A Strategic Analysis of Program Distribution for Toronto Parks & Recreation

July 23, 2025

1 Summary

This report analyzes the distribution of Toronto's Parks and Recreation programs through two distinct lenses: the strategic alignment of children's programs with demographic demand, and the socio-economic equity of program distribution. Our analysis reveals a misalignment between the supply of child-focused programs and the geographic concentration of the child population, which is quantitatively confirmed by near-zero correlation between the child population in a neighbourhood and the number of child programs available. 34 specific neighbourhoods that are a priority for intervention due to high child populations and low program availability are identified. Conversely, the study did not find statistically significant differences among programs in varying socio-economic areas, including Neighbourhood Improvement Areas (NIAs). We conclude that while program allocation is equitable on a per-capita basis, it is not strategically optimized to provide support where demographic demand is greatest or where communities face greater socio-economic barriers. We recommend a transition to a more dynamic, needs-based framework that prioritizes expansion in underserved, child-dense neighbourhoods and provides weighted resources to high-need communities, ensuring both strategic alignment and a deeper commitment to equity.

2 Results

2.1 Child-focused programs are not optimally aligned with the child population

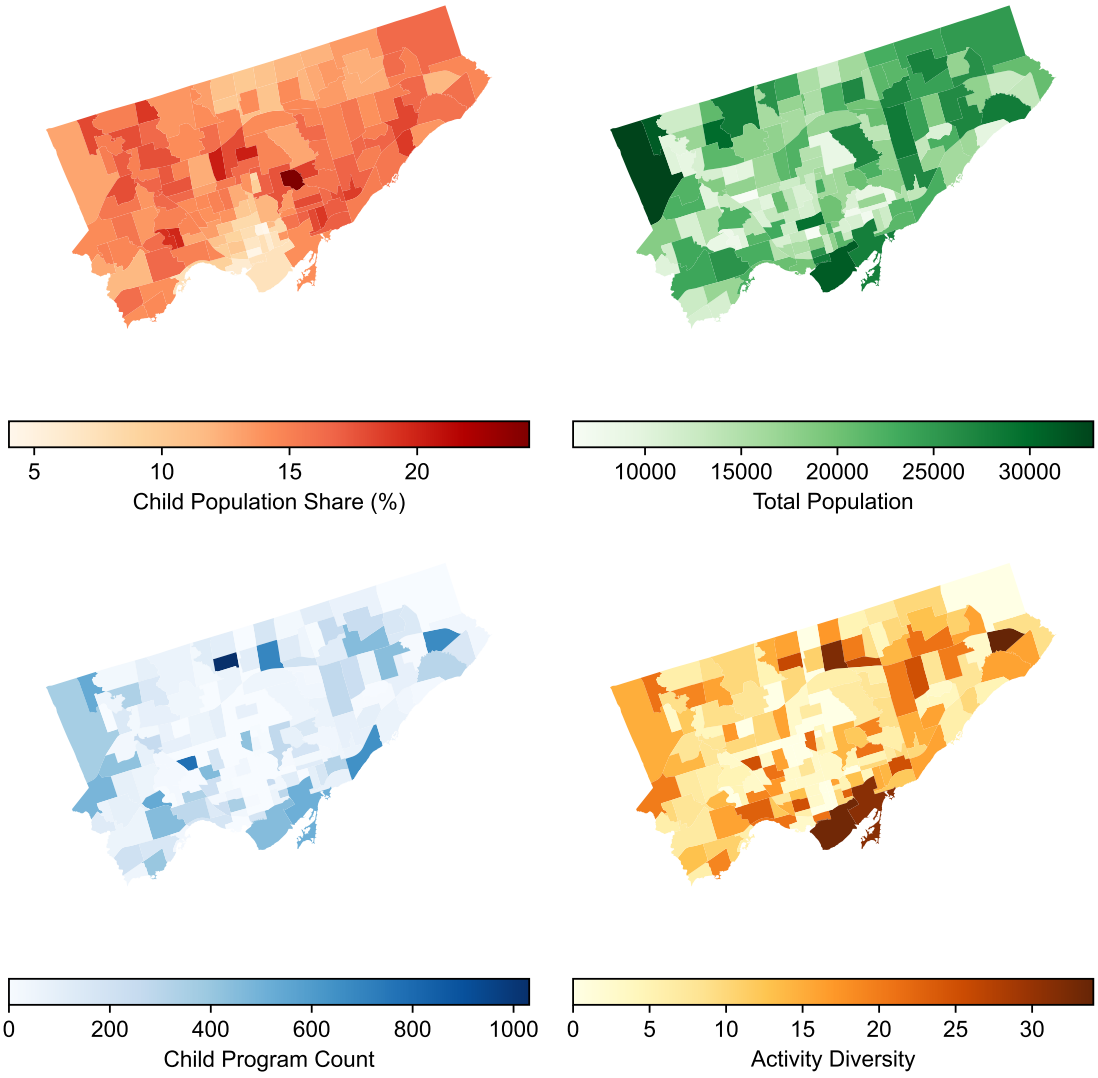


Figure 1. Geographic distribution of the population and programs for children aged 0-14. Toronto neighbourhoods colored by (**top left**) child population share (%); (**top right**) total population; (**bottom left**) total number of child programs; (**bottom right**) diversity of available program activities, calculated as the number of distinct program types.

Figure 1 visualizes the geographic distribution of demographics and children's program availability across Toronto. The central downtown core exhibits a high total population but a low percentage of children, whereas suburban areas in Etobicoke, North York, and Scarborough have a significantly higher child population shares exceeding 15%. For program availability, areas with high percentages of children do not consistently align with the areas having most programs for children. Furthermore, activity diversity (the number of distinct program types) is heavily concentrated in the downtown core and a few other neigbourhoods with small child populations. This indicates that families in

suburban, child-dense neighbourhoods may not have access to an appropriate number and diversity of child programs close to where they live.

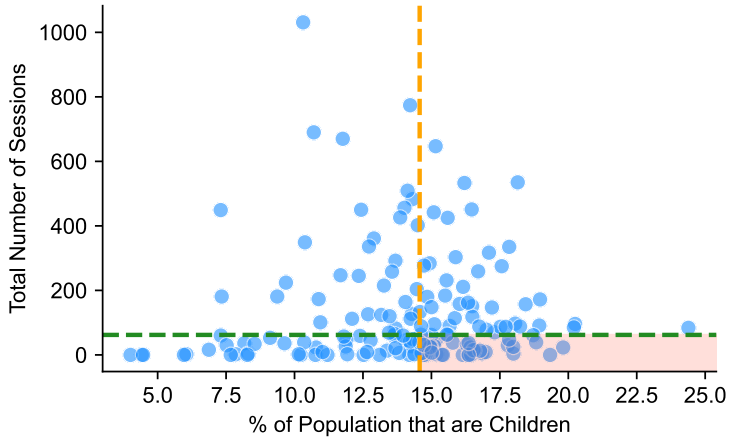


Figure 2. Identification of neighbourhoods with low program availability and high child population density. The total number of programs versus the percentage of the population that are children for each neighbourhood. The orange dashed line indicates the city-wide median child population share, and the green dashed line indicates the city-wide median number of programs. The shaded region highlights neighbourhoods with fewer than the median number of programs and greater than the median child population.

Figure 2 reveals a weak correlation between the percent of children in a neighbourhood and the number of program sessions offered. Crucially, many neighbourhoods with an above-median child population share are shown to have very low program availability, with fewer than the median number of total sessions offered. The map (Figure 3) pinpoints the locations of these underserved neighbourhoods. This analysis corroborates the spatial mismatch observed in Figure 1, demonstrating that many of the communities with high concentrations of children have comparatively few programs accessible.

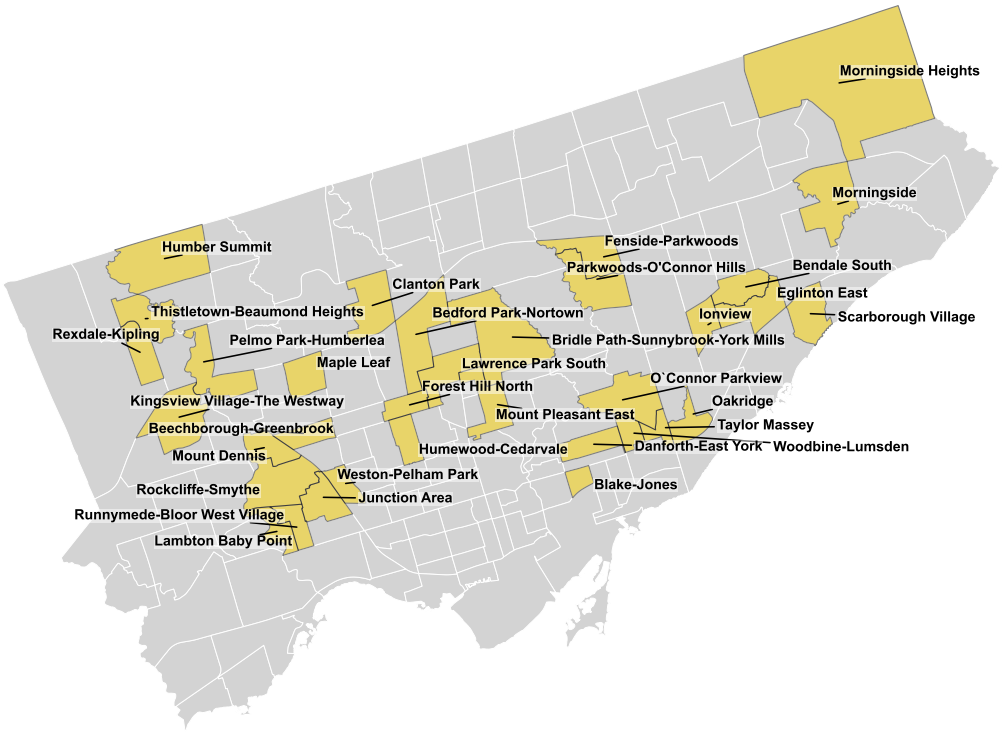


Figure 3. Geographic location of underserved neighbourhoods. Map of the 34 neighbourhoods in Toronto classified as underserved based on the analysis in Figure 2. An underserved neighbourhood is defined as having an above-median child population share and below-median number of child programs.

To systematically explore the factors associated with program availability, we calculated the correlations between demographics and program metrics at the neighbourhood level (Figure 4). The most striking finding is the near-zero correlation between the Child Population Share and the Total Number of Child Programs ($\rho = 0.026$), Total Number of Child Sessions ($\rho = 0.032$), and Activity Diversity ($\rho = 0.093$). This quantitatively confirms that the proportion of children in a neighbourhood has little relationship with the level of child program services available, demonstrating that program provision is not optimally aligned with the relative child population.

