Integrating Sentinel 2 imagery with high resolution elevation data for automated inundation monitoring in vegetated floodplain wetlands

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Supplementary material

Drone imagery classification

Orthomosaic RGB images obtained from DJI Mavic 3E & 3M drones are classified into two classifications. The inundation classification defines the image into inundated and not-inundated areas. The cover classification separates the image into sparsely covered and vegetated areas.

Inundation classification

To apply the inundation classification, a preliminary automatic classification was applied which was then manually refined. The preliminary classification is achieved by deriving indices using the RGB image to enhance areas likely to be open water. Key characteristics of open water bodies is high absorption of light and a smooth surface. To take advantage of these characteristics, a brightness index is calculated from the RGB image (Equation 1) with value normalised to range between 0-255 (equation 1). A focal analysis is applied to the brightness index to calculate the standard deviation of brightness values within the 10 x 10 pixel neighbourhood of each individual pixel in the image. Pixels with low standard deviation are indicative of being in regions with low variability of brightness values which is typical of smooth surfaces. A threshold is applied to the standard deviation image so that values less than 5 and brightness values less than 100 are considered water. This is further refined using an object-based analysis so that small clusters of water pixels (<10 pixels) are removed to reduce noise in the classification. Remaining water pixels are then converted to vector format as polygon features that can then be manually refined.

$$Brightness = \frac{\sqrt{R^2 + B^2 + G^2}}{3} \qquad \text{Equation S1.}$$

Manual refinement of water polygons typically addresses 3common errors in the initial classification process. Firstly, like water, shadows have low reflectance and low standard deviation of brightness meaning removal of misclassified shadows is required. Secondly, due to specular reflection, some areas of water may appear bright and requires manually including as water (Figure 1A). Thirdly, as most sites contain flood dependent vegetation, water is often obscured by vegetation cover. In these instances, visual interpretation of the image is required to manually delineate the extent of inundation under vegetation. When evaluating woodlands and forests, water is often visible between branches, allowing reasonable estimation of extent (Figure 1 B). In other areas, vegetation obscuring potential water may be sparse, allowing the visual interpolation of open water areas adjacent to vegetated areas. The use of best available digital elevation models facilitates this process as it allows visualisation of depression boundaries which often define the reasonable limit of inundation extent under vegetation (Figure 1, C and 3D).

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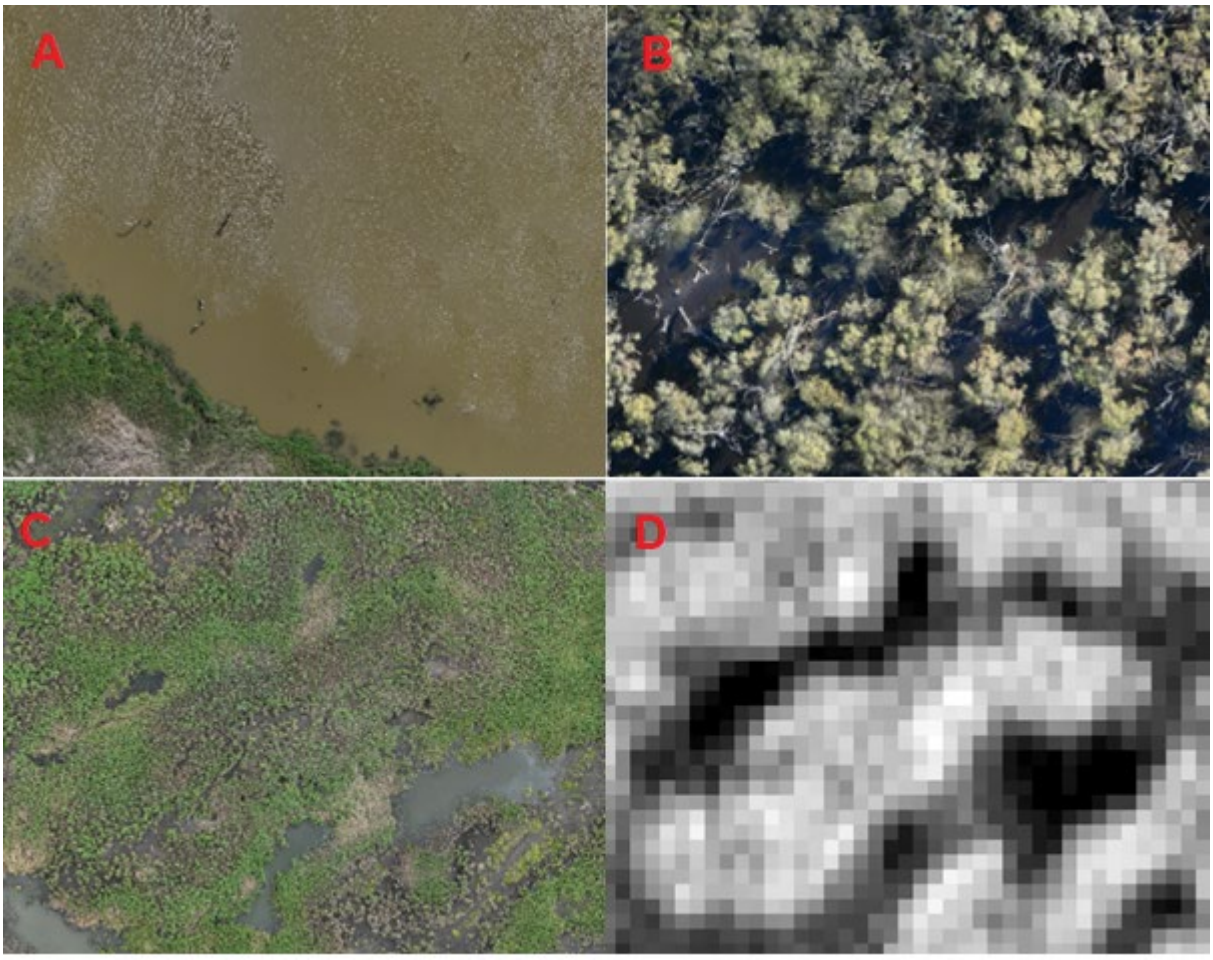


Figure S1. Examples of issues encountered classifying inundation status of drone imagery. Includes specular reflection (A), inundated forests (B), dense non-woody vegetation (C) and an example of high-resolution DEM of the same extent shown in C (D).

Cover classification

As with the inundation classification a preliminary classifier was applied to identify areas of sparse cover. In this initial classification, the RGB image was converted into unit vector form (equation 2 and 3). The color components of this RGB unit vector is used to calculate a blue difference index (equation 4)

$$|RGB| = \sqrt{R^2 + G^2 + B^2} \qquad \text{Equation 2.}$$

$$\widehat{RGB} = \frac{RGB}{|RGB|} \qquad \text{Equation S3.}$$

$$BDI = \left(\hat{R} + \hat{G}\right) - 2\hat{B} \qquad \text{Equation S4.}$$

Cover classes that contain limited amounts of vegetation (e.g. bare soil, timber) will have lower proportions of green in the RGB image. As a result we found a threshold of less than 0.15 adequately separated non-vegetation from vegetation. A binary erosion followed by dilation is applied to remove noise in the classification and the resulting map converted to vector for manual refinement.