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Data Paper

A map of pollinator floral resource habitats in the agricultural landscape of Central New York

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Abstract

We created a spatially and temporally-explicit model of floral area in Central New York State, USA, using public data from federal and state governmental agencies and non-governmental organisations. This model incorporates remote sensing-derived natural habitat, crop and land-use data products with roads GIS data to predict land cover indicative of floral resources for pollinators. The resulting dataset provides the necessary land-cover data to quantify floral resources available within a user-specified area (e.g. 2 km radius around the location of a bee hive). When paired with phenological data of species within the communities associated with our land-cover classes, users can predict pollinator floral resources over any specified period in a year. This dataset would be of use to both researchers and practitioners, allowing them to estimate floral resource availability around crops or hive placements. It could also identify habitat restoration to most effectively boost native pollinator populations. We present the methodology for the creation of the spatial dataset and usage information.

Keywords

land cover, floral resources, floral resources, USA, agroecology, landscape ecology, ecosystem services

Overview and background

Pollinators provide an important ecosystem function and service (Klein et al. 2007, Ollerton et al. 2011), but are declining worldwide (Potts et al. 2010, Zattara and Aizen 2021). Many pollinators rely on the availability of floral resources, both nectar and pollen, at broad scales across the landscape for survival (Hines and Hendrix 2005, Steffan-Dewenter and Westphal 2008, Du Clos et al. 2020). Furthermore, the abundance and diversity of floral resources in a landscape change over the growing season (Guezen and Forrest 2021). The provision of floral resources depends on the composition of the flowering plant community, which varies with habitat and land use (Mallinger et al. 2016). Some habitats, such as deciduous forests, may have a narrow period of high flower production, whereas other habitats may provide fewer resources over an extended period. Since most pollinators do not produce substantial quantities of honey to store floral resources, their population is limited by the time of year when floral resources are scarcest.

Human-modified land uses, such as agricultural and urban areas, may significantly alter the distribution of floral resources in space and time. For example, mass-flowering crops concentrate flowering to an intense, limited period, which has an effect on pollinator behaviour (Holzschuh et al. 2011, Holzschuh et al. 2013). Urban environments can provide important pollinator resources (Tew et al. 2021), though the prevalence of exotic species may also shift the pollinator community (Wilson and Jamieson 2019, Theodorou et al. 2020). Development also creates new floral habitats, such as roadside ditches.

Therefore, estimates of floral resources for pollinators must take into account the land use and land cover within a heterogeneous landscape in order to model variability over space and time (Lonsdorf et al. 2009). An important step in developing this understanding is characterising the landscape into land-cover classes that can be translated to potential pollinator communities (Koh et al. 2015). Further, fine-scale information may play an important role in understanding pollinator distributions in some landscapes (Lonsdorf et al. 2009). Here we describe the process we used to create a spatial dataset that classifies land cover into categories relevant to their flowering vegetation communities at a high resolution (1 m) within a region of Central New York State. This dataset can be combined with data on flowering area and flowering phenology of plant communities in each land-cover category to predict floral resources available to pollinators over the year (Iverson et al., in prep.).

Context

The focal area of this dataset covers 12 counties in New York State, within the United States of America (USA): Cayuga, Chemung, Cortland, Monroe, Onondaga, Ontario, Schuyler, Seneca, Tioga, Tompkins, Wayne and Yates (Fig. 1). We produced dataset versions that include crop data for the years 2012-2019.

