr>
<tr>
<td>0.3%</td>
<td>0.1%</td>
</tr>
<tr>
<td>0.7%</td>
<td>98.9%</td>
</tr>
<tr>
<td>1.0%</td>
<td>99.0%</td>
</tr>
</tbody>
</table>

Table 3-9 presents statistical measures of classification accuracy calculated for each model, threshold, and date combination shown in the tables above. Prevalence and the overall diagnostic power measure the proportion of positive, and negative cases respectively. Note the very high proportion of negative (non standing water) cases for each selected date. When the distribution of values is heavily biased towards either negative or positive instances direct measures of classification accuracy, such as the correct classification rate, cannot adequately measure performance. Instead, consideration of several measures simultaneously is needed.

Table 3-9: Selected classification accuracy measures of the two alternative models.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>31</td>
<td>35</td>
<td>31</td>
</tr>
<tr>
<td>Threshold:</td>
<td>≥ 0.5</td>
<td>≥ 0.8</td>
<td>≥ 0.5</td>
</tr>
<tr>
<td>Correct Classification Rate</td>
<td>0.994</td>
<td>0.993</td>
<td>0.994</td>
</tr>
<tr>
<td>Misclassification Rate</td>
<td>0.006</td>
<td>0.007</td>
<td>0.006</td>
</tr>
<tr>
<td>True Positive Rate</td>
<td>0.342</td>
<td>0.412</td>
<td>0.182</td>
</tr>
<tr>
<td>False Positive Rate</td>
<td>0.002</td>
<td>0.003</td>
<td>0.001</td>
</tr>
<tr>
<td>True Negative Rate</td>
<td>1.000</td>
<td>0.997</td>
<td>1.000</td>
</tr>
<tr>
<td>False Negative Rate</td>
<td>0.658</td>
<td>0.588</td>
<td>0.818</td>
</tr>
<tr>
<td>Positive Predictive Power</td>
<td>0.504</td>
<td>0.465</td>
<td>0.561</td>
</tr>
<tr>
<td>Negative Predictive Power</td>
<td>0.996</td>
<td>0.996</td>
<td>0.995</td>
</tr>
<tr>
<td>Prevalence</td>
<td>0.006</td>
<td>0.006</td>
<td>0.006</td>
</tr>
<tr>
<td>Overall Diagnostic Power</td>
<td>0.994</td>
<td>0.994</td>
<td>0.994</td>
</tr>
</tbody>
</table>
The correct classification rate (CCR) and misclassification rate (MR) describe the proportion of estimates that were correct and incorrect respectively. The difference in CCR and MR for each model, threshold, and date is marginal. The measures suggest excellent agreement between predicted and actual inundation, however, as noted above absolute measures of performance do not take into account sampling bias.

Another common measure of classification accuracy is the Cohen’s Kappa index. Values range from 0 to 1, where 1 indicates perfect agreement and 0 indicates no agreement, or agreement arising by chance. Landis and Koch (1977) and Fielding and Bell (1997) provide the following interpretation of the Kappa statistic: poor Kappa < 0.4; good 0.4 < Kappa < 0.75 and excellent Kappa > 0.75. The results listed in Table 3-9 range from 0.273 to 0.644, indicating poor to good levels of agreement between predicted and actual inundation.

In this study Cohen’s Kappa in addition to geometric g-means 2, true and false positive, and true and false negative should be considered when evaluating model performance. The true positive and true negative rate indicate the proportion of cases correctly identified as positive and negative respectively, while the false positive and false negative rates measure the inverse. Of interest is the high false negative rate which implies significant under-prediction. Again, the difference between model 31 (five variable model) and 35 (three variable model) is marginal. Also of note is the high true negative rate (~100%), this is expected given the bias towards negative responses. That is to say, the high proportion of negative cases identified correctly is understandable because the vast majority of classification cases were negative (non-water).

A visual analysis of the model results was used to supplement the statistical quantification above. A series of figures showing the fractions of standing water obtained with models 31 and 35 in the five regions and in the three dates are shown in Appendix A.