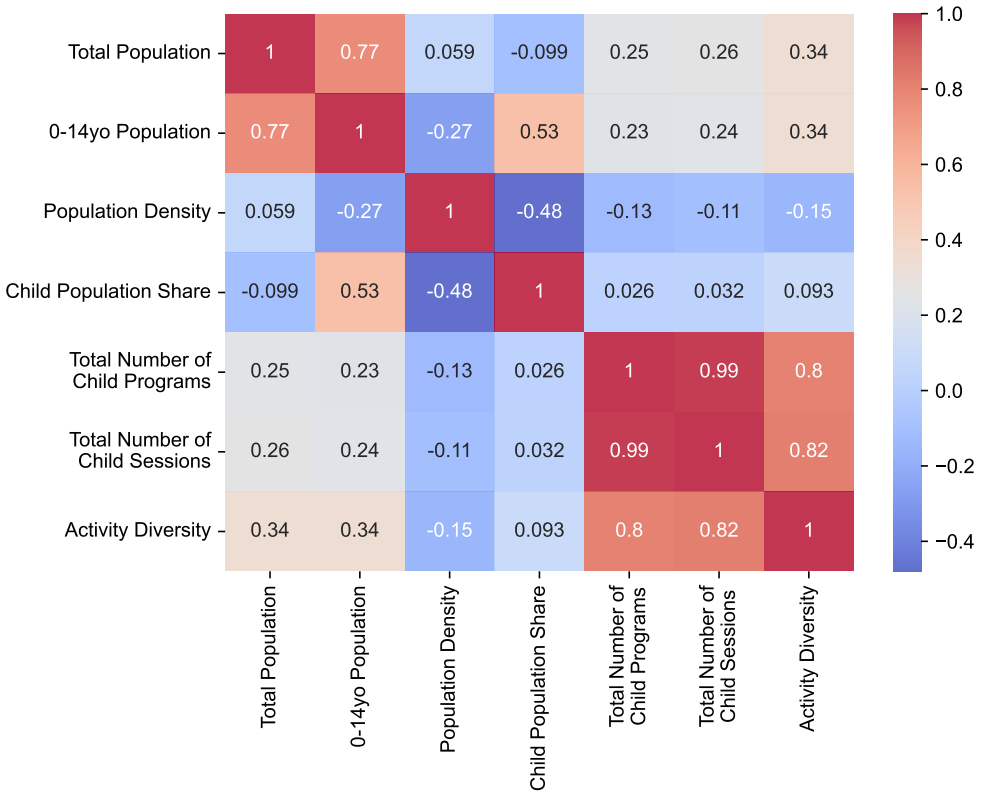


Figure 4. Pearson correlations between neighbourhood demographics and program availability metrics.

2.2 Program distribution is equitable but not always strategically targeted towards NIAs or low-income neighbourhoods

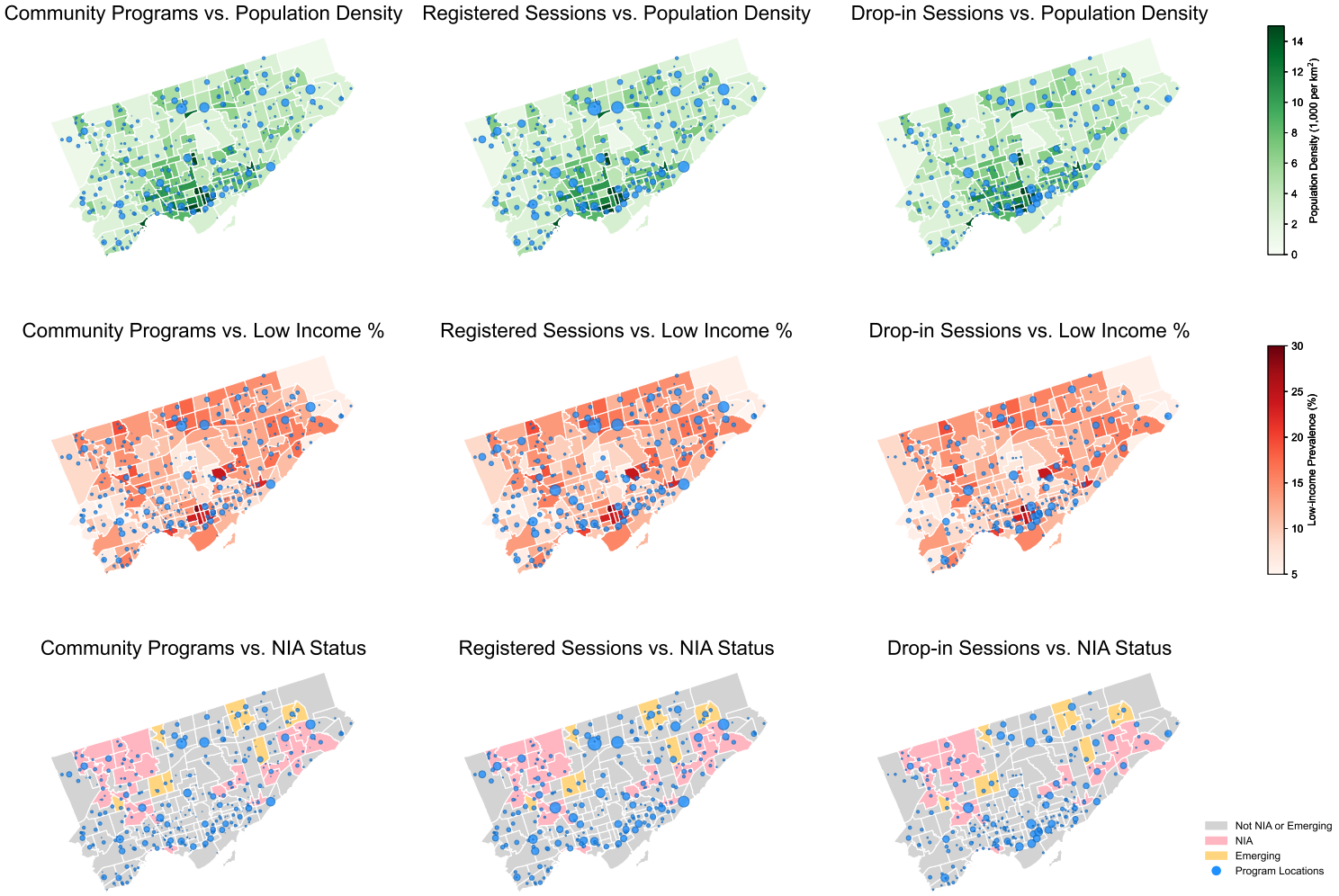


Figure 5. Geographic distribution of program types relative to socio-demographic factors. Maps of Toronto colored by demographic metrics and overlaid with points indicating the locations and numbers of programs. Columns show the locations of different program metrics: All Programs (**left**); Registered Sessions (**middle**); and Drop-in Sessions (**right**). Rows overlay these program locations (blue dots) on different neighbourhood characteristics: Population Density (**top**), Low-income Prevalence (**middle**), and Neighbourhood Improvement Area (NIA) status (**bottom**). The sizes of points indicate the number of programs at a particular location.

To visually assess the geographic alignment of program provisioning, we mapped program locations against select neighbourhood indicators (Figure 5). The maps demonstrate a broad distribution of programs across the city, being present both within and outside of areas with high population density, high low-income prevalence, and designated Neighbourhood Improvement Area (NIA) status. To some extent, the density of drop-in programs is higher in the downtown core, whereas registered programs are more prevalent in suburban/rural areas. Notably, some densely populated neighbourhoods in the downtown area that have the highest prevalences of low-income people also show a distinct lack of programs. However, these neighbourhoods have not been designated as

NIAs or Emerging neighbourhoods, which is possibly related to other factors (e.g. walkability) in the Neighbourhood Equity Index used to determine NIA classification (Social Policy Analysis and Research, 2014).

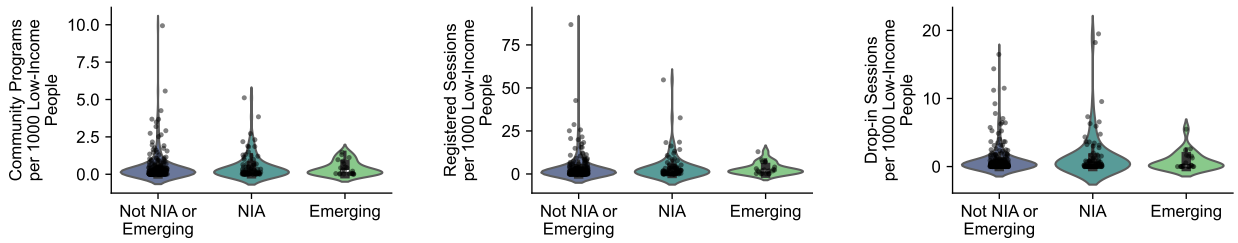


Figure 6. Program density across neighbourhood types The distribution of (**left**) the total count of Community Programs); (**middle**) the total volume of Registered Sessions; (**right**) the total volume of Drop-in Sessions. All metrics are normalized by the low-income population and separated by neighbourhoods categorized as Not NIA or Emerging, NIA, and Emerging.

To quantify these geographic patterns, we analyzed program density across different neighbourhood types (Figure 6), finding that the distributions of program density is relatively similar across NIA, Emerging, and non-NIA/Emerging neighbourhoods. This visual observation is formally confirmed by an ANOVA test, which found no statistically significant difference in the mean program density per capita among the neighbourhood categories ($p > 0.2$ for all program metrics). This provides evidence for an equitable distribution of programs that is not focused towards NIAs or Emerging neighbourhoods. Overall, this suggests that while programs avoid systemic inequity, it does so through a uniform allocation model rather than a strategically optimized one.

3 Recommendations

Based on our analysis, the current model for program allocation is successful in maintaining broad socio-economic equity but fails to strategically align resources with demographic demand. To address this, we recommend a shift from a uniform distribution model to a data-driven, needs-based framework.

Prioritize Program Expansion in Underserved, Child-Dense Neighbourhoods. Our analysis identified 34 neighbourhoods with above-median child population shares but below-median child program availability (Figures 2 & 3). The City should use this list as an immediate-action guide. We recommend prioritizing these specific neighbourhoods for the next phase of program expansion, focusing on increasing both the total number of child programs and session availability to match the local child population.

Reallocate to Improve Program Diversity in Suburban Areas. Activity diversity is heavily concentrated in the downtown core, while many child-dense suburban neighbourhoods have a limited range of program types (Figure 1). To better serve families, the City should not only increase program counts in underserved areas but also deliberately broaden the variety of activities offered. This requires a strategic reallocation of specialized programs and instructors away from saturated markets towards areas with high demand and low diversity.