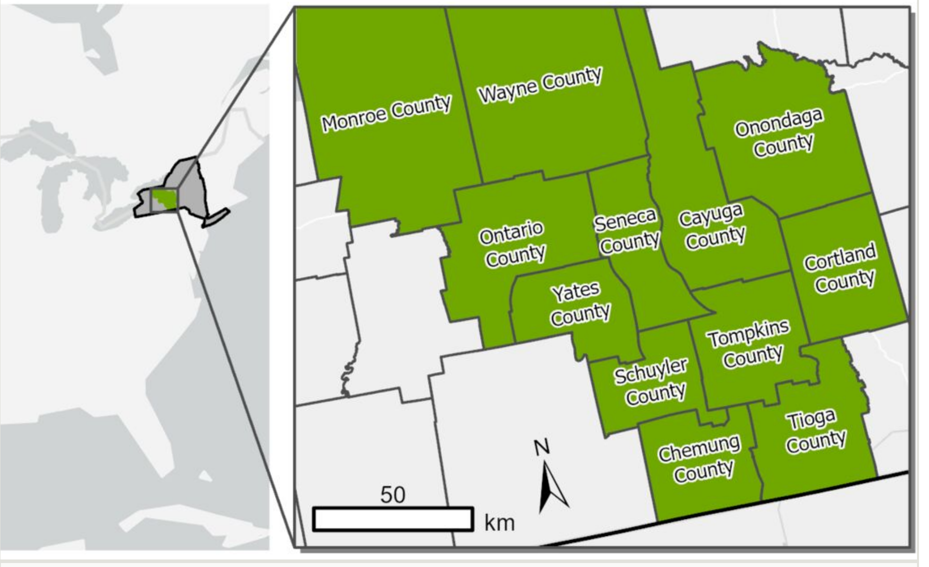

Figure 1.

Coverage of dataset includes 12 counties in New York State (USA): Cayuga, Chemung, Cortland, Monroe, Onondaga, Ontario, Schuyler, Seneca, Tioga, Tompkins, Wayne and Yates Counties.

Methods

We combined land-cover data relevant to estimating floral resources, including natural habitat types (including wetlands), crops, grasses (like pasture, hayfields, oldfields and urban lawns), roadside ditches and urban areas (see Table 2). This involved combining and reclassifying annual crop cover data from the Cropland Data Layer (CDL) (Boryan et al. 2011) and a natural habitat layer covering the northeast US and Atlantic Canada (Ferree and Anderson 2013) into classes relevant to predicting flowering plant communities. We then downscaled the land-cover classification information from the combined crop and habitat layer to a 1 m resolution lidar-based dataset that classifies, based on vegetation height and impervious cover (Chesapeake Conservancy 2020), for most (nine) of the counties within our study area. Counties not covered by this high resolution layer were still downscaled to 1-m resolution to match the rest of the data for further processing. To the downscaled data, we added wetland and waterbody delineations derived from the National

Wetland Inventory (USFWS 2018) and our own delineations of roadside ditches, based on road vector data.

Table 1.

Description of datasets used to map floral resources of pollinators for Central New York.

Layer	Source	Data format	Information extracted
Cropland Data Layer (CDL)	United States Department of Agriculture	Raster, 30 m resolution	Annual crop data and land-cover boundaries
Terrestrial Habitat Map for the northeast US and Atlantic Canada	The Nature Conservancy	Raster, 30 m resolution	Natural vegetation class land cover
Percent Impervious Land Cover, National Land Cover Database	United States Geological Survey	Raster, 30 m resolution	Percent impervious cover
Chesapeake Bay Land Cover Data	Chesapeake Conservancy	Raster, 1 m resolution	High resolution vegetation type (height class) and development land cover
National Wetland Inventory	United States Fish and Wildlife Service	Vector, polygons	Wetland polygons
New York State streets	New York State Government	Vector, lines	Road centre-lines for estimating roadside ditches
New York State civil boundaries	New York State Government	Vector, polygons	Boundaries of urbanised areas for excluding ditches

Table 2.

Land-cover classes of the final combined land-cover dataset and the numeric code used to represent them in the output raster layers. The data origin column gives the input dataset that was used to provide information for the coverage of each land-cover class (CDL = Cropland Data Layer, Chesapeake = Chesapeake Bay Land Cover Data Project, NY Street = New York State Goverment roads layer, TNC = The Nature Conservancy Terrestrial Habitat Map, NWI = National Wetlands Inventory). Where there was information available from the high resolution Chesapeake Conservancy layer, more detailed delineations from that layer were used, based on the vegetation type.

