Benefits of urban vegetation in Ōtautahi/ Christchurch

Outline of methods used to generate web map layers

This methods document describes the generation of map layers used in the “Benefits of urban vegetation in Ōtautahi/ Christchurch” online map. This research is currently under review, so this document is provided as an interim guide to the datasets and may be subject to change following peer-review. The datasets provided for online viewing and download have been resampled to a lower resolution.

Summary of files contained in this dataset

Index	Unit	Resampled resolution	Filename
Biomass carbon	Kg Carbon	~1 ha	carbon.tif
Runoff retention	Percentage incoming runoff retained	~0.1 ha	runoff.tif
Erosion control	Percentage potential erosion prevented	~0.1 ha	erosion.tif
Air pollution removal	g of PM10 removed per day	~0.04 ha	pm10.tif
Shade provided by vegetation	Percentage of time that vegetation was providing shade	~0.1 ha	shade.tif
School green space	Percentage of green cover at closest school	~0.001 ha	school.tif
Private green space	Percentage green cover in private gardens	~20 ha	privategreen.tif
Public outdoor spaces	Closest distance to public outdoor space	~20 ha	publicgreen.tif
Bird biodiversity	Number of bird species	~0.1 ha	birds.tif

Overarching datasets

Vegetation was mapped using combined remote sensing datasets to identify green regions. High-resolution aerial photographs (7.5 cm pixel size resampled to approximately 1 m) were captured at a single snapshot in time (between December 2018 and February 2019; LINZ 2020a). Due to the discoloration of some vegetation under Christchurch's hot summer, this snapshot dataset was combined with a time series composite vegetation index provided by a lower resolution satellite image dataset from the Sentinel-2 Level-1C archive (approximately 10 m pixel size). The time series composite was the median Normalised Difference Vegetation Index (NDVI) from all cloud-free images available between January 1st 2017 and December 31st 2020, composited using Google Earth Engine (Gorelick et al., 2017). The NDVI composite was resampled to match the spatial extent and resolution of the aerial photograph dataset. From the aerial photograph dataset we extracted the Red-Green-Blue Vegetation Index (RGBVI). We also identified grey areas of the images (typically indicating concrete or asphalt) by calculating the standard deviation and mean values from the Red, Green, and Blue (RGB) colour bands. Grey pixels were defined as those with mean RGB values of between 80 and 230, and standard deviation RGB values of less than 3. Vegetation was defined as pixels with either Sentinel-2 NDVI value of greater than 0.5, or an aerial photograph RGBVI value of greater than 0.1, that were not otherwise defined as grey pixels, and did not overlap with an authoritative polygon dataset of building outlines (LINZ 2021a).

Vegetation types were defined in relation to height classes obtained by overlaying the vegetation map with 1 m-resolution digital elevation and digital surface models obtained by airborne Light Detection and Ranging (LiDAR) and collected in summer 2018-2019 (LINZ 2020b; LINZ 2020c). Vegetation canopy height was quantified by subtracting the digital elevation model from the digital surface model for vegetated pixels (Dissegna et al., 2019). We defined five vegetation classes depending on height; short grass (approximately 0 m), tall grass (0-0.5 m), shrubs and scrub (0.5-2 m), small trees (2-6 m) and taller trees (greater than 6 m). In addition to the categorical vegetation classification, we retained a continuous measurement of vegetation height for use in some models. Surface water was mapped by cross-referencing with an authoritative national land cover map from 2018 (LCDB, 2019).

The accuracy of the vegetation type classification was quantified by visual assessment of 50 randomly located truthing points from each class (five vegetation classes and non-vegetated cover). Each truthing point was visually inspected using the original aerial photographs and interpreted by a human surveyor. The agreement between the remote sensing and human classification was compared as a proportion and using Cohen's Kappa scores (Landis et al., 1977). The overall agreement between the human and map classifications was 79.7% with a Kappa score of 75.6. The highest user's accuracy was found for tall tree vegetation and lowest user's accuracy for short grass vegetation, which was most commonly misclassified as either tall grass or unvegetated.