Adopt a Needs-Based Equity Model for Resource Allocation. The analysis shows that while the City avoids systemic inequity, its uniform per-capita allocation model is insufficient for communities facing greater socio-economic barriers. We recommend implementing a needs-based funding supplement for Neighbourhood Improvement Areas (NIAs) and other neighbourhoods with high low-income prevalence. This would mean that in addition to the baseline per-capita funding, these high-need areas receive weighted or additional resources to account for residents having fewer alternatives and facing greater barriers to participation.

Prioritize Low-Barrier Program Models in High-Need Neighbourhoods. Simply increasing the number of programs in NIAs may not be effective if cost and accessibility are not addressed. The analysis of program types (Figure 5) suggests different models have different geographic footprints. Therefore, when expanding services in low-income areas, the City should prioritize low-barrier program models. This includes increasing the number of free drop-in sessions, which offer flexibility and require no pre-registration, and ensuring that any new registered programs have an adequate number of subsidized spots that are easily accessible. This ensures that new investment directly translates into increased participation by removing the most common financial and logistical obstacles.

4 Methods

Libraries. The analysis was conducted in Python 3, primarily utilizing libraries such as Pandas and NumPy for data manipulation, GeoPandas and Shapely for geospatial operations, and Matplotlib and Seaborn for data visualization. Statistical tests were performed using the SciPy library.

Data Sourcing. Data was programmatically acquired from Toronto's Open Data portal, which is powered by the CKAN platform. We used the CKAN API to identify and download the relevant datasets, ensuring reproducibility and access to the most current data versions.

Data Preprocessing. Program data was enriched by calculating the total number of sessions, providing a more accurate measure of service volume than a simple course count. The method for this calculation differed by program type. For registered programs, which run on specific days of the week, the number of sessions was calculated by parsing the start and end dates and counting the occurrences of the designated weekdays within that period. For drop-in programs, which are assumed to be available daily, the number of sessions was calculated as the total number of days in the program's active date range. Demographic data was cleaned by standardizing column names and selecting key indicators.

Geospatial Analysis. A critical step was the assignment of each program to a specific neighborhood. Full addresses for program locations were constructed and normalized to correct for inconsistencies. These normalized addresses were then used to geocode each program, assigning it precise geographic coordinates by joining with the city's municipal address point dataset. Geospatial data for neighbourhood boundaries was initially processed using the WGS 84 geographic coordinate system (EPSG:4326). To ensure accurate area and density calculations, geometries were re-projected to a suitable projected coordinate system (UTM Zone 17N, EPSG:32617), which uses meters as its unit. A spatial join was then performed to determine which neighborhood polygon each program point fell within, thereby enabling neighborhood-level aggregation and analysis.

Statistical Methods. In the analysis of child-focused programs, Pearson correlation coefficients were calculated to quantify the strength and direction of the linear relationship between demographic indicators (e.g. Child Population Share) and program availability metrics (Total Number of Programs, Total Sessions, and Activity Diversity). For the equity analysis, an Analysis of Variance (ANOVA) was used to test for significant differences in mean program density across three neighborhood types (NIA, Emerging, and Not NIA/Emerging), while a separate Pearson correlation was used to measure the association between program density and low-income prevalence.

Statement on AI Use. Throughout this project, we used GPT-4 and Gemini as assistive tools for the implementation of the data analysis and the preparation of the report. In the data analysis phase, the models were employed to: (1) generate Python code for data loading and utility functions; (2) assist in debugging complex data transformations and logical errors; and (3) refactor Pandas and GeoPandas operations for improved readability. During report preparation, their role was to improve the grammar, syntax, and overall clarity of the text. All AI-generated outputs, both code and text, were subjected to rigorous validation and significant modification by the author to ensure accuracy. This included testing and editing of each AI-produced function to confirm that expected outputs were produced, and confirming that the functions were comprehensible to the author. The author retains full and final responsibility for all analyses, interpretations, code, and written content presented in this work.

Reference

Social Policy Analysis and Research. (2014, March). TSNS 2020 neighbourhood equity index: Methodological documentation. City of Toronto, Social Development, Finance & Administration. http://www.toronto.ca/neighbourhoods

5 Code

Imports

[1]:
```
import json
import re
import requests
import warnings

from adjustText import adjust_text
import geopandas as gpd
from matplotlib.lines import Line2D
import matplotlib.patches as mpatches
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import scipy.stats
import seaborn as sns
from shapely.geometry import Point, Polygon, shape

warnings.filterwarnings("ignore")

plt.rcParams['font.family'] = 'sans-serif'
plt.rcParams['font.sans-serif'] = ['Arial']

EPSG = 4326
```

Functions for loading data

[2]:
```
def name_to_var(name: str) -> str:
    """Converts a string into a standardized Python variable name for a␣
 ↪DataFrame.

    Args:
        name (str): The input string, typically a file or resource name.

    Returns:
        str: The sanitized and formatted variable name.
    """
    name = re.sub(r'\.\w+$', '', name)
    name = re.sub(r'\W+', '_', name)
    return name.lower() + "_df_raw"


def load_ckan_data(package_id, filetype):
    """Loads data of a specific file type from a CKAN package into global␣
 ↪DataFrames.

    Fetches the resource list for a given CKAN package ID from Toronto's Open
```

```
    Data portal. It then finds all resources matching the specified `filetype`,
    reads them into pandas DataFrames, and assigns them to variables in the
    global namespace.

    The variable names are generated from the resource names using the
    `name_to_var` helper function.

    Args:
        package_id (str): The unique identifier for the CKAN package.
        filetype (str): The desired file format to load, e.g., 'csv' or 'xlsx'.
    """
    url = "https://ckan0.cf.opendata.inter.prod-toronto.ca/api/3/action/
↪package_show"
    res = requests.get(url, params={"id": package_id})
    res.raise_for_status()
    resources = res.json().get("result", {}).get("resources", [])

    print(f"\nPackage: {package_id}")
    for r in resources:
        if r["format"].lower() == filetype:
            df = pd.read_csv(r["url"]) if filetype == 'csv' else pd.
↪read_excel(r["url"])
            var_name = name_to_var(r["name"])
            globals()[var_name] = df
            print(f"== {var_name} loaded ==")
```

Function for processing demographic data

[3]:
```
relevant_columns = [
    'Neighbourhood Name',
    'Neighbourhood Number',
    'TSNS 2020 Designation',
    'Total - Age groups of the population - 25% sample data',
    '  0 to 14 years',
    '  15 to 64 years',
    '  65 years and over',
    '    Children',
    '      With children',
    '    One-parent-family households',
    '    Median total income in 2020  among recipients ($)',
    'Prevalence of low income based on the Low-income measure, after tax␣
↪(LIM-AT) (%)'
]

rename_dict = {
    'Neighbourhood Number': 'AREA_SHORT_CODE',
    'TSNS 2020 Designation': 'TSNS',
```

```
    'Total - Age groups of the population - 25% sample data': 'Total␣
 ↪Population',
    '  0 to 14 years': '0_14 years',
    '  15 to 64 years': '15_64 years',
    '  65 years and over': '65 years and over',
    '    Children': 'Children',
    '      With children': 'Couple families with children',
    '    One-parent-family households': 'One parent families',
    '    Median total income in 2020  among recipients ($)': 'Median total␣
 ↪income',
    'Prevalence of low income based on the Low-income measure, after tax␣
 ↪(LIM-AT) (%)': 'low income (%)'
}


def set_first_row_as_header(df: pd.DataFrame) -> pd.DataFrame:
    """Set the first row of a DataFrame as its header.

    Args:
      df: The input DataFrame whose first row should become the header.

    Returns:
      A new DataFrame with updated column headers and reset index.
    """
    new_header = df.iloc[0]
    df = df[1:]
    df.columns = new_header
    return df.reset_index(drop=True)


def demographics_df_process(
    raw_df: pd.DataFrame,
    relevant_columns: list[str]=relevant_columns,
    rename_dict: dict[str, str]=rename_dict
) -> pd.DataFrame:
    """Process the raw neighbourhood demographic DataFrame to extract and
    standardize key columns.

    This function transposes the input DataFrame, sets the first row as the
    header, selects the first occurrence of relevant columns, renames them
    using a dictionary,
    and returns a cleaned version.

    Args:
      raw_df: The raw demographic DataFrame to process.
      relevant_columns: A list of column names to retain from the raw data.
```

```
    rename_dict: A dictionary mapping original column names to standardized␣
↪names.

  Returns:
    A cleaned and processed demographic DataFrame with selected and renamed␣
↪columns.
  """
  raw_df = raw_df.copy()
  df = raw_df.T.reset_index(names='Neighbourhood Name')
  df = set_first_row_as_header(df)
  first_occurrence = {}
  for idx, col in enumerate(df.columns):
      if col in relevant_columns and col not in first_occurrence:
          first_occurrence[col] = idx

  missing = [col for col in relevant_columns if col not in first_occurrence]
  if missing:
      print(f"Warning: missing columns: {missing}")

  col_indices = [
      first_occurrence[col]
      for col in relevant_columns if col in first_occurrence
  ]
  demographics_df = df.iloc[:, col_indices].copy()

  demographics_df.rename(columns=rename_dict, inplace=True)
  if 'TSNS' in demographics_df.columns:
      demographics_df['TSNS'] = demographics_df['TSNS'].replace(
          to_replace=r'Neighbourhood Improvement Area.*',
          value='Neighbourhood Improvement Area', regex=True
      )

  return demographics_df
```