Floral resources landcover	Vegetation type	Code	Data origin
Alfalfa	Low vegetation	101	CDL
Apples	Tree canopy	102	CDL
Apricots	Tree canopy	115	CDL
Cherries	Tree canopy	103	CDL
Corn	Low vegetation	104	CDL
Grass/hay	Low vegetation	105	CDL
Pasture	Low vegetation	106	CDL
Peaches	Tree canopy	107	CDL

Floral resources landcover	Vegetation type	Code	Data origin
Perennial	Low vegetation	108	CDL
Plums	Tree canopy	109	CDL
Non-resource crop	Low vegetation	110	CDL
Non-resource crop-wintercover	Low vegetation	111	CDL
Soybeans	Low vegetation	112	CDL
Strawberries	Low vegetation	113	CDL
insect-pollinated crop	Low vegetation	114	CDL
Developed low intensity	NA	201	CDL
Developed med intensity	NA	202	CDL
Lawn	Low vegetation	203	CDL
Urban tree	Tree canopy	204	CDL/Chesapeake
Ditch	Ditch	701	NY streets
Conifer/mixed forest	Tree canopy	301	TNC
Dry oak forest	Tree canopy	302	TNC
Mesic upland forest	Tree canopy	303	TNC
No resource	NA	402	CDL
Old field	Low vegetation	501	CDL
Shrubland	Tree canopy	502	TNC
Water	Water	801	NWI/Chesapeake
Swamp	Tree canopy	602	NWI
Wet emergent	Low vegetation	603	NWI
Wet shrub	Tree canopy	604	NWI

All input geographic datasets are publicly available from the sources listed in Table 1. We converted these layers to the same projected coordinate system, USA Contiguous Albers Equal Area Conic USGS (ESRI WKID: 102039), within the geographic coordinate system North American 1983 (EPSG: 4269). Geoprocessing was conducted using tools in ArcGIS ESRI (2020) available under the spatial analyst and data management licences and were scripted with the ArcGIS visual programming application “ModelBuilder”. The full modelling workflow is described in Suppl. material 1.

Crop and natural habitat land-cover information

As a starting point for characterising vegetation communities, we derived crop and other land-cover information from annual versions of the Cropland Data Layer (CDL), a raster dataset released annually by the US Department of Agriculture (USDA) (Boryan et al. 2011). Where the CDL indicated natural vegetation land cover, we referenced the Terrestrial Habitat Map for the northeast US and Atlantic Canada, produced by The Nature Conservancy (Ferree and Anderson 2013), to identify the natural habitat classification. This latter layer is a map of ecoregions based on field survey data, abiotic geographic data and existing ecological mapping products including the USDA Forest Service ECOMAP ecological province classification; National Wetlands Inventory wetland delineations; and land-cover and canopy density estimations made from the National Land Cover Dataset classifications of Landsat imagery. Both layers are originally 30 m resolution.

The land-cover classes of the final dataset (Table 2) aggregate crop and natural habitat classifications into classes that are sufficiently narrow to capture major variation in floral characteristics, yet coarse enough to allow for feasible sampling with replication within the study region (Suppl. material 1). Major annual and perennial crops in the region that provide floral resources are indicated by their species. Other perennial crops are grouped together ("perennial"), reflecting a similar weed community resulting from the common growing practice of using mowed grass alleyways between crop rows. Remaining annual crop types are categorised into two general groups, "insect-pollinated crops" and "non-resource crops". We use the term "insect-pollinated crops" for crops that flower under cultivation (e.g. sunflower). We use "non-resource crops" for any crop that does not produce insect-pollinated flowers, ecologically (e.g. wind-pollinated crops like wheat) or as it is cultivated (e.g. insect-pollinated plants that are harvested prior to flowering, like broccoli). While some of our "non-resource crops" are pollinated by insects if allowed to flower, we use this term to represent the actual availability of floral resources, based on management practices. Additionally, “non-resource crops-wintercover” indicate non-resource crops that are sown in autumn to overwinter, as opposed to grown within one growing season. Some discrepancies between the CDL and Terrestrial Habitat layers inevitably emerge, when the CDL classifies a 30 m grid cell as natural habitat, but no natural habitat is indicated at that cell in the Terrestrial Habitat layer. We resolved these mismatches by referring to the nearest Terrestrial Habitat class (processing workflow in Suppl. material 1).

High resolution landscape features

We derived high resolution delineations of landscape features from data layers on vegetation cover, wetland inventories and roads data.

