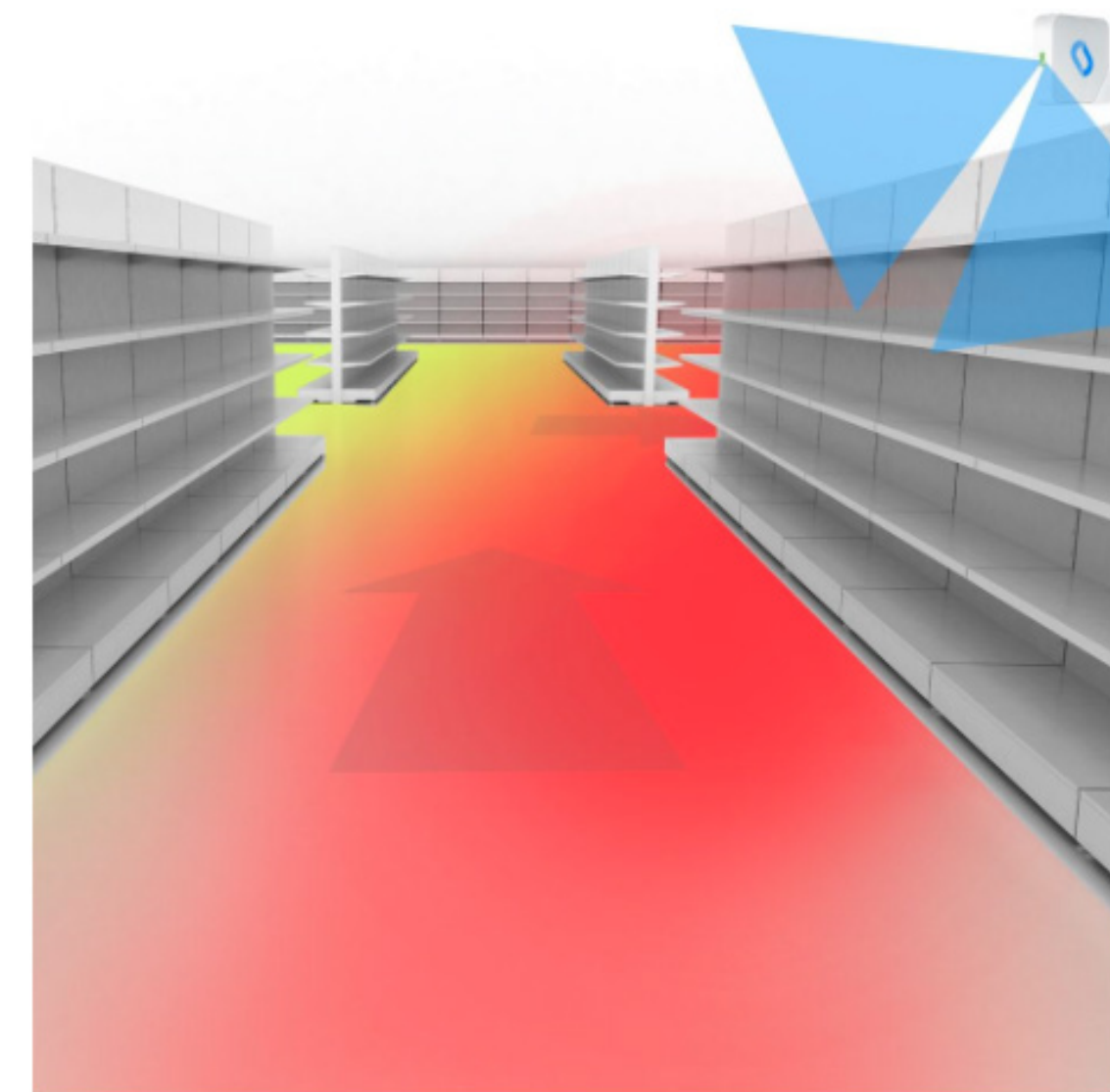


“Crowds”

Urban Sensing with Wifi-Data



Example: “Sensalytics”

Counting visitors, finding Hot-spots, knowing location details. Suitable for stationary stores, events, fairs and public buildings.

Source: <https://sensalytics.net/en>



Example: “Sensalytics”
Get data in real-time.

Source: <https://sensalytics.net/en>

Urban WiFi Characterization via Mobile Crowdsensing

Arsham Farshad and Mahesh K. Marina
The University of Edinburgh

Francisco Garcia
Agilent Technologies

Abstract—We present a mobile crowdsensing approach for urban WiFi characterization that leverages commodity smartphones and the natural mobility of people. Specifically, we report measurement results obtained for Edinburgh, a representative European city, on detecting the presence of deployed WiFi APs via the mobile crowdsensing approach. They show that few channels in 2.4GHz are heavily used; in contrast, there is hardly any activity in the 5GHz band even though relatively it has a greater number of available channels. Spatial analysis of spectrum usage reveals that mutual interference among nearby APs operating in the same channel can be a serious problem with around 10 APs contending with each other in many locations. We find that the characteristics of WiFi deployments at city-scale are similar to that of WiFi deployments in public spaces of different indoor environments. We validate our approach in comparison with wardriving, and also show that our findings generally match with previous studies based on other measurement approaches. As an application of the mobile crowdsensing based urban WiFi monitoring, we outline a cloud based WiFi router configuration service for better interference management with global awareness in urban areas.

I. INTRODUCTION

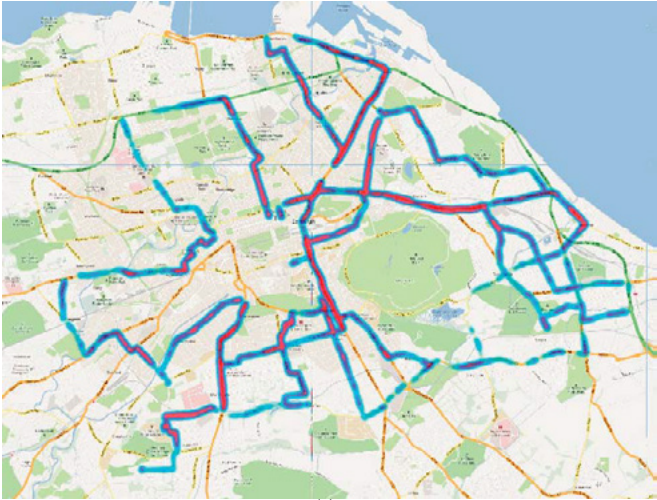
Significant interest in mobile phone sensing in recent years can be attributed to several factors, including: their ubiquitous nature; rapid evolution toward smartphones with several built-in sensors; carried by humans, making them natural to be used for “mobile” sensing; and the possibility of leveraging the cloud via several available connectivity options for computing power, storage and “centralization”. Not surprisingly then, mobile phone sensing applications have been realized or envisioned in diverse domains (e.g., transportation, social networking, health monitoring) [1], [2]. When a group/community of participants (a *crowd*) is engaged with suitable incentives, mobile phone sensing becomes even more compelling for continual and fine-grained spatio-temporal monitoring of the phenomenon of interest in a *cost-effective* manner. Indeed, as Xiao et al. note in [3], the focus of mobile sensing research and applications is shifting towards *mobile crowdsensing*, which is defined as “individuals with sensing and computing devices collectively share data and extract information to measure and map phenomena of common interest” [4]. Several mobile crowdsensing applications have been developed and deployed (e.g., [5], [6]) and it remains a very active area of research.

