Universität Zürich[UZH]

Department of Geography

Spatial and Temporal Dynamics of the Distribution of Children with Developmental Delay in the Canton of Zurich

GEO 511 Master's Thesis

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Abstract

Early childhood development plays a fundamental role in lifelong health, well-being, and social participation. Children affected by a developmental delay – such as language delay, autism spectrum disorder (ASD) or attention-deficit / hyperactivity disorder (ADHD) – do not achieve developmental milestones compared with children the same age range. The number of children diagnosed with developmental impairments has been increasing in recent years. Early identification and intervention for children at risk of developmental delays allow for the initiation of optimal care support and thus significantly enhance their long-term health and educational outcomes. Understanding the geographic distribution of these conditions is essential for assessing the spatial influence of potential risk factors. This thesis applies spatial epidemiological methods – including disease mapping, cluster detection, and regression modelling – to examine the spatial distribution and potential risk factors of developmental delays among children living in the canton of Zurich. This analysis focuses on cases of premature birth, isolated language delay, and ASD, based on data from children assessed at the University Children's Hospital Zurich in 2018 and 2023. The study identified significant spatial clusters for all three diagnoses, primarily located in urban areas north of Lake Zurich. Regression models identified several environmental and social factors associated with increased incidence: higher air pollution ($PM_{2.5}$) consistently correlated with elevated risk, while green space coverage appeared protective across all diagnoses, while access to healthcare and socioeconomic status may be associated with the incidence of isolated language delay and ASD.

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1 Introduction

1.1 Child Development and Developmental Delay

Early childhood development forms the basis for health, well-being, and social participation throughout life and is essential for realizing one's full human potential (Richter et al., 2017). To monitor this development, developmental milestones are acknowledged as reliable indicators of developmental status (Daniel et al., 2009). Children affected by developmental delays do not achieve developmental milestones compared with children in the same age range (Choo et al., 2019; Riou et al., 2009). A significant delay is characterized by a developmental gap of at least 25 percent compared to the expected rate or a deviation of 1.5 to 2 standard deviations from the norm (Poon et al., 2010). According to Choo et al. (2019), developmental delays encompass developmental disorders, developmental arrests and regression and developmental disabilities. In this thesis, the term delay is used to refer to this broad range of developmental challenges. To classify and diagnose developmental delays, two major international systems are used: the Diagnostic and Statistical Manual of Mental Disorders (DSM), published by the American Psychiatric Association, and the International Classification of Diseases (ICD). A delay affecting two or more developmental domains is classified as global development delay (GDD) (Poon et al., 2010). Delays can also be isolated to one domain like in the case of a developmental speech and language disorder (Poon et al., 2010). This diagnose is characterized by significant deviations – both in timing and linguistic content – on one or more linguistic levels, falling at least 1.5 standard deviations below age-appropriate developmental norms (Kiese-Himmel and Neumann, 2022). The term language delay is used to describe a developmental lag in language acquisition up to the age of 36 months (Neumann et al., 2023). An autism spectrum disorder (ASD) in contrast is classified as a neurodevelopmental disorder (Lauritsen, 2013). The core symptoms of ASD involve significant difficulties in social interactions and communication, along with distinctive patterns of interests and behaviors and hypo- or hyperactivity in response to sensory input (Daniel et al., 2009; Lordan et al., 2021). Autism exists on a broad spectrum, with each autistic child displaying a distinct combination of symptoms that vary in intensity (Lord et al., 2000). Until the publication of the DSM-5, ASD was subdivided into the diagnoses Autistic Disorder, Asperger's Disorder, and Pervasive Developmental Disorder. These categories have been merged into a single ASD diagnosis (Freitag, 2014). Another frequently diagnosed neurodevelopmental condition is Attention-Deficit/Hyperactivity Disorder (ADHD), which characteristics are inattentiveness, hyperactivity, and/or impulsivity (American Psychiatric Association, 2013). It affects approximately 5.3 percent of children and adolescents (Polanczyk et al., 2007).

1.2 Etiology of Developmental Delays

Developmental delays may arise from a wide range of causes (Choo et al., 2019). In many cases, the exact etiology remains unknown, known contributing factors may include genetic, environmental, and/or psychological factors (Khan and Leventhal, 2025). The following section provides an overview of the most frequently discussed causes in literature, with a particular focus on developmental language delays (DLD), ASD and ADHD.

Genetic predispositions play a central role in shaping a child's development, influencing various domains from early life onwards (Bellman et al., 2013). They are also considered an important factor in the development of neurodevelopmental disorders such as language impairments and ASD. Genetic influences are a key contributor to the development of Specific Language Impairments (SLI) (Moyle et al., 2011). The etiology of ASD is assumed to result from a complex interaction between genetics and the environment, with heritability values estimated between 40 to 80 percent (Chaste and Leboyer, 2012; Liu et al., 2023).

Prematurity poses developmental risks that may affect the premature born child's health, well-being, and overall development (Vogel et al., 2018). The World Health Organization (WHO) defines premature or preterm birth as birth occurring before 37 weeks of gestation are completed (WHO, 2023). Prematurity poses developmental risks that may affect the prematurely born child's health, well-being, and overall development (Vogel et al., 2018). Worldwide, premature birth is the primary cause of death among children under the age of five years (WHO, 2023). Due to these risks, implementing standardized developmental surveillance and screening for high-risk newborns is beneficial to ensure early detection of developmental delays, provide parental counselling, and ensure quality control and monitoring to improve neonatal care (Miller et al., 2020; Spittle et al., 2021). In Switzerland, developmental follow-up care for at-risk children is standardized and quality-assured through specialized centers (Kümin, 2025). The recommendations for neurodevelopmental follow-up assessments in Switzerland were first published in 2014. Since then, advancements in clinical care and new research have prompted updates to the guidelines, which now focus on extremely preterm infants (born before 28 weeks gestational age), in contrast to the 2014 guidelines, which included infants born before 32 weeks (Kümin, 2025).

Environmental factors that may negatively impact brain development can occur before birth, particularly in the early embryonic stages, or after birth (Bellman et al., 2013). Air quality and pollution may contribute to developmental risks. Exposure to fine particulate matter ($PM_{2.5}$) has been found to be associated with an increased risk of premature birth and the development of ASD and ADHD (Chang et al., 2022; Guo et al., 2018; Liu et al., 2023). A child's living environment may also influence their developmental outcomes. The study by Wu and Jackson

(2017) found that in California, within school districts with high road density, higher levels of urban green spaces were associated with lower prevalence of childhood autism. The authors suggest that the observed positive associations between road density and autism prevalence in children may be linked to the impact of air pollution caused by traffic. Environmental factors such as lead and PCBs (Polychlorinated biphenyls) have been recognized as possible risk factors for the development of ADHD (Banerjee et al., 2007).

1.3 Regional Disparities

Previous research on children with developmental delays is highly diverse and encompasses a broad range of etiological and risk factors. Studies incorporating spatial aspects show significant regional variation in the prevalence of developmental delays (Valla et al., 2015).

For instance, countries with higher income and Human Development Index (HDI) are linked to a greater prevalence of ASD (Talantseva et al., 2023). Preterm birth rates likewise show significant global disparities across the globe. Countries with lower income levels tend to experience a higher proportion of preterm births, while upper-middle and high-income countries generally report the lowest rates (March of Dimes, PMNCH, Save the Children, & WHO, 2012). Socioeconomic Status (SES) is an important factor that has been strongly associated with health outcomes (House, 2002). Numerous studies found an association of ASD diagnosis with socioeconomic status (SES) (Thomas et al., 2012). SES refers to a person's combined economic and social standing, including income, education, and occupation (Baker, 2014). The impact of SES on behavior likely starts in early childhood, as childhood socioeconomic status influences both health outcomes and the socialization of behaviors, tastes, and preferences (Baker, 2014). Economic and social standing also influence the timing of ASD diagnoses. Research has shown that the timing of ASD diagnosis varies significantly across geographic regions (Adelman and Kubiszyn, 2017; Ghahari et al., 2021; Rosenberg et al., 2011). Higher maternal education and employment have been associated with earlier ASD diagnoses, potentially due to increased family resources and access to health services (Ghahari et al., 2021; Shattuck et al., 2009).

The Autism and Developmental Disabilities Monitoring (ADDM) Network is a surveillance system funded by the Centers for Disease Control in the United States (Centers for Disease Control and Prevention [CDC], 2024). Reports from the ADDM Network highlight ongoing regional differences in ASD prevalence among monitoring sites, along with changing disparities between demographic groups, which underline the necessity of better understanding the causes of this variability (Maenner, 2023).

1.4 Increase in Children Diagnosed with Developmental Delays

The number of children diagnosed with developmental delays such as ASD or ADHD has been increasing in recent years (Zablotsky et al., 2019). According to data from the National Health Interview Survey (NHIS), approximately 17 percent of the children aged 3 to 17 years in the United States were reported to have a development delay between 2009 and 2017 (Zablotsky et al., 2019). During this period, the overall prevalence of developmental disabilities increased significantly, driven primarily by rising rates of ASD, ADHD, and intellectual disability (Zablotsky et al., 2019). Figure 1 from Zablotsky et al. (2019) illustrates the prevalence of any developmental disability among U.S. children aged 3 to 17 years, highlighting the overall upward trend over the past two decades. Similarly, the incidence of premature birth has also risen. Blencowe et al. (2012) reported that among 65 countries with reliable premature birth data, 62 countries saw increases between 2000 and 2010.

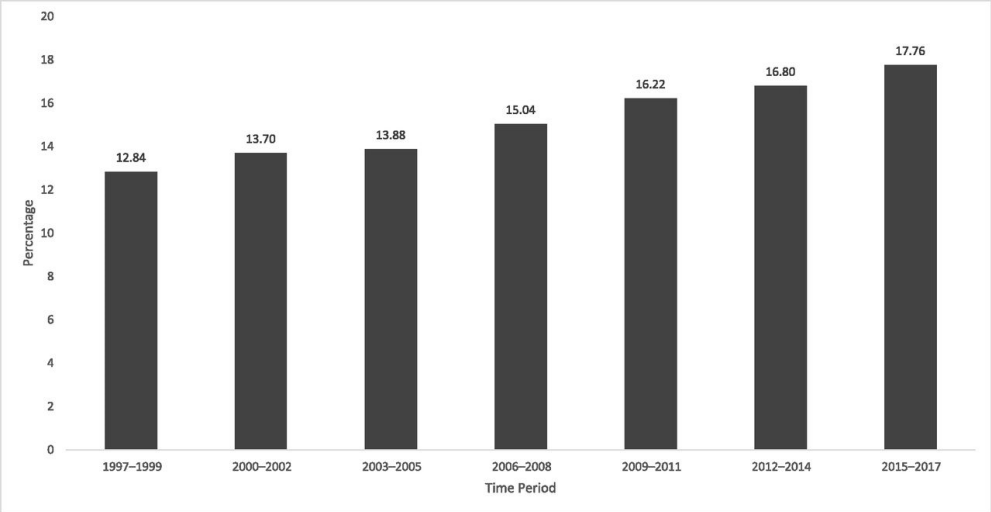


Figure 1: Prevalence of Developmental Delays in the United States among Children in 2009–2017 (Source: Zablotsky et al., 2019)

In the Canton of Zurich, the University Children's Hospital Zurich has also observed a rise in the number of children diagnosed with developmental delays and early educational needs in the last years (Personal data, Special Education Office Canton of Zurich). According to the Units of Special Needs Education (USNE), there has been an over 70 percent increase in initial registrations for special educational measures over the past 10 years. In the same period, referrals for school assessments at kindergarten age have doubled (Personal data, AJB Kanton ZH).