High resolution vegetation data

We obtained 1 m resolution vegetation coverage data from a land-cover dataset produced by the Land Cover Data Project of the Chesapeake Conservancy (Chesapeake Conservancy 2020). This layer was created, based on lidar data obtained from the Federal Emergency Management Administration and the US Geological Survey (USGS), ortho-imagery from the National Agriculture Imagery Program, county-level planimetrics data, statewide data on roads from the US Census and information from the National Wetlands Inventory. However, these data are only available for nine of the 12 counties in the study area (Cayuga, Chemung, Cortland, Onondaga, Ontario, Schuyler, Tioga, Tompkins and Yates Counties). Vegetation within this dataset is classified as either trees or low vegetation, with additional classes for water and impervious land-cover types. For our purpose, we reclassified all categories related to impervious cover as “no resource” to reflect no floral resources. We overlaid the high-resolution vegetation data with additional 1 m resolution features representing wetland and roadside ditch delineations derived from vector-based data, described below.

Vector-based wetland and water features

We used delineations from the vector-based National Wetland Inventory (NWI) dataset (USFWS 2018) to define wetlands and, in some cases, waterbodies, within the final output land-cover data layer. To do this, we converted the NWI layer from vector to raster using the resolution of the Chesapeake Conservancy layer (1 m). We inserted wetland features within the Chesapeake Conservancy land-cover layer, using the latter layer’s vegetation height classes to update NWI wetland cells as low or high wetland types, i.e. emergent or shrub wetlands, respectively. In areas not covered by the high resolution Chesapeake Conservancy layer, we maintained the NWI layer's wetland classifications and used the NWI waterbody delineations to replace the open water grid cells in the 30 m datasets, filling missing areas with the nearest non-water land-cover class from the CDL or Terrestrial Habitat layers.

Roadside ditches

Road verges and ditches can be an abundant source of floral resources for pollinators (Phillips et al. 2020). Remotely sensing ditches from imagery requires very high resolution imagery and substantial analytical effort (Ayana et al. 2017); so instead, we based our prediction of likely flowering ditch locations on a roads layer obtained from the New York State Government (Winters 2018). We did not consider roads that intersected with a city and village boundaries layer (Gehrer 2018) because these were unlikely candidates for roads with ditches that are clearly differentiated from adjacent land covers (e.g. unmowed ditch next to agriculture or forest). We excluded road lines that were classified as "Parking lot" in the "Jurisdiction" layer attribute because these represented contiguous paved areas. Additionally, we excluded roads classified as a "Town Road" (a broad jurisdiction category that includes both city streets and rural roads) that did not contain "road" in its name (i.e. "street", "place" "boulevard", "avenue" etc.). This last criterion is based on our observation that the latter names are given to urban streets as opposed to rural roads in the region. Based on these criteria, we eliminated most urban and suburban streets from consideration, which were not likely to have a clearly differentiated 'ditch' habitat. We informally checked the buffer distances used to predict ditch locations against aerial photos, in order to assess the accuracy of our ditch placement parameters.

We then simulated ditches along the selected roads using a buffer from the road centre-line, at a width dependent on the road type (full description in Suppl. material 1, Step 1c) and assigning a ditch width of 3 m, the average size in our study region, on each side of the road. We erased the portions of simulated ditches that intersected water features in the NWI layer.

Combining crop and natural habitat information with high resolution landscape features

We downscaled land-cover information from the combined crop and natural habitat land cover raster from 30 m to 1 m resolution, using Table 2 to assign the 30 m land-cover classes to the vegetation types in the 1 m resolution layer (see Suppl. material 1 for further reclassification details). Wetland, water and ditch features, which were already added to the high-resolution layer as described above, were preserved in this process and did not take on the crop or habitat land-cover classes from the 30 m resolution layer.

In cases where the vegetation type indicated in the 1 m resolution land cover layer (i.e. tree canopy or low vegetation) differed from the overlaying 30 m combined crop and habitat layer, we assigned the nearest height-matching vegetation land-cover class from crop or natural habitat land cover (further details in Suppl. material 1, Step 2). For the three counties that were not covered by the high-resolution layer (Monroe, Seneca and Wayne Counties), crop and habitat land-cover delineations remained the same as the 30 m combined crop and habitat layer, though we upscaled the raster to 1 m resolution so that wetland, water and ditch delineations could be added.