We consider the application of the mobile crowdsensing paradigm to wireless network monitoring. Besides the many

sensors, modern mobile phones feature several wireless network interfaces as connectivity options (e.g., cellular, WiFi, Bluetooth, NFC). Discussions of mobile phone sensing have been mostly centered around the use of built-in sensors and/or specialized add-on sensors (e.g., GasMobile [5], CellScope¹, NETRA²) with connectivity options serving as a means for data sharing (see [2], for example). We expand this commonly held view to treat network interfaces also as sensors. GPS, which is an integral part of all smartphones today, presents an example of a network interface that sits at the boundary of these two views — GPS is seen as a location sensor for mobile phone sensing applications whereas it is actually a RF communication system in which GPS receiver on a phone uses signals transmitted from satellites for localization. Technical specifications of some smartphones do acknowledge this view. See [7], for example. A more obvious example is the use of cellular interface on smartphones for crowdsourcing based active/passive measurement of mobile networks as in [8], [9]. As yet another example, in a recent work [10], we developed a system that exploits the WiFi interface on smartphones for low-cost and automated monitoring of WiFi networks in indoor environments like enterprises and public buildings (e.g., shopping malls).

In this paper, we focus on mobile crowdsensing based characterization of WiFi deployment and configuration in urban areas at a city level using the WiFi interface on smartphones as a measurement sensor. Specifically, we report results from a mobile crowdsensing based WiFi measurement study conducted in Edinburgh, leveraging participants with mobile phones traveling on public transport buses. Our findings and contributions are as follows:

- WiFi spectrum usage is quite unevenly distributed across 2.4GHz and 5GHz unlicensed bands as well as among various channels within the 2.4GHz (section IV.A).
- Many WiFi access points (APs) contend on the same channel with around 10 other APs (and their clients) in the nearby vicinity, thereby potentially experience severe interference. This is a result of the common practice of uncoordinated and non-adaptive channel assignment to home WiFi routers which are often left to use preset factory configuration settings for channel etc. (section IV.B).
- We also look into the distribution of open APs, which could be leveraged for vehicular WiFi access [11].



(a)

	Min	Median	Mean	Max
Location Error (m)	4	8	9.6	1095

(b)

Total number of measurements (scans)	147488
Distinct measurement locations	11225
Distinct APs detected	13800
Distinct open access APs detected	2977

(c)

Fig. 1. (a) Mobile crowdsensing based WiFi AP scanning measurements shown as a heatmap; (b) Location error statistics for the collected measurement dataset; (c) Filtered measurement dataset summary.

III. METHODOLOGY

Our mobile crowdsensing based urban WiFi characterization study is done using Android phones, specifically Samsung Galaxy S III [7] phones which feature a 802.11a/b/g/n radio that can operate in both 2.4GHz and 5GHz unlicensed bands. We rely solely on passive scanning based measurement, listening to AP beacons. The information available at the user level with the Android API for passive scans is limited to: SSID, BSSID, channel, RSSI and the security scheme in use. For the measurements, we use the freely available RF Signal Tracker app [24], which keeps passively scanning for WiFi access points (APs) in the background every three seconds or on passing 5 meters; it locally stores the result of each scan tagged with GPS location and timestamp on the phone in a CSV file. As this app does not log location errors and is not open source, we have developed an auxiliary app that runs alongside and records location errors. Measurement data from phones is subsequently transferred to a back-end server where custom python scripts are used to import the data into a database, which then is used for further querying, analysis and mapping of data.

As mentioned at the outset, our urban WiFi characterization focuses on the city of Edinburgh, which is a typical European city [25] — smaller in size and densely populated, especially in the center. For proof-of-concept and wider spatial coverage with fewer participants in a short measurement period, we focus on a measurement scenario where participants are travel-

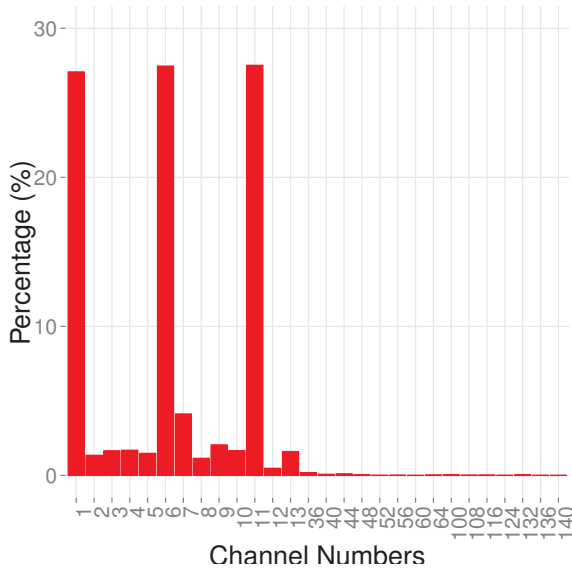


Fig. 2. Relative usage of different channels across 2.4GHz and 5GHz bands by the detected APs.

ling on public transport vehicles. Specifically, our measurement results are obtained from phones carried by participants during the times they travel at low to moderate speeds on buses in the city operated by a local bus company called Lothian Buses [26]. In this sense, it follows a participatory sensing approach along the lines of earlier urban air/noise pollution monitoring studies [5], [6]. Measurements reported in this paper correspond to traveling over 31 buses over a 15 hour period in total. Note that in principle crowdsourcing based measurement can be done in a fully opportunistic manner, covering all modes of movement including walking, standing, etc. The limits we place are for above mentioned reasons. Also note that there is an assumption underlying our study that visible APs from next-door neighbors can also be seen from the street and vice versa.

Fig. 1(a) shows the total set of measurements as a heatmap. Red areas in the map indicate places where there is a high density of APs as well as those places with multiple measurements due to overlapping road segments between different bus routes. Fig. 1(b) lists the location error statistics across all measurements in our dataset. We observe that while the maximum error can be over 1Km reflecting locations that do not get a GPS fix, the error is under 50m in 95% of the cases. To obtain reliable spatial distribution of APs on the map, we filtered out the 5% of the measurements with location errors greater than 50m. Fig. 1(c) presents a summary of the resultant dataset. From closer inspection, we observe that majority of the APs correspond to home WiFi networks interspersed with the rest (e.g., WiFi hotspots).

IV. RESULTS

A. Spectrum Usage

We begin by looking at the channel usage of WiFi APs in our dataset. Fig. 2 shows the relative usage of different channels across 2.4GHz and 5GHz bands. Clearly, the channel