There is growing concern about the increasing prevalence of developmental delays among children. Several factors may contribute to this rise. In recent years, the increased public awareness of, and improved public health response to, ASD and ADHD could explain the rise in diagnoses (French et al., 2023; Zeidan et al., 2022). Another possible contribution for the rising prevalence of observed ASD rates may be the changing definitions and diagnostic criteria (Matson and Kozlowski, 2011). Despite these potential explanations, there is no clear agreement on the extent to which each factor contributes to the increase in autism diagnoses (Mazumdar et al., 2013).

Considering the increasing number of children with developmental delays, a geographical viewpoint is valuable for identifying potential spatial risk factors. Epidemiology studies the patterns of health and determinants in populations and the reasons behind them (Last, 1995). Taking location into account provides an important perspective, as it helps to understand how the environment and living conditions influence health outcomes (Kirby et al., 2017). The rising prevalence underscores the need for future research to understand the contributing factors. Despite the increasing prevalence of developmental delays and the observed rise in referrals for early educational assessments, little is known about the spatial patterns of affected children and the environmental or socio-economic factors that might contribute to these developments in Switzerland. To address these gaps, this thesis focuses on a geographic viewpoint of children diagnosed with developmental delays in the Canton of Zurich.

1.5 Research Gaps und Research Questions

Early identification and intervention for children with developmental risks significantly improve their long-term health and educational outcomes; therefore, providing optimal care for children with developmental delays requires early identification to initiate support early in life (Cioni et al., 2016). The increasing prevalence of developmental delays in children further highlights the need for continuous monitoring to understand the influence of potential environmental factors (Li et al., 2023). There is strong evidence suggesting that ASD and ADHD remain underdiagnosed in many countries around the world, and further research and awareness building are needed (French et al., 2023). The long-term outcomes of living with ADHD appear to place significant burdens on both individuals and society (Bernfort et al., 2008). Therefore, an early diagnosis has a significant impact on gaining access to appropriate help and care (French et al., 2020).

The reason behind the observed substantial rise in referrals to developmental assessments at the University Children's Hospital remains unclear. To this date, no study has systematically examined the spatial distribution in the Canton of Zurich of children diagnosed with developmental delay or how this distribution changes over time. This thesis aims to provide insight into the spatial and temporal distribution, as well as potential contributors, among children living in the Canton of Zurich. This thesis aims to provide insight into the spatial and temporal distribution of these children and explore potential contributing factors.

Research question 1: How are the residential locations of children diagnosed with a developmental delay spatially distributed in the Canton of Zurich?

This question investigates whether spatial clusters can be identified and where these clusters are located in the Canton of Zurich.

Research question 2: Do the spatial distribution patterns of children diagnosed with a developmental delay change over time?

By comparing data from 2018 and 2023, this question aims to determine whether temporal shifts or new spatial trends have emerged.

Research question 3: Which socioeconomic and environmental factors could be associated with the increase of children diagnosed with a developmental delay?

The final question explores potential correlations between developmental delays and environmental and social factors, such as SES, air quality, or living environment. The aim of the thesis is to better understand how geographic factors may interfere with child development. A better understanding of the catchment area and spatial distribution of children referred to a developmental assessment could provide valuable insights to better understand the causes of these increases.

2 Methods

2.1 Datasets and Preprocessing

This section provides an overview of the datasets used in this study, as well as the preprocessing steps required to prepare them for spatial analyses. The main dataset, provided by the University Children's Hospital Zurich, includes information about children assessed in 2018 and 2023. Additional datasets, such as demographic data, location geometries, environmental exposures, and social indicators, were prepared. All datasets were processed using R software (R Core Team, 2024). This study focuses on the Canton of Zurich as the study area.

2.1.1 Children's Hospital Dataset

The University Children's Hospital Zurich has the largest unit for developmental pediatric assessments in Switzerland, with more than 2'000 children per year undergoing extensive diagnostic workups. Therefore, its database provides the opportunity to analyse information about clinical and socioeconomic as well as spatial characteristics. Due to the protection of data privacy, the dataset was anonymised as much as possible. The Children's Hospital Dataset was provided as an xlsx file. The data contains information on the age, gender, postcode, and diagnosis(es) of the children for the years 2018 and 2023. The column containing the diagnoses is a free text field with no standardized rules for recording diagnoses.

To gain an initial overview of the diagnoses contained in the dataset, text mining techniques were applied using R. In order to analyse word frequencies in the free-text diagnosis entries, the text was first tokenized. German stopwords from the Snowball stopwords list (Benoit et al., 2021) were removed, along with a set of custom stopwords defined specifically for this project. This included numeric values, filler words, and other contextually irrelevant terms. As a next step, the frequency of each remaining word was calculated. The 20 most frequent words were selected and visualized in the form of a word cloud, highlighting the most commonly occurring terms in the dataset (Figure 2).

Figure 2: Word cloud of the 20 most frequent terms occurring in the free-text diagnosis column

2.1.1.1 Selection of Key Diagnoses for Analysis

Following the text mining process, the focus was placed on the diagnoses ASD, ADHD, isolated language delay, and premature birth. In this context, isolated language delay refers to language impairments without any additional confirmed developmental diagnoses.

The frequent appearance of terms such as *Autismus* (autism) and *Spektrum* (spectrum) highlights the relevance of ASD within the dataset. Similarly, the prominence of language-related terms such as *Spracherwerbsstörung* (language acquisition disorder), *Sprachentwicklungsstörung* (language development disorder) and *sprachlich* (linguistic, language-related), indicates the importance of language delay. Furthermore, references to birth-related concepts, including *GG* (birth weight) and *SSW* (gestational week), suggest that premature birth is a recurring theme.

The selection of these key diagnoses is also based on their conceptual relevance in the study. Language delay, for instance, is a common developmental concern, and because it affects only one domain, globally harmful causes such as environmental toxins appear less likely compared to more global disorders such as ASD.

Preterm birth was included due to its frequent appearance in the dataset and its potential significance for the analysis. On the one hand, the prevalence of preterm birth might be influenced by environmental factors; on the other hand, prematurity itself may contribute to an increased risk of developmental delays (Vogel et al., 2018).

2.1.1.2 Filtering of Diagnoses

To extract the rows containing the chosen diagnoses, word fragments were identified for each diagnosis and then used for filtering. After this preliminary step, the rows were manually checked according to specific criteria for the diagnoses isolated language delay, ASD and ADHD. The criteria ensured that only IDs with confirmed diagnoses were retained in the dataset. Due to the unstructured text data, manual review was necessary to verify that the filtered terms correctly referred to the child's diagnosis, rather than indicating a suspected diagnosis, a reference in the anamnesis, or a diagnosis of a sibling. This process was conducted separately for each diagnosis; comorbidities were not taken into account. If an ID with a confirmed diagnosis occurred in multiple years, only one entry was retained. In such cases, the year that was deemed most appropriate based on contextual information was manually selected.

The filtering for premature birth was more straightforward, as this condition is clearly defined and therefore not noted as suspected. As a result, only 50 rows of the preliminary filtered rows were manually checked, all of which were correct. If a row occurred more than once, the entry with the later date was deleted in R.

2.1.2 Localities

In order to establish the spatial reference for the postcodes included in the children's hospital dataset, the official directory of towns and cities, published by the Federal Office of Topography, short swisstopo, was used. The dataset includes the names, post codes and geographical coordinates in vector format of all localities in Switzerland (swisstopo, 2024). Since a locality can belong to multiple municipalities, and a municipality can include several localities (swisstopo, 2024), an exact assignment of localities to municipalities was not possible.

Some localities with the same name and unique postal code are located in more than one municipality and/or canton. Therefore, localities were assigned to municipalities and cantons using a spatial intersection approach. In cases where a locality overlapped with multiple municipalities or cantons, the one with the largest intersection area was selected. The original geometries of the localities were preserved, and the resulting dataset included added columns indicating the assigned municipality and canton. Since SaTScan, the software that was used to conduct the cluster analyses (Section 2.2.2), requires constant geographical areas, the same geographical datasets were used for both 2018 and 2023. Since no relevant changes occurred in the boundaries of the cantons between the years 2018 and 2023, data from 2023

was used. There were changes in the municipality borders between 2018 and 2023, caused by merges of certain municipalities. Since the borders of 2023 closely resemble those of 2024, and most of the data are available based on the current municipal borders, the 2024 dataset was used.

2.1.3 Population

To contextualize the number of children diagnosed with developmental delays, Population and Households Statistics (STATPOP) from the Federal Statistical Office (BFS, 2024) was used. The STATPOP statistics form part of the Swiss national census system. They provide detailed annual information on the size and structure of the resident population at the end of each calendar year. The data are provided as a hectare grid (100 meter resolution), where each hectare is represented by a point.

The dataset was aggregated by locality, and the number of females, males, and total population aged 0-19 years was included for the years 2018 and 2023. Each point was spatially joined with the corresponding locality from the AMTOVZ dataset using a within-geometry spatial join. The number of children per locality was then aggregated by summing the respective point values. This enabled the precise estimation of the child population per locality.

2.1.4 Pediatricians

To account for regional differences in access to pediatric care, the availability of pediatricians was included as an indicator of healthcare access. The dataset used in this study originates from the Medical Ambulators Structure (MAS) survey, in which all working physicians active in the outpatient, inpatient or other sectors were obliged to participate (Grüebler, 2021). The dataset was prepared by Etienne Grüebler (2021) in the context of her master's thesis, in which she assessed pediatric accessibility in the canton of Zurich. It includes physicians who reported pediatric and adolescent medicine as their main activity. This group was included as a social factor because of their central role in early identification of developmental delays through routine developmental surveillance and screenings (Choo et al., 2019). For the present analysis, the data was aggregated by locality to estimate the availability of pediatric care across regions.