Figure 4-2 to Figure 4-15 show the fraction of standing water from models 31 and 35, and observed standing water from the object oriented classification. Included is the difference between each alternate model estimate calculated as: model 35 minus model 31. Typically, positive values (blue) show areas where model 35 estimated a higher fraction of standing water relative to model 31, while negative values (red) indicate the opposite. Values close to 0 result when both the three and five variable model estimates are similar. Landsat TM band 5 was used as the background imagery for each figure; inundated cells are shown as dark gray, or black.

### 3.3. The effects of the use of different MODIS products

#### 3.3.1. Use of daily vs. composited reflectance data

Standing water fractions estimated using daily and composited MODIS reflectance data were compared. The model used was 31, i.e. the best 5-variable model as selected in section 2.4.1. As discussed in section 2.4.2, the per-cell maximum daily MOD09GA estimate of standing water fraction for each MOD09A1 equivalent 8 day period were identified. The result is a composite MOD09GA time-series of the maximum standing water fraction in the 8 day period that can be directly compared to the MOD09A1 estimates. As described in section 2.2 the 8-day MOD09A1 composites are generated using the "best" reflectance value for each pixel taken during the 8-day period using the lowest possible cloud-free viewing angle. It was hypothesised that in a flood event where water moves quickly through the landscape,
the use of an 8-day composite will “miss” some or all the standing water, depending on what particular day out of the 8 possible is selected for each pixel.

Figure 3-5 shows the standing water algorithm applied to daily Terra images from December 10 to 17, 2004. The first two dates were affected by clouds. The first cloud-free observations made were on Dec 12th and shows a large area in the floodplain affected by flooding. During the 5th, 6th and 8th days in the series it can be observed that standing water tends to decrease in area, likely by infiltration and evaporation, but it is also evident that large amounts of water flow downstream. When a composite from these 8 days is created using the maximum standing water area value per-pixel and is compared to the result obtained when the algorithm is applied to the 8-day reflectance composite MOD09A1 the result is an underestimation of water area. The reason is that in this particular 8-day period the MOD09A1 product uses data mostly from the 12 December date because it’s the lowest viewing angle with cloud-free conditions. As a result the standing water estimate derived from MOD09A1 is “missing” the water that has flowed downstream from 13 to 17 December which confirms the initial hypothesis. Nevertheless, most of the water that was missed by the MOD09A1 in those 8 days, was later detected by the MOD09A1 in the following 8 day period (Figure 3-6). In that particular case, the 8-day composite used data mostly from the 4th day in the period.
Figure 3-5: Standing water dynamics from 10 to 17 December 2004 estimated by daily Terra images (top 8 images). Result of aggregating the daily images using the maximum value (MOD09GA-8 Day Max), comparison with the results obtained by using the 8-day composite MOD09A1 and day of the period used in the MOD09A1 composite.
Figure 3-6: Standing water dynamics from 18 to 25 December 2004 estimated by daily Terra images (top 8 images). Result of aggregating the daily images using the maximum value (MOD09GA-8 Day Max), comparison with the results obtained by using the 8-day composite MOD09A1 and day of the period used in the MOD09A1 composite.

Figure 4-16 to Figure 4-30 in Appendix B show the analyses described above for the five selected areas and provide more detail on the differences between the algorithm applied to the daily and the composited MODIS data. Note the maximum flood extent shown in regions A and B for the period 24/11 to 1/12 2004 (Figure 4-16 and Figure 4-17). The extent of inundation, and the fraction of standing water per-pixel is significantly lower in the MOD09A1 estimate. Similarly, the MOD09A1 estimate underestimates standing water for the 8 day period 10-17 December 2004. Note the high fraction of water mapped in the south-east of region A (Figure 4-21a), the south-west of region B (Figure 4-22a), and the central-west of region C (Figure 4-23a).
Again, the difference in standing water fraction is included in each figure. For each site and date combination the combined daily estimates produce a higher fraction of standing water compared to the best pixel MOD09A1 estimates.

3.3.2. Use of 500m vs. 250m MODIS data

Model estimates calculated using 250 and 500 meter MODIS reflectance data were compared. The MOD09GA estimates were over sampled to 250 meters to allow a direct pixel to pixel comparison with the MOD09GQ derived fraction of standing water.

Figure 4-31 to Figure 4-45 in Appendix C provide a qualitative comparison of the MOD09GA and MOD09GQ estimates at the five validation regions. On initial inspection there does not appear to be any significant difference between the two estimates. Both datasets capture the same basic flood dynamics. See Figure 4-36 to Figure 4-39, inundation extent is similar in each example and the calculated difference between each estimate is typically small.