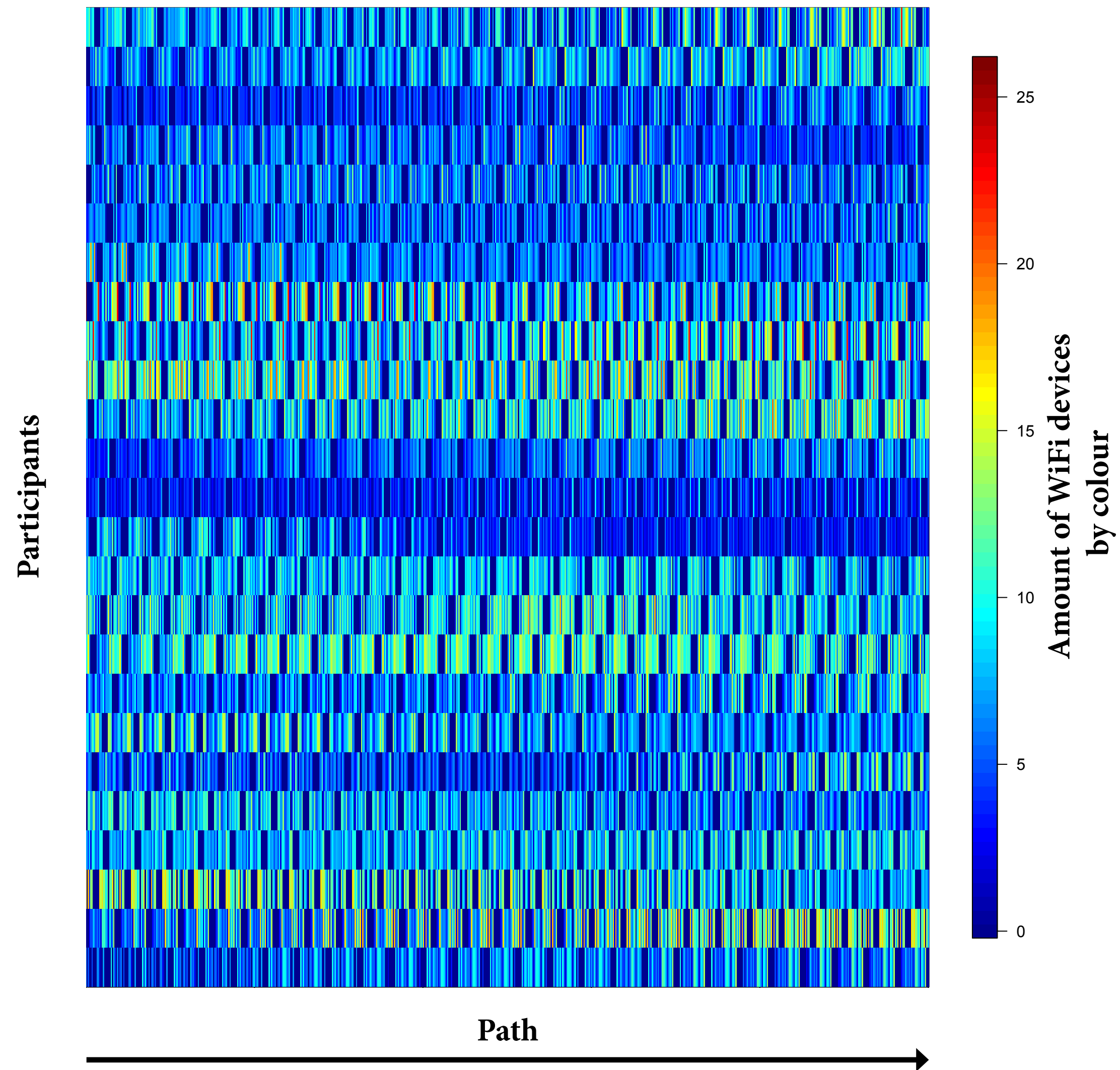
This work was supported in part by a Cisco Research Award.

¹<http://cellscope.berkeley.edu/>

²<http://web.media.mit.edu/~pamplona/NETRA/>

Example: “Urban WiFi Characterization via Mobile Crowdsensing”
Analysis concerning the WiFi quality in cities.

Source: <http://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=6838233>

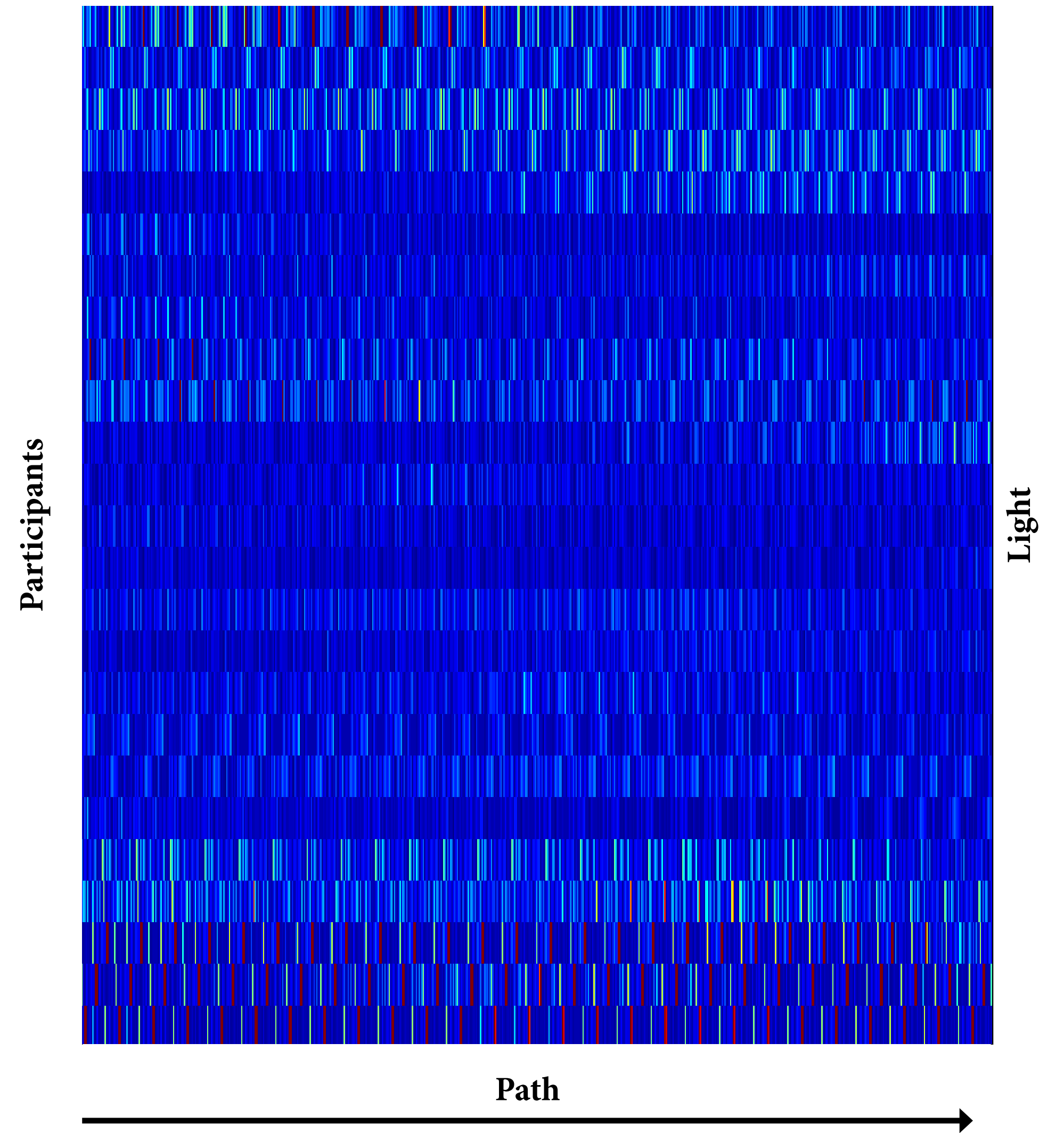
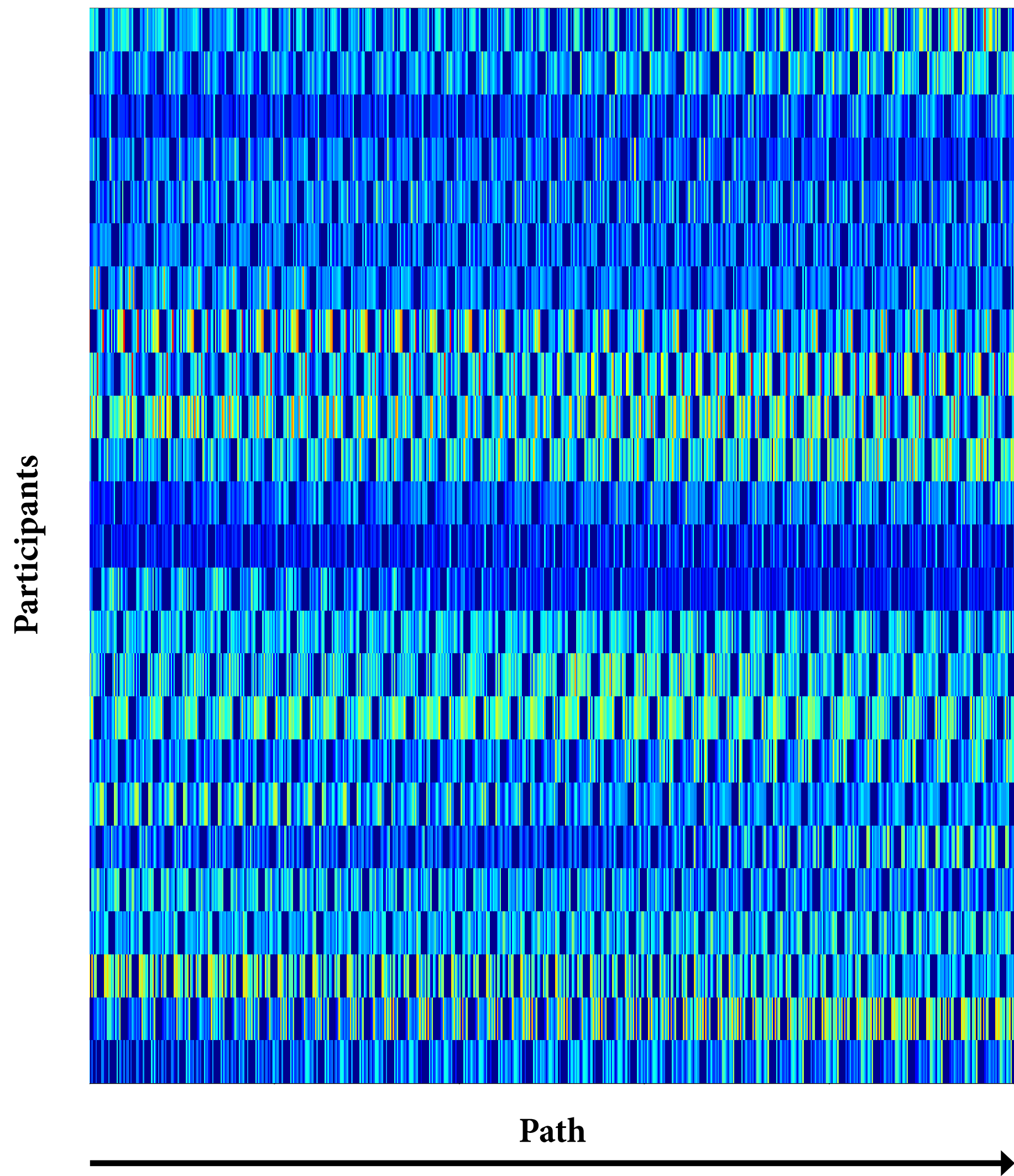