2.1.5 Swiss Neighbourhood Index of Socioeconomic Position

To account for the socioeconomic status of the study population, the Swiss Neighbourhood Index of Socioeconomic Position was used Panczak et al. (2023). The dataset is owned and provided by the Swiss Federal Statistical Office (SFSO) and was used under a legal agreement for research purposes. To define the Swiss Neighbourhood Index, the authors defined neighbourhoods of around 50 households and characterized them based on socioeconomic indicators such as rent, education, occupation, and crowding using principal component analysis.

For this study, the hybrid version Swiss-SEP 3 was used. As described by Panczak et al. (2023), this version combines detailed information on the socioeconomic characteristics of existing neighbourhoods with newer data for areas that have been developed in more recent years. The dataset was provided as point data and aggregated at the location level, with the median values of SwissSEP3 calculated for each location.

2.1.6 Pollutants

To account for air quality, the dataset of air pollution emissions from the canton of Zurich was used. This dataset contains emission data for various pollutants for each municipality in Zurich. As with the locality-level adjustments described earlier, the air pollution data was adapted to the locality level using a spatial intersection approach, assigning municipalities to the localities based on the largest intersection area.

2.1.7 Land Cover

Data on land use and cover were obtained from the Swiss Federal Statistical Office's Arealstatistik 2020/25 (BFS, 2024). The dataset provides spatial information on different land cover categories. Green spaces were identified based on selected codes from the LC25_27 (27 basic categories of land cover of Arealstatistik 2020/25; see Appendix A1 for a detailed list of selected codes) classification system. Traffic areas were filtered using the land use code 120 from the LU25_10 (10 categories of land use of Arealstatistik 2020/25), which represents all traffic areas.

Both green spaces and traffic areas were spatially joined with the locality boundaries. The number of green space units per locality was aggregated and divided by the total area of each locality to calculate the relative green space coverage. The same procedure was applied to calculate the relative share of traffic areas per locality.

2.2 Analysis Methods

As spatial relationships are a key factor in understanding disease patterns and their determinants, Geographic Information Systems (GIS) are increasingly used to analyze and interpret the geographic dimensions of health-related data (Kirby et al., 2017). According to Elliott et al. (2000), spatial analyses in epidemiology can be grouped into four categories: disease mapping, geographical correlation studies, risk assessment related to point or line sources, and cluster detection and disease clustering.

In this thesis, disease mapping, geographical correlation analysis, and cluster detection methods were applied to examine spatial patterns and potential influencing factors for selected developmental diagnoses. To conduct the cluster and regression analyses, R version 4.4.1 (Posit team, 2024) was used, along with the software SaTScan version v10.2.5 (Kulldorff, 2024), which was accessed through R using the package rsatscan. The cluster analyses were conducted with all the filtered diagnoses, meaning isolated language delay, ASD, ADHD and premature birth. The regression modeling was conducted only with isolated language delay, premature birth, and ASD.

2.2.1 Disease Mapping

To visualize the spatial distribution of the selected diagnoses, incidence maps were created for each diagnosis. These maps serve to provide an initial overview of regional patterns and potential spatial disparities in the occurrence of developmental delay. The incidence rate was calculated as the number of cases per locality divided by the population of that locality, multiplied by 100’000. The resulting rates were categorized into five quantile-based groups to allow for a consistent classification across all diagnoses, despite differing case numbers. To increase statistical robustness and improve the visibility of spatial patterns, both birth cohorts (2018 and 2023) were combined in this analysis.

2.2.2 Cluster Analysis

Cluster detection methods are widely used to detect and monitor potential public health hazards (Kulldorff and Nagarwalla, 1995). A cluster refers to a group of health events occurring in close proximity in space and / or time (Moore and Carpenter, 1999). For detecting clusters in space and time, Kulldorff’s SaTScan (Kulldorff, 2024) was used. SaTScan was selected based on strong recommendations in the literature regarding its high performance compared to other spatial analysis methods. SaTScan™ is a freely available software program used to detect and analyze spatial, temporal, and space-time patterns in data by applying scan

statistics. A variable-sized scanning window systematically moves across the study area, calculating the probability for each window that it contains a cluster of events. The window with the highest probability is identified as the most likely cluster (Han et al., 2016). SaTScan can be run either through its graphical user interface or programmatically via R using the rsatscan package (Kleinman, 2025). In this thesis, SaTScan was executed directly from R in order to reduce redundant manual work and make the workflow more efficient.

To identify spatial clusters of varying sizes while avoiding pre-selection bias, a series of analyses was conducted using different maximum cluster sizes (10, 20, 30, 40, and 50 percent of the population at risk). These values were implemented in an automated function, which iteratively performed SaTScan runs for each specific threshold. This approach ensured that cluster detection is not biased by a priori assumptions about spatial extent (Kulldorff, 2024). Only clusters with a p-value over 0.05 were selected and visualized.

For ADHD in 2018, no clusters were found when using 50 percent of the population at risk as the maximum spatial cluster size. In 2023, only one very large cluster was identified. Due to the lack of meaningful smaller clusters and the inconsistency in cluster detection across years, this diagnosis was excluded from further spatial analysis.

2.2.3 Regression Modelling

Regression modelling is often used to analyze how exposures – whether binary, categorical, or continuous – affect response variables (Bender, 2009). To address the research question of whether a certain exposure has an impact on the number of children with developmental delays, Poisson regression was applied. This approach, which is particularly suitable for modeling count data, assumes that the outcome variable follows a Poisson distribution (Plan, 2014; Sellers et al., 2012). Poisson regression belongs to the family of generalized linear models and allows for the inclusion of multiple predictors to assess their individual and combined effect on the outcome (McCullagh & Nelder, 1989).

2.2.3.1 Pearson Correlation

To assess potential multicollinearity among the predictors, Pearson correlation coefficients were calculated. The analysis revealed strong correlations among air pollutants, with the exception of NH_3 (ammonia). To avoid redundancy and multicollinearity in the regression models, only two pollutants – $PM_{2.5}$ and NH_3 – were retained. All other predictors showed acceptable levels of correlation and were therefore included in the regression models without further adjustments.

2.2.3.2 Model Selection

A stepwise model selection procedure was. Both forward and backward selection were used iteratively choose the best-fitting model based on the Akaike Information Criterion (AIC). This approach allowed for identification of most relevant subset of predictors for each outcome while minimising the risk of overfitting. Separate models were run for each diagnosis, using the combined data from both years to increase the number of cases and thus improve statistical power and representativeness. To account for potential differences between the years, the year was included as a categorical variable in all the models. Each model used the number of cases per locality as the outcome variable, with the population size per locality included as an offset to adjust for varying population sizes of the localities. The following predictors were included in all the models in the model selection step:

- Number of paediatricians per locality
- Median SwissSEP 3.0 median
- Relative area covered by green spaces
- Relative area covered by traffic infrastructure
- Emissions of NH_3
- Emissions of $PM_{2.5}$
- Year

3 Results

To examine the distribution patterns of residential locations of children diagnosed with premature birth, isolated language delay, and ASD, disease mapping, and cluster detection were applied, while regression modelling was used to assess potential social and environmental factors. This chapter begins with a descriptive overview of the children included in the dataset, followed spatial distributions and clusters. The final section presents potential social and environmental factors associated with these developmental delays.

3.1 Study Cohort

A total of 2’860 children were included in the dataset, 1’426 in the year 2018 and 1’434 in the year 2023. These children were all assessed at the University Children’s Hospital during those respective years. For the purposes of this study, only children who were residing in the Canton of Zurich at the time of their assessment were considered. The following sections provide an overview of the study cohort and the chosen diagnoses.

3.1.1 Cohort Description and Demographics

A total of 2’156 children were assessed at the University Children's Hospital in Zurich in the years 2018 and 2023.In 2018, a total of 1’084 children were included in the dataset. The mean age was 5.4 years, with ages ranging from 0.2 to 18.1 years. Of these children, 37.5 percent were female and 62.5 percent male.

In 2023, 1’072 children were assessed. The mean age in this year was slightly higher with 5.7 years, with a minimum age of 0.3 years and a maximum of 17.8 years. The proportion of female participants was 32.5 percent, while 67.5 percent were male.

An overview of the key demographic characteristics is presented in Table 1. In addition, Figures 3 and 4 provide visual representations of the age and gender distributions for the 2018 and 2023 cohorts, respectively. A more detailed overview of the entire dataset, as well as breakdowns for each diagnosis and year, can be found in Appendix A3.

Table 1: Overview of all children assessed in 2018 and 2023, residing in the Canton of Zurich

Characteristic	2018	2023
Number of Children (n)	1’086	1’073
Mean Age (years)	5.4	5.7
SD Age (years)	3.8	3.6
Gender (female / male)	37.5% / 62.5%	32.5% / 67.5%

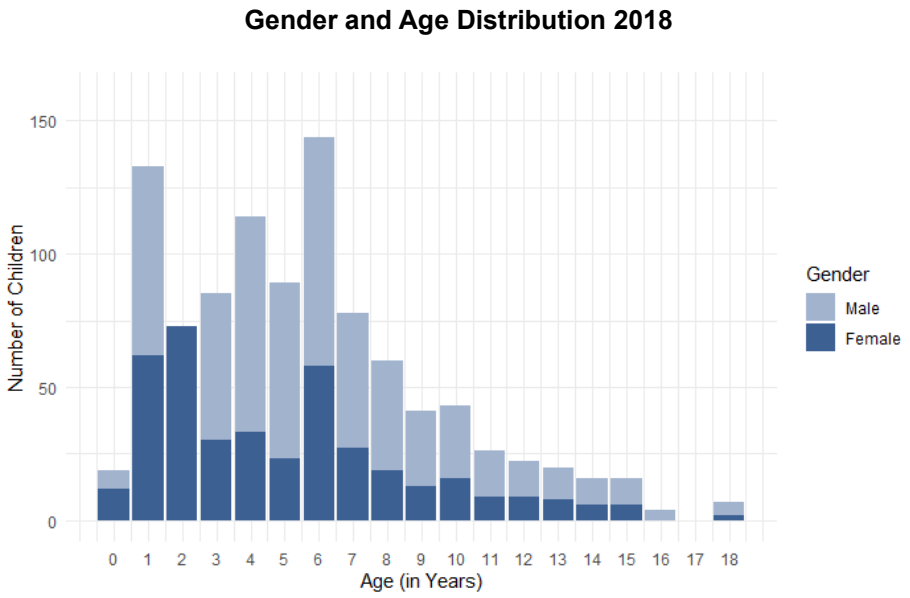


Figure 3: Age and gender distribution of children residing in the Canton of Zurich assessed in 2018

