Runnability index

Creation of an extended runnability index with weather influences

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Abstract

This research focuses on the effect of precipitation on running behaviour of people in the city of Utrecht. From scientific literature, different features of the built environment are identified that influence running behaviour. These different features are used to create a benchmark runnability index, which is then extended with a variable depicting influences on running behaviour depending on the precipitation level. By analysing running routes scraped from Endomodo, the differences between dry, moderate precipitation and heavy precipitation runs were found, which were used to quantify the influences of the environment given the precipitation level. With these new models, the runnability scores at road level and neighbourhood level were determined, which showed that there exist some hotspots in Utrecht for running. Furthermore, with a correlation analysis between the different runnability indices and running data, it was found that the extended runnability indices described the running behaviour for different precipitation levels better, which shows that including weather in the runnability index is useful. Further research should be focused on getting more running data to analyse the differences and similarities between runs with different precipitation levels. With this knowledge, the runnability index could then be improved even further.

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Introduction

Mental and physical health is a broadly discussed subject in different research areas and receives great attention from decision-makers. The Dutch government has allocated 60 million euros every year for preventive measures described in the 'National Prevention Agreement' (Ministry of Health, Welfare and Sport, 2020). The Dutch government mentions physical activity to reduce the risk of physical and mental illness. Furthermore, not only does the Dutch government emphasise the importance of exercise, but several studies have shown the benefits of physical activity on the physical and psychological well-being of humans (Mandolesi et al., 2018; Scully et al., 1998; Yeung, 1996).

During the COVID-19 pandemic, the focus on mental well-being became even more important. As people weren't able to perform their regular social and physical activities due to the restrictions, their mental and physical health decreased causing stress, burn-outs and other related disorders (Agha, 2021; Villani et al., 2021). As a response to this, people were recommended to perform outdoor physical activities to reduce the risk of these diseases and increase psychological health (Maugeri et al., 2020; Polero et al., 2021). A widely adopted physical exercise during the COVID-19 pandemic was running as this physical activity does not require much equipment and can be done almost anywhere (Gogoi, 2021; Ling, 2020).

For further promotion of physical activities such as walking, urban planning and design can play an important role. It is found that some features of the built environment are associated with higher levels of walking or other forms of physical activity (Abley et al., 2011; Frank, Lawrence et al., 2003; Kamruzzaman et al., 2016; McCormack & Shiell, 2011; Saelens & Handy, 2008). To quantify this association Frank developed a walkability index, which can be used by urban planners to design 'walkable' neighbourhoods (Frank, Lawrence D. et al., 2010). However, the relationship between the built environment and walking behaviour differs for purposive walking and discursive walking, where purposive walking is often used as a form of transport, while discursive walking is a physical and recreational activity.

Running can be compared with discursive walking; some people like to run as a physical and recreational activity. Thus running behaviour of a person may depend on the built environment and its characteristics, but simply using the components of walkability would produce wrong results (Ettema, 2016; Shashank et al., 2021). Therefore, Shashank et al. (2021) proposed a Rough Runnability Index (RRI) which uses features of the built environment that promote or hinder running, which are converted to affordances for running.

The RRI of Shashank et al. (2021) considers the environment a person runs in as static, i.e. it is not changing, but it should be considered dynamic as weather, seasons, etc. are ever-changing (Bamberg et al., 2018). Furthermore, not only the environmental features and thus behaviour of a runner is changed, but also the performance of a runner is influenced by different weather types. From a study on the Boston Marathon times, it was even found that precipitation significantly worsened the performance of runners (Knechtle et al., 2019). As the environment is changing so will the runnability index change depending on the type of weather. To include this effect due to the dynamic behaviour of the weather and thus the environment, an additional feature depicting the weather influences should be included in the RRI. Therefore, this research will focus on improving the runnability index by taking into account the dynamics of the environment caused by changes in the weather. The research will be conducted in the City of Utrecht and the following research question will be answered

> *"To what extent can the rough runnability index of Shashank et al.* (2021) *be improved by incorporating the effects of precipitation?"*

To answer the research question the following sub-questions are developed

- *How can precipitation be measured as a factor for the runnability index?*
- *How does precipitation influence running behaviour?*
- *How well can running behaviour be described by the indices for the different precipitation levels?*

First, a small literature review is performed on walkability and runnability to determine the differences and the features used for the RRI. Next, some data exploration and preparation will be done, such that the available data can be used for the newly proposed RRI. Third, the creation of the benchmark RRI and the new RRI will be elaborated and correlation analysis with the running data will be explained to compare the models on performance. Then, the results of both RRIs will be given and analysed, which will be used to answer the research question. Finally, a conclusion will be given and possible further research opportunities will be presented.

Literature review

Designing cities or neighbourhoods that are more 'walkable' such that people use less motorized transportation, is essential to increase physical activity (Frank et al., 2003; Lavizzo-Mourey & McGinnis, 2003). How 'walkable' a neighbourhood is, depends on the built environment and its sociodemographic characteristics (Saelens et al., 2003; Saelens & Handy, 2008). To assess this, Frank (2010) developed a walkability index, which is used to explore relationships between the built environment and forms of active transportation such as walking. This index can be used by urban planners to determine whether a neighbourhood needs transportation enhancements or redevelopment to promote active transportation in a neighbourhood (Frank et al., 2010). Walkability can thus be described as: *"the extent to which the built environment is walking-friendly"* (Abley et al., 2011).

As described before, runnability differs from walkability as the purpose of both activities often differs; transportation or recreation. However, both activities can be discursive or purposive; for example, some people like to walk as physical activity. It is necessary to make a distinction between the two forms of activities as both have different demands and preferences. To make a distinction between the two purposes, this research will regard walking as a purposive activity and running as a discursive activity. The association between running behaviour and the built environment will differ from the relationship between walking behaviour and the built environment (Shashank et al., 2021). However, the description provided by Abley can be rephrased to: "*the extent to which the built environment is running friendly*". Runnability can thus be described by how attractive an environment is to run and how many running people it will attract. Running has become more popular over recent years, but little research has been done into a runnability index. Most researchers focus on what makes an area runnable but do not propose a runnability index or other models to quantify how 'runnable' an environment is. These researches mostly focus on the stated preferences of runners through surveys and interviews, but this may not resemble their actual preferences (Wardman, 1988). By creating a runnability index the revealed preference and the actual influences of the built environment and other features on running behaviour can be determined.

A lot of research on the features of environments that support or hinder physical activity has been done over recent years. Lee & Moudon (2004) performed a literature review and identified unsafe road conditions, traffic, dogs and crowdedness as safety barriers for people to participate in physical activities.

Other aspects such as land use mix, connectivity, population density and green space or nature were also found as important features affecting participation in physical activities (Bamberg et al., 2018; Jansen et al., 2018; McCormack & Shiell, 2011). Associations between the different features and running behaviour are not as widely discussed in comparison with the association between walking and the built environment. Features of the built environment that were mentioned most often to influence running behaviour are road surface, intersections, street trees, traffic calming infrastructure, parks, street lights, major roads and trucking routes (Ettema, 2016; Schuurman et al., 2021; Shashank et al., 2021).

One phenomenon that is not considered by the researchers but which heavily interacts with the environment and is not static is weather variation (Katapally et al., 2015). These weather variations interact with the environmental features which influence running behaviour such as road surfaces or trees. Bodin & Hartig (2003) found that recreational runners prefer to run in parks with dirt paths and gravel roads, but running on muddy, poor roads is not preferred by most runners (Ettema, 2016). Van Renswouw et al. (2019) found that the running paths of people differ during dry and rainy days, resulting in different hotspots for running depending on the weather. Not only the environment is changed by the weather, but also the performance of a runner. Many different types of weather exist, such as hot and cold, dry and rain, sunny or cloudy, etc. The effect of the different types of the weather depends on the type of runner, but increasing precipitation has a decreasing effect on the performance of all different types of runners (Knechtle et al., 2019). Furthermore, it was found that poor weather, such as heavy rain, causes humans to run shorter distances below their average (Wang et al., 2021).

For this research, the runnability index of Shashank et al. (2021) will be used. To create their index they use an affordance-based framework to quantify the features of a built environment that enable people to run. The affordance-based framework was proposed by James Gibson to describe the abilities a natural environment gives to an animal. Affordances can thus be described as a set of constraints and opportunities an environment gives to an animal to perform a certain activity (Gibson, 1977). This framework can also be applied to humans: what abilities the built environment gives to a human. This can, for example, be seen as the opportunity to walk quickly from one location to another without a big detour. This framework is used by different researchers for the creation of '-ability' indices, such as 'climb-ability' and 'walkability' (Jonietz et al., 2013; Lennon et al., 2017; Warren, 1984). Affordances described by Gibson assume binary values: an affordance is present or not.

However, to use an affordance-based framework for an index such as runnability, affordances should be represented by scaled values: i.e. how much different features create opportunities or barriers to run for people (Jonietz et al., 2013). This affordance score can be seen as a score for how attractive an environment is for running.

An affordance-based framework has not been applied before to create a runnability index, besides the RRI of Shashank et al. (2021). However, as it is used to create other 'ability' indices and has shown to be useful, this research will use an affordance-based framework to create a RRI (Garau et al., 2020; Jonietz et al., 2013). From this literature review, it is found that weather has a great effect on the environment and if a certain area is 'runnable'. Furthermore, it is shown that precipitation has a great effect on the running frequency and running distance of humans. Therefore, the runnability index of Shashank will be used as a benchmark and extended with an additional variable for the influence of weather on the affordances of the different features. The performance of this new runnability index will be compared with the RRI to answer the research question. 'Runnability' in this research will thus be a score, indicating if a road is suitable for running. Higher scores indicate higher suitability and thus a higher probability of running.

Data

In this section, the variables used for the runnability indices are selected and the data on these variables is explored. Furthermore, the preparation steps of the variables for the runnability indices will be given.

Variable selection

As there is not much literature available on runnability indexes or runnability, the selected variables are found in the literature on running. Moreover, literature on what makes a person run, what features hinder or promote a run and what increases the performance of a run was used. Most of them were discussed in the literature review and below in table 1 a brief overview of the variables described in the literature on runnability and used for the newly proposed RRI is given. In this table, some features are combined, such as road surface, road density or road size into road characteristics.

Research paper	*Lighting*	*Trees*	*Proximity to parks*	*Connectivity*	*Traffic calming*	*Land use mix*	*Population density*	*Road characteristics*	*Slope*	*Weather*
Bodin & Hartig (2003)								√		
Lee & Moudon (2004)								√		
Saelens & Handy (2008)			√	√		√				
McCormack & Shiell (2011)			√	√	√	√	√			
Ettema (2016)	√		√			√		√		
Jansen et al. (2018)			√			√		√		
Bamberg et al. (2018)		√	√							√
Knechtle et al. (2019)										√
Schuurman et al. (2021)	√	√						√		
Wang et al. (2021)		√	√					√		√
Shashank et al. (2021)	√	√	√	√	√			√	√	
Benchmark RRI	√	√	√	√	√			√		
New RRI	√	√	√	√	√			√		√

Table 1: Related literature

Although the benchmark RI is based on the RRI from Shashank et al. (2021), not all features used by Shashank will be included in the RRI. As can be seen from the table, Shashank included slope in their RRI to account for the ascent and descent during a run. However, their research was conducted in an environment with lots of height variation, but in Utrecht, this variation is relatively small and is therefore not used in the new RRI. Furthermore, it is interesting to see how different researchers include the same features in their view of runnability, such as Saelens and Handy (2008) whose view is included in the work of McCormack and Shiell (2011). Furthermore, how the different features affect the runnability index is discussed in the methods section, where the creation of the runnability index is elaborated.