Function for processing registered_program and drop_in data

[4]:
```
def registered_program_process(registered_programs_df: pd.DataFrame) -> pd.
↪DataFrame:
  """Clean and enrich registered programs data with date ranges and session␣
↪counts.

  This function parses date ranges, handles missing age values,
  converts day names to weekdays, and calculates the number of sessions per␣
↪program.

  Args:
```

```
    registered_programs_df: The raw DataFrame containing registered program␣
↪data.

    Returns:
      A cleaned DataFrame with additional columns:
      'First Date', 'Last Date', 'days_of_the_week_set', and 'num_of_sessions'.
    """
    registered_programs_df = registered_programs_df.copy()
    date_split = registered_programs_df['From To'].str.split(' to ',␣
↪expand=True)
    registered_programs_df['First Date'] = pd.to_datetime(date_split[0].str.
↪strip(), format='%b-%d-%Y')
    registered_programs_df['Last Date'] = pd.to_datetime(date_split[1].str.
↪strip(), format='%b-%d-%Y')
    registered_programs_df['Max Age'] = registered_programs_df['Max Age'].
↪fillna(100)

    registered_programs_df['days_of_the_week_set'] =␣
↪registered_programs_df['Days of The Week'].apply(
        lambda x: set(x.split(','))
    )
    day_name_to_weekday = {'Mon': 0, 'Tue': 1, 'Wed': 2, 'Thu': 3, 'Fri': 4,␣
↪'Sat': 5, 'Sun': 6}

    registered_programs_df['weekday_nums'] =␣
↪registered_programs_df['days_of_the_week_set'].apply(
        lambda x: set(day_name_to_weekday[day.strip()] for day in x)
    )

    def count_sessions(row):
        date_range = pd.date_range(start=row['First Date'], end=row['Last␣
↪Date'])
        return sum(d.weekday() in row['weekday_nums'] for d in date_range)

    registered_programs_df['num_of_sessions'] = registered_programs_df.
↪apply(count_sessions, axis=1)

    registered_programs_df.drop(
    columns=['Days of The Week', 'From To', 'weekday_nums'],
    inplace=True
    )

    return registered_programs_df


def drop_in_process(drop_in_df: pd.DataFrame) -> pd.DataFrame:
```

```
    """Clean and process drop-in program data.

    This function fills missing age values, renames columns for consistency,
    converts date columns, and calculates the number of sessions.

    Args:
      drop_in_df: The raw DataFrame containing drop-in program data.

    Returns:
      A cleaned DataFrame with standardized age columns,
      parsed dates, and a 'num_of_sessions' column.
    """
    drop_in_df = drop_in_df.copy()
    drop_in_df['Age Max'] = drop_in_df['Age Max'].fillna(100)
    drop_in_df.rename(columns={'Age Max': 'Max Age'}, inplace=True)
    drop_in_df.rename(columns={'Age Min': 'Min Age'}, inplace=True)
    drop_in_df['First Date'] = pd.to_datetime(drop_in_df['First Date'])
    drop_in_df['Last Date'] = pd.to_datetime(drop_in_df['Last Date'])
    drop_in_df['num_of_sessions'] = (drop_in_df['Last Date'] -␣
↪drop_in_df['First Date']).dt.days + 1
    return drop_in_df
```

Load the data

[5]:
```
load_ckan_data("registered-programs-and-drop-in-courses-offering",'csv')
load_ckan_data("neighbourhood-profiles",'xlsx')
load_ckan_data('address-points-municipal-toronto-one-address-repository','csv')
load_ckan_data("neighbourhoods",'csv')
```

```
Package: registered-programs-and-drop-in-courses-offering
== locations_df_raw loaded ==
== drop_in_df_raw loaded ==
== registered_programs_df_raw loaded ==
== facilities_df_raw loaded ==

Package: neighbourhood-profiles
== neighbourhood_profiles_2021_158_model_df_raw loaded ==

Package: address-points-municipal-toronto-one-address-repository
== address_points_4326_df_raw loaded ==
== address_points_2952_df_raw loaded ==

Package: neighbourhoods
== neighbourhoods_4326_df_raw loaded ==
== neighbourhoods_2952_df_raw loaded ==
== neighbourhoods_historical_140_4326_df_raw loaded ==
== neighbourhoods_historical_140_2952_df_raw loaded ==
```

[6]:
```
registered_program_df = registered_program_process(registered_programs_df_raw)
```

[7]:
```
drop_in_df = drop_in_process(drop_in_df_raw)
```

[8]:
```
demographics_df =␣
↪demographics_df_process(neighbourhood_profiles_2021_158_model_df_raw)
```

[9]:
```
locations_df = locations_df_raw.copy()
address_points_4326_df = address_points_4326_df_raw.copy()
neighbourhoods_4326_df = neighbourhoods_4326_df_raw.copy()
```

Merge Data

[10]:
```
demographics_geo_df = pd.merge(demographics_df, neighbourhoods_4326_df,␣
↪on='AREA_SHORT_CODE', how='outer')
```

[11]:
```
demographics_geo_df.drop(['_id', 'AREA_ID', 'AREA_ATTR_ID', 'PARENT_AREA_ID',␣
↪'AREA_LONG_CODE',
       'AREA_NAME', 'AREA_DESC', 'CLASSIFICATION', 'CLASSIFICATION_CODE',
       'OBJECTID'], axis=1, inplace=True)
```

[12]:
```
def parse_geometry(geom_string):
    return shape(json.loads(geom_string))


def normalize_address(address):
    address = address.upper().replace('.', '')
    address = address.replace(' LN', ' LANE')
    address = address.replace('BERNER TRL', 'BERNER TRAIL')
    address = address.replace(' CIR', ' CRCL')
    address = address.replace(' TERR', ' TER')
    address = address.replace(' PLACE RD', ' PL')
    address = address.replace('2955 DON MILLS RD W', '2955 DON MILLS RD')
    address = address.replace('105 COLBORNE LODGE DR W', '105 COLBORNE LODGE␣
↪DR')
    return address


def create_full_address(row):
    parts = [
        row['Street No'],
        row['Street Name'],
        row['Street Type'],
        row['Street Direction']
    ]
    string_parts = [str(part).strip() for part in parts if pd.notna(part) and␣
↪str(part).strip()]
    return normalize_address(' '.join(string_parts))
```

```python
def make_programs_with_coords_df(
    all_programs_df: pd.DataFrame,
    locations_df: pd.DataFrame,
    address_points_4326_df_: pd.DataFrame
) -> pd.DataFrame:
    """Merge program data with location and coordinate information.

    This function creates full addresses, normalizes them,
    joins with spatial address data, and assigns geometries to programs.

    Args:
      all_programs_df: DataFrame containing all program records.
      locations_df: DataFrame containing location metadata for each program.
      address_points_4326_df_: DataFrame of normalized addresses with spatial␣
 ↪geometry.

    Returns:
      A DataFrame of programs with assigned geometry coordinates,
      excluding those without valid spatial matches.
    """
    address_points_4326_df = address_points_4326_df_.copy()
    programs_with_locations_df = pd.merge(all_programs_df, locations_df,␣
 ↪on='Location ID', how='left')
    programs_with_locations_df['ADDRESS_FULL'] = programs_with_locations_df.
 ↪apply(create_full_address, axis=1)
    address_points_4326_df['ADDRESS_FULL'] =␣
 ↪address_points_4326_df['ADDRESS_FULL'].apply(normalize_address)
    address_geom_df = address_points_4326_df[['ADDRESS_FULL', 'geometry']].
 ↪copy()

    programs_with_coords_df = all_programs_df.copy()
    programs_with_coords_df['ADDRESS_FULL'] =␣
 ↪programs_with_locations_df['ADDRESS_FULL']

    programs_with_coords_df = pd.merge(programs_with_coords_df,␣
 ↪address_geom_df, on='ADDRESS_FULL', how='left')
    num_no_coord = programs_with_coords_df[programs_with_coords_df['geometry'].
 ↪isna()].shape[0]
    print(f'Number of programs for which coordinates could not be found:␣
 ↪{num_no_coord} out of {len(programs_with_locations_df)}')
    programs_with_coords_df = programs_with_coords_df.
 ↪dropna(subset=['geometry'])
    print('Filtered out programs without coordinates')
```

```
    programs_with_coords_df['geometry'] = programs_with_coords_df['geometry'].
 ↪apply(parse_geometry)
    return programs_with_coords_df


def get_neighborhood_area(geom) -> float:
    """Calculate the area of a geometry in square kilometers.

    Args:
      geom: A geometry object representing a neighborhood boundary.

    Returns:
      The area of the geometry in square kilometers.
    """
    gdf = gpd.GeoDataFrame(geometry=[geom], crs=f'EPSG:{EPSG}')
    gdf_projected = gdf.to_crs(epsg=32617)
    area_in_sq_meters = gdf_projected.geometry.area[0]
    return area_in_sq_meters / 1e6


def process_demographics_geo_df(
    df: pd.DataFrame,
    epsg=EPSG,
    population_col: str = 'Total Population'
) -> gpd.GeoDataFrame:
    """Convert a demographics DataFrame into a GeoDataFrame with area and␣
 ↪population density.

    This function parses geometries, calculates area and population density,
    converts relevant columns to float, and assigns a coordinate reference␣
 ↪system.

    Args:
      df: The input DataFrame containing demographic and geometry data.
      epsg: The EPSG code for the output GeoDataFrame's coordinate reference␣
 ↪system.
      population_col: The column name representing total population.

    Returns:
      A GeoDataFrame with area, population density, and properly typed columns.
    """
    df_copy = df.copy()
    df_copy['geometry'] = df_copy['geometry'].apply(parse_geometry)
    df_copy['area'] = df_copy['geometry'].apply(get_neighborhood_area)
    df_copy['population_density'] = df_copy[population_col] / df_copy['area'] /␣
 ↪1000
    df_copy['population_density'] = df_copy['population_density'].astype(float)
```

```
    df_copy['low income (%)'] = df_copy['low income (%)'].astype(float)
    gdf = gpd.GeoDataFrame(df_copy, geometry='geometry').set_crs(epsg=epsg)
    return gdf


def get_area_code(
    demographics_geo_df: pd.DataFrame,
    area_geom_col: str = 'geometry',
    area_code_col: str = 'AREA_SHORT_CODE'
):
    """Return a function to map Point geometries to their corresponding area␣
 ↪codes.
    Args:
      demographics_geo_df: DataFrame containing area geometries and codes.
      area_geom_col: The name of the column containing area geometries.
      area_code_col: The name of the column containing area codes.

    Returns:
      A function that takes a Point geometry and returns the matching area code␣
 ↪or None.
    """
    if isinstance(demographics_geo_df[area_geom_col].iloc[0], str):
        temp_df = demographics_geo_df.copy()
        temp_df['geometry'] = temp_df[area_geom_col].apply(parse_geometry)
    else:
        temp_df = demographics_geo_df.copy()
        temp_df = temp_df.rename(columns={area_geom_col: 'geometry'})

    areas_gdf = gpd.GeoDataFrame(temp_df, geometry='geometry', crs='EPSG:4326')

    def _get_area_code(point):
        match = areas_gdf[areas_gdf.contains(point)]
        if not match.empty:
            return match.iloc[0][area_code_col]
        return None

    return _get_area_code
```

[13]:
```
registered_program_gdf = make_programs_with_coords_df(registered_program_df,␣
 ↪locations_df, address_points_4326_df_raw)
```

```
Number of programs for which coordinates could not be found: 26 out of 19644
Filtered out programs without coordinates
```

[14]:
```
drop_in_gdf = make_programs_with_coords_df(drop_in_df, locations_df,␣
 ↪address_points_4326_df)
```

```
Number of programs for which coordinates could not be found: 1 out of 3762
```