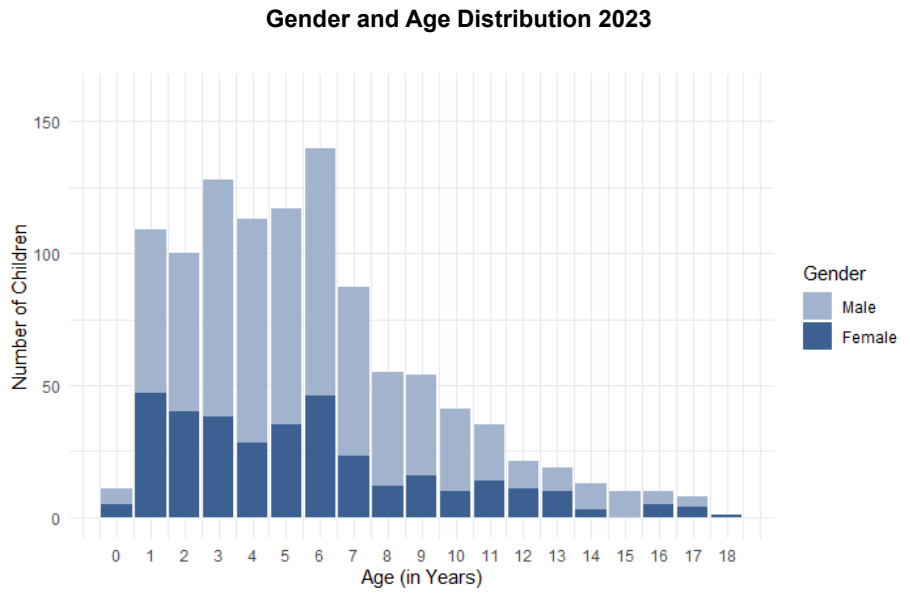


Figure 4: Age and gender distribution of children residing in the Canton of Zurich assessed in 2023

3.1.2 Prevalent Diagnoses and their Frequency

As shown in Figure 5, premature birth was the most prevalent diagnosis in both years, with a notably higher frequency in 2018 compared to 2023. The second most prevalent diagnosis was isolated language delay, which showed a similar number of cases in both years. ASD ranked third in frequency, with a marked increase in diagnoses observed in 2023. ADHD was the least frequently diagnosed condition among the four, but also exhibited an increase in 2023, although still significantly less frequent than ASD.

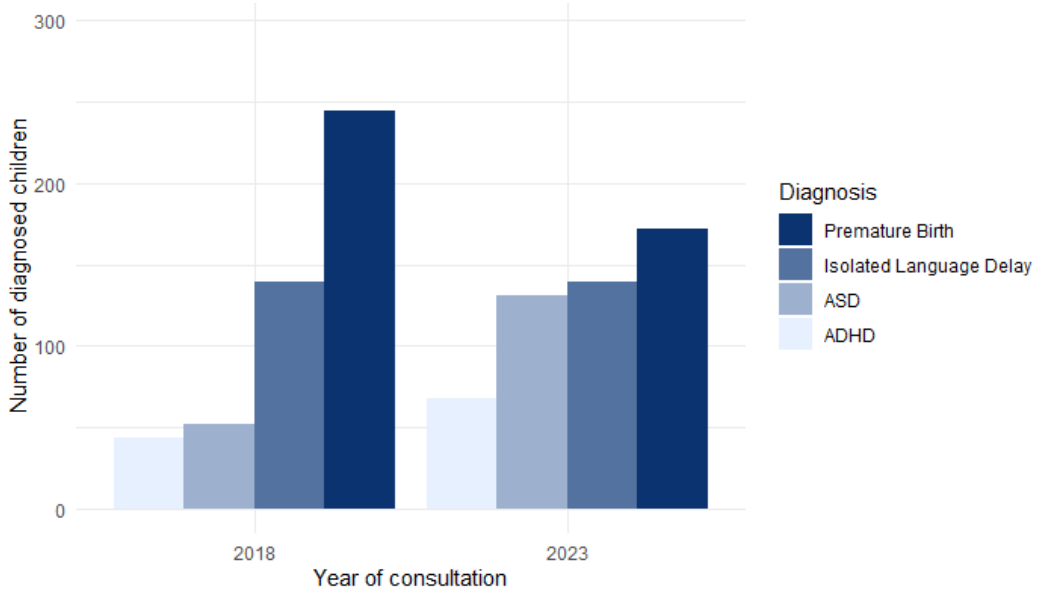


Figure 5: Frequency of the selected diagnoses premature birth, isolated language delay, ASD and ADHD in the study cohort for the years 2018 and 2023

3.2 Spatial Distribution of Incidence Rates

This section presents the results of the disease mapping for each diagnosis, expressed as the incidence rate per 10’000 children based on the background population data from STAPOP. Both years were combined to increase the number of cases, thereby providing more meaningful results. For each diagnosis, the cases were divided into quantiles to ensure better comparability across the different development delays.

3.2.1 Premature Birth

The spatial distribution of premature birth (Figure 6) is particularly concentrated around Zurich and along its northern shore, including the urban center of Zurich. Elevated incidence rates are also observed in the northern region of the canton, extending up to Weiach. Both north and south of Lake Zurich, increased rates reach toward the cantonal borders. In contrast, the northeastern part of the canton shows the lowest incidence. Some municipalities in the northernmost part of the canton, such as Flurlingen, Uhwiesen, and Marthalen, exhibit medium incidence rates, as do Attikon and Gundetswil on the northeastern edge.

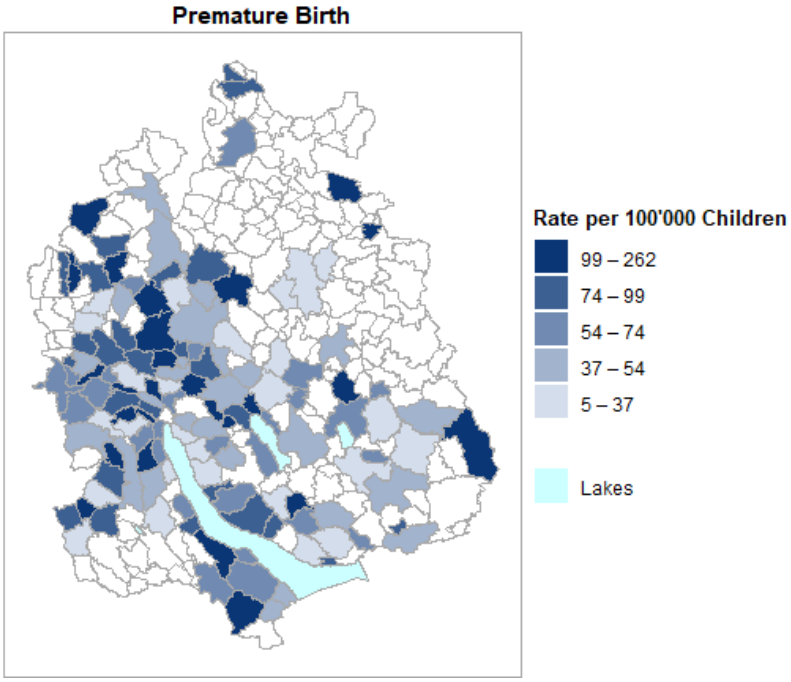


Figure 6: Incidence of premature birth per 100’000 children

3.2.2 Isolated Language Delay

Incidence rates of isolated language delay (Figure 7) are highest in urbanised localities, particularly in the northern part of Lake Zurich, including localities such as Kloten. However, elevated rates are again not limited to these urban centers – they also extend further north to localities such as Höri and Bachenbülach. As in the patterns of premature birth, the northeastern part of the canton shows the lowest incidence. Uhwiesen, in the far north of the canton, again exhibits increased rates. Similarly, the localities surrounding Lake Zurich continue to show elevated incidence.

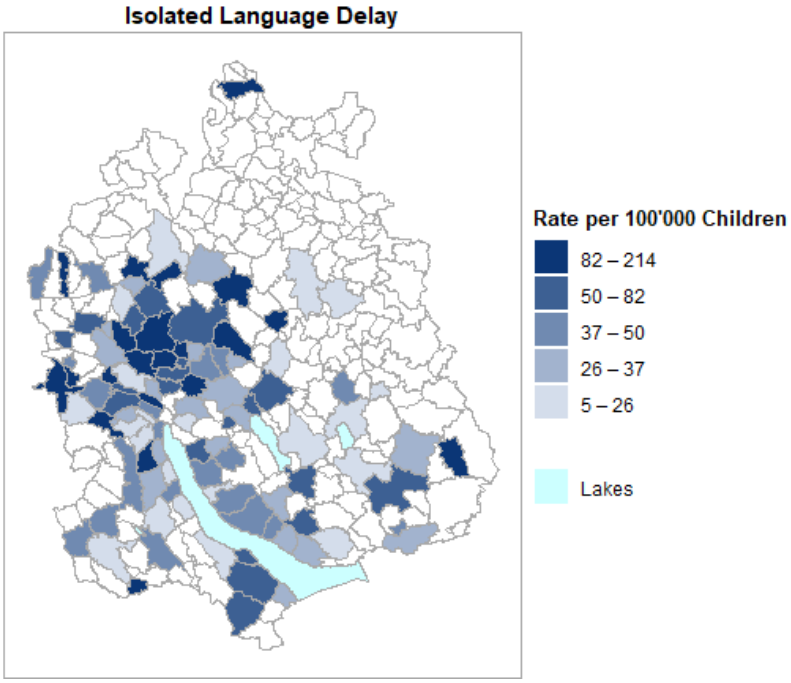


Figure 7: Incidence of isolated language delay per 100’000 children

3.2.3 ASD

The spatial patterns of ASD incidence (Figure 8) is comparatively less distinct but still shows elevated rates in urban localities around Lake Zurich. Higher incidence is particularly observed in the northwestern part above the lake. Additionally, some municipalities at the southeastern edge of the canton - such as Sternenberg, Steg im Tösstal, and Gibswil - also show elevated rates. While the area surrounding Lake Zurich continues to display increased incidence, the difference across regions are less pronounced compared to the patterns observed for premature birth and isolated language delay.