Data exploration & preparation

Now that the variables for the benchmark RI and new RRI are known, the required data is gathered and explored. First, the running data which is scraped from Endomodo by Zhiyong Wang is analysed on their patterns using rain data. This running data contains running routes from people in the Netherlands from 14-12-2014 until 08-09-2015. By visualizing the running paths with QGIS it can be seen that there exist some faulty records; runs that have a straight line or are running too fast (figure 1). In the running data, there is a column on the running length and average speed, but these also contain some wrong information. Using QGIS the real length of a line is calculated and this length is used to filter out the runs that are longer than 50 km as it can be assumed that these runs are not performed by recreational runners. Next, the runs that have an average speed above 30 km/h are deleted as even the fastest runners on this planet cannot run faster than this speed (figure 2). Finally, the running paths are clipped to the polygon of the city of Utrecht, such that only the runs that are performed in Utrecht are selected, which resulted in 1978 runs(figure 3).

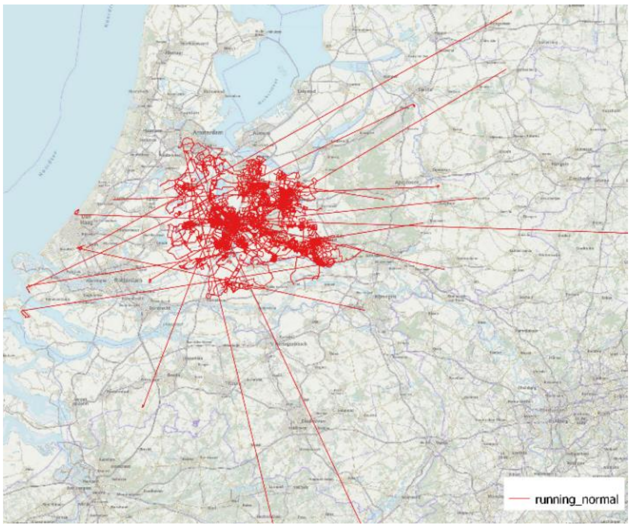

Figure 1: All runs through the Province of Utrecht from Endomodo

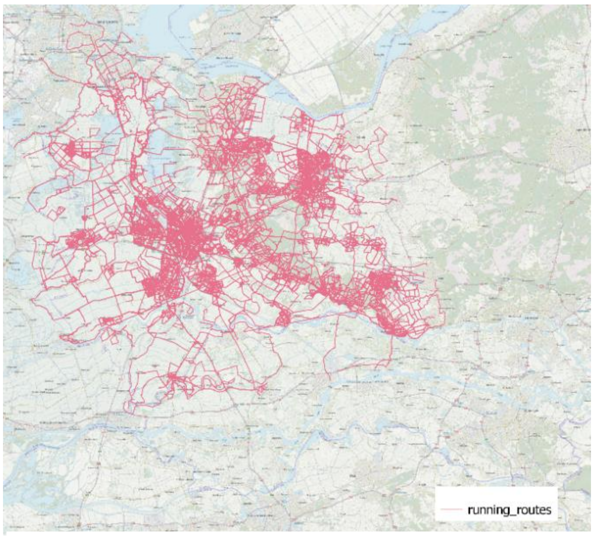

Figure 2: Selected runs in the province of Utrecht

Next, precipitation per day was obtained for the years 2014 and 2015 from KNMI as the runs were also performed in this time frame (KNMI, 2022). With the precipitation per day, rainy and dry runs are selected to explore if there are noticeable differences between these days. For rainy days the two different levels of precipitation are 2.6 mm/h to 7.6 mm/h for moderate rainfall and 7.7 mm/h or higher for heavy rainfall. For dry runs, the upper limit is 2.5 mm/h for observing purposes and running in light levels of precipitation can be beneficial (*Rain - Glossary of Meteorology*. n.d.; Chertoff, 2020). This resulted in 1467 dry runs, 256 moderate rain runs and 225 heavy rain runs (figure 4), which verifies the findings in the literature on the decrease in running frequency during rainy periods. From figure 4, it can be seen that dry and rainy run patterns differ. Where rainy runs mostly stay on bigger roads, dry runs are more performed on smaller (gravel or dirt) roads. Furthermore, in table 2 the basic statistics from the dry runs and rainy runs are listed, such as average distance, duration, speed and frequency per day, which is calculated by the number of runs divided by the number of days of dry, moderate or heavy precipitation levels. From this table, it can be seen that with moderate rain, the average distance, and duration of the runs decrease, which is as expected. However, a noticeable difference is found between the moderate and heavy rain runs, where the average distance increases as well as the duration and the average speed. This can be explained by the fact that most experienced runners will still run during heavy rainfall, while novice or less experienced runners will postpone or cancel their run. However, this can be neglected as there is still a noticeable difference between the running routes during dry and rainy runs, which were used in this research.

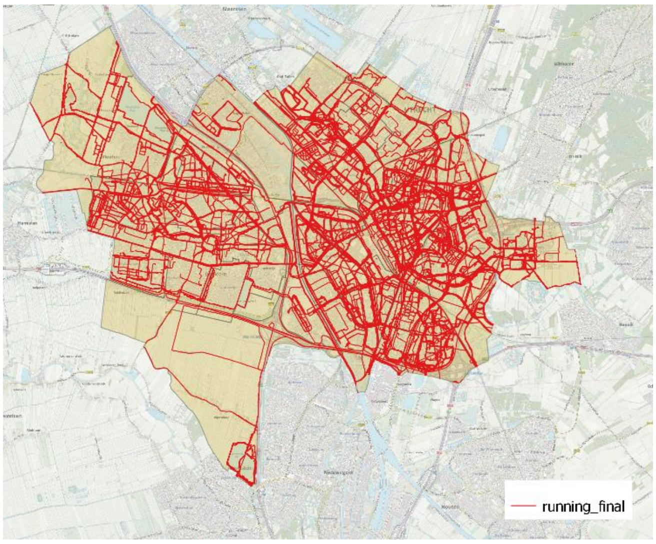

Figure 3: Runs clipped to the city of Utrecht

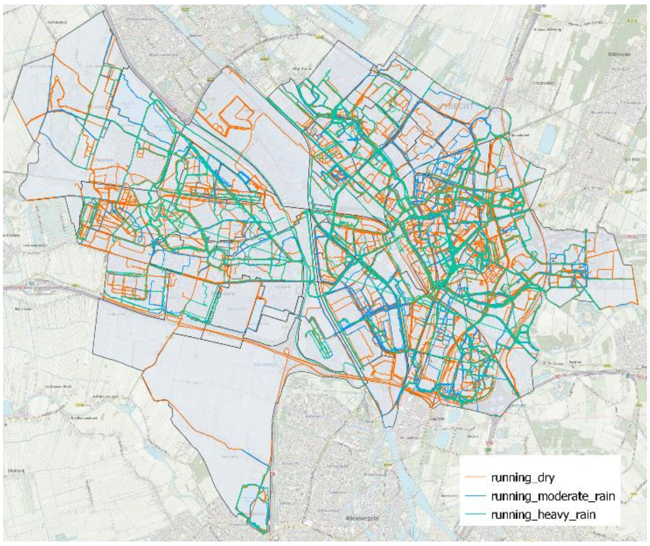

Figure 4: Dry, moderate and heavy rainy runs

	Dry runs	**Moderate rain runs**	**Heavy rain runs**
Average distance	5.77 km	5.25 km	6.10 km
Average duration	2900 sec	2266 sec	2785 sec
Average speed	9,03 km/h	9,17 km/h	9,71 km/h
Average frequency per day	1467/196 = 7.48	256/61 = 4.19	225/47 = 4.79

Table 2: Statistics on the different types of runs

Next, the datasets for the different variables are obtained and analysed for completeness. It is assumed that the environment has not changed much after 2015, so the most recent datasets are used. For lighting, data on the lampposts is obtained from ckan.dataplatform.nl which contains the type of lamppost, neighbourhood, street and geocoordinates of all lampposts managed by the Municipality of Utrecht (figure 5) (Municipality of Utrecht, 2022). This dataset is updated frequently with its last update on 10-05-2022 and is assumed to be complete.

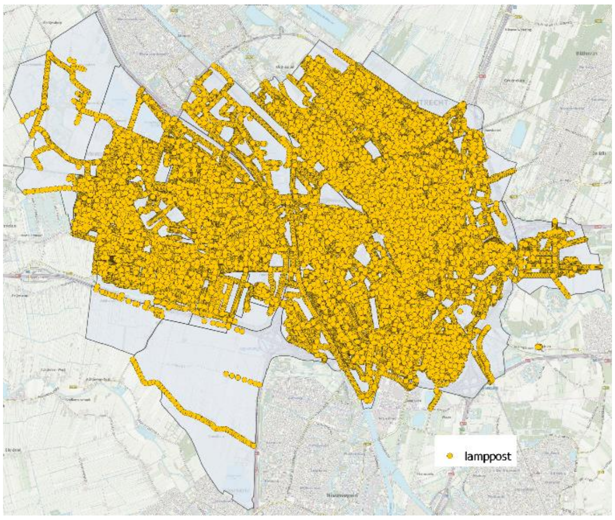

Figure 5: Lampposts in Utrecht

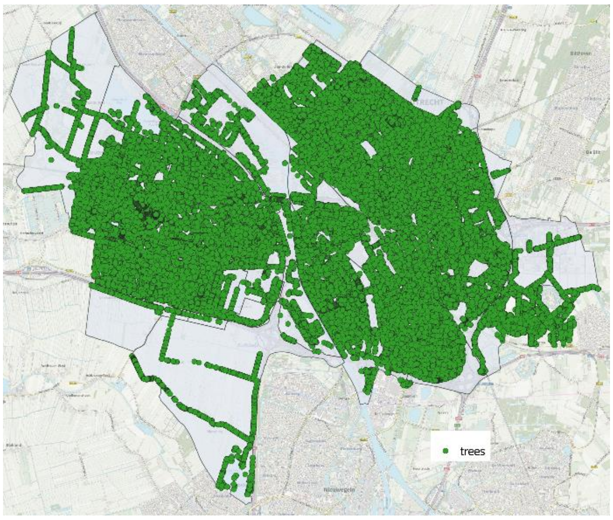

Figure 6: Trees in Utrecht

The trees were also obtained from ckan.dataplatform.nl, which contains around 160000 trees that grow on public grounds and are maintained by the Municipality of Utrecht (Municipality of Utrecht, 2020). This dataset is updated quarterly and the dataset obtained from this website is updated in November 2021 (figure 6). The parks and green spaces were obtained from OpenStreetMap (OSM) and assessed on completeness with the help of data on the green index of the Netherlands (OpenStreetMap, 2022b; OpenStreetMap 2022c; RIVM, 2022). To obtain the parks and green spaces the following key-value pairs were used

- Leisure:park
- Landuse:recreation_ground

In figure 7, the map of the parks, the green index of Utrecht and the boundaries of the PC4 areas are shown, from which it can be seen that most of the parks are stored in the OSM dataset, so it is assumed that this dataset is complete as well.