Backback data heatmap

There seem to be days with fewer people on the streets.

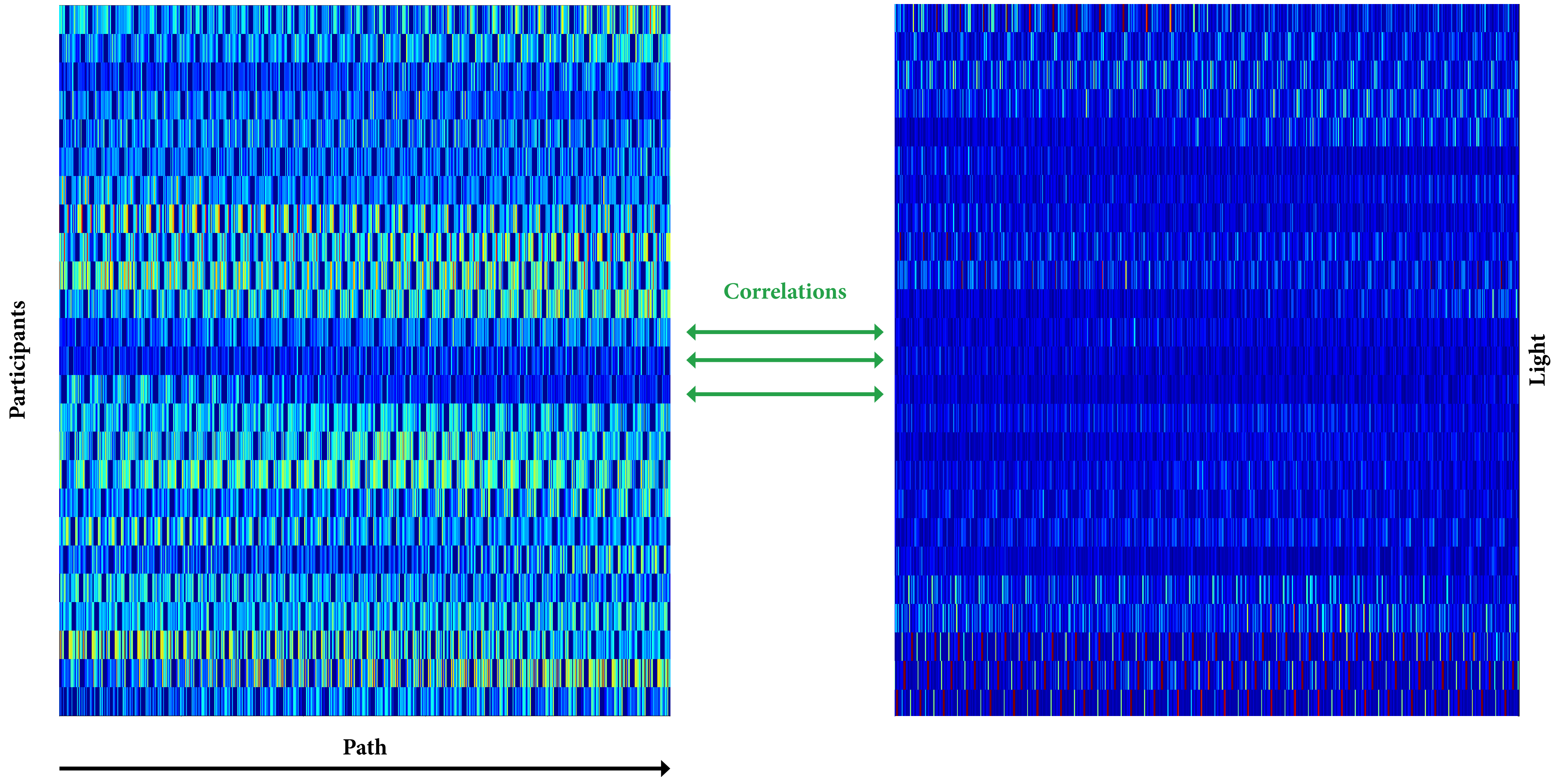
Assumption: Bad weather is responsible for this.

Question: Is there a link between the weather and the amount of people in the streets?