Filtered out programs without coordinates

[15]:
```
demographics_gdf = process_demographics_geo_df(demographics_geo_df)
```

[16]:
```
registered_program_gdf['AREA_SHORT_CODE'] = registered_program_gdf['geometry'].
↪apply(get_area_code(demographics_geo_df))
```

[17]:
```
drop_in_gdf['AREA_SHORT_CODE'] = drop_in_gdf['geometry'].
↪apply(get_area_code(demographics_geo_df))
```

Analysis for 0-14 Children Program supply vs demand

[18]:
```
demographics_child_gdf = demographics_gdf.copy()
demographics_child_gdf = demographics_child_gdf.drop(
    columns=[
        '15_64 years',
        '65 years and over',
        'Children',
        'Couple families with children',
        'One parent families',
        'Median total income',
        'low income (%)'
    ]
)
demographics_child_gdf['Child Population Share'] = (
    demographics_child_gdf['0_14 years'] /
    demographics_child_gdf['Total Population'] *
    100
)
```

[19]:
```
def get_child_program_summary_df(program_gdf: pd.DataFrame) -> pd.DataFrame:
    """Generate a summary DataFrame for child programs grouped by area.

    This function filters programs suitable for children (age 0-14),
    then aggregates total program counts and sessions by area,
    and also counts courses by section.

    Args:
      program_gdf: DataFrame containing program data with age and session␣
↪details.

    Returns:
      A summary DataFrame indexed by 'AREA_SHORT_CODE' with total counts and␣
↪section-wise course counts.
    """
    child_program_gdf = program_gdf[
        (program_gdf['Min Age'] <= 14) & (program_gdf['Max Age'] >= 0)
    ].copy()
```

```
    summary_df = child_program_gdf.groupby('AREA_SHORT_CODE').agg(
        total_course_count=('Course_ID', 'count'),
        total_sessions=('num_of_sessions', 'sum')
    )
    section_counts = (
        child_program_gdf
        .groupby(['AREA_SHORT_CODE', 'Section'])['Course_ID']
        .count()
        .unstack(fill_value=0)
    )
    summary_df = summary_df.join(section_counts)
    return summary_df


def merge_child_programs_with_demographics(
    demographics_child_gdf: pd.DataFrame,
    registered_program_child_gdf: pd.DataFrame,
    dropin_program_child_gdf: pd.DataFrame
) -> pd.DataFrame:
    """Merge child demographic data with registered and drop-in child program␣
 ↪summaries.

    This function merges demographic data with registered and drop-in program
    summaries on AREA_SHORT_CODE,summing total course counts and sessions,
    and cleans up intermediate columns.

    Args:
      demographics_child_gdf: GeoDataFrame or DataFrame with child demographic␣
 ↪data indexed by AREA_SHORT_CODE.
      registered_program_child_gdf: DataFrame summarizing registered child␣
 ↪programs by AREA_SHORT_CODE.
      dropin_program_child_gdf: DataFrame summarizing drop-in child programs by␣
 ↪AREA_SHORT_CODE.

    Returns:
      A merged DataFrame with combined course counts and session totals.
    """
    key = 'AREA_SHORT_CODE'

    merged = demographics_child_gdf.merge(
        registered_program_child_gdf,
        how='left',
        on=key,
        suffixes=('', '_registered')
    )
    merged = merged.merge(
        dropin_program_child_gdf,
```

```
        how='left',
        on=key,
        suffixes=('', '_dropin')
    )
    merged['total_course_count'] = (
        merged['total_course_count'].fillna(0) +
        merged['total_course_count_dropin'].fillna(0)
    )

    merged['total_sessions'] = (
        merged['total_sessions'].fillna(0) +
        merged['total_sessions_dropin'].fillna(0)
    )
    merged = merged.drop(columns=['total_course_count_dropin',␣
↪'total_sessions_dropin'])
    return merged


def clean_activity_gdf(gdf: pd.DataFrame) -> pd.DataFrame:
    """Clean and standardize activity data in the DataFrame.

    This function converts specified columns to numeric, replaces NaNs in␣
↪activity columns with zeros,
    and calculates activity diversity.

    Args:
      gdf: Input DataFrame containing activity and demographic data.

    Returns:
      A cleaned DataFrame with numeric conversions, filled NaNs, and an added␣
↪'activity_diversity' column.
    """
    cols_to_convert = ['Total Population', '0_14 years', 'Child Population␣
↪Share']

    for col in cols_to_convert:
        gdf[col] = pd.to_numeric(gdf[col], errors='coerce')

    exclude_cols = ['Neighbourhood Name', 'AREA_SHORT_CODE', 'TSNS',
                    'Total Population', '0_14 years', 'geometry',
                    'area', 'population_density', 'Child Population Share']

    activity_cols = gdf.columns.drop(exclude_cols, errors='ignore')

    gdf[activity_cols] = gdf[activity_cols].fillna(0)
    activity_variety_cols = activity_cols.
↪drop(['total_course_count','total_sessions'], errors='ignore')
```

```
    gdf['activity_diversity'] = (gdf[activity_cols] > 0).sum(axis=1)

    return gdf


def set_splines_topright(ax):
    """Hide all spines (borders) of a matplotlib axis."""
    ax.spines['top'].set_visible(False)
    ax.spines['right'].set_visible(False)
```

[20]:
```
registered_program_child_gdf = get_child_program_summary_df(registered_program_gdf)
```

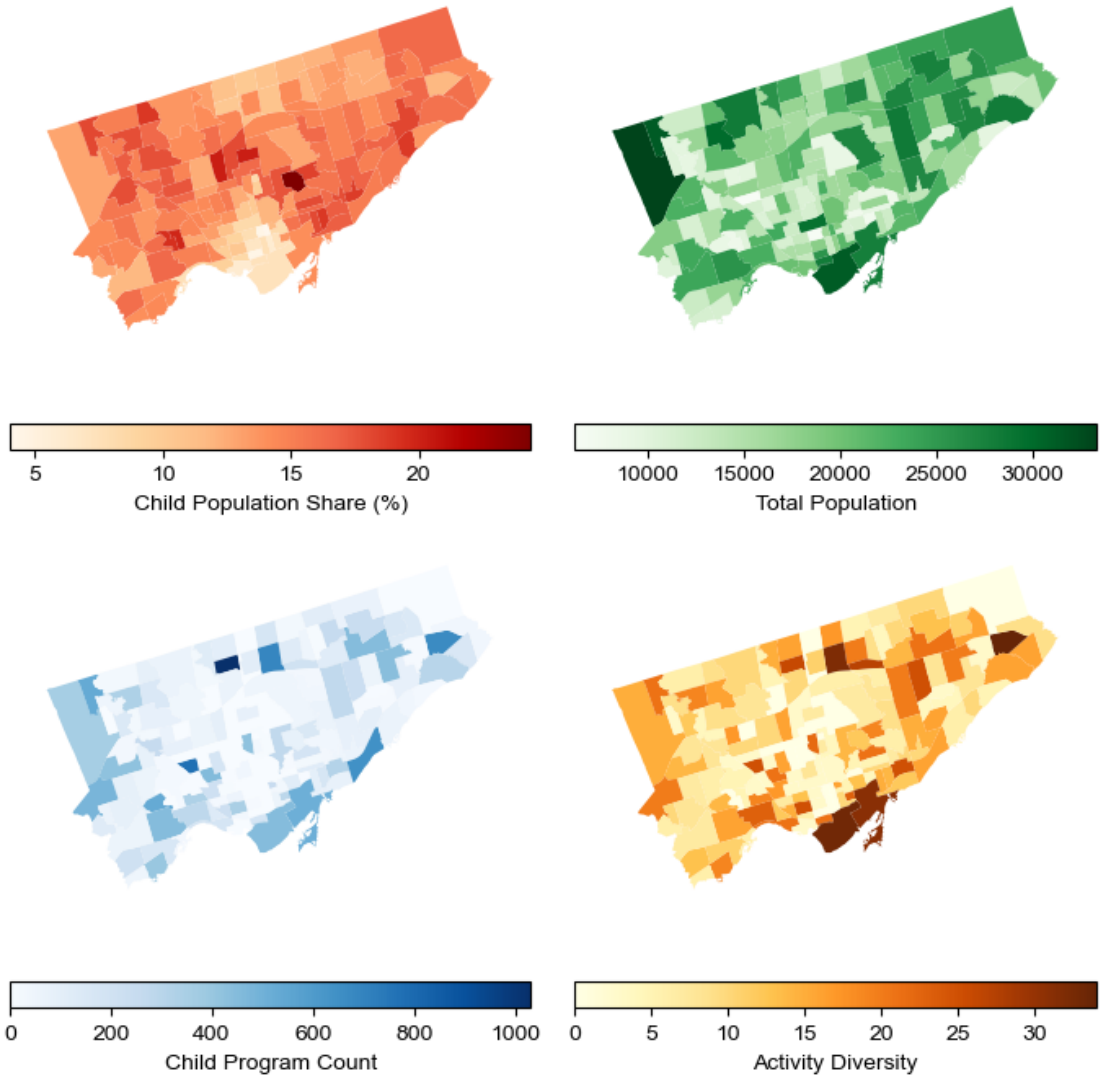
[21]:
```
drop_in_child_gdf = get_child_program_summary_df(drop_in_gdf)
```

[22]:
```
child_gdf = merge_child_programs_with_demographics(
    demographics_child_gdf,
    registered_program_child_gdf,
    drop_in_child_gdf
)
```