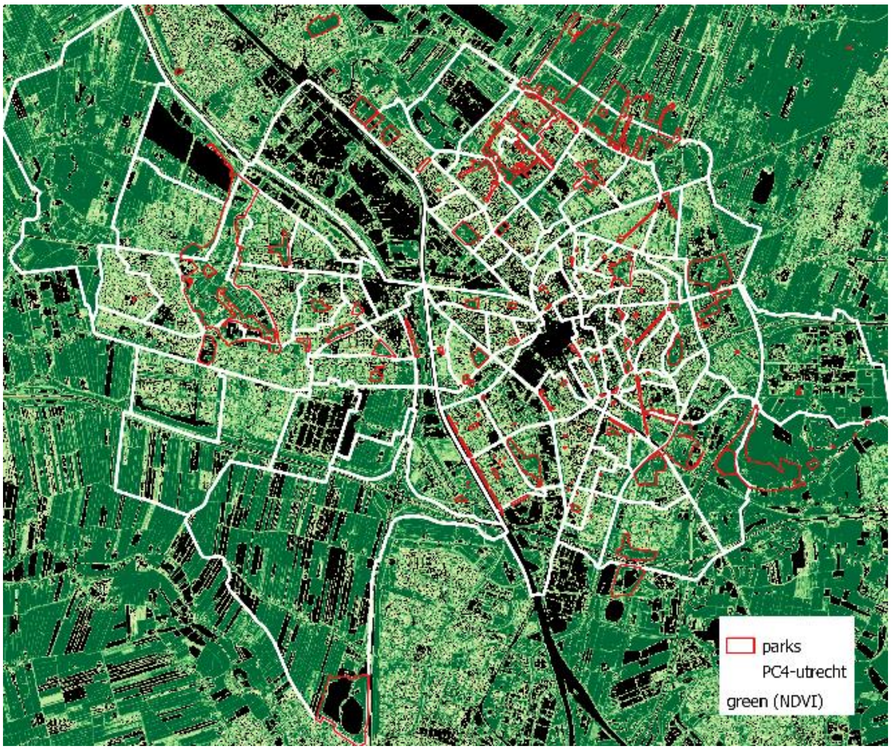

Figure 7: Map of the parks, green index and neighbourhoods boundaries in Utrecht

For the connectivity, traffic calming and road characteristics, data on the roads in Utrecht is used (OpenStreetMap, 2022a). This data is also obtained from OSM and it is assumed that it is complete. Furthermore, data on the trucking routes is obtained from the Province of Utrecht, which contains roads that meet the following criteria: >9800 trucks/24h on highways, >2300 trucks/24h on N-roads, >1300 trucks/24h on provincial roads and >600 trucks/24h on municipal roads (Province of Utrecht, 2022). To get the major roads in the city of Utrecht the following key-value pairs were used in OSM

- highway-primary
- highway-secondary
- highway-tertiary

The traffic calming objects were also obtained from OSM with the key: traffic_calming resulting in the following maps (figure 8 & 9). Furthermore, the roads that are unsuitable for running are excluded from the road network, such as highways or provincial ways.

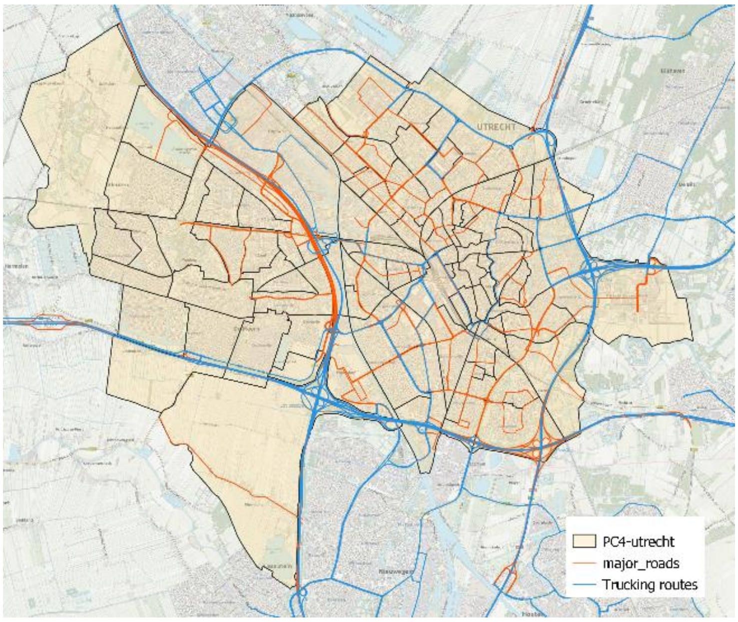

Figure 8: Major roads & trucking routes in Utrecht

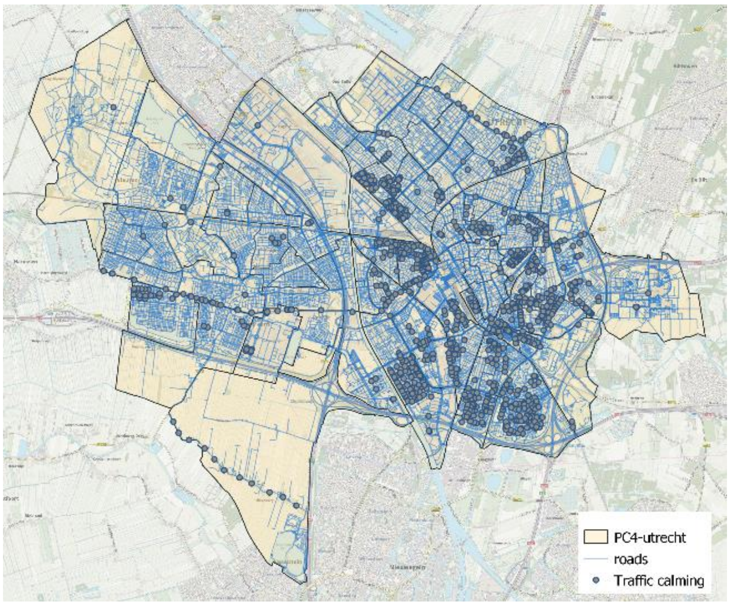

Figure 9: Running roads and traffic calming infrastructure in Utrecht

Methods

In this section, the methods to create the benchmark RRI and the extended RRI with a weather variable are discussed. First, the benchmark RRI is created which is based on the work of Shashank et al. (2021). Next, an additional variable is introduced to create the extended RRI, which is used to answer the research question.

Spatial units

For this research, the appropriate spatial unit needs to be selected, which will be used for all maps and the aggregation of the maps. As there is a lot of environmental variation alongside roads and different neighbourhoods, it is best to use the smallest possible spatial unit (Leslie et al., 2007). This will cause a low variation within this spatial unit and a big variation between spatial units. This thesis will calculate the RRI on the road level as this is the smallest spatial unit possible and best captures the differences between different road segments. Therefore, the scores of the different features are also calculated on road level. Furthermore, with the RRI calculated on the road level, a RRI on neighbourhood level is aggregated as well since the running data on some roads is sparse, which makes validating the RRI for these roads more difficult. The methods for this aggregation and how it is used for validation are discussed below in the validation section.

Benchmark RRI

For the benchmark RRI proposed by Shashank et al. (2021), different raster maps are created which are later combined using a Multi-Criteria Evaluation (MCE) model, which allows giving weights to variables. All maps are based on features which provide affordances to people to run on a certain road segment. For the network where runners would run, some roads from the road network are excluded such as motorways and other bigger roads where running is not possible. Furthermore, a buffer of 5 meters around the roads is created, such that all raster data can be clipped by mask using this dataset to obtain the different scores for each feature on the different road segments. These resulting maps are then used for calculating the final runnability score of each road segment.

Intersections

First, the intersections are calculated using the line intersections tool from the toolbox in QGIS, which results in a point dataset with all intersections from the road network. It is found that intersections hinder runners to perform a run and increase the risk of injuries, which can be seen as a barrier to running on a certain road for people (Pollack et al., 2014; Schuurman et al., 2009;

Shashank et al., 2021). The Euclidean Distance tool is used to calculate proximity to the intersections for the road network, where a bigger distance from the intersections causes less hindrance and thus a higher runnability score. Next, the raster is clipped to the road buffer layer and normalized to values between 0 and 1 using a linear rescale function (Shashank et al., 2021).

Parks

Green environments such as parks promote running and can be seen as attractive environments for runners (Bodin & Hartig, 2003; Deelen et al., 2019; Ettema, 2016). Therefore, roads near parks enable people to run in or near a green environment and thus cause a higher runnability score. Using the Euclidean Distance tool from QGIS the distance to parks is calculated. To obtain the distances to the parks for each road segment the distance raster was clipped to the road buffer layer. Next, the distances were normalized between 0 and 1 using a small fuzzy membership function. This function assigns high values to pixels on the raster with low values, which is needed here as roads closer to parks are more attractive.

Lighting

Well-lit running routes are also frequently mentioned as preferences for road runners, as it provides a feeling of safety (Barnfield, 2016; Boyce et al., 2000; Schuurman et al., 2021). Being close to a lamppost increases the chance of being seen and thus increases safety. Therefore, the proximity to street lighting was calculated using the Euclidean Distance tool. To get the final scores for the lighting, the same approach from the parks dataset was used, which resulted in locations close to lighting having the highest scores.

Major roads and trucking routes

Major roads and trucking routes increase exposure to pollution, which can cause breathing difficulties and thus hinder running or decrease running performance (Hodgson & Hitchings, 2018). Cars and trucks have a limited effect on the air pollution around major roads and trucking routes: i.e. when someone is at a great distance from a road, he or she might not experience air pollution (Europe, WHO Regional Office, 2013). First, the distance from major roads and trucking routes is calculated with the Euclidean Distance tool and next it is clipped to a buffer of 300 meters around this road to account for this limited effect. After that, the raster is normalized to values between 0 and 1 using the linear rescale function in QGIS. Finally, all areas outside the buffer are filled with 1 and the raster is again clipped to the road buffer layer to obtain the values for each road segment. This layer did not need to be normalized again, as the resulting values already range from 0 to 1.

Trees

Like parks, trees increase the visual attractiveness of running routes, but they also reduce air pollution, which increases the overall attractiveness of road segments for running (Tallis et al., 2011). For trees, the density of trees nearby a road segment is calculated, where higher densities allow for a higher reduction of air pollution and increase the attractiveness of a running route. With the Kernel Density Estimation function, the density of the trees on a radius of $50m^2$ is calculated. This density raster is then clipped to the road buffer layer and normalized to values of 0 to 1 using the large fuzzy membership function. This function assigns high scores to high pixel values, so areas, where the tree density is high, will receive a score close to 1.