Special considerations for counties without high-resolution vegetation data

For the three counties without high-resolution vegetation data, we used an alternative approach to estimate the area of lawn and urban tree coverage within the developed land-cover areas. In these counties, developed areas are represented by two development intensity classes, which should be converted to an average value for proportion of lawn and urban tree coverage. The conversion values in Table 3 were calculated from the average relationship between the two developed classes and the underlying proportion of lawn and urban tree coverage for the nine-county area where these 1 m-resolution data are available. The centroids of 30 m-cells were used as centres for 30 m-wide buffers to sample the proportional lawn and urban tree coverage within the 1 m data. The values in Table 3 are the averages across the study years of the average 30 m pixel coverage over the sampled region. We also explored an alternative method converting a continuous permeable surface coverage variable to estimated urban lawn and tree coverage, but this approach requires additional processing steps and does not improve predictions over the class-based averages (Suppl. material 1, Step 6).

Steps

The order of data synthesis is outlined below. These are encoded as ArcGIS Modelbuilder tools that were developed for this project and are uploaded to the repository associated with this article. More details on the geoprocessing routines within each step are described in Suppl. material 1.

1. Prepare high-resolution data layers: reclassify relevant vegetation height classes (where available), rasterise national wetland inventory and estimate ditches.

2. Combine high resolution layers prepared in step 1.
3. Reclassify natural habitat 30 m raster to represent vegetation categories relevant to floral resources and erase wetland classes in preparation for combination with high resolution wetland data.
4. Combine reclassified natural habitat layer prepared in step 3 with crop layer, reclassified to reflect relevant floral resources land-cover classes.
5. Downscale the combined natural habitat and crop layer to 1 m resolution and add the high-resolution vegetation, wetland and ditch features.
6. In three counties where the high resolution vegetation data are not available, use developed land-cover classes or percent permeable land cover to estimate urban lawn and tree coverage.

Table 3.

Modelled mean (and standard deviation) of lawn and urban tree proportional coverage in the 1 m resolution layer, for developed (low and medium intensity) land-cover classes in the 30 m data. Values represent the average (and propagated standard deviation) across the study years of average 30 m pixel coverage in the sampled region.

	Lawn	**Urban tree**
Developed, low intensity	0.3600 (0.0824 SD)	0.2229 (0.0827 SD)
Developed, medium intensity	0.2406 (0.0804 SD)	0.0747 (0.0507 SD)

Quality control

Since we downscaled the 30 m resolution input data to 1 m resolution, the final land-cover data layer may not always match the classification indicated by the originating land-cover layer at a given point. This is due to the inclusion of fine-scale landscape information from the high resolution layers (the Chesapeake Conservancy, NWI and ditches layers). The additional details provided by these layers may indicate mismatches in vegetation type (e.g. trees mixed within field) or finer scale landscape features (e.g. ditches or small waterbodies), which were not included in the coarser resolution layers. In order to check that the data processing steps downscaled the 30 m resolution land-cover information with adequate fidelity, we compared the final land-cover class to the classes of the originating data layers using contingency tables based on 10,000 randomly placed points that sampled the land-cover identity in the final and input layers. In Table 4, we calculate the percent of the sample points whose land cover in the final layer matches the land cover of the originating layer ("Fidelity"). Higher percent fidelity classes deviate less from the originating layers indicated in the "Data origin" column of Table 4.

In general, agricultural classes are preserved in the downscaled dataset, with fidelity values above 80% and, in many cases, above 90%. This reflects the homogeneity of agricultural areas, which makes it unlikely that the high resolution vegetation layer would indicate an unexpected vegetation type (e.g. trees in alfalfa cells). Exceptions to this could be along field edges bordering forest or other contrasting land-cover types or cases where the CDL was misclassified (Lark et al. 2021).

Table 4.

Comparison of final land-cover data layer class to the input data layer class. The "fidelity" column quantifies the percent of sample points within the final land-cover class that matches the same general class in the originating layer. These values are the averages of the percent values taken for each of the eight years for which we generated separate data layers. In cases where multiple originating land-cover classes were aggregated to form the final land-cover class, these classes are indicated in the "Original class(es)" column. Land-cover classes present in Table 2, but not present here, were not sampled by the 10,000 random points used to generate these statistics and are rare land covers for this region.