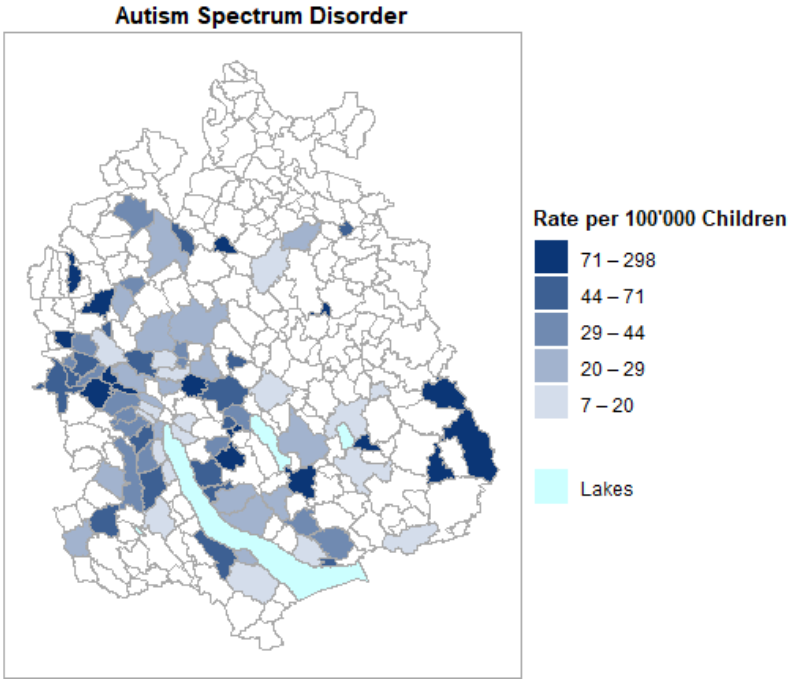


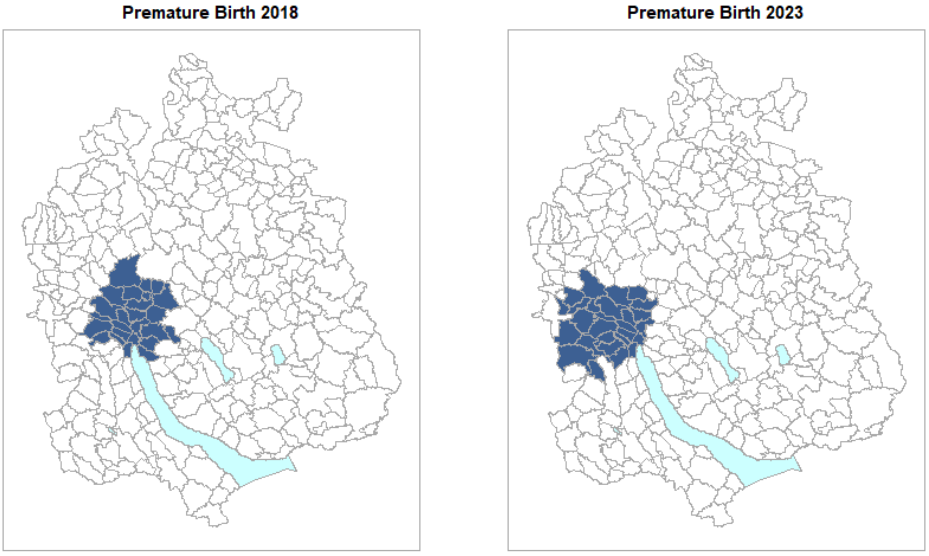
Figure 8: Incidence of ASD per 100’000 children

3.3 Spatial Clustering of Developmental Delays

This section presents the results of the spatial analysis using the Discrete Poisson model implemented in the SaTScan software, focusing on the diagnoses Isolated Language Delay, Premature Birth, and ASD. The population at risk was set to 50 percent, while the maximum spatial cluster size was fixed at 20 percent of the population for all analyses, as this size yielded the best clusters in terms of size and extent across all diagnoses and years. All reported clusters for all tested sizes can be found in Appendix A3. For each diagnosis and year, at least one significant cluster was identified. For each cluster, the corresponding p-value and relative risk (RR) are reported.

3.3.1 Premature Birth

As illustrated in Figure 9, in both 2018 and 2023, the clusters for premature birth were located north of Lake Zurich, corresponding to the urban area of Zurich and its surroundings. These clusters primarily included locations within the city of Zurich, with the upper boundary extending to the regions of Rümlang and Regensdorf. While the 2018 cluster was smaller and confined to the urban area, the 2023 cluster expanded further into the areas west of the city, reaching as far as Birmensdorf. In 2018, the RR of 2.091 suggests a more than double risk of premature birth in the cluster areas. The year 2023 shows an even higher RR of 2.646, reflecting a stronger association between a broader geographic spread.



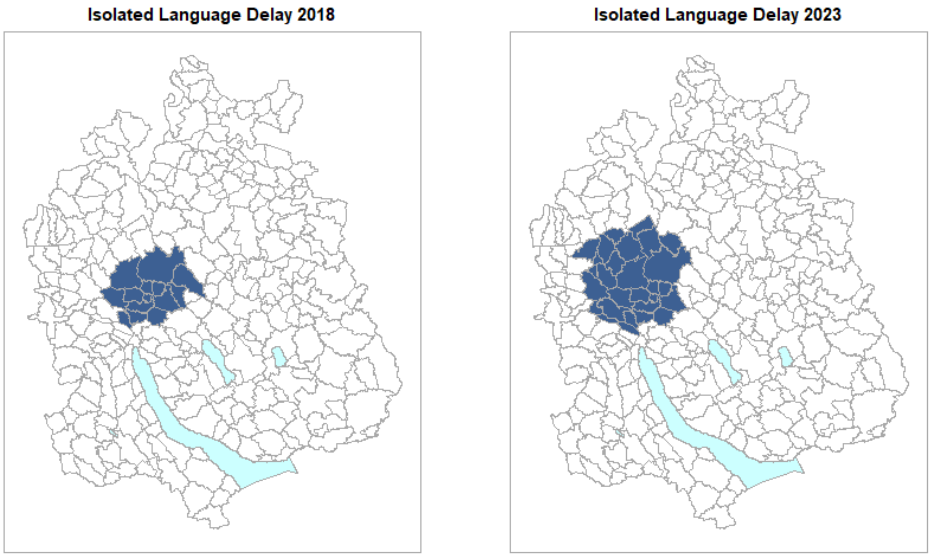
P-Value	RR
0.000431423	2.091

P-Value	RR
7.3333e-06	2.646

Figure 9: Spatial Cluster for Premature Birth in 2018 and 2023, identified using SaTScan

3.3.2 Isolated Language Delay

In both 2018 and 2023, the clusters for isolated language delay (Figure 10) were again located north of Lake Zurich, but began not directly along the lakeshore, but in the middle to upper parts of the city of Zurich. The cluster in 2018 extended north to Kloten and east to Oberengstringen, encompassing urban regions and immediately adjacent localities. The 2023 cluster, in contrast, was larger and expanded further north to Bachenbülach, incorporating both urban and peri-urban areas. In 2018, the RR of 3.876 indicates a notably higher risk of isolated language delay in the cluster areas, while the 2023 RR of 2.863 reflects a slightly lower, but still significant, risk in the expanded region.



P-Value	RR
2.66e-08	3.876

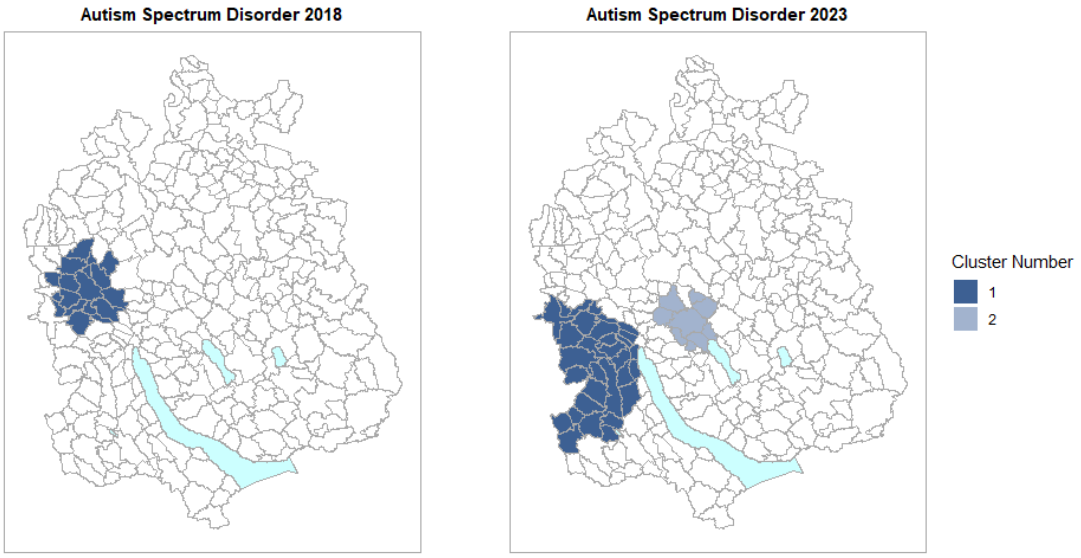
P-Value	RR
4.8654e-05	2.863

Figure 10: Spatial Cluster for Isolated Language Delay in 2018 and 2023, identified using SaTScan

3.3.3 ASD

As shown in Figure 11, in 2018, a significant cluster for ASD was identified in the western region of the canton of Zurich, including the localities of Dielsdorf, Buchs, Oberhalden, and parts of the urban area of the municipality of Zurich. The RR of 4.67 indicates a significantly higher risk of ASD in these areas compared to others.

In 2023, two significant clusters were detected (Figure 11). The first cluster, much larger in size, extended west of the upper and middle parts of Lake Zurich. It spanned from the upper Zurich Lake area to Dietikon and reached the border at Oberfelden, including parts of the city of Zurich. The second cluster, located above Greifensee, was smaller and included only a few localities, with Dübendorf being the central locality in this area.



P-Value	RR
0.011	4.67

Cluster	P-Value	RR
Nr. 1	0.0019590604	2.545
Nr. 2	0.0041414973	3.51

Figure 11: Spatial Cluster for Premature Birth in 2018 and 2023, identified using SaTScan

3.4 Correlation with Environmental Factors

This section presents the results of Poisson regression models assessing the association between social and environmental factors and the cases of the diagnoses premature birth, ASD and isolated language delay in relation to the background population. The models were built using stepwise selection to identify the most relevant predictors for each outcome. Data from both 2018 and 2023 were combined in a single model, with year included as covariate to account for temporal effects.