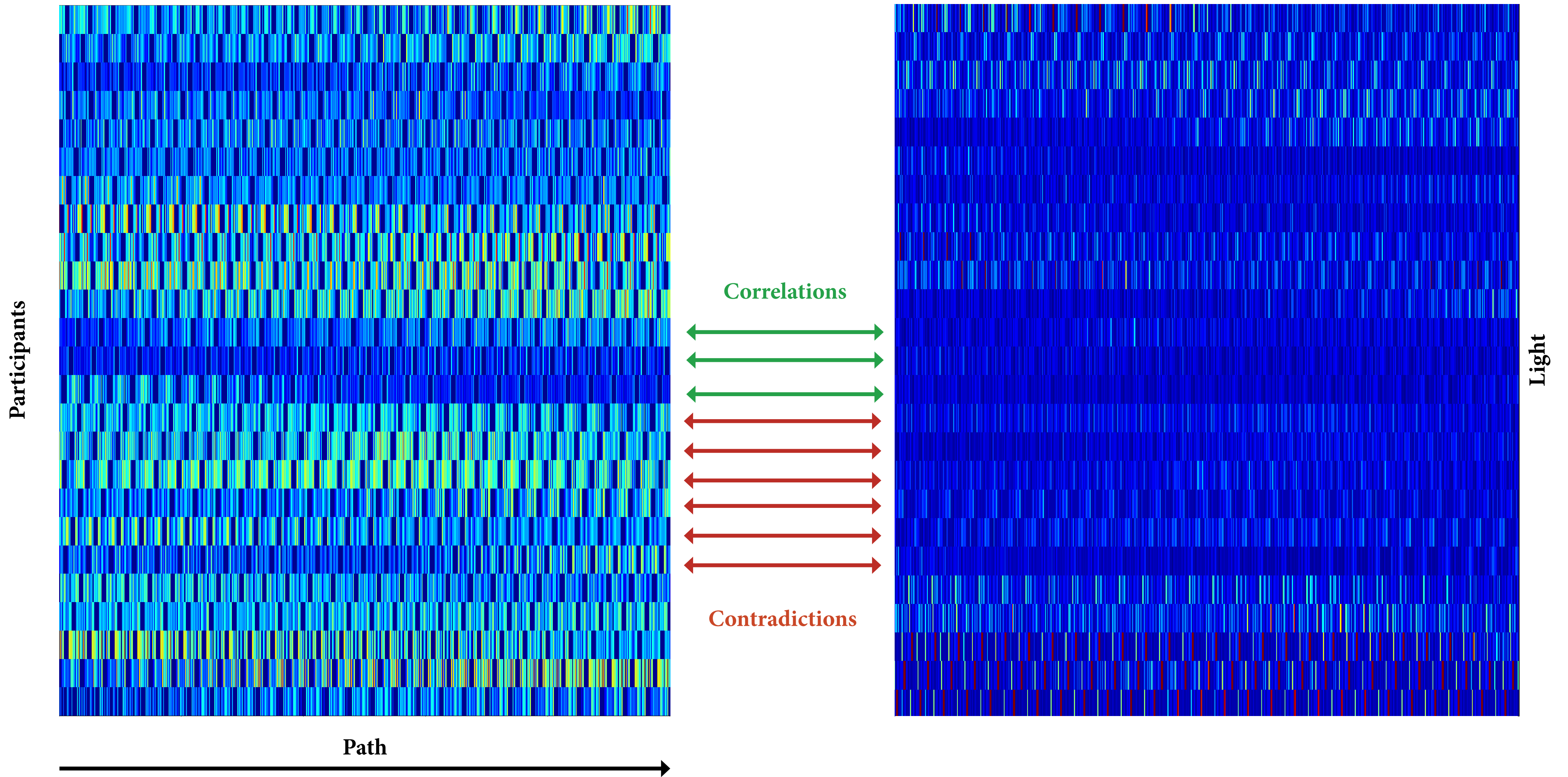
Comparison with light sensor data.

Green colour displays direct sunlight. Exclusively blue lines are cloudy days.



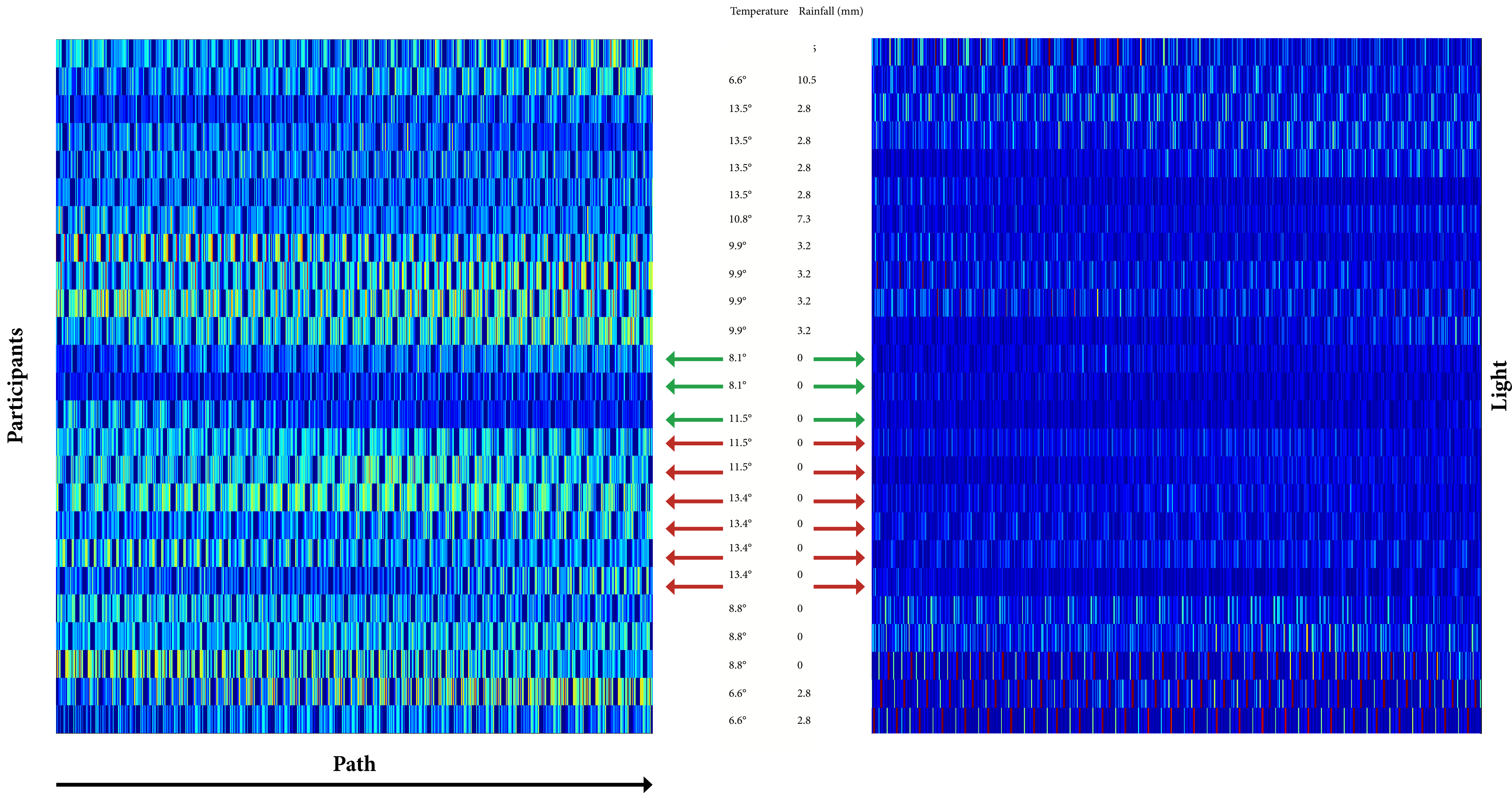
Searching for obvious correlations

Proof: If there is no sunshine over the timespan of three participants and obviously fewer people on the street.