Final land cover class	Fidelity (%)	Data origin	Original class(es)
Alfalfa	95	CDL	Alfalfa; Clover/Wildflowers
Apples	87	CDL	Apples; Pears
Corn	96	CDL	Corn; Sorghum; Sweet Corn
Developed low intensity	100	CDL	
Developed med intensity	100	CDL	Developed med and high intensity
Grass/hay	71	CDL	Other Hay/Non Alfalfa; Sod/Grass Seed; Switchgrass
Lawn	87	CDL	Developed Open Space; Developed med and high intensity
Old field	88	CDL	Fallow/Idle Cropland
Pasture	81	CDL	Grass/Pasture
Perennial	93	CDL	Caneberries; Hops; Grapes; Christmas Trees; Other Tree Crops; Blueberries
Non-resource crop	92	CDL	Barley; Spring Wheat; Oats; Millet; Flaxseed; Sugarbeets; Potatoes; Other Crops; Onions; Carrots; Garlic; Broccoli; Dbl Crop Soybeans/Oats; Cabbage; Cauliflower; Radishes
Non-resource crop-wintercover	97	CDL	Winter Wheat; Other Small Grains; Dbl Crop Winter Wheat/Soybeans; Rye; Speltz; Triticale; Dbl Crop WinWht/Corn; Dbl Crop Oats/Corn; Dbl Crop Barley/Corn; Dbl Crop Barley/Soybeans
Soybeans	98	CDL	
Strawberries	100	CDL	
Urban tree	100	CDL	Trees within low and med intensity developed CDL classes
insect-pollinated crop	99	CDL	Sunflower; Buckwheat; Dry Beans; Misc Vegs & Fruits; Watermelons; Cucumbers; Peas; Tomatoes; Peppers; Squash; Pumpkins
Conifer/mixed forest	88	TNC	Laurentian-Acadian Pine-Hemlock-Hardwood Forest
Dry oak forest	90	TNC	Dry Oak-Pine Forest, Central Apps and Southern Piedmont; Northeastern Interior Dry-Mesic Oak Forest

Mesic upland forest	78	TNC	Appalachian (Hemlock)-Northern Hardwood Forest
Shrubland	42	TNC	Shrubland/grassland; mostly ruderal shrublands, regenerating clearcuts
Swamp	100	NWI	Freshwater Forested/Shrub Wetland
Water	93	NWI	Freshwater point; Lake; Riverine
Wet emergent	51	NWI	Freshwater Emergent Wetland
Wet shrub	69	NWI	Freshwater Forested/Shrub Wetland

Vegetation in developed land-cover classes have 100% fidelity because cells with these two land-cover classes are only found outside of the coverage of the high resolution land-cover dataset and generally do not coincide with waterbodies or ditches that would change their identity in the final layer. Within the coverage of the high resolution land-cover dataset, low vegetation is reclassified as "lawn" and tree canopy is reclassified as "urban trees".

Natural areas have lower fidelity, likely because these land covers are more heterogeneous. Classifications at 30 m resolution represent the most predominant land cover, whereas the 1 m vegetation data can better reflect a mix of land-cover types. Our downscaling process approximated this by taking land-cover information from nearby areas with the appropriate vegetation type, but this would lead to more cases where the final land cover differed from the class of the originating layer. This is shown in more detail in Suppl. material 2, which provides the full contingency tables across all land-cover combinations. Shrubland, which has 42% fidelity in Table 4, also occurs prominently in areas classified as agricultural land in the TNC dataset (38% in Suppl. material 2). This could indicate woody vegetation in old fields undergoing succession that border shrublands. Likewise, wet emergent vegetation falling outside the original NWI delineations occur mainly within shrub wetland, likely representing low wetland vegetation that would not have been noted in the NWI dataset, but was mapped by the high resolution vegetation layer.

In addition to the full contingency tables associated with Table 4, Suppl. material 2 also contains contingency tables comparing how well the original land cover is preserved in the final land-cover data, i.e. the percentage of sample points whose original classification matches the final dataset. These tables give an idea of the composition of the coarser resolution cells, once downscaled. The two types of contingency tables are roughly analogous to "user's" and "producer's" accuracy typically used in remote sensing classification (Lillesand et al. 2015), except that we compare the final land-cover classifications to professionally-produced input land-cover datasets rather than field data. User's accuracy estimates how often the map class is present on the ground, while producer's accuracy estimates how often the habitat on the ground is mapped correctly. An exhaustive field validation of the final land-cover dataset is beyond the scope of this project, though extensive methods documentation and accuracy assessments are available for many of the input layers, for example, Boryan et al. (2011), Ferree and Anderson (2013), Lark et al. (2021). Likewise, the accuracy of flowering ditch locations were not validated to field conditions, but could be the subject of future resesearch.