The 250 meter data provide a better delineation of flood boundaries and a more precise estimate of standing water extent. This feature is most noticeable when flooding is less extreme. Note the permanent water bodies delineated in the MOD09GQ estimate more closely resembles those of the segmentation-based classification. This is not surprising given the greater spatial resolution of the 250m product.

3.4. Generation of a time series of standing water for the Australian continent and derived metrics

The same 5 variable model described in previous sections was applied to the MOD09A1 collection from 2000 to 2010 to produce a time series dataset of standing water fraction for the whole Australian continent in a 8-day time step. The dataset includes 46 images per year and at the time of writing this report it expands from 18 Feb 2000 (when the MODIS Terra sensor commenced to operate) until the 8-day period starting on 14 Sep 2010.

As it was discussed in section 3.3.1, the standing water fractions derived from the MOD09A1 composites “miss” water during flood events when compared to using daily MODIS data because only one out of eight possible days are used. However, using daily data for such a large area (all Australia) and such a long period of time (10 ½ years) is presently impractical due to the large volumes of data involved. We reasoned that the dataset produced here is a good representation, although probably an underestimation in flood events, of the dynamics of standing water over Australia in the last 10 ½ years.

The main summary statistic derived from the time series generated is the number of times a given pixel has standing water above a certain fractional threshold. Such statistic is referred hereon as the standing water recurrence and is expressed as a fraction or percentage. In all cases, the fraction is calculated using the valid observations (i.e. not affected by clouds).

A classification was derived from the standing water recurrence maps following the criteria described in Table 3-10 below.

<table>
<thead>
<tr>
<th>Class name</th>
<th>Standing water fraction</th>
<th>recurrence</th>
<th>colour</th>
</tr>
</thead>
<tbody>
<tr>
<td>Permanent Water Body</td>
<td>&gt;70%</td>
<td>&gt;90%</td>
<td></td>
</tr>
<tr>
<td>Semi-permanent water body</td>
<td>&gt;70%</td>
<td>75 to 90%</td>
<td></td>
</tr>
</tbody>
</table>
As the classes are not mutually exclusive, they are prioritised in the order shown in Table 3-10. For example, if a pixel has 50% water for 50% of the time and 80% water the other 50% of the time it would belong to the classes Mixed Intermittent water and Intermittent water body simultaneously. In that hypothetical case, the first class in the list takes precedence and the pixel is assigned to the Intermittent water body class.

Figure 3-7 shows time series dynamics of each class from selected examples and Figure 3-8 and Figure 3-9 shows the spatial distribution of such classes in the Australian continent. A permanent water body corresponds to an area with high fraction of standing water (>70%) most of the time (>90) and is exemplified with a pixel from Lake Hume (Figure 3-9d). A semi-permanent water body also has high fractions of standing water, but occur with less frequency. Those classes are represented by an area in the southern part of the Hume Dam which in some limited occasions dries up (semi-permanent) and two adjacent dams in the Gwydir catchment which are intermittently filled and emptied (Figure c). Intermittent water bodies occur at large in the Diamantina region (Figure 3-9b). A pixel taken in the southern part of Cooper Creek, which is mostly dry with the exception of 3 large flooding events in the period analysed exemplifies this class. An infrequent mixed inundation area is illustrated by a pixel taken in the Gwydir floodplain which is regularly occupied with standing water, although only in a portion.
Figure 3-7: Time series of standing water fractions for selected pixels used as examples of the classification performed. The graph on top shows an example of a permanent water body (Lake Hume North), an infrequent total inundation (in the Diamantina region), and an Infrequent mixed inundation (floodplain in the Gwydir). The bottom graph shows an example of a semi-permanent water body (south portion of Lake Hume), and two examples of intermittent water bodies (reservoirs in the Gwydir catchment).
Figure 3-8: Map showing the results of the classification performed with the time series of standing water fractions. Four areas are shown with more detail in Figure 3-9.
Figure 3-9. Same as Figure 3-8 in four selected areas.

