Landsat Based Woody Vegetation Change Detection using the Google Earth Engine

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Land clearing detection at the state level in Australia has largely been the province of governments because of the considerable expense, expertise, sustained duration of activities and staffing levels needed. State Governments responsible for mapping woody vegetation change release mapping results several years after the clearing has occurred, are at Ministerial discretion and there is no guarantee they will continue being made public. This makes it imperative to develop capacity to detect land clearing independently. Hence, the main objective of this research project was to develop and apply a robust and rapid woody vegetation change detection approach using publically available computing capabilities and data. This was done using the Google Earth Engine, and two selected Landsat scenes, in the Brigalow Belt and Mulga Lands biogeographic regions in Queensland, Australia, where land clearing is known to have occurred. Validated woody vegetation clearing data were available for the study sites from 2004-2010.

Four change detection approaches were investigated using the Google Earth Engine Application Programming Interface: (1) visual identification of areas of presumptive clearing, used to train change detection algorithms in GEE and then extrapolate a detection model across the scenes of interest; (2) CART and Random Forest classifiers trained using existing validated woody vegetation clearing information for different time epochs; (3) a normalised time-series of NDVI mean and standard deviation values combined with a spectral index; and (4) a normalised time-series of Foliage Projective Cover (FPC) mean and standard deviation values combined with a spectral index. The initial research shows that the CART and Random Forest classifiers produced the highest mapping accuracies (user’s and producer’s accuracies of clearing were 77-92% and 54-77%, respectively) when detecting woody vegetation change between 2004 and 2010 from which training data were available. However, for prediction of woody vegetation change using extrapolation within epochs from where no training data were available, the classification accuracies were significantly reduced. This was mainly because of variations in rainfall, and associated vegetation greening and senescence, between the years with and without training data. The normalised time-series of NDVI and FPC mean and standard deviation values combined with a spectral index did not yield accuracies as high as the CART and Random Forest classifiers, but proved to be more robust, as this approach did not rely on training data and took advantage of time-series information. The approach, using visual identification of presumptive clearing for training, yielded the lowest land clearing classification accuracies. The methods developed in this research project provide new knowledge and techniques significantly contributing to applied remote sensing and environmental monitoring, i.e. assessment of the relative capacity and accuracy of commonly available image processing algorithms for mapping woody vegetation changes from a globally accessible, free online database of Landsat image data. It also provides more detailed information, suited to Australian conditions, on woody vegetation loss than other existing approaches relying on publically available image and computing facilities. This research is a critical building block for any further work in this area.