Traffic calming

Traffic calming objects increase the perception of safety, which increases the attractiveness of a road segment. The KDE is also used to estimate the density of the traffic calming objects within a radius of $100m^2$. The smaller radius for the trees is used as the dataset has a high level of detail, which allows for more precise estimation (Shashank et al., 2021). This density layer is then again clipped to the road buffer layer and normalized to values between 0 and 1 using a linear rescale function. Furthermore, in table 3 a brief overview is given of the different features, their distance tool and membership function.

Multi-Criteria Evaluation model

To generate a final map with the runnability scores for the different road segments, all created layers are summed using equal weights, where the sum of the weights is equal to 1. This results in a raster map with scores between 0 and 1, with higher scores indicating road segments with higher suitability and attractiveness for running, which may promote running and increase running frequency (Ettema, 2016). Next, the RRI for each neighbourhood is calculated, such that the index can be validated and compared with the extended RRI and actual running data. To calculate the RRI for each neighbourhood, the proposed method by Shashank et. al. (2021) is used. This neighbourhood level score is obtained by summing the RRI scores for the respective neighbourhood and dividing it by the length of all running roads in this neighbourhood. Furthermore, the method used for validating and comparing both RRIs is discussed in the validation section below. For a detailed overview of the methods for creating the different maps, the flowcharts can be found in appendix A.

Variable	**Distance tool**	**Membership function**
Trees	Kernel Density (50m)	MS large
Traffic calming	Kernel Density (100m)	Linear rescale
Intersections	Euclidean distance	Linear rescale
Parks	Euclidean distance	Small
Street lights	Euclidean distance	MS Small
Major roads	Euclidean distance	Linear rescale
Trucking routes	Euclidean distance	Linear rescale

Table 3: Variables for the runnability indices and their distance tool and membership function

Extended RRI

For the extended RRI, the variable for the weather is introduced into the model. As found from the literature review, precipitation influences the built environment, which in turn influences the running behaviour. Furthermore, it is also found that precipitation reduces the running frequency, which also imposes a problem as there is no data available on why people don't run.

To account for the rain in an area, the precipitation level is divided into three categories: no rain (0-2.5 mm/h), moderate rain (2.6-7.6 mm/h) and heavy rain (>7.6 mm/h), which makes it easier for observational purposes (*Rain - Glossary of Meteorology*. n.d.). During rainy periods people change, cancel or postpone their walking trips depending on the purpose of the trip (Cools et al., 2010). Road surfaces become more slippery during rainfall and road inundations appear, causing people to change their route or making a specific road less attractive for running (Hewawasam et al., n.d.). Furthermore, over the past years, rainfall has increased and proper drainage infrastructure is necessary to prevent sidewalks and other pathways from flooding (*Walkable communities: Implications of Climate Change*, n.d.). As larger roads often have a better drainage infrastructure, people tend to run closer to these roads to avoid large puddles and slippery roads. This can also be seen from the visual analysis of the running data, where it is noticed that most rainy runs are performed on bigger street segments.

Susanna (2016) also identified the affordances of walking routes depending on the weather by interviewing different people. Shelter or protection from rainfall along a running route is often mentioned by her respondents together with the negative association of water or mud on the roads with their perceived attractiveness of the road.

Furthermore, it was found from statistical analysis of the different types of runs, that heavy rain runs travel longer distances through parks on average and a higher percentage of the total runs go through a park(table 4). This distance was found by calculating the length of a run through a park for all runs and averaging this distance. Therefore, in this new map, the distance to parks is also included. As a closer distance to parks will increase the attractiveness of a road depicted by the longer distance and higher percentage of runs through parks, the score will be higher for locations closest to this feature when precipitation is higher.

	Dry	**Moderate precipitation**	**Heavy precipitation**
Average running distance through parks (m)	1361m	1312 m	1717 m
Percentage of runs through parks	65%	69%	68%

Table 4: Running distance through parks and percentage of runs through parks

As mentioned before the precipitation levels are divided into 3 categories; dry, moderate and heavy. In table 5 below, a factor based on the weather for each precipitation level is given. This factor will be used to create the maps which depict the affordances at road level for the different precipitation levels.

Precipitation level	**Factor**
Dry (0 – 2.5 mm/h)	0
Moderate (2.6 – 7.6 mm/h)	0.5
Heavy (>7.6 mm/h)	1

Table 5: Factor depending on the precipitation level

First, the maps with the affordance scores of the road segments for the distances to parks and major running roads depending on the different precipitation levels are combined by multiplying both raster maps by 0.5 and summing them up. Next, a base map was created which assigns a score of 1 to all road segments.

To create the final runnability score based on the precipitation level, the map with scores depending on the distances to parks and major running roads is multiplied by a factor of 0, 0.5 or 1 depending on the precipitation level and subtracted from the base map. This way an affordance score between 0 and 1 is obtained for the different road segments depending on the amount of rainfall and distance to parks and major running roads. These maps can then be used to create 3 different runnability maps for the different scenarios. These final maps are created with the same method as the benchmark RRI by multiplying the raster maps depicting the affordance scores of the road segments depending on the features with equal weights and summing them up.

Validation method

To validate and compare the runnability indices on their performance two different validation methods are used; one on road level and one on neighbourhood level. Even though the running data is sparse, the running density on the road level is compared with the runnability score. This is done with the GRASS plugin in QGIS, which enables the calculation of the correlation between two raster maps. For this method, three different density raster maps are created with the density of the running routes at dry, moderate and heavy precipitation levels. This is done with the line density function of QGIS, which assigns high scores to road segments with many running routes. As it is assumed that there exists a linear relationship between the runnability scores and the amount of running on a road a correlation analysis can be performed to assess this. The correlation between the density maps and their corresponding runnability map is calculated, which provides different scores that can be compared. One advantage of correlation analysis is that the units of the two maps do not need to be the same, which allows for a comparison of the density values and the RRI scores. Even though the running data is sparse, this method will provide some results which can be compared and used for validation.

Furthermore, a score was assigned to each neighbourhood which depicted the ratio of running length and road length in a specific neighbourhood. This was done to standardize the amount of running through an area to comparable values as it can be assumed that an area with more roads will have a higher amount of running routes. Next, the RRI scores for each neighbourhood were used in a correlation analysis to see whether the RRI scores on neighbourhood level have a statistical relationship with the amount of running in this neighbourhood. For this test, the Pearson correlation coefficient was used as it is assumed that both variables have a linear correlation: higher RRI scores describe higher running amounts.

The Pearson correlation coefficient is calculated with a script written in R, which reads the CSV file created in QGIS with the different runnability index scores for the neighbourhoods and the measurement for the amount of running in a neighbourhood. The coefficient values range from +1 to -1 indicating a positive or negative correlation. Higher coefficient values indicate a stronger linear relationship between the variables and a coefficient of 0 indicates no linear relationship is present. To calculate the Pearson correlation coefficient, R is used with its build-in function cor.test(), in which the method is set to 'Pearson'

Results

From the different maps with the affordance scores for each feature at each road segment, the benchmark RRI and the new RRI maps are created. This resulted in 4 different maps for the different scenarios; benchmark, dry, moderate precipitation and heavy precipitation. The different maps for each feature can be found in appendix B, together with some bigger maps of the RRI scores on road level in appendix C.

Benchmark

From the benchmark RRI map, it can be seen that Utrecht city has some hotspots for running, which are located close to parks (figure 10). Furthermore, on average most roads have the same runnability score, indicating that most roads in Utrecht have the same set of features; i.e. trees alongside the roads and good lighting infrastructure, and are in general suitable for running. With this map, the RI score for the neighbourhoods was determined, by summing the runnability scores of each road segment in a neighbourhood and dividing it by the total length of roads in each neighbourhood (figure 11).

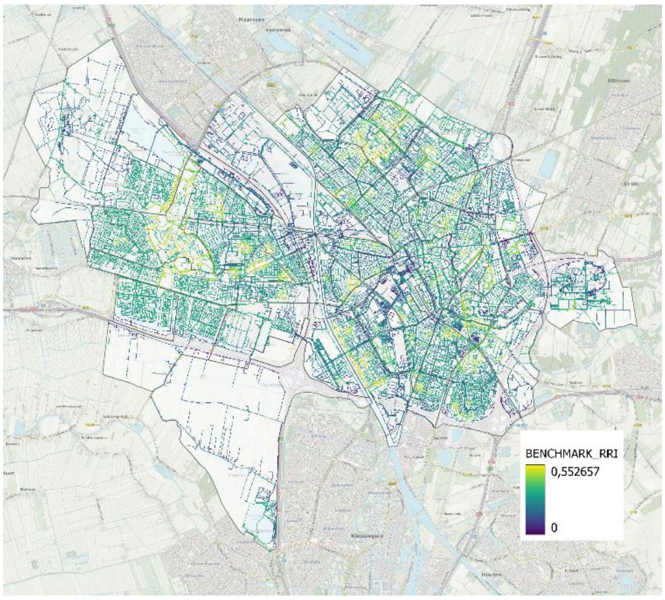

Figure 10: Road level benchmark RRI

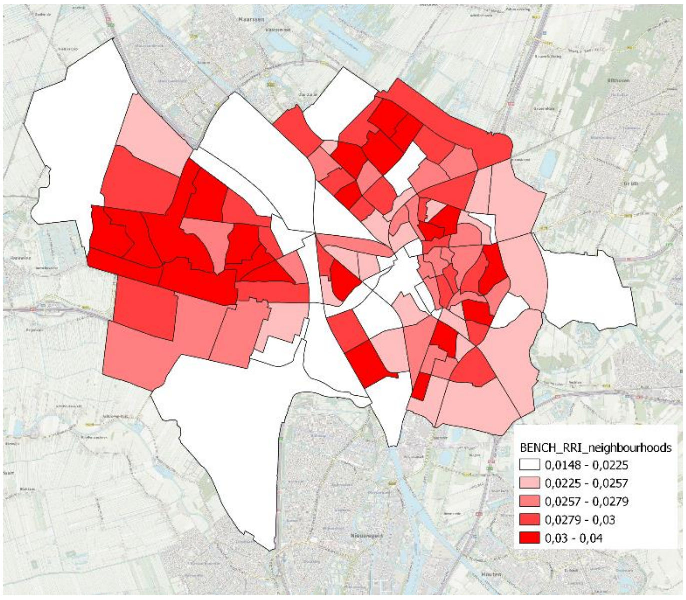

Figure 11: Neighbourhood level benchmark RRI

Extended RRI

With the extended RRI three different maps for the different precipitation levels are created; dry, moderate, heavy. Furthermore, with the same approach used with the benchmark RI, three different maps are created with RI values for each neighbourhood. From these maps it can be seen that the areas with parks nearby receive a higher runnability score. Furthermore, it is observed that the runnability score decreases on average when precipitation increases, which is in line with the findings from the literature review. In figures 12 – 17, the different maps for the different scenarios can be found with the runnability scores on road level and on neighbourhood level.