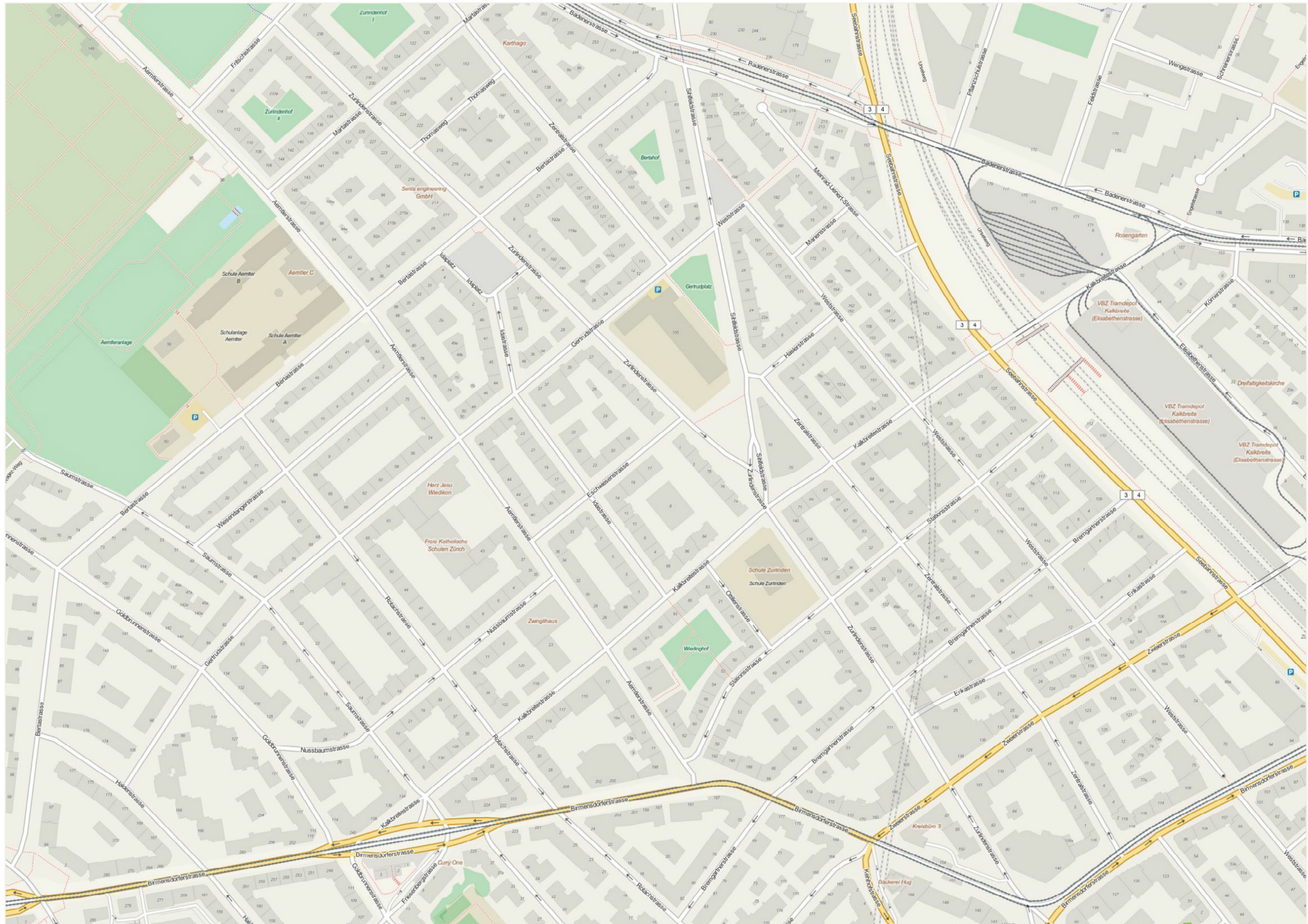
Contradictions

There are some contradictory days, where there is no sun but still many people on the street.



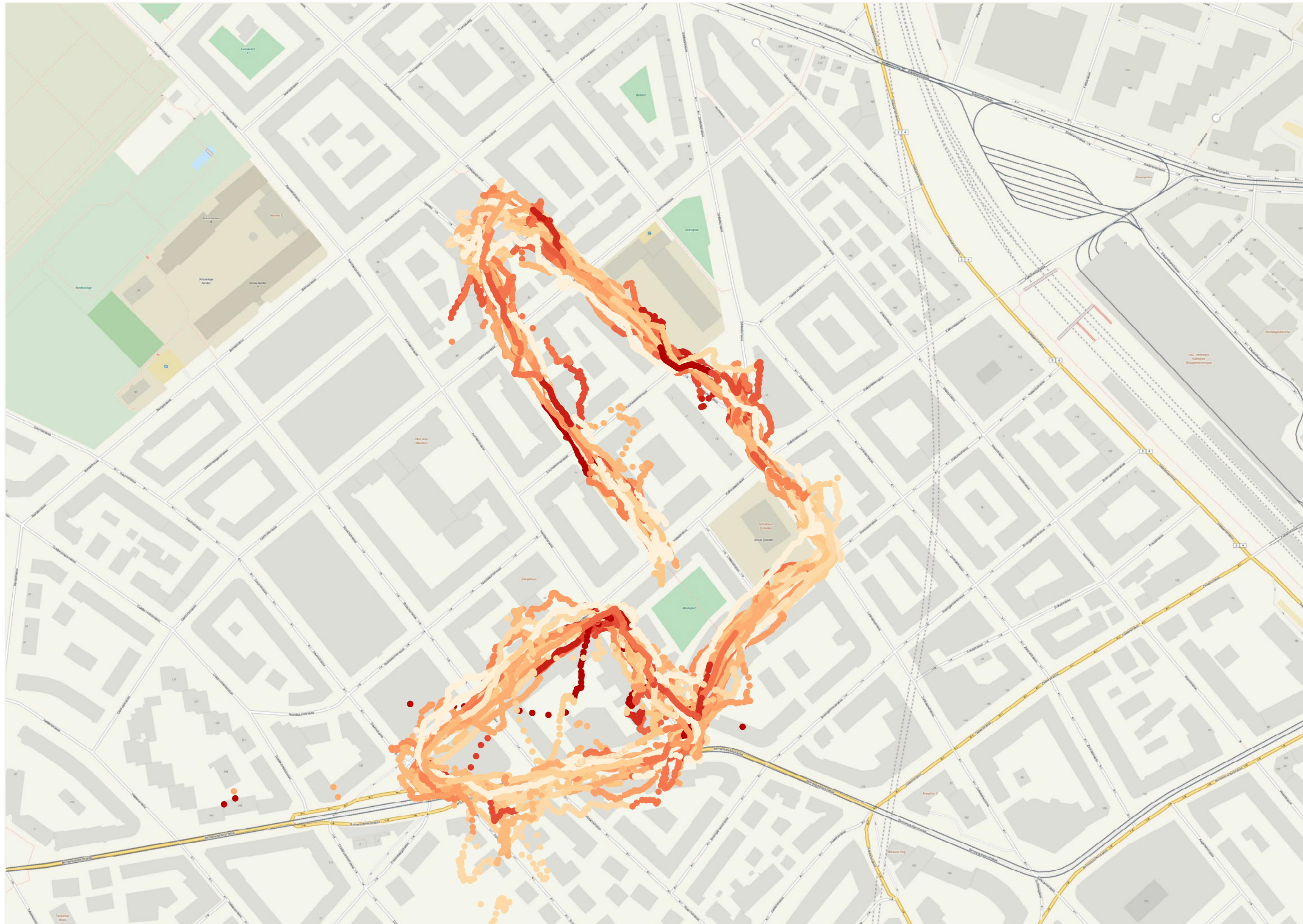
Contradictions

The contradictions could be explained by looking at the average temperature on those days.



QGIS

Question: Is it possible to monitor the amount of people in the streets via QGIS?