The results shown in Figure 3-8 and Figure 3-9 suggest some areas where the standing water algorithm developed may still need future refinement. The first is the case of salt lakes, e.g. Lake Eyre, Lake Frome and others in the centre and west of the continent. Large parts of those areas were classified as permanent or semipermanent water bodies but this is possibly due to an overestimation of the fractions of standing water. Salt lakes, when dry, have a very high reflectance in the visible portion of the spectrum, but mid to low reflectance in the mid infrared likely due to the presence of very shallow moisture (Jupp et al, unpublished).

Another area where the algorithm may still need further validation and refinement is in the high ranges of the NSW and VIC alps. Possibly the DEM derived MrVBF is not completely removing the effects of shades and as a consequence those areas tend to be mapped as partial water.
4. CONCLUSIONS

This report has presented a novel method for quantifying the fractions of standing water present in a MODIS pixel, based on the pixel's reflectance and an auxiliary variable derived from a DEM. The algorithm appears to be robust and is able to track the dynamics of standing water with an acceptable level of accuracy. This method is suitable for estimating standing water in flood events and in natural and man-made reservoirs, either permanently or temporarily filled with water. The spatial resolution of the sensor used determines the size of the water bodies that it can detect. Although the method allows the estimation of sub-pixel water coverage, it is not recommended for making inferences on water bodies smaller than the size of the pixel.

This algorithm can be applied on temporally aggregated MODIS data, however it is noted that the standing water estimates derived are an underestimation, although an acceptable approximation, particularly in rapidly changing events such as floods. It is still a good approach for characterising standing water dynamics in large areas and over long periods of time, such as in retrospective flood analysis, as using daily data would become a logistic problem because of the large volumes of data involved.

The algorithm developed was applied to 10 ½ years of MOD09A1 data for the Australian continent, to generate a description of flood recurrence at 500m pixel resolution. A classification scheme was adopted to characterise each 500m grid cell in the continent with respect to the recurrence of inundation and the fraction of the area affected. The classification results qualitatively agree with the general patterns of the hydrological network in Australia, and highlight some areas where the algorithm may need further refinement, particularly in the salt lakes and some areas of the New South Wales and Victorian alps.

The algorithm developed here is recommended for its implementation and testing within the Australian Water Resources Assessment system (AWRA), particularly for the dynamic estimation of surface water extent in the AWRA-L model which needs such information for the quantification of evaporative losses. It is also suggested that the algorithm is further validated and tested and improvements made in future versions as needed.

Future research should also focus on integrating this type of approach with passive or active microwave data (radar) which allows the problems associated with cloud coverage to be overcome. It is also recommended that the derivation of water volume is explored by combining optical remote sensing with terrain modelling from DEMs and/or remote sensing-derived altimetry.
APPENDIX A

Figures showing the fraction of standing water from models 31 and 35, and observed standing water from the object oriented classification. Included is the difference between each alternate model estimate calculated as: model 35 minus model 31. Typically, positive values (blue) show areas where model 35 estimated a higher fraction of standing water relative to model 31, while negative values (red) indicate the opposite. Values close to 0 result when both the three and five variable model estimates are similar. Landsat TM band 5 was used as the background imagery for each figure; inundated cells are shown as dark gray, or black.