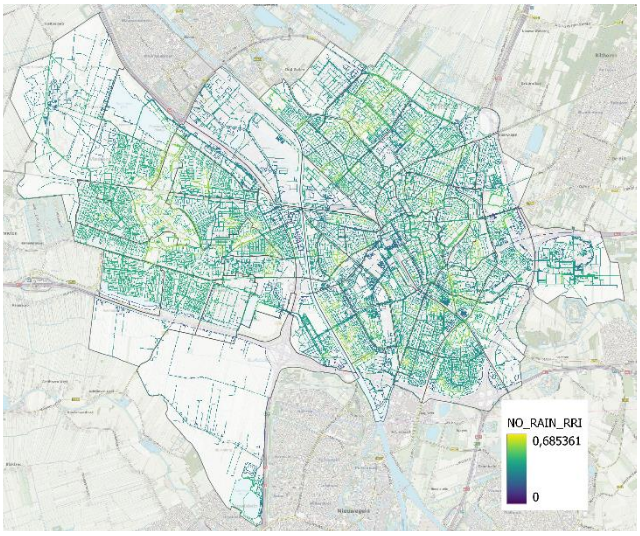

Figure 12: Road level no precipitation RRI

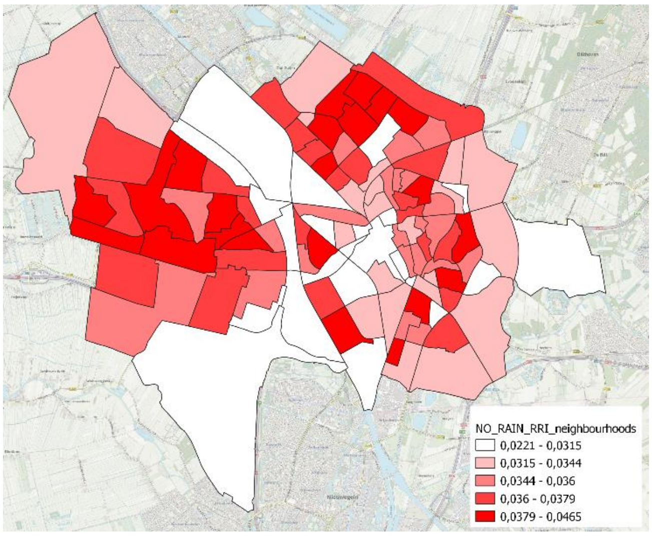

Figure 13: Neighbourhood level no precipitation RRI

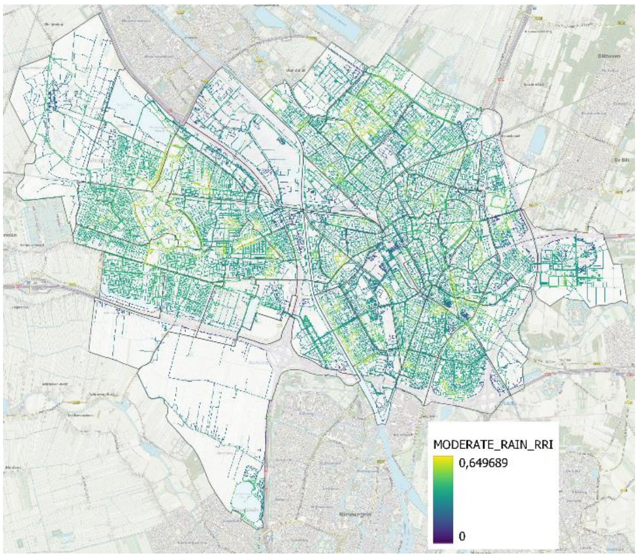

Figure 14: Road level moderate precipitation RRI

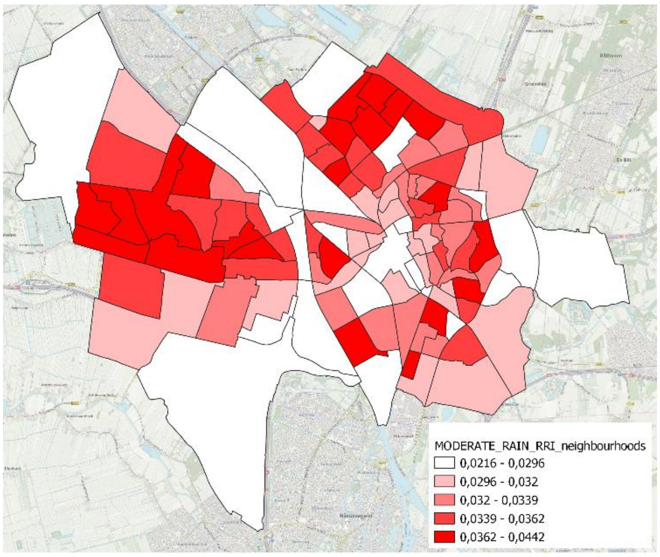

Figure 15: Neighbourhood level moderate precipitation RRI

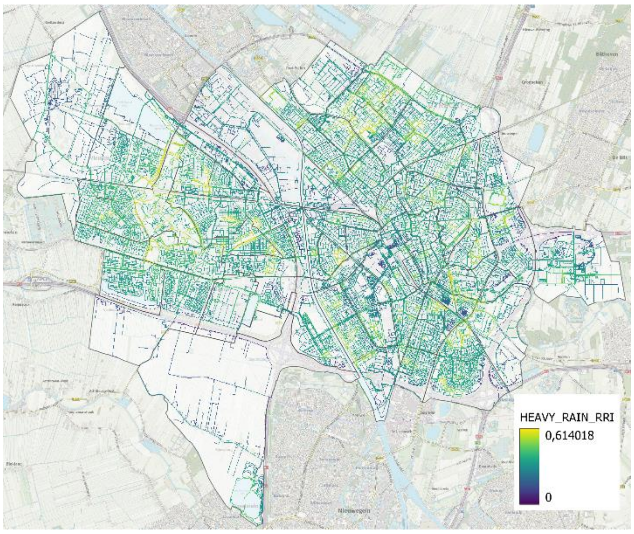

Figure 16: Road level heavy precipitation RRI

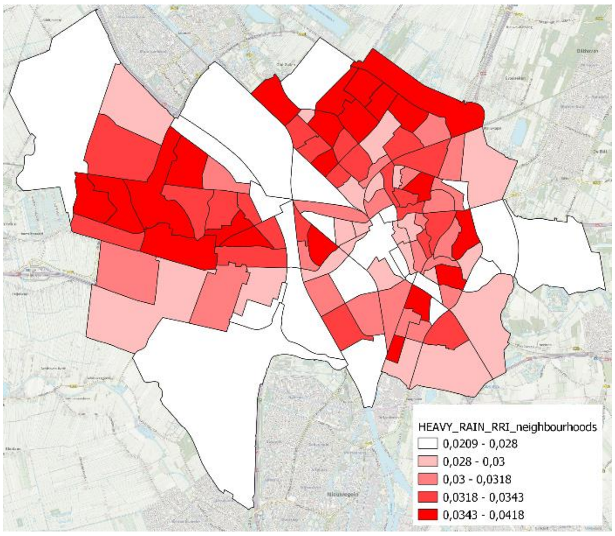

Figure 17: Neighbourhood level heavy precipitation RRI

Validation

With the benchmark RRI, the extended RRI and the dataset with different running routes for the different scenarios, correlation analysis is performed to see whether the new runnability indices perform better. As the running data is sparse, it is difficult to perform a good validation on the road level. However, this research will still analyse the result of the RRI on road level, to see if there are any noticeable differences. As the measurements for the RRI and the amount of running per neighbourhood are not in the same units, which makes it hard for comparison, a correlation analysis will be performed.

Correlations between the raster maps are calculated with the r.covar function from the GRASS plugin module in QGIS. From this, the correlation scores in table 6 are found. It is found that there exists a positive correlation between the different maps. However, as can be seen, the correlation is lower for the extended RRI for the moderate rain and heavy rain scenarios. Assuming that there exists a linear relationship between the runnability index and the amount of running on a road, these results suggest that the extended RRI is worse in describing the running behaviour on road level for moderate and heavy precipitation levels.

	No rain runs	**Moderate rain runs**	**Heavy rain runs**
Benchmark RRI	0.242158	0.237753	0.214877
No rain RRI	0.243328	-	-
Moderate rain RRI	-	0.217496	-
Heavy rain RRI	-	-	0.199714

Table 6: Correlations between road level RRI scores and running densities

Next, the Pearson correlation coefficient was calculated between the different runnability index scores of the neighbourhoods. It is found that for the heavy precipitation level the correlation coefficient is really low for both the benchmark and the heavy rain runnability model (table 7). However, it is still interesting to see that the correlation is higher for the new indices, which indicates that the runnability scores from the new indices better describe the running behaviour at dry, moderate and heavy precipitation levels on neighbourhood level. Furthermore, from the correlation analysis in R, it was found that for the correlations between "No Rain RRI" – "No rain runs" and "Moderate rain RRI" – "Moderate rain runs" had a p-value <0.05 indicating that these correlations are statistical significant.

	No rain runs	**Moderate rain runs**	**Heavy rain runs**
Benchmark RRI	0.175	0.172	0.0763
No rain RRI	0.203	-	-
Moderate rain RRI	-	0.193	-
Heavy rain RRI	-	-	0.104

Table 7: Correlations between neighbourhood RRI's and running amounts

Conclusion

As the importance of regular physical exercise becomes more important for the physical and psychological health of people, urban planners are encouraged to design cities or neighbourhoods which promote physical activities. The attractiveness of a neighbourhood to engage in physical activities depends on many different aspects such as personal preference, type of physical activity and features of the built environment, which all have received great attention in scientific literature. For example, different indices are created over the past year to quantify how 'walkable' different neighbourhoods are. However, as running purposes often differ from walking purposes, just copying the walkability index for a runnability index would create wrong results. Therefore, a new runnability index is created to visualize the relationship between running behaviour and the built environment.

In this research, four different runnability indices are created based on the work of Shashank et. al. (2021). With the help of an affordance-based framework, the opportunities and barriers that different features of the built environment provide to a runner are quantified. With these four runnability indices and running data scraped from Endomodo, the research question can be answered: *"To what extent can the runnability index of Shashank et al.* (2021) *be improved by incorporating the effects of precipitation?".*

It was found that people tend to run closer to and longer through parks when the precipitation level increases as these routes provide more shelter. Furthermore, from visual analysis, it was found that runs are performed on bigger roads when precipitation increases. These findings were used to create a new RRI with three different precipitation levels; dry, moderate and heavy. These were then compared to the benchmark RRI on performance with the help of a correlation analysis.

Even though the results show no significant improvement, it is found that the new runnability index performs slightly better on neighbourhood level, describing the running behaviour at different precipitation levels better. The results on road level show no improvement, but this can be explained by the fact that the running data is missing for most roads, while the runnability indices provide a score for each road segment. This research has shown that by including a weather variable describing the precipitation level, improvement of the runnability index is possible.