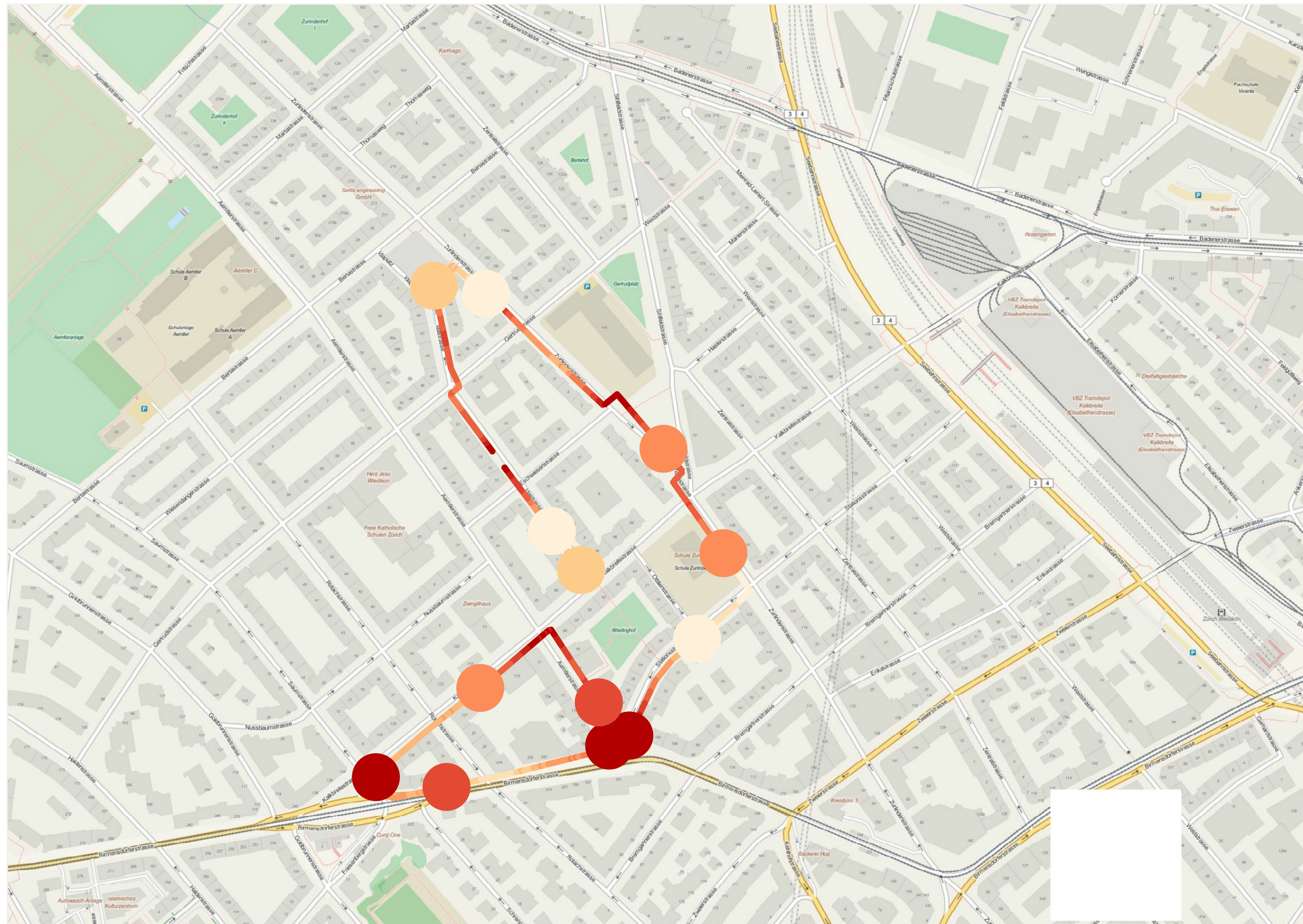
Raw data input

Representing all the participants WiFi sniffer data on one map.



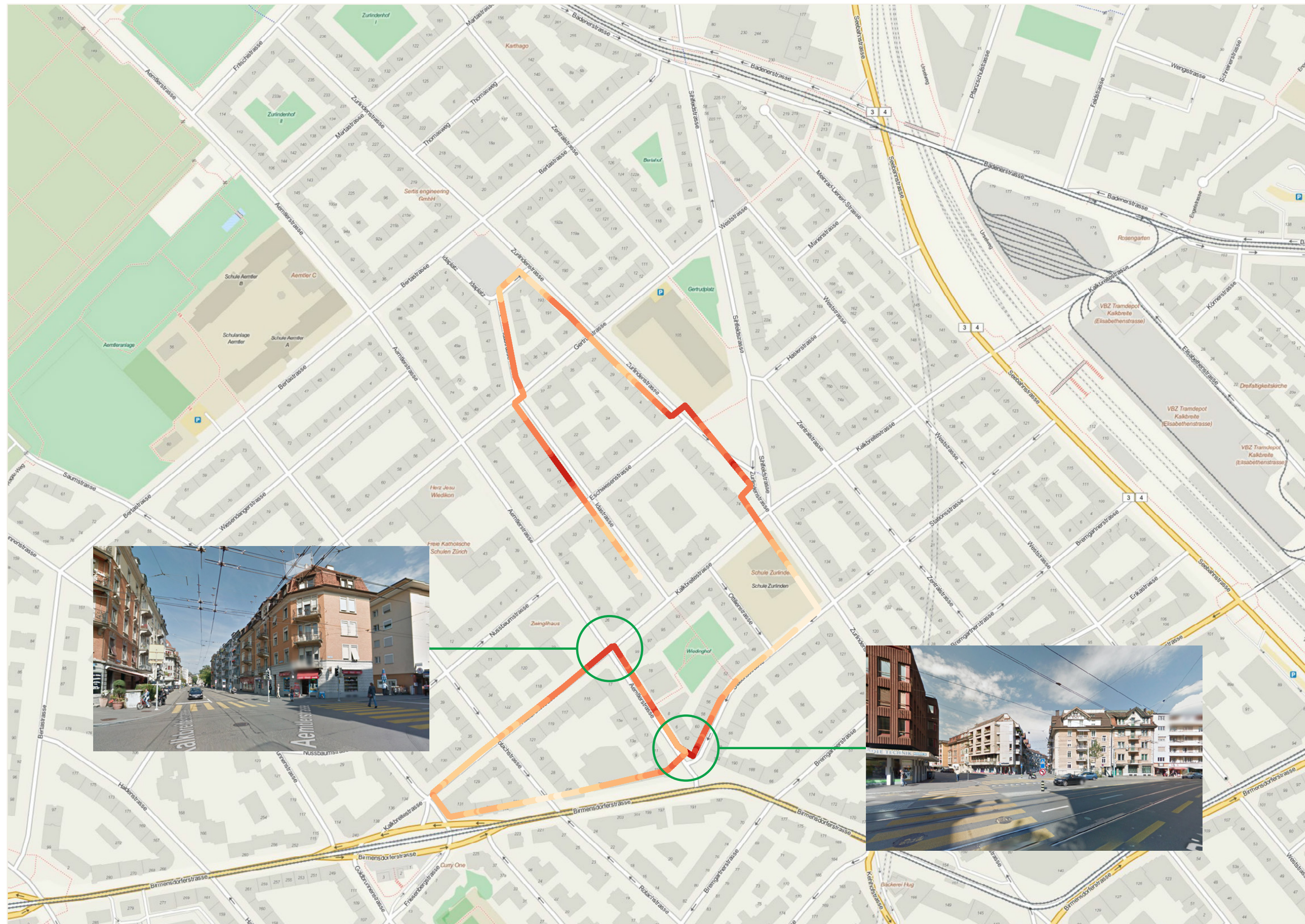
Average values for better display

Creating a standard path with the average data of all participants. There seem to be some areas with more people on the streets.