Nature's contributions to people

Carbon stocks

Above-ground tree biomass carbon stocks for the tree vegetation classes were quantified using an allometric approach. All individual tall tree locations were extracted from the vegetation canopy height layer using a variable window filter method (Popescu and Wynne, 2004) implemented in the ForestTools package for R (Plowright and Roussel, 2021). We used a minimum canopy height of 2 m, maximum window diameter of 111 m, and moving window of approximately 10 m diameter. The maximum height of each tree canopy was extracted by the variable window filter algorithm, and we used this height to estimate the diameter at breast height (DBH) of each tree using an empirical multi-species allometric equation derived from field measurements of tree height and DBH taken from 15,681 trees in Christchurch city (Quan et al., 2021). The fitted allometric equation described a log-log relationship between DBH and height, with an R^2 of 0.29. Above- and belowground biomass carbon stocks were estimated from tree DBH using one of two empirical equations developed from sampled urban and forest trees in New Zealand (Beets et al., 2012; Schwendenmann and Mitchell, 2014). We used the urban tree equation for trees smaller than 0.4 m in DBH as the empirical data underlying this equation were mainly from trees of around this size (Schwendenmann and Mitchell, 2014) and the general forest tree equation for larger trees (Beets et al., 2012). We excluded trees larger than 30 m in height as these are unlikely within the study region and may have been caused by minor inaccuracies in the underlying spatial datasets.

Runoff retention

We quantified the proportion of incoming rainfall retained by vegetation using a curve number approach (Mockus, 1972). Soil hydrological group maps were extracted from a globally available dataset (Ross et al., 2018). For each combination of vegetation class and soil hydrological group, we collated suitable curve numbers by referring to urban and rural planning guidelines from New Zealand authorities (Auckland Regional Council, 1999; Ministry for the Environment, 2010; Srinivasan et al., 2007). We modelled runoff under an extreme rainfall event, defined as the 24 hour average return interval for Christchurch Botanic Gardens, which is equivalent to 137 mm (National Institute for Water and Atmospheric Research, 2022).

Erosion control

We quantified the proportion of potential soil erosion prevented by vegetation following an approach derived from the Revised Universal Soil Loss Equation (Guerra et al., 2014). We implemented a modified soil loss equation model developed for New Zealand, which estimates the mean annual erosion rate due to surficial processes (Dymond, 2010). The model is the product of precipitation, slope gradient and slope length factors, a soil factor, and a vegetation factor which were parameterised based on the topographic model for each landscape and based on assumptions about the soil erosion factor and precipitation rates. Mean annual precipitation was extracted from a national dataset (McCarthy et al., 2021). The vegetation factor was parameterised for vegetation type based on expert assessment of the relative ability of each vegetation cover to reduce erosion, following previous work (Dymond, 2010; Lavorel et al., 2022).

Particulate matter removal from air

The contribution of vegetation to removing particulate matter pollution from the air was quantified using a standard approach based on the leaf area index of vegetation, background concentration, and deposition velocity of particles (Nowak et al., 2013, 2006). Winter-heating is the primary source of air pollution in Christchurch, hence we focussed on particulate removal over winter. Tree canopy leaf area index was estimated from a composite Landsat 8 satellite image using an empirical relationship developed from sampled locations in a central Christchurch park (Kato et al., 2013). Cloud-free calibrated top-of-atmosphere reflectance Landsat 8 images were composited by taking the median of all available wintertime images from between 2016 and 2020, using Google Earth Engine (Gorelick et al., 2017). We calculated the reduced simple ratio from this composite image (Brown et al., 1994), and applied the empirical regression relationship between leaf area index and reduced simple ratio quantified by the previous Christchurch study (Kato et al., 2013). To parameterise the particulate matter removal equation for particulate matter smaller than 10 μm in diameter (PM_{10}) we assumed a concentration of 22 μg/ m^3, which is the winter daily average calculated between 2017 and 2020 (Stats NZ, 2022). We assigned removal and recirculation velocities per unit leaf area from previous studies in Christchurch and around the world (Cavanagh, 2008; Cavanagh et al., 2009; Richards et al., 2022; Tan et al., 2021).