We estimated the error associated with predicting lawn and urban tree cover in counties without high resolution data by using the developed land-cover factors in Table 3 to calculate urban lawn and tree cover in the nine counties where this information is available. We calculated the root mean square error (RMSE) comparing between high resolution coverage estimates and category-based predictions for 100 points randomly placed in developed areas, for buffers ranging from 15 m to 1 km radius. The results in Table 5 show that the RMSE of both lawn and urban tree percent cover estimates decreases (i.e. prediction accuracy improves) with increasing buffer size. An alternative method of estimating lawn and urban tree cover using continuous permeable land-cover data had similar error values (Suppl. material 1, Step 6). However, we recommend estimating lawn and urban tree coverage using the simpler category-based method presented here, as the alternative method does not offer any improvement in prediction accuracy while adding more processing steps.

Table 5.

Estimated root mean square error (RMSE) of lawn and urban land cover predictions using developed land-cover variables. Error is calculated, based on buffers around 100 random points placed in the nine counties where high resolution data are available. Calculated error is for the 2016 dataset.

Buffer radius	Lawn % cover RMSE	Urban tree % cover RMSE
15	23.67	18.77
30	18.40	11.38
100	15.70	6.25
250	13.04	4.95
500	10.43	3.64
1000	8.95	2.84

Dataset description

The output floral resources land-cover layers (Fig. 2) are stored as 1 m resolution rasters in the USA Contiguous Albers Equal Area Conic USGS projection (ESRI WKID: 102039). Data are available on Zenodo. The dataset covers 12 counties: Cayuga, Chemung, Cortland, Monroe, Onondaga, Ontario, Schuyler, Seneca, Tioga, Tompkins, Wayne and Yates. Of these, nine counties (Cayuga, Chemung, Cortland, Onondaga, Ontario, Schuyler, Tioga, Tompkins and Yates) have 1 m resolution delineations of low vegetation and tree canopies, which take on appropriate classifications based on the underlying 30 m data or nearby appropriate land covers, as described above. Outside of these counties, land covers follow the delineations of the 30 m layers, except for wetland, water and ditch features.

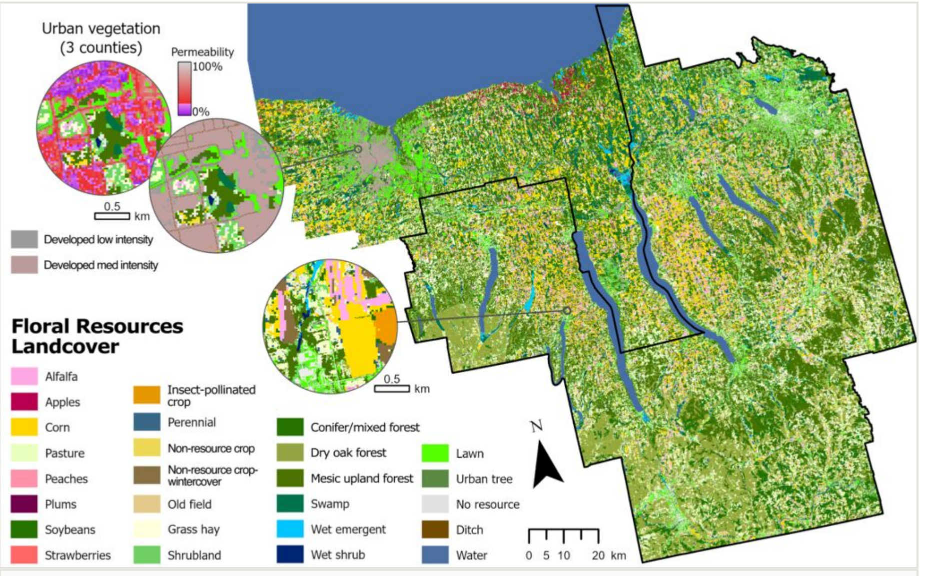

Figure 2.

Final land-cover layer (2016 shown). Area with high resolution vegetation data is outlined in black (majority of south-eastern region). The three counties without detailed vegetation data are available with urban vegetation represented by alternative methods shown in the two inset callouts in the upper left: either as a continuous percent permeability value (upper callout) or as low and medium developed intensity categories (middle callout). In the area with high resolution vegetation data that covers most of the region, urban vegetation consists of lawn or urban tree categories (example in lower callout).