![Figure 4-1: The fraction of standing water for region B, 26 November 2004. Model 35 estimate (a); model 31 estimate (b); observed standing water (c); the difference between model estimates 35 and 31.](image)
Figure 4-2: The fraction of standing water for region A, 26 November 2004. Model 35 estimate (a); model 31 estimate (b); observed standing water (c); the difference between model estimates 35 and 31.
Figure 4-3: The fraction of standing water for region C, 26 November 2004. Model 35 estimate (a); model 31 estimate (b); observed standing water (c); the difference between model estimates 35 and 31.
Figure 4-4: The fraction of standing water for region D, 26 November 2004. Model 35 estimate (a); model 31 estimate (b); observed standing water (c); the difference between model estimates 35 and 31.
Figure 4-5: The fraction of standing water for region E, 26 November 2004. Model 35 estimate (a); model 31 estimate (b); observed standing water (c); the difference between model estimates 35 and 31. Yellow pixels show cloud or missing data.
Figure 4-6: The fraction of standing water for region A, 12 December 2004. Model 35 estimate (a); model 31 estimate (b); observed standing water (c); the difference between model estimates 35 and 31.
Figure 4-7: The fraction of standing water for region B, 12 December 2004. Model 35 estimate (a); model 31 estimate (b); observed standing water (c); the difference between model estimates 35 and 31.
Figure 4-8: The fraction of standing water for region C, 12 December 2004. Model 35 estimate (a); model 31 estimate (b); observed standing water (c); the difference between model estimates 35 and 31. Yellow pixels show cloud or missing data.
Figure 4-9: The fraction of standing water for region D, 12 December 2004. Model 35 estimate (a); model 31 estimate (b); observed standing water (c); the difference between model estimates 35 and 31. Yellow pixels show cloud or missing data.
Figure 4-10: The fraction of standing water for region E, 12 December 2004. Model 35 estimate (a); model 31 estimate (b); observed standing water (c); the difference between model estimates 35 and 31. Yellow pixels show cloud or missing data.
Figure 4-11: The fraction of standing water for region A, 28 December 2004. Model 35 estimate (a); model 31 estimate (b); observed standing water (c); the difference between model estimates 35 and 31. Yellow pixels show cloud or missing data.
Figure 4-12: The fraction of standing water for region B, 28 December 2004. Model 35 estimate (a); model 31 estimate (b); observed standing water (c); the difference between model estimates 35 and 31. Yellow pixels show cloud or missing data.
Figure 4-13: The fraction of standing water for region C, 28 December 2004. Model 35 estimate (a); model 31 estimate (b); observed standing water (c); the difference between model estimates 35 and 31.
Figure 4-14: The fraction of standing water for region D, 28 December 2004. Model 35 estimate (a); model 31 estimate (b); observed standing water (c); the difference between model estimates 35 and 31.
Comparison of the object-based classification of standing water and the model estimates show that model 35 (three variable model) overestimates standing water at fractions less than 0.2 (20%). Note the statistical analysis above did not detect the over-prediction because of the threshold parameters used.

Visually, both models provide a reasonable estimate of standing water when compared to the observed data. The three and five variable models differ only slightly in their indicated extent of inundation. Figure 4-2d, Figure 4-3d, Figure 4-4d, Figure 4-11d, and Figure 4-12d show that for small water bodies the three variable model calculates a comparatively high fraction of standing water. By comparison, model 31 estimates a higher fraction of standing water during large flood events (see Figure 4-6 to Figure 4-10). Note the flooding in the south east of region A on the 12th December (Figure 4-6) and the flooding in the central-east of region B on the same date (see Figure 4-7). The three variable model appears to underestimate standing water at the aforementioned locations. Again, the size of the underestimation per-region is highlighted in map (d). Figure 4-6 and Figure 4-7 also suggest that the five variable model provides a better delineation of flood boundaries.
APPENDIX B

Figures showing comparisons of standing water estimates using 8-day composites (MOD09A1) and using daily images (MOD09GA).

Figure 4-16: The fraction of standing water for region A, 24 November to 1 December 2004. Composite MOD09GA estimate (a); MOD09A1 estimate (b); the difference between model estimates.
Figure 4-17: The fraction of standing water for region B, 24 November to 1 December 2004. Composite MOD09GA estimate (a); MOD09A1 estimate (b); the difference between model estimates.
Figure 4-18: The fraction of standing water for region C, 24 November to 1 December 2004. Composite MOD09GA estimate (a); MOD09A1 estimate (b); the difference between model estimates.
Figure 4-19: The fraction of standing water for region D, 24 November to 1 December 2004. Composite MOD09GA estimate (a); MOD09A1 estimate (b); the difference between model estimates.
Figure 4-20: The fraction of standing water for region E, 24 November to 1 December 2004. Composite MOD09GA estimate (a); MOD09A1 estimate (b); the difference between model estimates.
Figure 4-21: The fraction of standing water for region A, 10-17 December 2004. Composite MOD09GA estimate (a); MOD09A1 estimate (b); the difference between model estimates.
Figure 4-22: The fraction of standing water for region B, 10-17 December 2004. Composite MOD09GA estimate (a); MOD09A1 estimate (b); the difference between model estimates.
Figure 4-23: The fraction of standing water for region C, 10-17 December 2004. Composite MOD09GA estimate (a); MOD09A1 estimate (b); the difference between model estimates.
Figure 4-24: The fraction of standing water for region D, 10-17 December 2004. Composite MOD09GA estimate (a); MOD09A1 estimate (b); the difference between model estimates.
Figure 4-25: The fraction of standing water for region E, 10-17 December 2004. Composite MOD09GA estimate (a); MOD09A1 estimate (b); the difference between model estimates.
Figure 4-26: The fraction of standing water for region A, 26 December 2004 to 2 January 2005. Composite MOD09GA estimate (a); MOD09A1 estimate (b); the difference between model estimates.
Figure 4-27: The fraction of standing water for region B, 26 December 2004 to 2 January 2005. Composite MOD09GA estimate (a); MOD09A1 estimate (b); the difference between model estimates.
Figure 4-28: The fraction of standing water for region C, 26 December 2004 to 2 January 2005. Composite MOD09GA estimate (a); MOD09A1 estimate (b); the difference between model estimates.
Figure 4-29: The fraction of standing water for region D, 26 December 2004 to 2 January 2005. Composite MOD09GA estimate (a); MOD09A1 estimate (b); the difference between model estimates.
Figure 4-30: The fraction of standing water for region E, 26 December 2004 to 2 January 2005. Composite MOD09GA estimate (a); MOD09A1 estimate (b); the difference between model estimates.
APPENDIX C