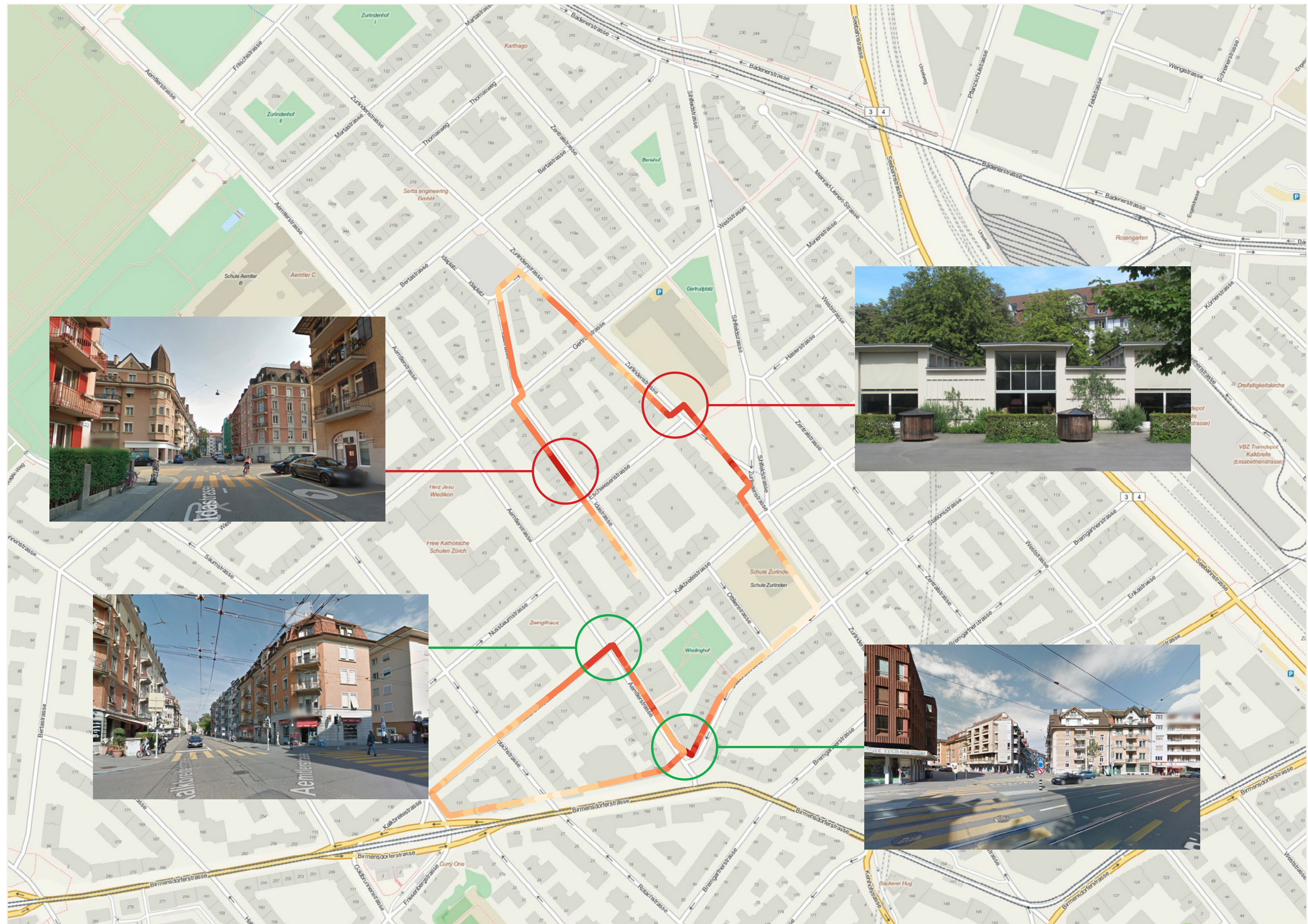
Survey data

The surveys that were taken along the path show some deviations from the WiFi data.



Site impressions

Two points seemed likely to be crowded ones. Cafes and pedestrians on the streets



Site impressions

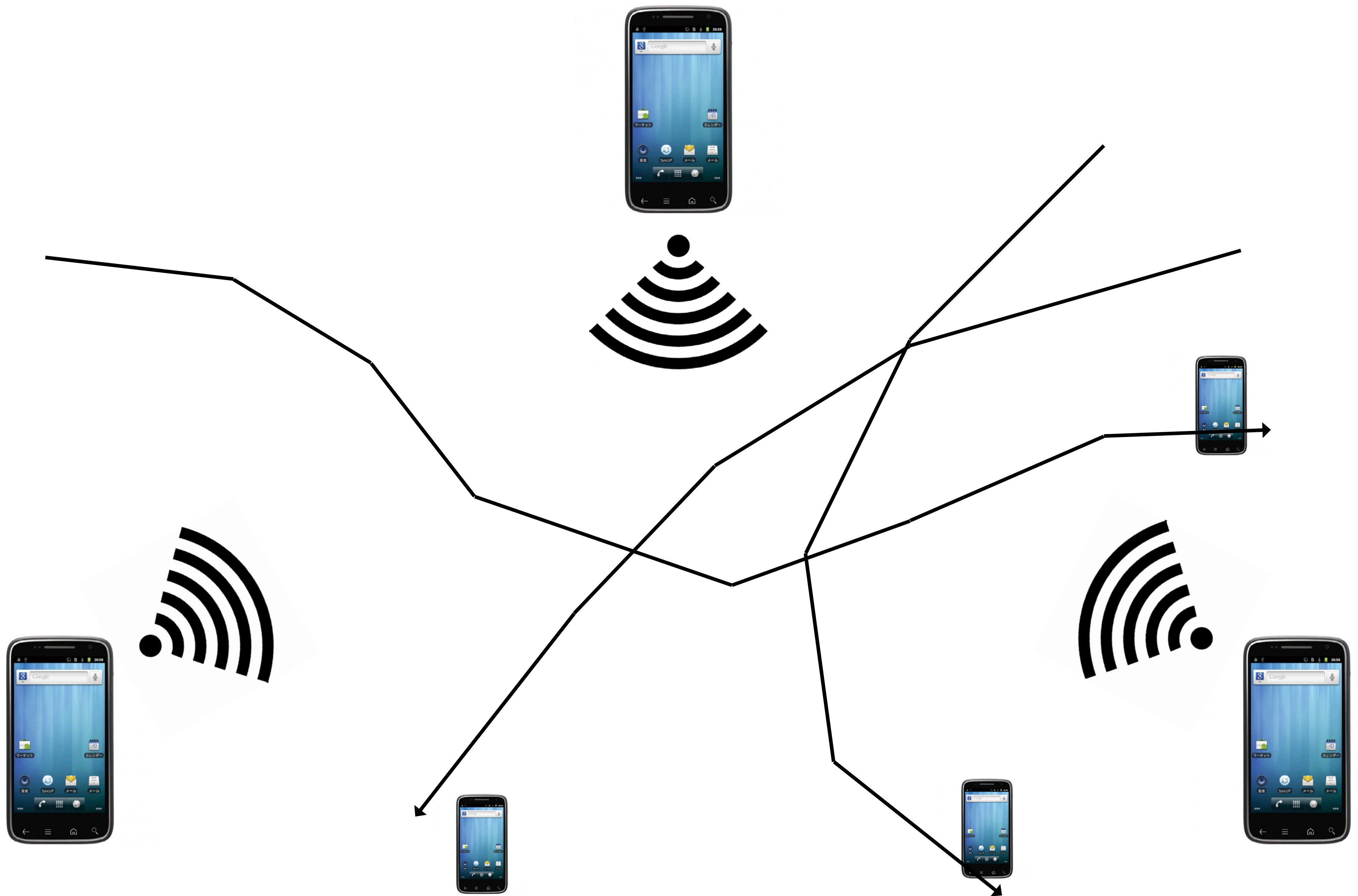
The two others seemed to be rather empty.

Stationary devices?

Possible Reason: Code contains also stationary devices and for some reason there are many of them.



Raw data shows a large amount of stationary devices at mentioned point.



Triangulating

Is it possible to determine the exact position of people via WiFi tracking?