3.4.1 Results of Poisson Regression Models

3.4.1.1 Premature Birth

As summarized in Table 2, the Poisson regression model indicates a significant negative association between the proportion of green spaces per locality and the incidence of premature birth, suggesting a potential protective effect of greener environments. In contrast, $PM_{2.5}$ concentrations were positively associated with incidence rates, indicating increased risk in areas with higher air pollution. A temporal comparison revealed a significantly lower incidence in 2023 compared to 2018.

Table 2: Results of Poisson Regression Models for Premature Birth

Characteristic	log(IRR)	95% CI	p-value
Green Spaces	-0.11	-0.19, -0.03	0.007 **
NH_3	0.00	-0.01, 0.00	0.12
$PM_{2.5}$	0.01	0.00, 0.01	<0.001 ***
Year (2023)	-0.39	-0.59, -0.20	<0.001 ***

Abbreviations: CI = Confidence Interval, IRR = Incidence Rate Ratio

3.4.1.2 Isolated Language Delay

For isolated language delay, several factors showed a significant association (Table 3). The density of paediatricians was negatively associated with incidence, suggesting higher access to pediatric care may be protective. Socioeconomic status also showed a marginally non-significant negative association. Green spaces again showed a significant negative association, while a higher proportion of traffic areas and $PM_{2.5}$ were positively associated with incidence. NH_3 showed a marginally non-significant negative association.

Table 3: Results of Poisson Regression Models for Isolated Language Delay

Characteristic	log(IRR)	95% CI	p-value
Pediatricians	-0.08	-0.16, -0.01	0.039 ***
Median SSEP-3	-0.02	-0.04, 0.00	0.081 .
Traffic Areas	0.02	0.00, 0.04	0.014 *
Green Spaces	-0.14	-0.26, -0.03	0.013 *
NH_3	-0.01	-0.01, 0.00	0.081 .
$PM_{2.5}$	0.00	0.00, 0.01	0.028 *

Abbreviations: CI = Confidence Interval, IRR = Incidence Rate Ratio

3.4.1.3 ASD

Table 4 shows that in the ASD model, higher values of SSEP-3 were significantly associated with incidence, indicating a link with socioeconomic status. NH_3 was negatively associated, while $PM_{2.5}$ showed again a significant positive association. Green space coverage displayed a marginally significant negative association.

Table 4: Results of Poisson Regression Models for ASD

Characteristic	log(IRR)	95% CI	p-value
Pediatricians	-0.07	-0.17, 0.02	0.15
Median SSEP-3	-0.04	-0.06, -0.02	0.001 **
Green Spaces	-0.12	-0.25, 0.00	0.054 .
NH_3	-0.01	-0.02, -0.01	0.002 **
$PM_{2.5}$	0.01	0.00, 0.01	0.005 **
Year (2023)	0.88	0.57, 1.2	<0.001 ***

Abbreviations: CI = Confidence Interval, IRR = Incidence Rate Ratio

4 Discussion

This study aimed to examine the spatial distribution and potential contextual factors associated with selected developmental delays, namely premature birth, isolated language delay, autism spectrum disorder (ASD), and attention deficit disorder (ADHD), among children assessed at the University Children's Hospital in Zurich in 2018 and 2023. Significant spatial clusters were identified for premature birth, isolated language delay, and ASD, primarily located in the urban areas north of Lake Zurich. Several environmental and social factors were associated with the observed distribution: elevated levels of air pollution ($PM_{2.5}$) were consistently linked to higher incidence rates, whereas greater green space coverage appeared to have a protective effect across all examined conditions. In the following sections, different aspects of the analyzed patterns as well as the study's strengths and limitations will be discussed.

4.1 Spatial Distribution

Regarding the spatial distribution of the target diagnoses, we found single significant spatial clusters for premature birth and isolated language delay in both years, and for ASD in 2018 in our disease mapping and cluster analyses. The lack of significant results regarding ADHD in 2018 may be due to the relatively low number of cases, which reduces statistical power and limits the detection of spatial patterns (Cohen, 1988). The cluster analysis for ASD in 2023 revealed two significant clusters with different relative risks, which may suggest that distinct regional factors are influencing the distribution.

The repeated appearance of clusters in similar geographic areas suggest that certain regions may be more affected by – or more sensitive to the detection of – developmental delay. This could be linked to a combination of socioeconomic, environmental, or healthcare-related factors. For instance, urban areas often provide greater access to diagnostic services, which may lead to a higher detection rate (Ghahari et al., 2021; Shattuck et al., 2009).

4.2 Temporal Changes of Spatial Distribution

To assess temporal changes in the spatial distribution of developmental delays, clusters identified in 2018 and 2023 were compared for each diagnosis. For premature birth, the cluster area expanded geographically from a smaller core around the urban center of Zurich in 2018 to a larger zone that extended westward into peri-urban locations such as Birmensdorf in 2023. The spatial expansion was accompanied by an increase in relative risk (RR from 2.091 to 2.646), indicating a growing concentration of premature births in a broader area.

For isolated language delay, the RR decreased from 3.876 to 2.863 between 2018 and 2023, yet the cluster grew in size and extended further north. While the intensity of risk decreased slightly, the geographic spread increased, possibly pointing toward broader but less densely concentrated risk areas.

The ASD clusters showed a particularly notable temporal change: from a single, compact cluster in the west of Zurich in 2018 (RR 4.67) to two spatially distinct clusters in 2023, one large and one smaller. The RR values in 2023 were lower (2.545 and 3.51). This shift could indicate changes awareness (Zeidan et al., 2022) or diagnostic practices.

4.3 Socioeconomic and Environmental Factors

The third research question addressed whether socioeconomic and environmental factors could be associated with the spatial distribution of the developmental delays, premature birth, isolated language delay, and ASD. The Poisson regression models yielded several relevant findings, many of which were consistent across diagnoses.

Socioeconomic status (SES), proxied by the hybrid version of the Swiss Neighbourhood Index of Socioeconomic Position, played different roles across diagnoses. While it showed a non-significant trend towards lower incidence of language delay, it was significantly associated with ASD incidence, with higher SES linked to lower incidence rates. This finding contrasts with several studies from other contexts, particularly from the United States, where higher SES has been associated with increased ASD prevalence (e.g., Thomas et al., 2012). A possible explanation of this could be that in Switzerland, access to healthcare services is more universal and less dependent on income or socioeconomic background, potentially reducing diagnostic disparities across SES strata, particularly reducing the cases of undiagnosed children with ASD in families with lower SES.

Health care access was approximated by the number of pediatricians per locality. For isolated language delay, a significantly negative association was observed. Speech and language delays are often diagnosed late due to wait-and-see approach, with early identification largely depending on primary care clinicians (Sunderajan and Kanhere, 2019). The negative association between the number of pediatricians and isolated language delay may reflect that pediatricians in areas with higher numbers were able to identify and address language delays earlier.

Green spaces emerged as a recurrent protective factor. For all three diagnoses, a higher proportion of green areas in a locality was associated with lower incidence rates. These findings are consistent with previous research, such as the study by Wu and Jackson (2017), who found that within school districts in California, a higher proportion of urban green spaces was associated with lower prevalence of childhood autism. The consistent negative correlation between green space coverage and incidence across all three diagnoses reinforces the potential protective effect of green environments.

In contrast, $PM_{2.5}$ concentrations were consistently positively associated with the incidence rate for all three diagnoses. The association between $PM_{2.5}$ and ASD and premature birth prevalence was consistent with previous studies (Guo et al., 2018; Liu et al., 2023). The fact that $PM_{2.5}$ was a significant risk factor in all three models further underlines its public health relevance, especially in urban regions with high traffic density. This is further supported by the finding that isolated language delay was positively associated with the proportion of traffic areas. This observed association may be indirectly linked to traffic-related air pollution, which tends to be higher in areas with dense traffic infrastructure.

The Poisson regression revealed varying temporal trends for the diagnoses of premature birth and ASD. Isolated language delay did not show a significant change in incidence between 2018 and 2023. For ASD, the data indicated a significant increase in incidence between 2018 and 2023. This is consistent with the growing public awareness and health (Zeidan et al., 2022). For premature birth, a significant reduction in incidence was observed between 2018 and 2023. This could be explained by the updated guidelines, which now focus on infants born before 28 weeks instead of infants born before 32 weeks (Kümin, 2025), leading to fewer cases being assessed as premature birth in 2023 compared to 2018.

4.4 Strengths and Limitations

One of the key strengths of this thesis is the novel spatial perspective it brings to the study of developmental delays in the Canton of Zurich. By integrating spatial analysis methods, this study provides a geographically nuanced understanding of how environmental and social factors may correlate with the distribution of the diagnoses of premature birth, isolated language delay, and ASD in this study area. Furthermore, the inclusion of a broad spectrum of diagnoses enables differentiated insight into potentially shared and distinct spatial patterns and risk factors.

The findings must be interpreted with caution due to a potential spatial bias. The data includes only children who were assessed at the University Children's Hospital in Zurich. As such, the higher incidence observed in the surrounding urban areas may partly reflect proximity to the hospital rather than a true elevated risk in these regions. Other major hospitals in the canton, such as Winterthur, also diagnose developmental delays, but children assessed at those institutions were not included in the dataset. This may have led to an underrepresentation in this region and an overrepresentation of diagnoses in the Zurich city areas as well as its surroundings. Despite these limitations, the repeated appearance of clusters in the same regions across both years suggest some stability in regional diagnostic patterns.

Another limitation of the thesis is the difficulty in precisely attributing the correct diagnoses to the correct ID. Since the diagnoses had to be filtered from a free-text section without a standardized structure, which often contains anamnesis information in addition to the diagnoses, there is uncertainty about whether all relevant diagnoses were accurately extracted. Due to data protection regulations, the residential information of the children was disclosed only at the postcode level. The information regarding the place of residence was recorded at the time when the child was diagnosed; there is no data on how long the child lived there, whether they changed their place of residence before or after, or where they spent the majority of their life. Additionally, the mother’s place of residence during pregnancy is unknown, which could be important information regarding environmental factors that may influence whether the child develops a developmental delay or not.

5 Conclusion

This thesis investigated the spatial distribution and potential contextual factors associated with selected development delays – namely isolated language delay and autism spectrum disorder (ASD) – as well as premature birth, based on data from children aged 0-8 who were assessed at the University Children's Hospital Zurich in 2018 and 2023. The major findings are that developmental delays and premature birth show consistent spatial clustering north of Lake Zurich, and that environmental and social factors, such as air pollution, green space availability, and access to pediatric care, were associated with regional variation in incidence rate. Pediatricians and therapists could use this spatial information to identify areas with higher risk of developmental delays and prioritize outreach and diagnostic screening in these regions. Such targeted interventions could help reduce early identification disparities and ensure that children receive appropriate support as early as possible.