Figures showing a qualitative comparison of the MOD09GA (500 meters) and MOD09GQ (250 meters) estimates of standing water at the five validation regions.

Figure 4-31: The fraction of standing water for region A, 26 November 2004. MOD09GA at 250m estimate (a); MOD09GQ estimate (b); observed standing water (c); the difference between the two model estimates.
Figure 4-32: The fraction of standing water for region B, 26 November 2004. MOD09GA at 250m estimate (a); MOD09GQ estimate (b); observed standing water (c); the difference between the two model estimates.
Figure 4-33: The fraction of standing water for region C, 26 November 2004. MOD09GA at 250m estimate (a); MOD09GQ estimate (b); observed standing water (c); the difference between the two model estimates.
Figure 4.34: The fraction of standing water for region D, 26 November 2004. MOD09GA at 250m estimate (a); MOD09GQ estimate (b); observed standing water (c); the difference between the two model estimates.
Figure 4-35: The fraction of standing water for region E, 26 November 2004. MOD09GA at 250m estimate (a); MOD09GQ estimate (b); observed standing water (c); the difference between the two model estimates.
Figure 4-36: The fraction of standing water for region A, 12 December 2004. MOD09GA at 250m estimate (a); MOD09GQ estimate (b); observed standing water (c); the difference between the two model estimates.
Figure 4-37: The fraction of standing water for region B, 12 December 2004. MOD09GA at 250m estimate (a); MOD09GQ estimate (b); observed standing water (c); the difference between the two model estimates.
Figure 4-38: The fraction of standing water for region C, 12 December 2004. MOD09GA at 250m estimate (a); MOD09GQ estimate (b); observed standing water (c); the difference between the two model estimates.
Figure 4-39: The fraction of standing water for region D, 12 December 2004. MOD09GA at 250m estimate (a); MOD09GQ estimate (b); observed standing water (c); the difference between the two model estimates.
Figure 4-40: The fraction of standing water for region E, 12 December 2004. MOD09GA at 250m estimate (a); MOD09GQ estimate (b); observed standing water (c); the difference between the two model estimates.
Figure 4-41: The fraction of standing water for region A, 28 December 2004. MOD09GA at 250m estimate (a); MOD09GQ estimate (b); observed standing water (c); the difference between the two model estimates.
Figure 4-42: The fraction of standing water for region B, 28 December 2004. MOD09GA at 250m estimate (a); MOD09GQ estimate (b); observed standing water (c); the difference between the two model estimates.
Figure 4-43: The fraction of standing water for region C, 28 December 2004. MOD09GA at 250m estimate (a); MOD09GQ estimate (b); observed standing water (c); the difference between the two model estimates.
Figure 4-44: The fraction of standing water for region D, 28 December 2004. MOD09GA at 250m estimate (a); MOD09GQ estimate (b); observed standing water (c); the difference between the two model estimates.
Figure 4-45: The fraction of standing water for region E, 28 December 2004. MOD09GA at 250m estimate (a); MOD09GQ estimate (b); observed standing water (c); the difference between the two model estimates.
REFERENCES