Discussion

This research is conducted with data on the city of Utrecht. However, it is found that the city of Utrecht has a very homogenous landscape; most roads are paved, lined by trees and well-lit. As the landscape is very homogenous and the features are evenly distributed over most of the neighbourhoods, different running routes in Utrecht will likely have the same distribution of features; the same amount of trees along a running route during dry and rainy periods. From visual analysis, it was found that the running routes differ a bit depending on the amount of precipitation, but this difference was not very significant. A quick analysis of a different place with built-up areas and forests, where there are no paved roads for example, showed that the runs indeed differ much depending on the precipitation level (figure 18). Therefore, it is suggested that this model is also used for determining the runnability indices at different locations with different characteristics to further analyse its performance.

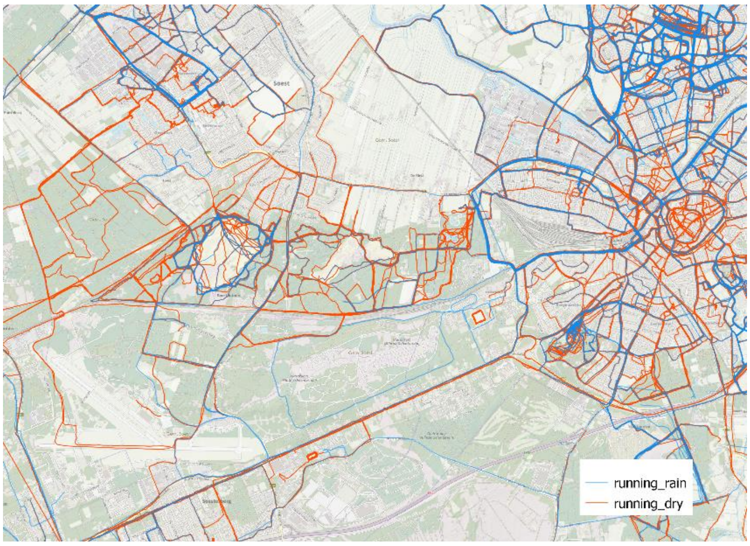

Figure 18: Running routes at a different location for dry and rainy days

Furthermore, the running data is only available on the runs performed, so it is known where and why people run, but it is not known why people don't run. Whether people run or don't run is based on their own preferences and environmental tolerances; some people like to run in the rain or have a higher heat tolerance (Turrisi et al., 2021). This suggests that the runnability index differs per person and person-specific runnability models under the different precipitation levels could shed a light on these dynamics. However, a lot of running data is required for this, which is often not available or requires much computing power to process.

Another limitation of this research is the sparse running data, which is also explained by the fact that people run less frequently when it rains. However, to improve the validation of these models more running data should be obtained by for example scraping more days from Endomodo or identifying areas where there is more running data available. With this extra running data, other pattern differences could be observed and linked to the features of the built environment: for example that most people like to run on paved roads instead of unpaved muddy roads when it is raining. Furthermore, with this extra information on the running patterns and the influences of different environmental features, linear regression could be performed with the different feature maps and the running density maps such that the effect of each feature becomes more clear.

Overall, this research has some limitations, but the results can still be used for interpretation and identifying possible further research directions. As shown, the runnability index is slightly improved by including weather influences, but further research is needed to assess the general effect of weather on the running behaviour in different environments.

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Appendix

A – Flowchart for creating

Figure 19: Flowchart for creating the different RRI score maps of the features

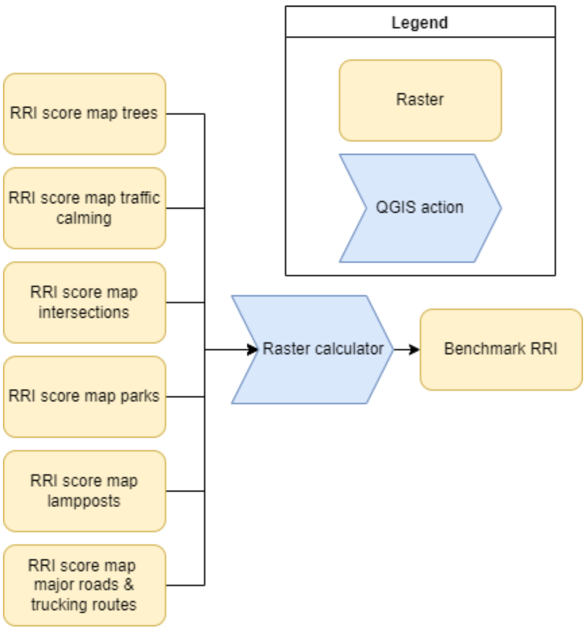

Figure 20: Flowchart for creating the benchmark RRI

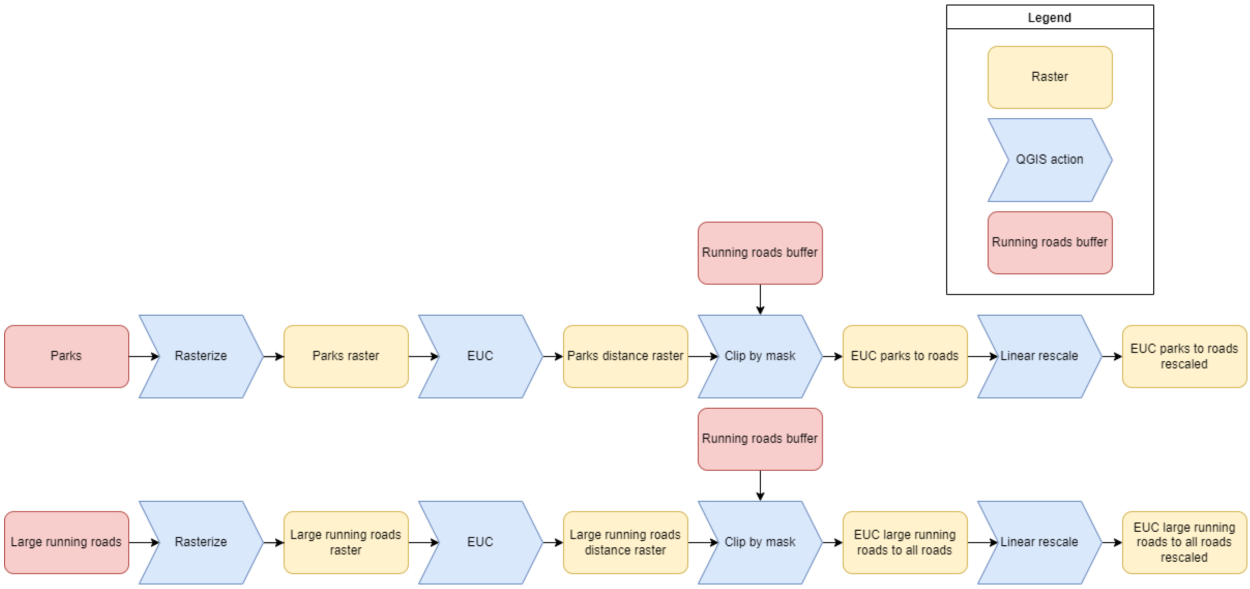

Figure 21: Flowchart for creating the different RRI score maps for the parks and running roads used for the extended RRI

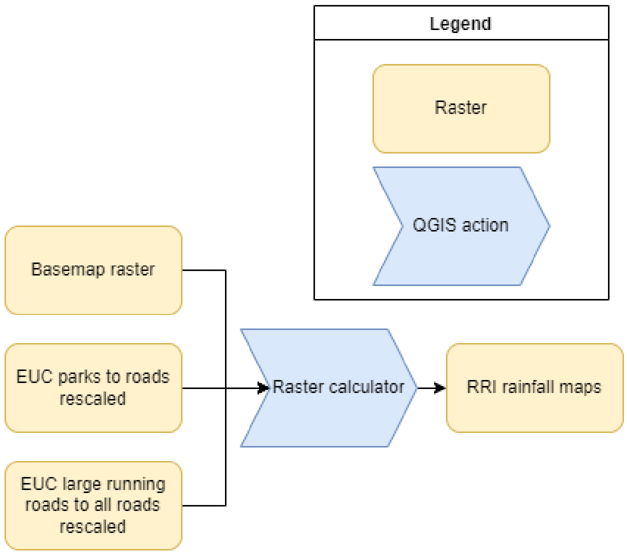

Figure 22: Flowchart for creating the RRI score maps for the different precipitation levels

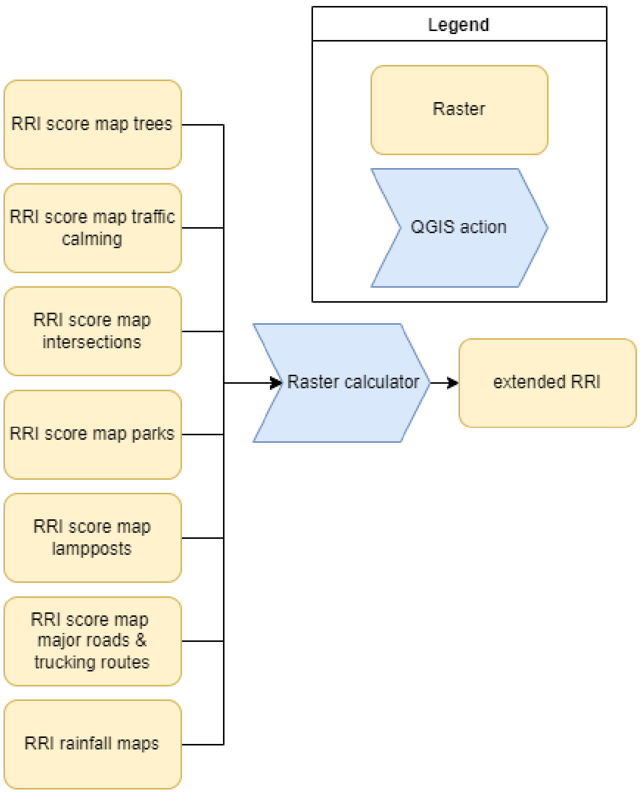

Figure 23: Flowchart for creating the extended RRI

B – Affordance score maps for the different features

Note: for the first three maps the roads are not visible as these have very low scores. This is the result of the rescaling functions used or the many intersections in Utrecht.