These findings underscore the importance of considering geographical and contextual socioeconomic and environmental factors when addressing developmental delays. While this study benefits from a spatially nuanced analysis, the potential bias due to the single hospital dataset may limit the generalizability of the findings. In future research, it would be advisable to include data from as many diagnostic centers as possible throughout the canton to obtain a more comprehensive picture of the assessed children. Moreover, conducting such analyses on a national level would provide valuable insights into regional disparities and broader spatial patterns across Switzerland.

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Appendix

A1 Selected Codes for Identification of Green Spaces

The following table provides the selected land cover categories from the LC25_27 classification system of the Arealstatistik 2020/25 (BFS, 2024), used for identifying green spaces in the study.

Code	Label German	Label Translated in English
14	Beetstrukturen	Bed structures
15	Rasen	Lawn
16	Bäume auf künstlich angelegten Flächen	Trees on artificially created surfaces
17	Gemischte Kleinstrukturen	Mixed small structures
21	Gras-, Krautvegetation	Grass and herbaceous vegetation
31	Gebüsch	Shrub
32	Verbuschte Flächen	Overgrown areas
33	Niederstammobst	Low-stem fruit trees
34	Reben	Vines
35	Gärtnerische Dauerkulturen	Horticultural permanent crops
41	Geschlossene Baumbestände	Closed tree stands
42	Waldecken	Forest corners
43	Waldstreifen	Forest strips
44	Aufgelöste Baumbestände	Dispersed tree stands
45	Gebüschwaldbestände	Shrub forest stands
46	Lineare Baumbestände	Linear tree stands
47	Baumgruppen	Groups of trees
64	Schilfbestände	Reed beds

A2 Descriptive Statistic of Diagnosed Children Living in Zurich

Isolated Language Delay 2018	Results
Number of Children	139
Mean Age (Years)	5.71
Min Age (Years)	1.43
Max Age (Years)	17.85
Standard Deviation (Years)	2.57
Female (%)	28.78
Male (%)	71.22

Isolated Language Delay 2023	Results
Number of Children	139
Mean Age (Years)	5.26
Min Age (Years)	1.33
Max Age (Years)	13.88
Standard Deviation (Years)	2.20
Female (%)	24.46
Male (%)	75.54

Premature Birth 2018	Results
Number of Children	245
Mean Age (Years)	3.04
Min Age (Years)	0.25
Max Age (Years)	15.02
Standard Deviation (Years)	2.45
Female (%)	44.08
Male (%)	55.92

Premature Birth 2023	Results
Number of Children	172
Mean Age (Years)	3.04
Min Age (Years)	0.37
Max Age (Years)	14.62
Standard Deviation (Years)	2.42
Female (%)	43.60
Male (%)	56.40

ADHD 2018	Results
Number of Children	44
Mean Age (Years)	9.95
Min Age (Years)	5.07
Max Age (Years)	18.06
Standard Deviation (Years)	2.81
Female (%)	27.27
Male (%)	72.73

ADHD 2023	Results
Number of Children	68
Mean Age (Years)	9.68
Min Age (Years)	4.46
Max Age (Years)	17.11
Standard Deviation (Years)	2.74
Female (%)	32.35
Male (%)	67.65

ASD 2018	Results
Number of Children	53
Mean Age (Years)	5.17
Min Age (Years)	1.94
Max Age (Years)	15.12
Standard Deviation (Years)	2.71
Female (%)	22.64
Male (%)	77.36

ASD 2023	Results
Number of Children	131
Mean Age (Years)	6.10
Min Age (Years)	2.46
Max Age (Years)	16.86
Standard Deviation (Years)	3.32
Female (%)	24.43
Male (%)	75.57

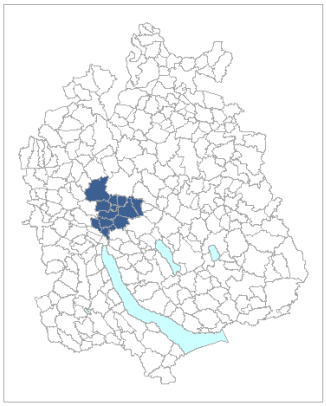
Whole Data 2018	Results
Number of Children	1,084
Mean Age (Years)	5.35
Min Age (Years)	0.18
Max Age (Years)	18.06
Standard Deviation (Years)	3.67
Female (%)	37.45
Male (%)	62.55

Whole Data 2023	Results
Number of Children	1,072
Mean Age (Years)	5.67
Min Age (Years)	0.27
Max Age (Years)	17.76
Standard Deviation (Years)	3.58
Female (%)	32.46
Male (%)	67.54

A3 Reported Cluster Sizes

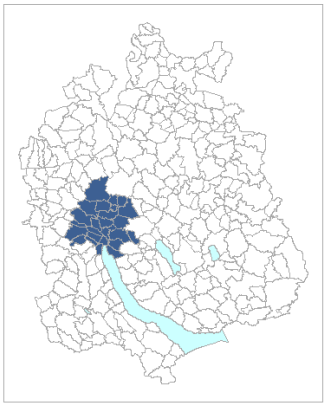
Premature Birth 2018

Clusters smaller than 10 percent



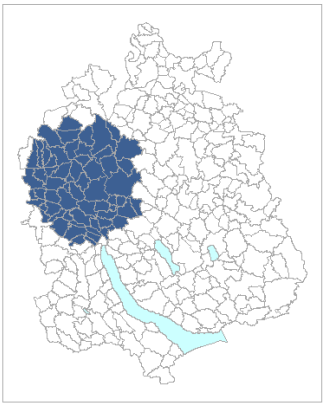
P-Value	Relative Risk
0.037	2.105

Clusters smaller than 20 percent



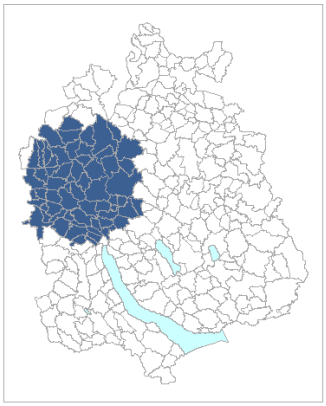
P-Value	Relative Risk
0.000431423	2.091

Clusters smaller than 30 percent



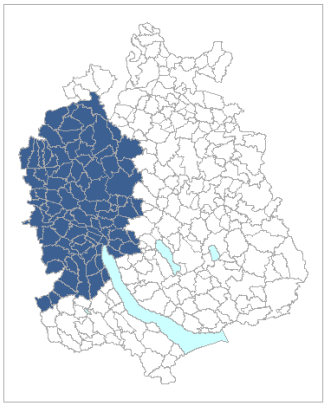
P-Value	Relative Risk
6.92663e-05	2.077

Clusters smaller than 40 percent



P-Value	Relative Risk
2.37453e-05	2.124

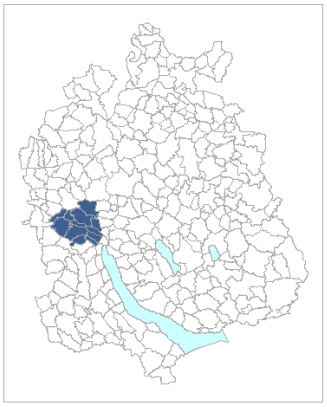
Clusters smaller than 50 percent



P-Value	Relative Risk
5.0055e-06	2.214

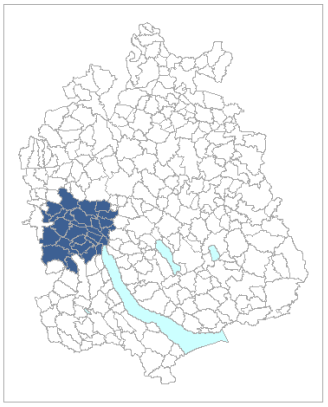
Premature Birth 2023

Clusters smaller than 10 percent



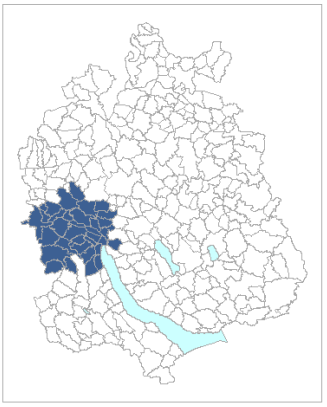
P-Value	Relative Risk
0.0010808303	2.687