[23]:
```
child_gdf = clean_activity_gdf(child_gdf)
```

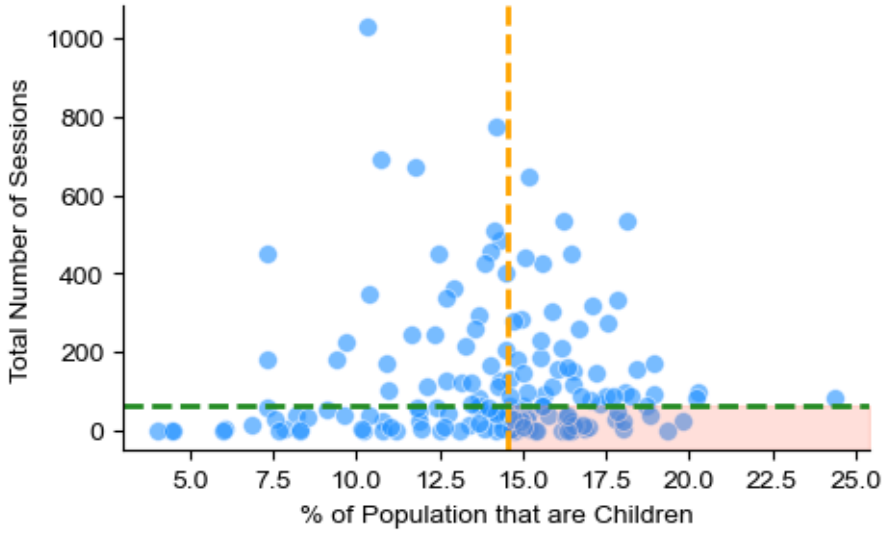
[24]:
```
fig, axes = plt.subplots(2, 2, figsize=(7, 7))

child_gdf.plot(
    column='Child Population Share',
    ax=axes[0, 0],
    legend=True,
    cmap='OrRd',
    legend_kwds={'label': "Child Population Share (%)", 'orientation': "horizontal"}
)
axes[0, 0].set_axis_off()

child_gdf.plot(
    column='Total Population',
    ax=axes[0, 1],
    legend=True,
    cmap='Greens',
    legend_kwds={'label': "Total Population", 'orientation': "horizontal"}
)
axes[0, 1].set_axis_off()

child_gdf.plot(
    column='total_course_count',
    ax=axes[1, 0],
```

```
    legend=True,
    cmap='Blues',
    legend_kwds={'label': "Child Program Count", 'orientation': "horizontal"}
)
axes[1, 0].set_axis_off()

child_gdf.plot(
    column='activity_diversity',
    ax=axes[1, 1],
    legend=True,
    cmap='YlOrBr',
    legend_kwds={'label': "Activity Diversity", 'orientation': "horizontal"}
)
axes[1, 1].set_axis_off()

plt.tight_layout()
plt.show()
fig.savefig("figures/child_population_program_map.pdf", bbox_inches='tight',␣
 ↪dpi=300)
```



[25]:
```
demand_median = child_gdf['Child Population Share'].median()
supply_median = child_gdf['total_course_count'].median()

fig, ax = plt.subplots(1, 1, figsize=(5, 3))
scatter = sns.scatterplot(
    data=child_gdf,
    ax=ax,
    x='Child Population Share',
    y='total_course_count',
    s=50,
    color='dodgerblue',
    edgecolor='white',
    alpha = 0.6
```

```
)

ax.axvline(demand_median, color='orange', linestyle='--', linewidth=2,␣
 ↪label='Demand Median')
ax.axhline(supply_median, color='forestgreen', linestyle='--', linewidth=2,␣
 ↪label='Supply Median')

xlim = plt.xlim()
ylim = plt.ylim()
ax.fill_between(
    x=[demand_median, xlim[1]],
    y1=ylim[0],
    y2=supply_median,
    color='tomato',
    alpha=0.2,
)
ax.set_xlim(xlim)
ax.set_ylim(ylim)
ax.set_xlabel('% of Population that are Children')
ax.set_ylabel('Total Number of Sessions')
set_splines_topright(ax)

plt.show()
fig.savefig("figures/child_population_program_scatter.pdf",␣
 ↪bbox_inches='tight', dpi=300)
```

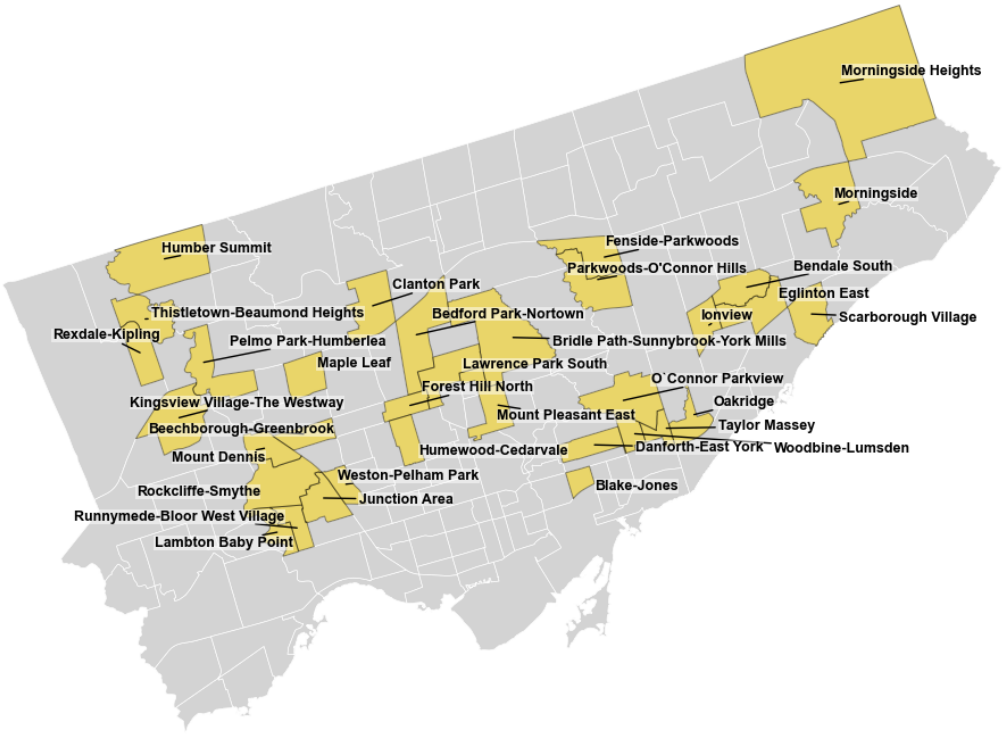


[26]:
```
bottom_right_quadrant = child_gdf[
    (child_gdf['Child Population Share'] > demand_median) &
```

```
    (child_gdf['total_course_count'] < supply_median)
]
```

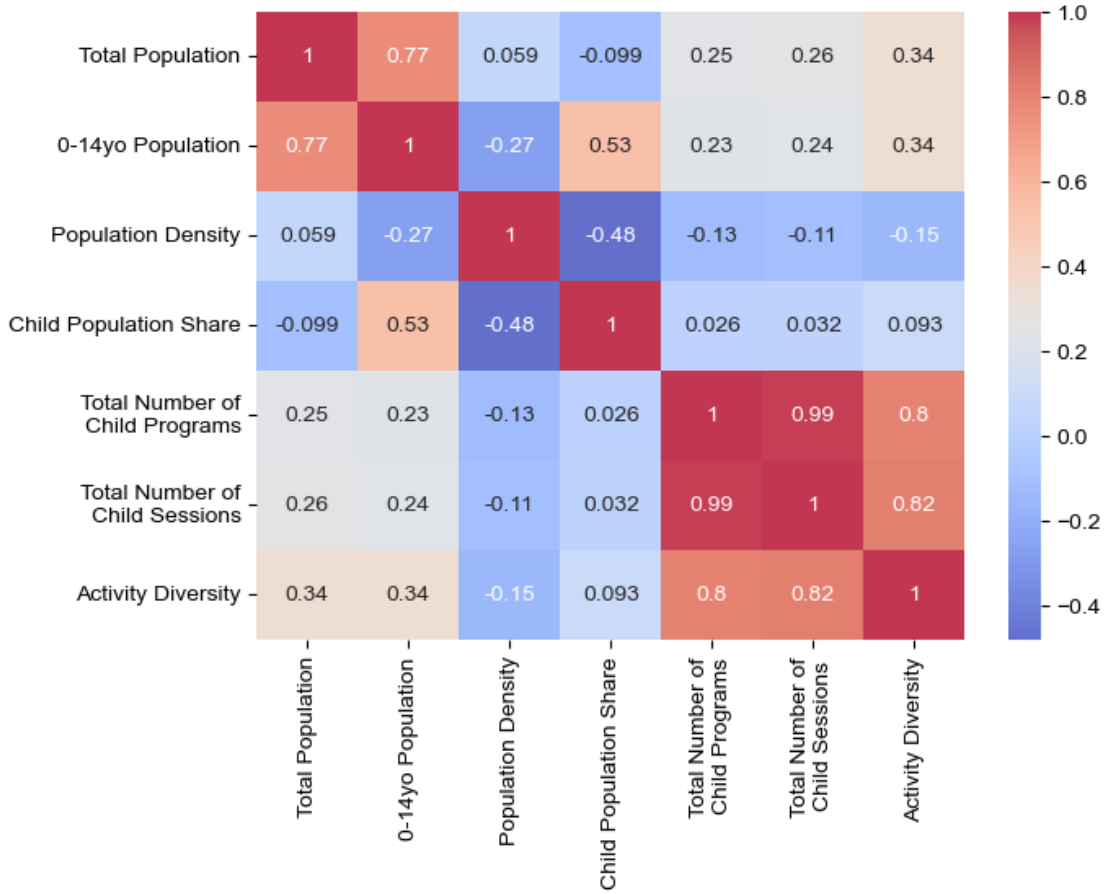
[27]:
```
fig, ax = plt.subplots(1, 1, figsize=(10, 10))

child_gdf.plot(
    ax=ax,
    color='lightgray',
    edgecolor='white',
    linewidth=0.5
)

bottom_right_quadrant.plot(
    ax=ax,
    color='gold',
    edgecolor='k',
    linewidth=0.7,
    alpha=.5
)

texts = []

for idx, row in bottom_right_quadrant.iterrows():
    centroid = row.geometry.representative_point()
    if centroid.is_empty:
        continue

    texts.append(
        ax.text(
            x=centroid.x,
            y=centroid.y,
            s=row['Neighbourhood Name'],
            fontdict={
                'fontsize': 9,
                'color': 'black',
                'weight': 'bold',
                'ha': 'center'
            },
            bbox=dict(facecolor='white', alpha=0.5, edgecolor='none', pad=0.2)
            )
    )

adjust_text(
    texts,
    ax=ax,
    arrowprops=dict(arrowstyle='-', color='black', lw=1)
)
```

```
ax.set_axis_off()
plt.tight_layout()
plt.show()

fig.savefig("figures/child_population_program_map_neighbourhoods_to_target.
 ↪pdf", bbox_inches='tight', dpi=300)
```



[28]:
```
corr_matrix = child_gdf[[
    'Total Population', '0_14 years', 'population_density',
    'Child Population Share', 'total_course_count', 'total_sessions',
    'activity_diversity'
]].rename(columns={
    '0_14 years': '0-14yo Population',
    'population_density': 'Population Density',
    'total_course_count': 'Total Number of\nChild Programs',
    'total_sessions': 'Total Number of\nChild Sessions',
    'activity_diversity': 'Activity Diversity'
}).corr()

fig, ax = plt.subplots(1, 1, figsize=(7, 5))
sns.heatmap(corr_matrix, ax=ax, annot=True, cmap='coolwarm', alpha=0.8)
```

```
fig.savefig("figures/child_population_program_correlations.pdf",␣
↪bbox_inches='tight', dpi=300)
```