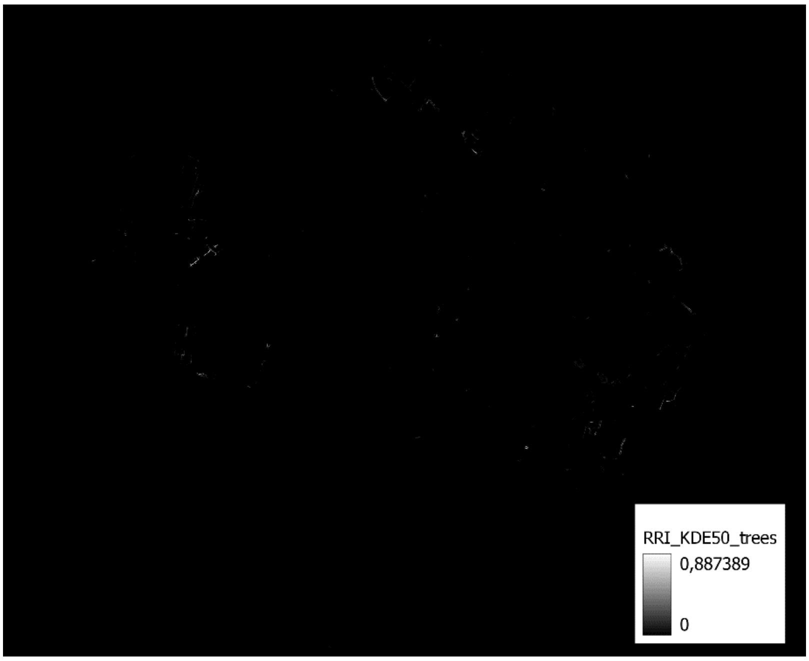

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Figure 1: RRI affordance scores KDE50 trees