Clusters smaller than 20 percent



P-Value	Relative Risk
7.3333e-06	2.646

Clusters smaller than 30 percent

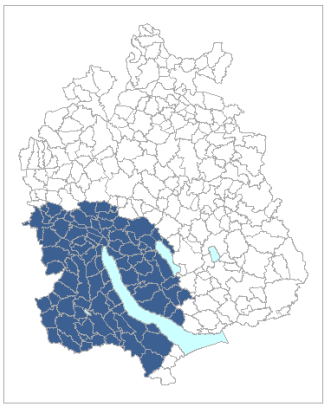


P-Value	Relative Risk
1.469e-06	2.666

Clusters smaller than 40 percent

P-Value	Relative Risk
9.92e-08	2.801

Clusters smaller than 50 percent



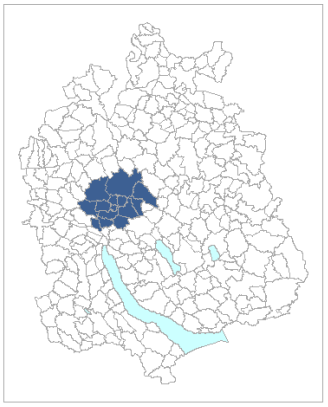
P-Value	Relative Risk
4.3e-09	3.268

Isolated Language Delay 2018

Clusters smaller than 10 percent

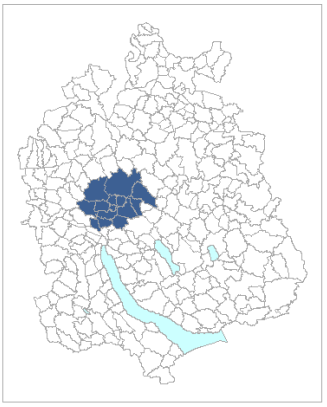
P-Value	Relative Risk
5.855e-07	4.406

Clusters smaller than 20 percent



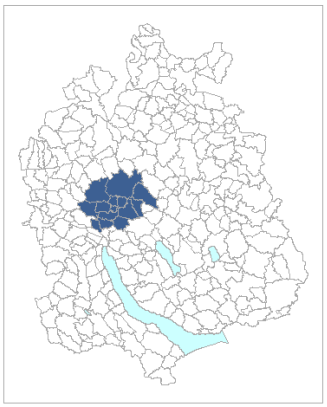
P-Value	Relative Risk
2.66e-08	3.876

Clusters smaller than 30 percent



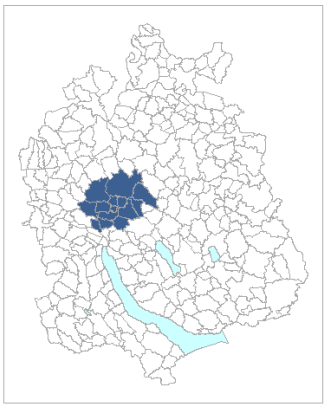
P-Value	Relative Risk
2.66e-08	3.876

Clusters smaller than 40 percent



P-Value	Relative Risk
2.66e-08	3.876

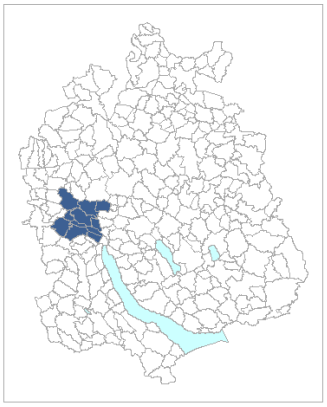
Clusters smaller than 50 percent



P-Value	Relative Risk
2.66e-08	3.876

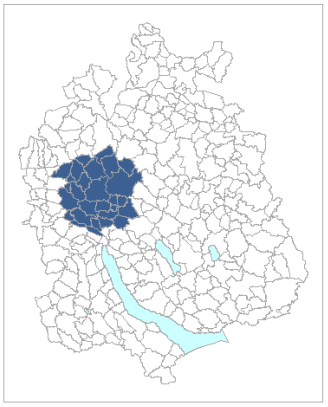
Isolated Language Delay 2023

Clusters smaller than 10 percent



P-Value	Relative Risk
0.0005312961	3.087

Clusters smaller than 20 percent



P-Value	Relative Risk
4.8654e-05	2.863

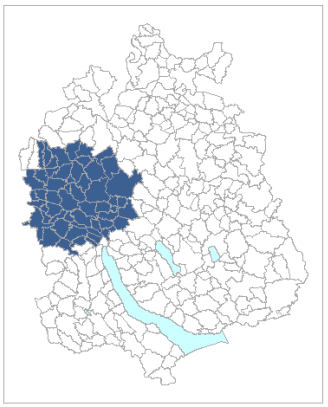
Clusters smaller than 30 percent

P-Value	Relative Risk
3.4762e-06	2.875

Clusters smaller than 40 percent

P-Value	Relative Risk
3.4762e-06	2.875

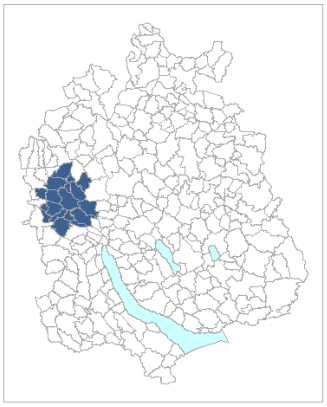
Clusters smaller than 50 percent



P-Value	Relative Risk
3.4762e-06	2.875

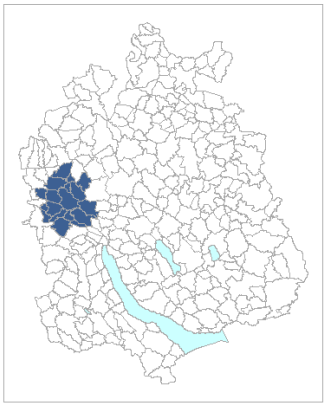
ASD 2018

Clusters smaller than 10 percent



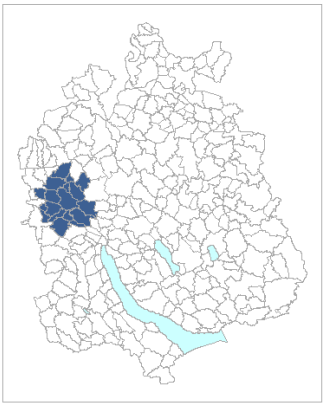
P-Value	Relative Risk
0.011	4.67

Clusters smaller than 20 percent



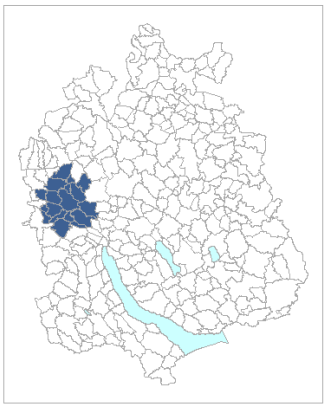
P-Value	Relative Risk
0.011	4.67

Clusters smaller than 30 percent



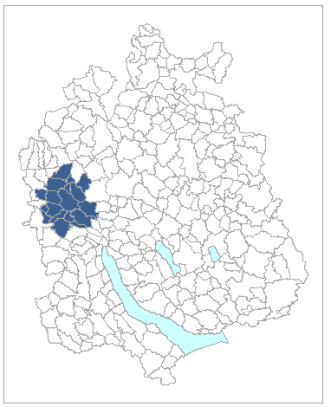
P-Value	Relative Risk
0.011	4.67

Clusters smaller than 40 percent



P-Value	Relative Risk
0.011	4.67

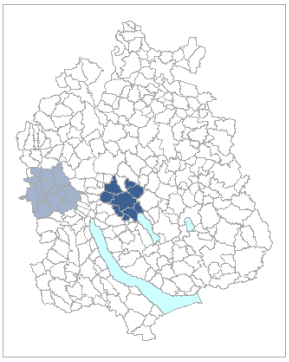
Clusters smaller than 50 percent



P-Value	Relative Risk
0.011	4.67

ASD 2018

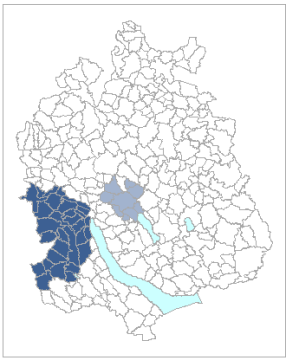
Clusters smaller than 10 percent



Cluster Number 1 2

Cluster Number	P-Value	Relative Risk
1	0.0041414973	3.51
2	0.011	2.88

Clusters smaller than 20 percent



Cluster Number 1 2

Cluster Number	P-Value	Relative Risk
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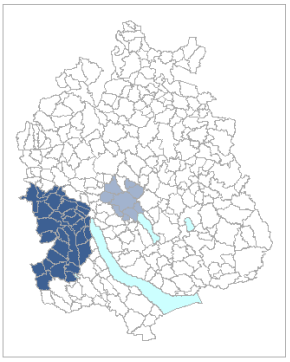
2	0.0041414973	3.51

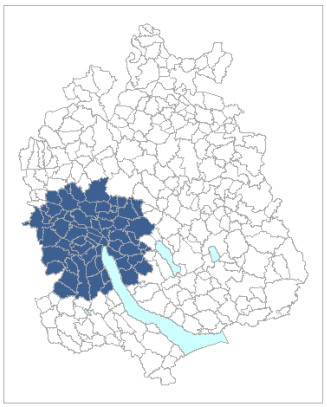
Clusters smaller than 30 percent



Cluster Number 1 2

Cluster Number	P-Value	Relative Risk
1	0.0019590604	2.545
2	0.0041414973	3.51

Clusters smaller than 40 percent



P-Value	Relative Risk
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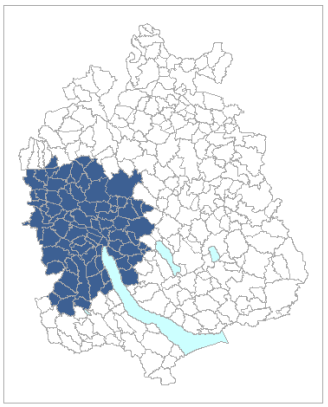
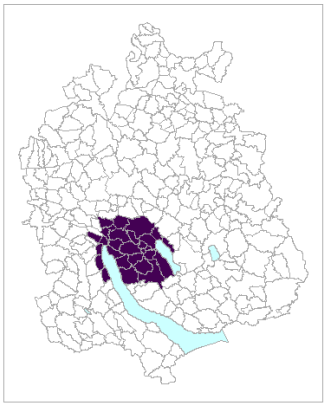
Clusters smaller than 50 percent



P-Value	Relative Risk
1.092e-07	3.497

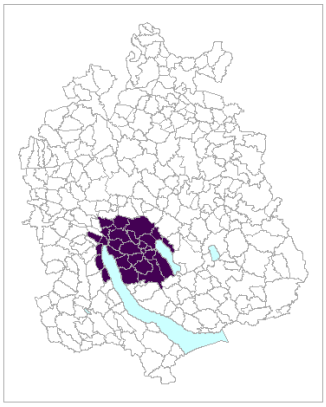
ADHD 2018

Clusters smaller than 20 percent



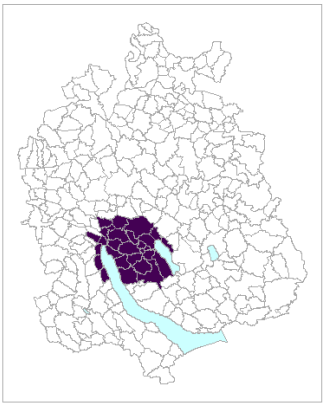
P-Value	Relative Risk
0.039	3.725

Clusters smaller than 30 percent



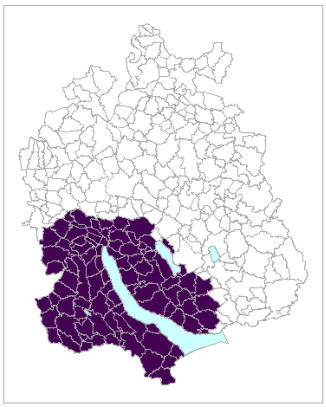
P-Value	Relative Risk
0.039	3.725

Clusters smaller than 40 percent



P-Value	Relative Risk
0.039	3.725

Clusters smaller than 50 percent



P-Value	Relative Risk
0.017	4.001

Personal Declaration

I hereby declare that the submitted thesis is the result of my own independent work. All external sources are explicitly acknowledged in the thesis.

I used the AI tool ChatGPT[1] for English proofreading and sentence refinement.

Tanja Falasca Bern, 25.04.2025

[1]Open AI. (2025). ChatGPT (Version 2) [large language model]. https://chatgpt.com/