Towards the Use of Crowdsourced Volunteered Meteorological Data for Forest Fire Monitoring

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***Abstract*— Static geosensor networks equipped with variety of sensors are used for collecting and transmitting physical data from their surrounding environment. These geosensor networks are used for monitoring potential disaster areas for early warning systems. Weather stations are an example of such static geosensor networks used for the collection of meteorological data, as temperature, humidity, pressure, wind direction and speed, used, for example, as input data for forest fire prediction and behavior systems. Nevertheless, static geosensor networks show some limitations, in terms of insufficient coverage, low density, nondynamical, limited power source and budget constraints. In recent years, the use of crowdsourced Volunteered Geographic Information (VGI) has emerged as a working methodology for retrieving real-time data in disaster areas; thus, allowing real-time and continuous aggregation of data and production of information. Using VGI methodologies, having the capacity of collecting dynamic real-time data can reduce deficiencies related to the use of static geosensor networks. This study is aimed at proving the feasibility of using VGI data as a reliable data source for reducing weather geosensor network limitations along with estimating the reliability and accuracy of crowdsourced data. This is done by analyzing the observations made by smartphones to prove their capacity. An example is presented to emphasize the potential of using crowdsourced VGI to densify and enhance static geosensor networks.**

Keywords-VGI; crowdsourcing; geosensor netowrk; densification; forest fires.

I. INTRODUCTION

Forest fires are vital natural phenomenon that maintains the health of ecosystems in reproducing, renewing and extending the diversity of species. Still, forest fires can also be a destructive natural disaster having devastating impact on the ecological, biological and social environment. Fast detection of fire and short arrival time of the fire brigades are key elements that can make the difference between small-scale disaster and mass casualty incident. Knowing in real-time crucial physical components that affect the spread and extent of forest fires enable the emergency agencies to act faster, and to be better prepared in case of forest fires. Because of the necessity for receiving - in real time - data from the area, early warning systems were developed.

A. Geoseneor Networks for Early Warning Systems

Early warning systems for disaster situations are usually based on static geosensor networks that monitor a predetermined stationary area for providing hazardous warning in cases of fires, floods, earthquakes and more. These geosensor networks are comprised of physical sensors aimed at warning of potential risk for disaster occurrence. Those sensors collect physical data from their environment and have the ability of transmitting it. Nevertheless, static geosensor networks show some limitations, in terms of insufficient coverage, low density, nondynamical, limited power source and budget constraints.

By using crowdsourced VGI working methodology, i.e., collecting data from volunteers in the area, limitations related to the use of static geosensor network can be reduced. For example, coverage and density of the network can be expanded using real-time user generated observations (negating the cost limitation), which if required, contribute to a more reliable data interpolation for acquiring information from unreachable areas. Moreover, the location of the reports varies in time, hence making the network dynamic and flexible. In addition, disabled sensors (e.g., damaged, blinded, or without power source) can be replaced with real-time data generated voluntarily by nearby citizens.

B. VGI for Disaster Situations

In recent years, the use of Volunteered Geographic Information (VGI) has emerged as a working methodology for retrieving real-time data in disaster areas. VGI is a subset of crowdsourcing paradigm, a working premise in which user-generated information is gathered and shared by individuals who participate voluntarily in a specific task. The reliability of information is usually derived by the number of volunteers in the area [1][2]. Geo-related crowdsourcing working paradigm that combines sensing and communication technologies, enables virtually everybody to collect data about the immediate environment - with almost no effort and expertise; thus, allowing real-time and continuous aggregation of data and production of information [2][3]. VGI is an effective method for data collection that can be used for expanding the variety of data sources and enhancing the resolution of sensor readings and reports, thus enriching and augmenting information derived from static sensors, especially when the nature of the geographic phenomena is dynamic [4].

In a disaster situation, geospatial data and tools have an essential part in many aspects of disaster management (planning, response, recovery and more). Using crowdsourcing tools, geo-tagged data can be collected by different means, allowing relief organizations to react better in case of emergencies and disasters [5]. It is widely acknowledged that real-time geospatial data are an essential source of information for all aspects of disaster management [6].

Generally, relying on user-generated data obtained in real-time from individuals nearby the interest area can augment the knowledge gap that might exist due to lack of accurate and updated data that is a result of inadequate sensor network deployment. Thus, enabling a more complete understanding of the disaster area. As in forest fires monitoring: fusing the crowdsourced sensor-data in real-time, and thus densifying existing static sensor-networks, have the potential to increase the likelihood to derive knowledge in respect to what is happening in real-time (i.e., now) – and where exactly. Also, to make a reliable and accurate assessment as to what will happen next, and consequently - how to respond.