Figure 2: RRI affordance scores KDE100 traffic calming

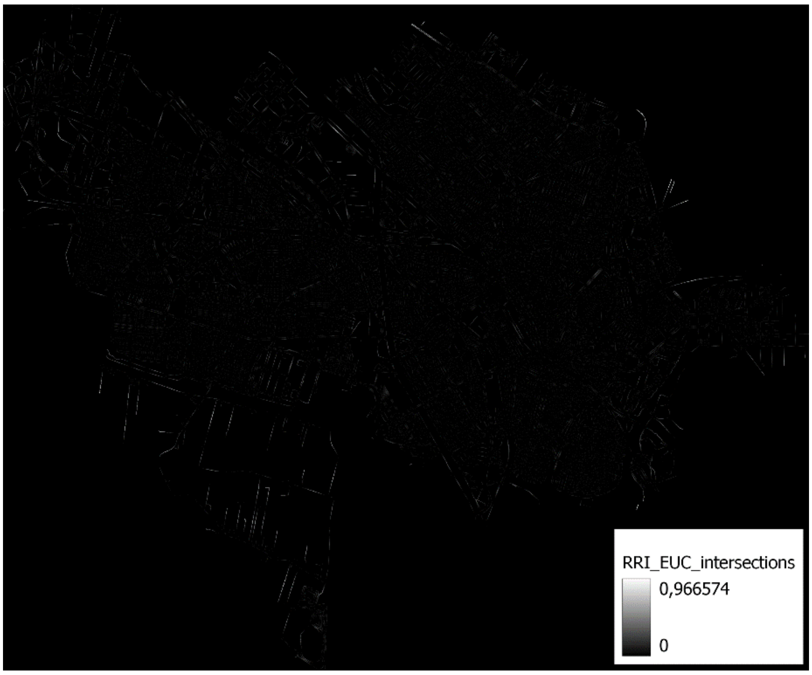

Figure 3: RRI affordance scores EUC intersections

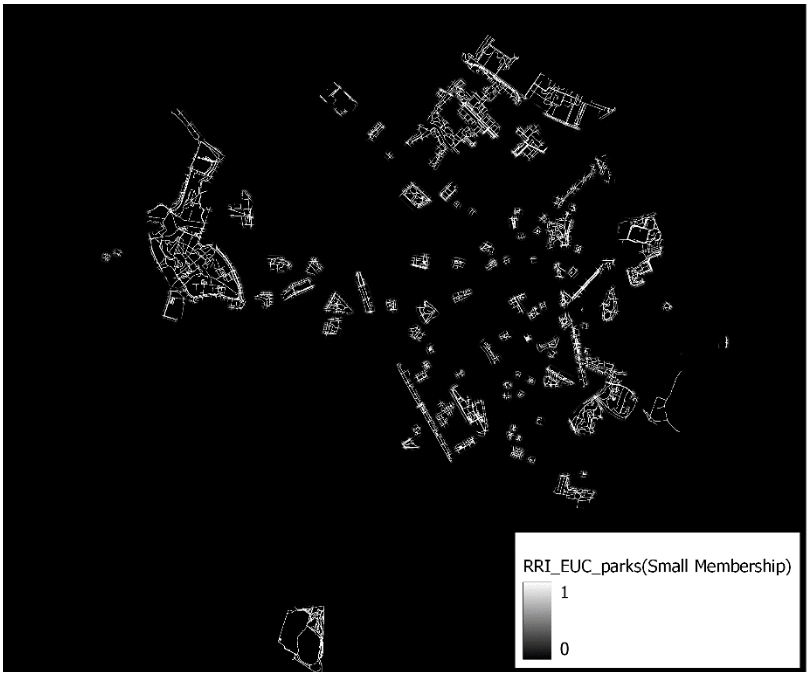

Figure 4: RRI affordance scores EUC parks

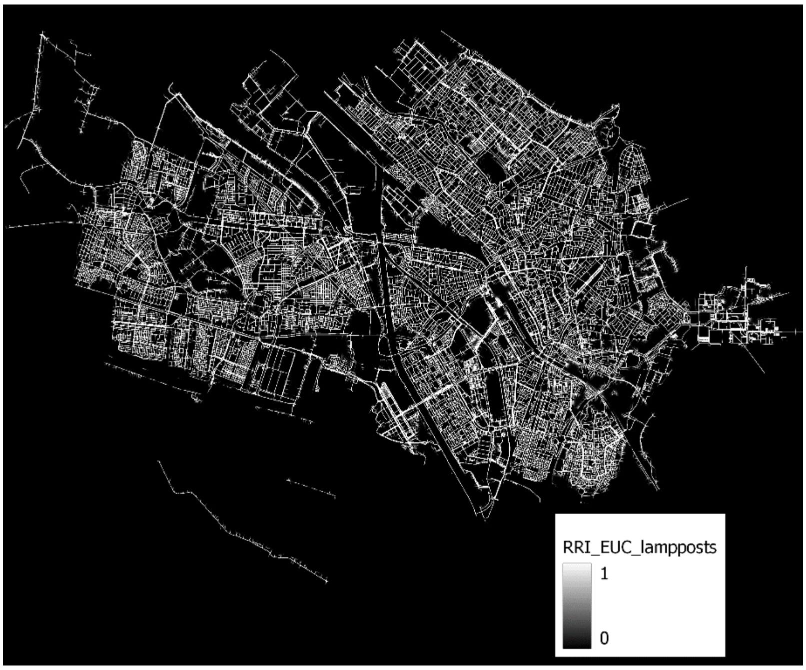

Figure 5: RRI affordance scores EUC lampposts

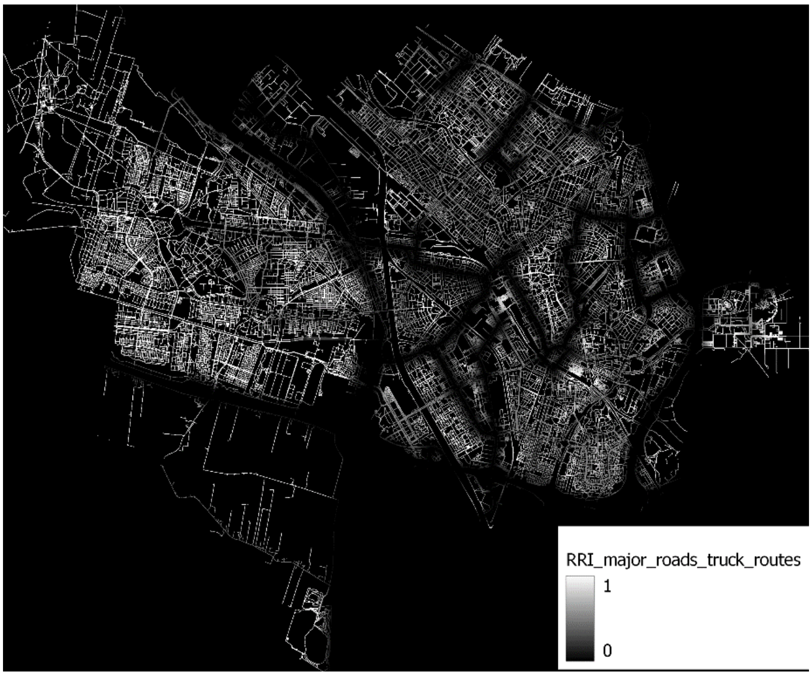

Figure 6: RRI affordance scores major roads & trucking routes

Figure 7: RRI affordance scores roads basemap

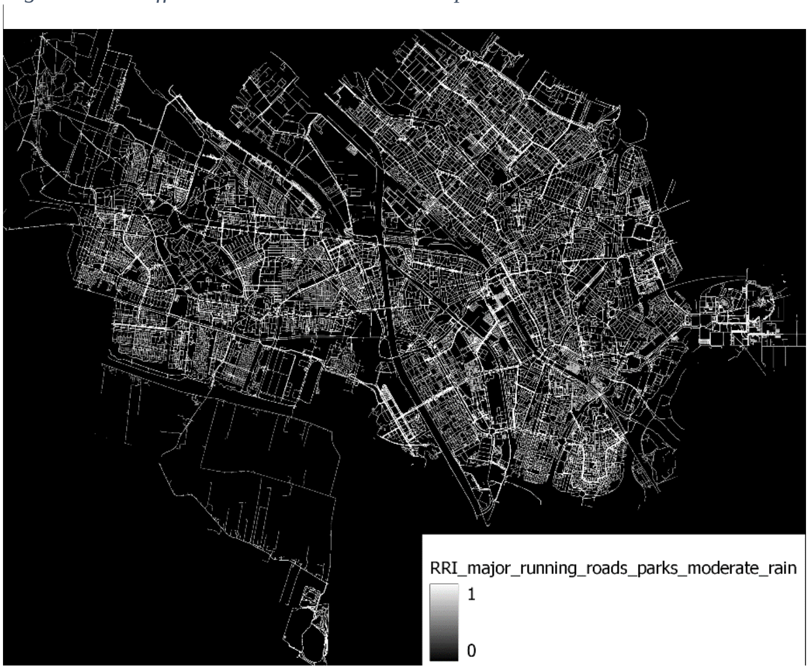

Figure 8: RRI affordance scores moderate rain

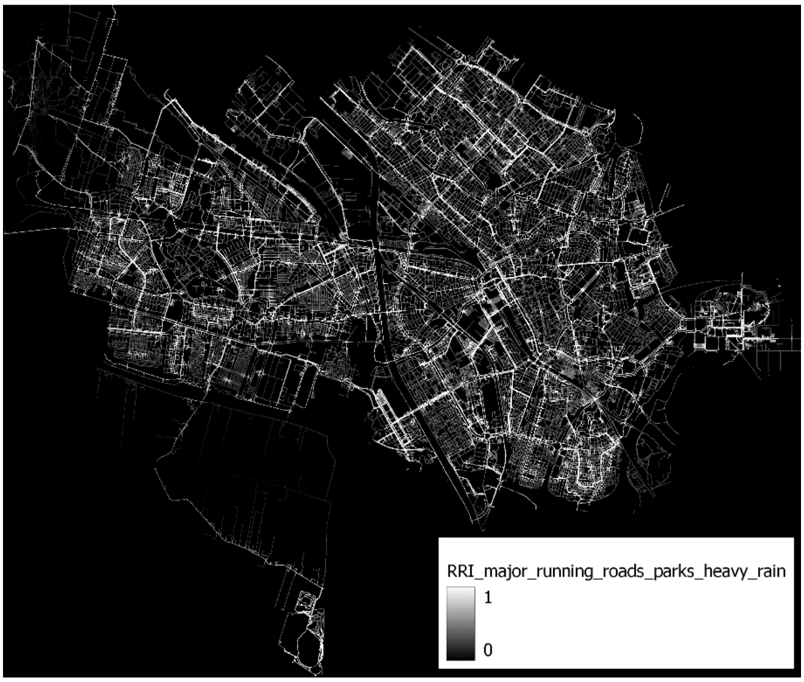

Figure 9: RRI affordance scores heavy rain

C – Bigger maps of the RRI on road level

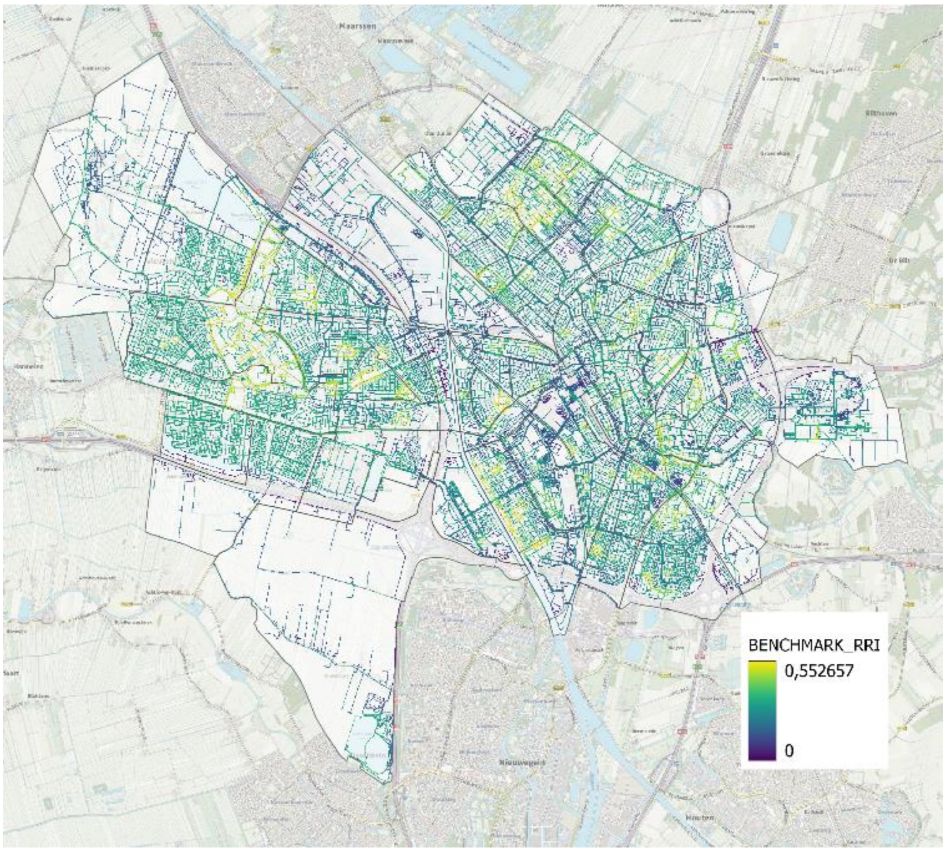

Figure 10: benchmark RRI road level

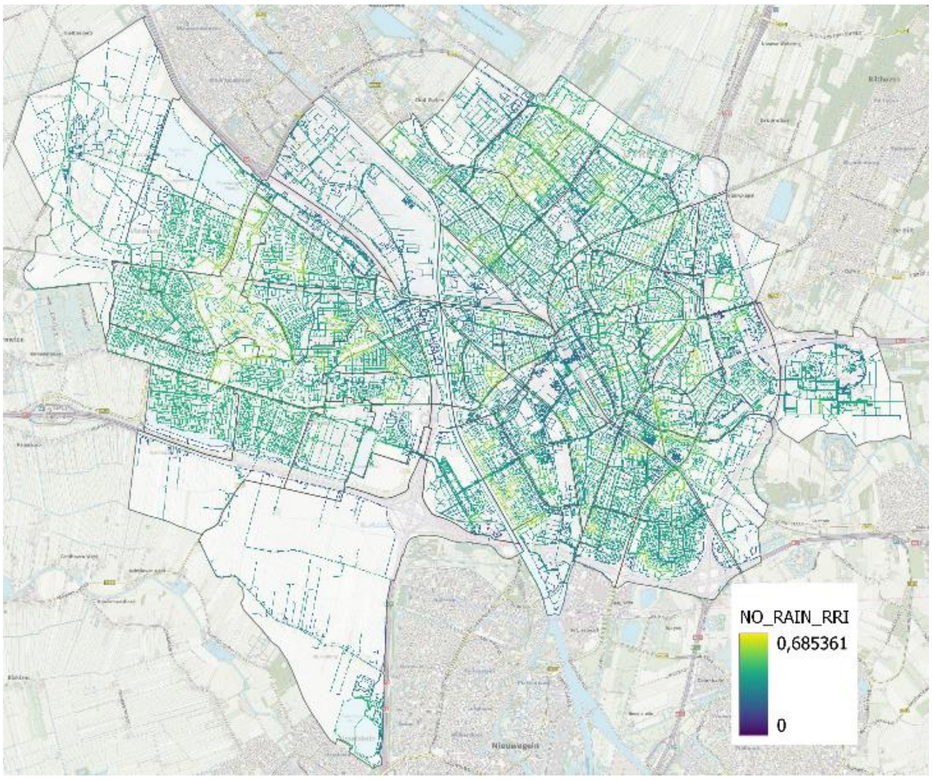

Figure 11: No rain RRI road level

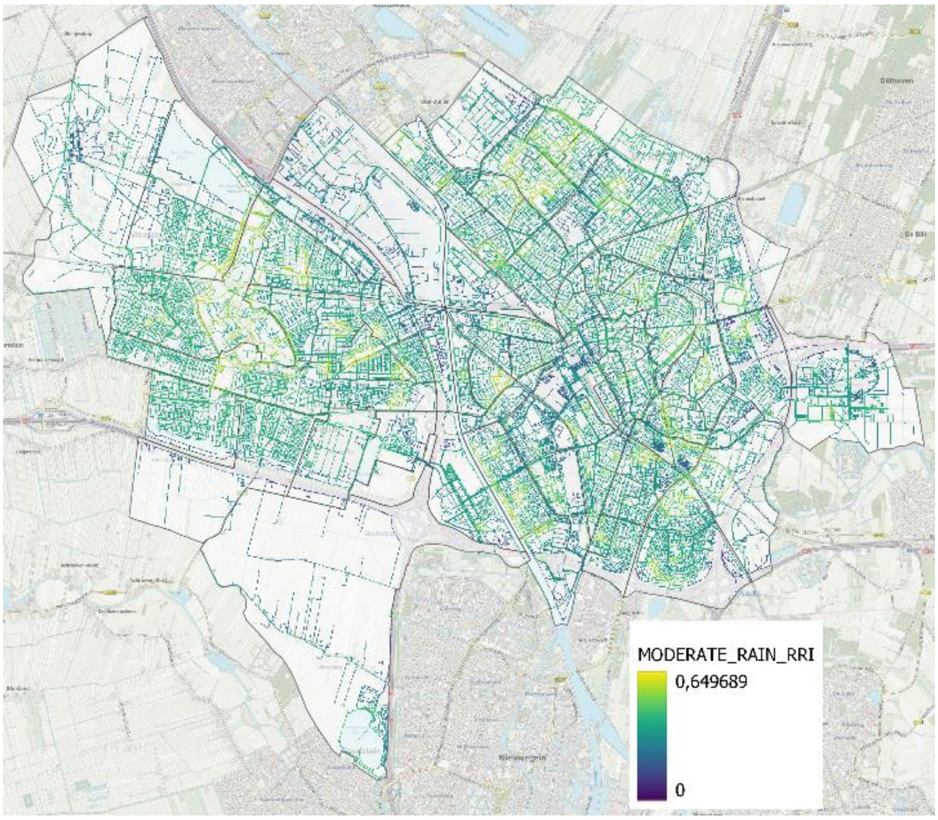

Figure 12: Moderate rain RRI road level

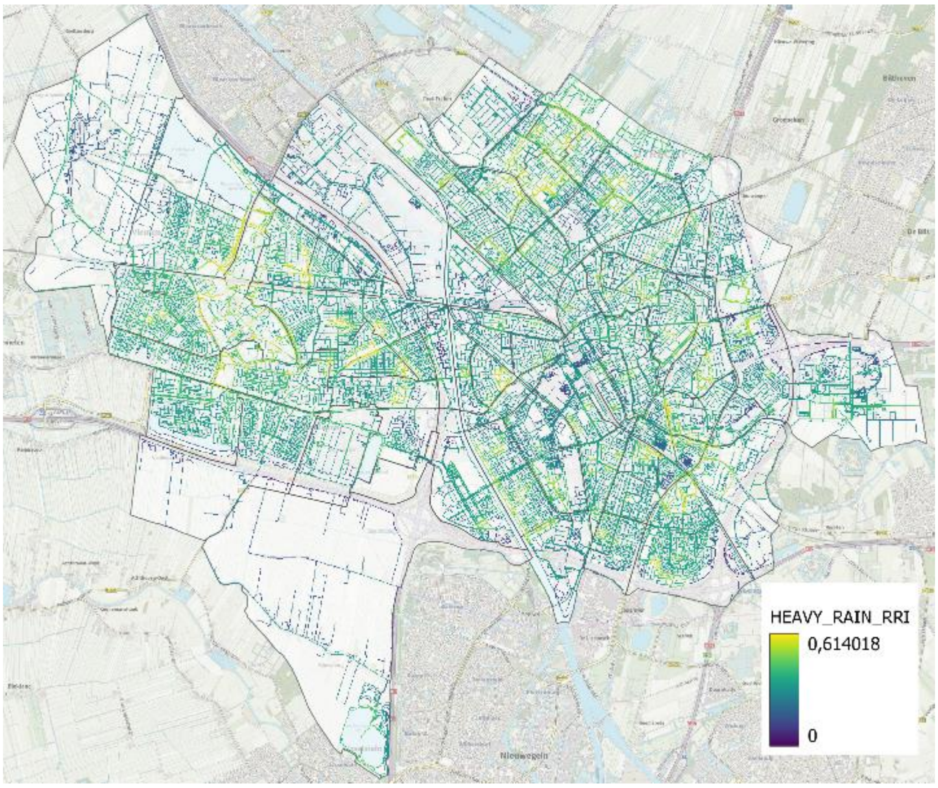

Figure 13: Heavy rain RRI road level