Analysis for Equity of Program Distribution: NIA/Emerging and low income area

[29]:
```
def summarize_all_by_address(registered_df: pd.DataFrame, dropin_df: pd.
↪DataFrame) -> gpd.GeoDataFrame:
    """Summarize program data by full address from registered and drop-in␣
↪datasets.

    This function combines registered and drop-in program data, aggregates
    session counts and program counts by address, and collects spatial and
    area metadata.

    Args:
      registered_df: DataFrame of registered programs with session info.
      dropin_df: DataFrame of drop-in programs with session info.

    Returns:
```

```
    A GeoDataFrame summarizing total sessions, program counts, and spatial␣
↪info by address.
    """
    combined_df = pd.concat([registered_df, dropin_df], ignore_index=True)
    registered_sessions = (
        registered_df.groupby("ADDRESS_FULL")
        .agg(registered_total_sessions=("num_of_sessions", "sum"))
    )
    dropin_sessions = (
        dropin_df.groupby("ADDRESS_FULL")
        .agg(dropin_total_sessions=("num_of_sessions", "sum"))
    )
    program_count = (
        combined_df.groupby("ADDRESS_FULL")
        .agg(program_count=("Course_ID", "nunique"))
    )
    meta = (
        combined_df.groupby("ADDRESS_FULL")
        .agg(
            geometry=("geometry", "first"),
            AREA_SHORT_CODE=(
                "AREA_SHORT_CODE",
                lambda x: x.mode().iloc[0] if not x.mode().empty else x.iloc[0]
            )
        )
    )
    summary = (
        meta.join(program_count)
            .join(registered_sessions, how="left")
            .join(dropin_sessions, how="left")
            .fillna(0)
            .reset_index()
    )
    summary["total_sessions"] = summary["registered_total_sessions"] +␣
↪summary["dropin_total_sessions"]
    summary[["registered_total_sessions", "dropin_total_sessions",␣
↪"total_sessions", "program_count"]] = \
        summary[["registered_total_sessions", "dropin_total_sessions",␣
↪"total_sessions", "program_count"]].astype(float)
    return gpd.GeoDataFrame(summary, geometry='geometry').set_crs(epsg=EPSG)
```

[30]:
```
location_summary_df = summarize_all_by_address(registered_program_gdf,␣
↪drop_in_gdf)
```

[31]:
```
def remove_ticks(ax):
    """Remove x and y axis ticks from a matplotlib axis."""
    ax.set_xticks([])
```

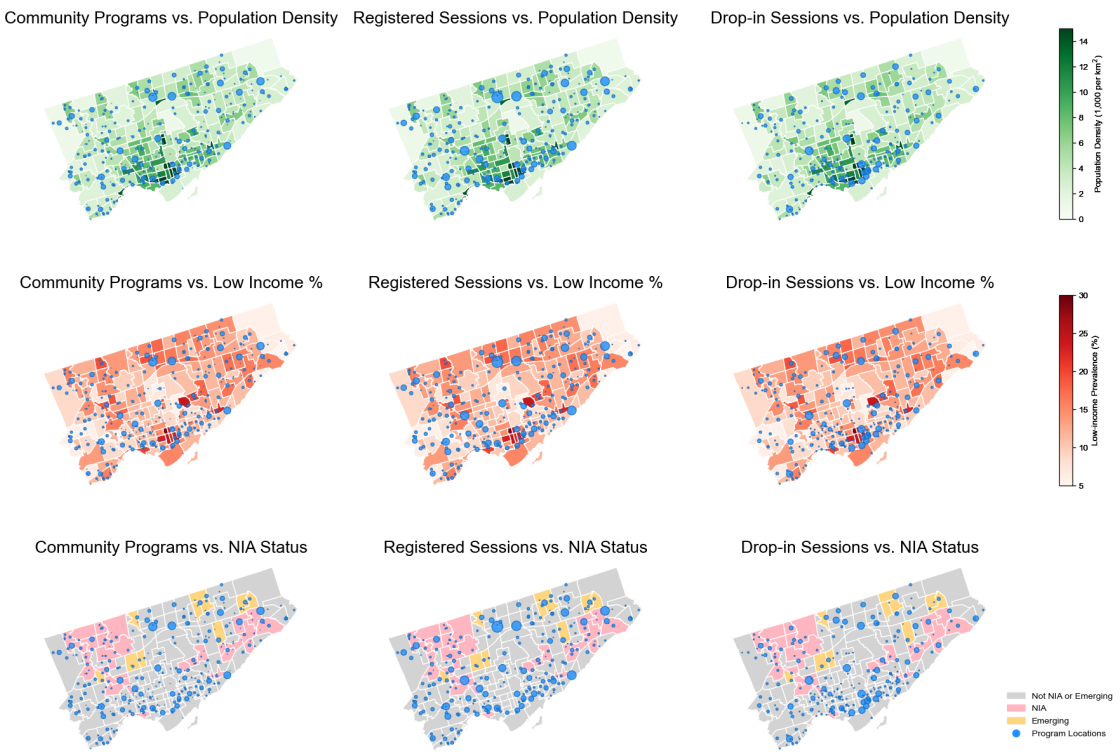
```
    ax.set_yticks([])


def plot_locations(ax, location_summary_gdf, marker_key='program_count',␣
 ↪marker_factor=0.1):
    """Plot program locations with marker sizes proportional to a key metric."""
    location_summary_gdf.plot(
        ax=ax,
        color='dodgerblue',
        markersize=location_summary_gdf[marker_key].astype(float) *␣
 ↪marker_factor,
        alpha=0.8,
        zorder=2,
        edgecolor='#136abe'
    )


def set_splines(ax):
    """Hide all spines (borders) of a matplotlib axis."""
    ax.spines['top'].set_visible(False)
    ax.spines['right'].set_visible(False)
    ax.spines['left'].set_visible(False)
    ax.spines['bottom'].set_visible(False)
```

[32]:
```
def plot_multi_maps(location_summary_df, neighborhoods_gdf, configs):
    """
    Plot a 3xN grid of maps for different program types and neighborhood␣
 ↪overlays.

    Args:
        location_summary_df: GeoDataFrame with program location summary.
        neighborhoods_gdf: GeoDataFrame with neighborhood demographic info.
        configs: List of dicts with keys:
                 - 'title': plot title
                 - 'key': column for marker size
                 - 'factor': marker size factor
    """
    n_cols = len(configs)
    fig, axes = plt.subplots(3, n_cols, figsize=(7 * n_cols, 15))
    if n_cols == 1:
        axes = axes.reshape(3, 1)

    # Common legend positions for colorbars
    legend_positions = [
        [0.92, 0.68, 0.01, 0.2],
        [0.92, 0.4, 0.01, 0.2],
        [0.92, 0.115, 0.01, 0.2],
```

```
    ]

    for col_idx, config in enumerate(configs):
        title = config['title']
        key = config.get('key', 'program_count')
        factor = config.get('factor', 0.1)

        # Row 1: Population Density
        ax = axes[0, col_idx]
        neighborhoods_gdf.plot(
            column='population_density',
            ax=ax,
            legend=True,
            cmap='Greens',
            edgecolor='white',
            legend_kwds={'label': 'Population Density (1,000 per km$^2$)',␣
↪'orientation': "vertical"},
            vmin=0, vmax=15,
            cax=fig.add_axes(legend_positions[0])
        )
        plot_locations(ax, location_summary_df, marker_key=key,␣
↪marker_factor=factor)
        ax.set_title(f'{title} vs. Population Density',fontsize=19)
        remove_ticks(ax)
        set_splines(ax)

        # Row 2: Low Income
        ax = axes[1, col_idx]
        neighborhoods_gdf.plot(
            column='low income (%)',
            ax=ax,
            legend=True,
            cmap='Reds',
            edgecolor='white',
            legend_kwds={'label': 'Low-income Prevalence (%)', 'orientation':␣
↪"vertical"},
            vmin=5, vmax=30,
            cax=fig.add_axes(legend_positions[1])
        )
        plot_locations(ax, location_summary_df, marker_key=key,␣
↪marker_factor=factor)
        ax.set_title(f'{title} vs. Low Income %',fontsize=19)
        remove_ticks(ax)
        set_splines(ax)

        # Row 3: NIA Status
        ax = axes[2, col_idx]
```

```
        color_map = {
            'Not an NIA or Emerging Neighbourhood': 'lightgray',
            'Neighbourhood Improvement Area': 'lightpink',
            'Emerging Neighbourhood': '#FFD580'
        }
        neighborhoods_gdf.plot(
            ax=ax,
            color=neighborhoods_gdf['TSNS'].map(color_map),
            edgecolor='white',
        )
        plot_locations(ax, location_summary_df, marker_key=key,␣
↪marker_factor=factor)
        ax.set_title(f'{title} vs. NIA Status',fontsize=19)
        remove_ticks(ax)
        set_splines(ax)

        if col_idx == n_cols - 1:
            legend_patches = [
                mpatches.Patch(color='lightgray', label='Not NIA or Emerging'),
                mpatches.Patch(color='lightpink', label='NIA'),
                mpatches.Patch(color='#FFD580', label='Emerging')
            ]
            program_handle = Line2D(
                [0], [0], marker='o', color='w',
                label='Program Locations',
                markerfacecolor='dodgerblue', markersize=10
            )
            ax.legend(handles=legend_patches + [program_handle], loc=(1.01, 0.
↪1), frameon=False)

    plt.subplots_adjust(hspace=0.3, wspace=0.0)
    fig.savefig('figures/All_Program_Types_Map.pdf', bbox_inches='tight',␣
↪dpi=300)
    plt.show()
```

[33]:
```
configs = [
    {'title': 'Community Programs'},
    {'title': 'Registered Sessions', 'key': 'registered_total_sessions',␣
↪'factor': 0.02},
    {'title': 'Drop-in Sessions', 'key': 'dropin_total_sessions', 'factor': 0.
↪05},
]

plot_multi_maps(location_summary_df, demographics_gdf, configs)
```