Shade provision

We quantified the proportion of time that vegetation was providing shade at ground level using a three-dimensional ray shading model (Morgan-Wall, 2022). To disentangle the impacts of vegetation and building shade, we applied the rayshading model three times to different three-dimensional models: (1) the full model including both vegetation and buildings, (2) an inverse vegetation canopy model quantified by subtracting the vegetation canopy height from the ground surface height, and (3) the building canopy model. The total canopy and inverse vegetation canopy models were used to quantify the total area of shade provided adjacent to buildings and vegetation, and shade provided beneath vegetation. Areas shaded by vegetation that would anyway be shaded by buildings were discounted by subtracting the building canopy modelled shade area. This three-dimensional approach to quantifying urban tree shade is comparable to similar studies from elsewhere in the world (Dissegna et al., 2021; Kong et al., 2022), and the comparison of vegetation-shaded and building-shaded area to quantify vegetation-specific shading follows an approach developed for analysis of sky-view factors (Richards and Edwards, 2017). As an indicator of shade provision under summer conditions when shade may be most needed, and deciduous tree canopies are most significant in providing shade, we quantified vegetation shade provision for 11 moments in time: every hour between 8 am and 6 pm on the 1st of February 2019 (Morgan-Wall, 2022). The proportion of the 11 occasions that each pixel was shaded by vegetation was taken as the indicator of shaded time.

Green spaces for education

We quantified the percentage of green cover within each school in Christchurch as an indicator of green space accessibility during formal education experience. The boundaries of all primary and secondary schools were taken from a national database of facilities, totalling

128 schools (LINZ 2021b). We included all vegetation types in our definition of school green cover. To map this indicator continuously, we assumed that each part of the study area took the value from the the closest school, by generating Voronoi polygons around each of the school locations.

Private green space

We quantified the area of private green space for each residential parcel by cross-referencing the vegetation cover map with the boundaries of individual residential properties. We extracted all property boundaries from a national dataset (LINZ, 2022) and subset only properties that were zoned for residential, rural residential, or mixed use according to the regional zoning plan (Christchurch City Council, 2020). We also excluded very large parcels (greater than 10,000 m^2) which are deemed less likely to be residential in use. In total, our analysis included 116,708 parcels. We included all vegetation types in our definition of private green cover.

Public recreation space

For each parcel we quantified the minimum distance to a public recreational outdoor space. Public outdoor recreational spaces were mapped using an authoritative dataset of land zoning, for which we extracted all open space and conservation space polygons (Christchurch City Council, 2020). We calculated the minimum Euclidean distance between each outdoor recreational space and each residential parcel. Euclidean distance has been widely used as an indicator of accessibility to outdoor recreational features in urban environments (Belcher et al., 2019; Huang et al., 2017; Richards et al., 2020) and is typically correlated with more complex geographical accessibility indicators (Higgs et al., 2012).

Bird biodiversity

Bird species richness is a common indicator of urban biodiversity (Belcher et al., 2018; Canedoli et al., 2017). We modelled urban bird species richness as a function of spatially-explicit explanatory variables to project species richness continuously across the study region (Divíšek and Chytrý, 2018). The model was parameterised using empirical records of species richness sampled by citizen scientists through the New Zealand Garden Bird Survey (MacLeod et al., 2022). Citizen scientists were asked to record all bird species observed over a one hour period, during a survey period lasting for nine days in midwinter (MacLeod et al., 2022; Spurr, 2012). Surveys were conducted across a range of land uses, but most typically within private gardens (MacLeod et al., 2022; Spurr, 2012). We extracted all records within the study area boundary from 2018, 2019, and 2020 New Zealand Garden Bird Surveys, and removed duplicate records that reported identical spatial locations. The total dataset included 936 records (2018 = 151, 2019 = 238, and 2020 = 547), with a minimum observed species richness of 0 and a maximum of 24.

We modelled bird species richness as a function of 13 variables calculated at three spatial scales (10-m cells and 100 m and 1 km radius moving windows). The variables included the proportional cover of grass, shrub/scrub, tree, and water quantified at each spatial scale. The vegetation maps were resampled to a 10 m resolution prior to calculating the spatial variables for speed processing. Furthermore, we included an indicator of spatial connectivity or fragmentation between patches of vegetation cover, quantified as the patch size of combined vegetation taller than 0.5 m. Bird species richness was modelled using a generalized boosted regression assuming a Poisson error structure, fitted using the gbm package for R (Greenwell et al. 2022). We fitted the model using 80% of the available data (n = 748) with the remaining 188 data points used to assess model fit. As an initial testing step, we fitted two models: one using the set of 13 explanatory variables listed above and a more complex model with 19 variables, in which the short grass and tall grass variables and small tree and tall tree variables were separated. The performance of the two models was similar, so we used the more parsimonious model with 13 explanatory variables. The most influential model parameters were the coverage of short grass within 100 m, coverage of water within 1 km, and coverage of shrub/scrub within 1 km.

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