There are two versions of the dataset, each consisting of eight rasters representing CDL crop data from years 2012-2019. The versions differ in their representation of the developed areas in the counties beyond the coverage of the high resolution vegetation layer (i.e. Monroe, Seneca and Wayne Counties). A simplified version classifies developed areas into "low" and "medium" development categories. An alternative version converts these areas to continuous values representing the percent permeable area. Either of these variables can be converted to an estimate of lawn and urban tree coverage, though we recommend the category-based version (see Usage Notes). Both versions are available online in the Zenodo repository.

Object name

A map of pollinator floral resource habitats in the agricultural landscape of Central New York.

Format names and versions

16-bit unsigned integer (1 band) GeoTIFF files. Version 1.0.

Creation dates

Final version (1.0) created March 2023.

Dataset creators

Kevin Li, Aaron L. Iverson

Dataset contributors

Jon R.B. Fisher, Alison G. Power

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Repository name

Zenodo

Repository location

Datasets for "A map of pollinator floral resource habitats in the agricultural landscape of Central New York". DOI: 10.5281/zenodo.8256488.

Geoprocessing tools for "A map of pollinator floral resource habitats in the agricultural landscape of Central New York". DOI: 10.5281/zenodo.10827759.

Publication date

Published 5 March 2024.

Usage notes

These layers are intended to be used to estimate available floral resources. Additional data collected within these habitats on flower phenology, abundance, size and community composition can be combined to understand landscape patterns in floral resources and associated bee abundance and richness over the growing season for this region (Kammerer et al. 2022, Iverson et al., in prep.). This information can also be the basis of floral availability scores that are the input of spatially-explicit pollinator abundance models, such as presented by Lonsdorf et al. (2009) or Zulian et al. (2013). The land-cover estimates, obtained from this dataset, are expected to be more accurate when aggregated over an area and should not be interpreted as a representation of on-the-ground conditions for a given location (i.e. pixel or point). Further, the land-cover categories in this dataset have combined multiple land-cover classes from the input layers based on similarities in floral resource characteristics, for example, flowering phenology, species composition and abundance. These groupings may not be appropriate outside of this original purpose.

Note that developed areas in Monroe, Seneca and Wayne Counties do not have high resolution spatial data of urban vegetation. Instead, the user must estimate urban vegetation in these counties by converting from either categorical development classes ("low" and "medium" categories) or a continuous percentage gradient of "permeable" land cover (the inverse of impervious cover). In order to estimate expected proportions of lawn and urban tree coverage within these areas, we present conversion factors, based on the relationships between the development categories and the proportional coverage of the two urban vegetation types (Table 3). We recommend using these categorical factors over converting percent permeable land cover (described in Step 6 of Suppl. material 1), because the former is simpler to use and has equivalent accuracy.

Details for replicability and reproducibility

Suppl. material 1 gives a detailed description of geoprocessing and the associated ArcGIS Modelbuilder toolbox that was developed is available in a Zenodo repository. The data layers used to create this dataset are publicly available and described in Table 1.

Author contributions

Aaron L. Iverson conceived of the project, conducted fieldwork, procured funding, supervised and contributed to writing the manuscript. Kevin Li conducted geoprocessing and analysis and wrote the manuscript. Jon R.B. Fisher and Alison G. Power provided light edits to the manuscript and minor guidance to the project design.

Conflicts of interest

The authors have declared that no competing interests exist.

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Supplementary materials

Suppl. material 1: Explanation of geoprocessing doi

Authors: Kevin Li, Jon Fisher, Alison G Power, Aaron L. Iverson
Data type: Document (pdf)
Brief description: This document explains the geoprocessing steps for creating the data. The steps detailed within correspond to the ArcGIS Modelbuilder Toolbox tools included in the online Zenodo repository (DOI: 10.5281/zenodo.10827759).
Download file (766.36 kb)

Suppl. material 2: Contingency tables doi

Authors: Kevin Li, Jon Fisher, Alison G Power, Aaron L. Iverson
Data type: Document (pdf)
Brief description: Contingency tables comparing input and final land-cover classes.
Download file (454.48 kb)