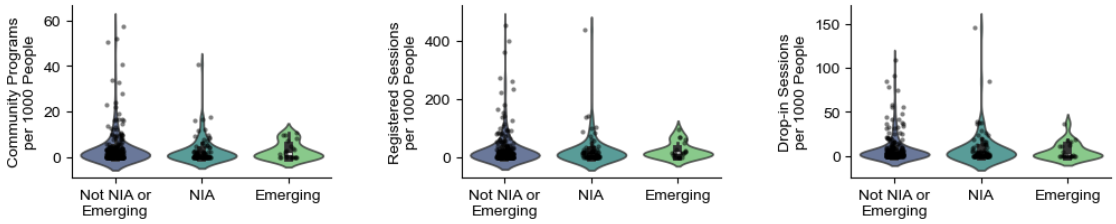
Statistical Analysis

[34]:
```
program_name_dict = {
    'program_count': 'Community Programs',
    'registered_total_sessions': 'Registered Sessions',
    'dropin_total_sessions': 'Drop-in Sessions',
}

def get_metric_df(df: pd.DataFrame, count_key: str = 'program_count') -> pd.
↪DataFrame:
    """Calculate program density metrics and map neighborhood types to␣
↪simplified labels.

    Args:
      df: DataFrame with demographic and program count data.
      count_key: The column name representing program counts.

    Returns:
      DataFrame with added density columns and simplified neighborhood type␣
↪labels.
    """
    df[f'{count_key}_density_1k'] = df[count_key] / df['Total Population'] *␣
↪1000
```

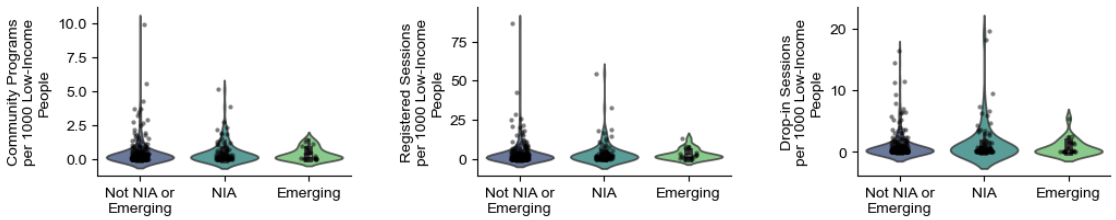
```
    df[f'{count_key}_density_1k_lowincome'] = df[f'{count_key}_density_1k'] *␣
 ↪df['low income (%)'] / 100
    df['TSNS_NEW'] = df['TSNS'].map({
        'Not an NIA or Emerging Neighbourhood': 'Not NIA or\nEmerging',
        'Neighbourhood Improvement Area': 'NIA',
        'Emerging Neighbourhood': 'Emerging',
    })
    return df


def plot_one_violin(df: pd.DataFrame, ax, count_key: str, lowincome: bool =␣
 ↪False):
    """Plot a violin plot with stripplot overlay for program density metrics by␣
 ↪neighborhood type.

    Args:
      df: DataFrame with metrics and neighborhood labels.
      ax: Matplotlib Axes object to plot on.
      count_key: Base metric key used for density columns.
      lowincome: Whether to plot low-income adjusted density metric.
    """
    string = f'{count_key}_density_1k_lowincome' if lowincome else␣
 ↪f'{count_key}_density_1k'
    ylabel_string = 'Low-Income\n' if lowincome else ''
    sns.violinplot(
        ax=ax,
        x='TSNS_NEW',
        y=string,
        data=df,
        palette='viridis',
        alpha=0.8,
    )
    sns.stripplot(
        ax=ax,
        x='TSNS_NEW',
        y=string,
        data=df,
        jitter=True,
        color='black',
        size=3,
        alpha=0.5
    )
    ax.spines['top'].set_visible(False)
    ax.spines['right'].set_visible(False)
    ax.set_ylabel(f'{program_name_dict[count_key]}\nper 1000␣
 ↪{ylabel_string}People')
    ax.set_xlabel('')
```

[35]:
```
location_stat_df = location_summary_df.merge(
    demographics_df[['AREA_SHORT_CODE', 'Total Population', 'low income (%)',␣
 ↪'TSNS']],
    how='left',
    left_on='AREA_SHORT_CODE',
    right_on='AREA_SHORT_CODE'
)
```

[36]:
```
fig, axs = plt.subplots(1, 3, figsize=(12, 2))
count_keys = ['program_count','registered_total_sessions',␣
 ↪'dropin_total_sessions']
for ax, count_key in zip(axs, count_keys):
    df = get_metric_df(location_stat_df, count_key=count_key)
    plot_one_violin(df, ax, count_key)
plt.subplots_adjust(wspace=0.5)
fig.savefig("figures/nia_analysis_violin.pdf", bbox_inches='tight', dpi=300)
```



[37]:
```
fig, axs = plt.subplots(1, 3, figsize=(12, 2))
for ax, count_key in zip(axs, count_keys):
    df = get_metric_df(location_stat_df, count_key=count_key)
    plot_one_violin(df, ax, count_key, lowincome=True)
plt.subplots_adjust(wspace=0.5)
fig.savefig("figures/nia_analysis_violin_lowincome.pdf", bbox_inches='tight',␣
 ↪dpi=300)
```



[38]:
```
class_name_dict = {
    'Not an NIA or Emerging Neighbourhood': 'Not NIA or Emerging',
```

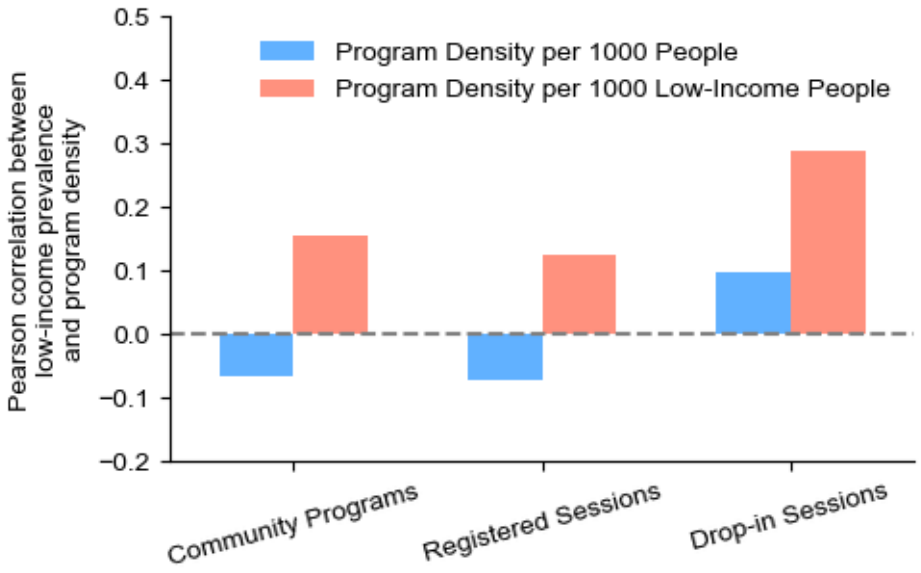
```
    'Neighbourhood Improvement Area': 'NIA',
    'Emerging Neighbourhood': 'Emerging',
}
for population in ['', '_lowincome']:
    for count_key in count_keys:
        column = f'{count_key}_density_1k{population}'
        print(count_key, population)
        means = location_stat_df.groupby('TSNS').agg(program_density=(column,␣
 ↪'mean'))
        stds = location_stat_df.groupby('TSNS').agg(program_density=(column,␣
 ↪'std'))
        strings = [f'{mean:.2f} ± {std:.2f}' for mean, std in zip(means.values.
 ↪squeeze(), stds.values.squeeze())]
        for class_, string in zip(means.index, strings):
            print(class_name_dict[class_],':', string)
        print()
```

```
program_count
Emerging : 3.24 ± 3.78
NIA : 3.11 ± 5.67
Not NIA or Emerging : 4.19 ± 8.16

registered_total_sessions
Emerging : 24.93 ± 27.37
NIA : 23.91 ± 53.37
Not NIA or Emerging : 29.47 ± 60.70

dropin_total_sessions
Emerging : 6.12 ± 9.62
NIA : 8.74 ± 19.60
Not NIA or Emerging : 8.15 ± 16.04

program_count _lowincome
Emerging : 0.40 ± 0.47
NIA : 0.51 ± 0.86
Not NIA or Emerging : 0.46 ± 0.99

registered_total_sessions _lowincome
Emerging : 3.08 ± 3.37
NIA : 3.83 ± 7.59
Not NIA or Emerging : 3.21 ± 7.65

dropin_total_sessions _lowincome
Emerging : 0.80 ± 1.35
NIA : 1.50 ± 3.25
Not NIA or Emerging : 0.99 ± 2.19
```

[39]:
```
# ANOVA to see if averages are different between 3 groups
for population in ['', '_lowincome']:
    for count_key in count_keys:
        column = f'{count_key}_density_1k{population}'
        grouped_data = [location_stat_df[column][location_stat_df['TSNS'] ==␣
 ↪cls] for cls in location_stat_df['TSNS'].unique()]
        f_statistic, p_value = scipy.stats.f_oneway(*grouped_data)
        print(f"{column} P-value: {p_value:.4f}")
```

```
program_count_density_1k P-value: 0.4671
registered_total_sessions_density_1k P-value: 0.7190
dropin_total_sessions_density_1k P-value: 0.8047
program_count_density_1k_lowincome P-value: 0.8774
registered_total_sessions_density_1k_lowincome P-value: 0.7885
dropin_total_sessions_density_1k_lowincome P-value: 0.2047
```

[40]:
```
population_corrs = []
for population in ['', '_lowincome']:
    corrs = []
    for count_key in count_keys:
        column = f'{count_key}_density_1k{population}'
        corr = scipy.stats.pearsonr(
            location_stat_df['low income (%)'].astype(float),
            location_stat_df[column].astype(float)
        ).statistic
        corrs.append(corr)
    population_corrs.append(corrs)

x = np.arange(len(count_keys))
width = 0.3
fig, ax = plt.subplots(1, 1, figsize=(5, 3))
ax.bar(x - width / 2, population_corrs[0], width=width, color='dodgerblue',␣
 ↪alpha=0.7, label='Program Density per 1000 People')
ax.bar(x + width / 2, population_corrs[1], width=width, color='tomato', alpha=0.
 ↪7, label='Program Density per 1000 Low-Income People')
ax.spines['top'].set_visible(False)
ax.spines['right'].set_visible(False)
ax.hlines(xmin=-0.5, xmax=len(x)-0.5, y=0, color='gray', linestyle='--')
ax.set_xlim([-0.5, len(x)-0.5])
ax.set_ylim([-0.2, 0.5])
ax.set_xticks(x, [program_name_dict[name] for name in count_keys], rotation=15)
ax.set_ylabel('Pearson correlation between\nlow-income prevalence\nand program␣
 ↪density')
plt.legend(frameon=False)
fig.savefig("figures/nia_analysis_correlations.pdf", bbox_inches='tight',␣
 ↪dpi=300)
```


Program Density per 1000 People
Program Density per 1000 Low-Income People
Pearson correlation between low-income prevalence and program density
0.5
0.4
0.3
0.2
0.1
0.0
−0.1
−0.2
Community Programs
Registered Sessions
Drop-in Sessions