This research is aimed toward improving and augmenting geosensor network deficiencies by using crowdsourced VG data. This paper presents preliminary examination of this research paradigm by analyzing meteorological data collected solely via smartphones (without the need of additional devices). The research is focused on determining the reliability and accuracy of the collected data when compared to authoritative meteorological geosensor networks. This will serve as a preliminary stage towards the feasibility of using the crowdsourcing paradigm for such scenarios.

The remainder of this paper is organized as followed: section II reviews related work in the field of VGI, section III introduces the methodologies used in this study, section IV describes the experiments, followed by analysis and evaluation of the results, which are detailed in section V. Section VI presents an example of the potential this paradigm have, and section VII concludes this paper and presents future work.

II. Related Work

Recent studies have proved that the public is collaborating in sharing and collecting information [7][8][9]. Furthermore, in cases of emergencies and disasters, the public's motivation for data collection is even bigger [10]. Various different VGI based solutions and platforms have emerged for emergency and disaster response. Ushahidi, for example, is a crowdsourcing platform used for the creation of crisis maps on the basis of integrating data from multiple sources and devices, as in the Haitian earthquake, Japanese tsunami, Kenyan post-election violence crisis [3]. OpenStreetMap (OSM) is a platform for creating GI by volunteering participants, which edit the map data by uploading GPS tracks, interpreting aerial imagery, out-of-copyright maps - and more [11]. This enables to use the platform for disaster situations characterized by the need for up-to-date maps (used in the 2010 Haitian earthquake) [3]. VGI can be used for flood damage estimation [12], radiation monitoring [13] or environmental sensing. Common Scent is an example of a crowdsourced based platform for environmental sensing that provides near real-time air quality data based on physical sensors mounted on bicycles [14]. Virtually, VGI enables to reduce the dependency on experts, while relying on the fact that accurate data is collected via diverse sources, consequently producing reliable information. The contribution of VGI for disaster situations is widely implemented in various different applications, assisting in better managing, controlling and recovering from such events, such as fires, earthquakes, violence riots, and also for environmental awareness, such as monitoring air quality, radiation level and other different hazards [5][15][16].

III. Methodology

A. Required Data for Forest Fire Model

The relevant crowdsourced data that is collected for fulfilling the objectives of this study can be divided to meteorological data and auxiliary data. The meteorological data are comprised of: (1) ambient temperature, and (2) relative humidity. These are the cardinal input data for fire spreading simulators (which generate information regarding ongoing fire: perimeter, growth, spreading rate and direction), and for fire danger rating systems (used for estimating the potential threat of a fire to ignite and spread over a large area) [17].

Auxiliary data assist in analyzing the reliability of meteorological data by describing the environmental conditions affecting the collection device. Since here data are collected via portable devices, auxiliary data are comprised of: (1) illumination – how exposed is the device to direct sunlight, (2) proximity - for detecting possible close by exterior disturbances, (3) battery properties – in terms of heating and current usage, and (4) GPS – acquiring the geographic position of the meteorological measurements. The readings of the first three give information that is relevant for the consistency of metrological data, since they might bias them and affect their reliability.

B. Data Collection Platform

Since crowdsourcing data collection relies on random individuals situated nearby the interest area, hence most probably portable devices will be used that have the capability to collect both the meteorological and auxiliary data and transmit it in real-time (via the internet). The more common and widespread the data collection platform is, the probability of citizens participating in gathering data increases, therefore enhancing the overall data – and hence information - accuracy, density and reliability. After examination of possible data collection platforms suitable for this purpose, the device that was chosen is the Samsung Galaxy S4 (SG4) model GT-I9500 (Samsung having a market share of 25% [18]). This model contains sensors required for the collection of all the aforementioned data types (such that no additional devices are needed). The application used for collecting and managing the data is 'WeatherSignal', which satisfies the collection requirements. The SG4 ambient temperature/relative humidity sensor model is SHTC1, manufactured by 'Sensirion'. The sensor is calibrated by the manufacturer for each device it is installed in before use in a controlled environment. The official accuracy of the sensor is depicted in Table I [19].

C. Reference Data

Analyzing the credibility of the crowdsourced collected data, it is necessary to have reliable and accurate sets of reference measurements of the same meteorological parameters; these will be used for comparison and evaluation purposes. For this, data from the Israel Meteorological Service (IMS) weather stations, which comply with the World Meteorological Organization (WMO) standards – also in terms of accuracy (depicted in Table II) [20] - are used.

IV. FIELD EXPERIMENTS

To determine the accuracy of the SG4 ambient temperature and relative humidity measurements, data were collected in three different scenarios, which differ by the collection duration and location (environmental conditions), to enable a more qualitative assessment of collected data and measuring conditions.

In the first scenario, the aim was to verify that the measurements' accuracy is compatible with the official manufacturer accuracy (shown in Table I), and also in non-laboratory conditions only, i.e., field conditions as well. Therefore, data were collected continuously for a long duration (about 20 hours), while the SG4 was positioned statically nearby an IMS station in a shadowed place to eliminate the heating impact of exposure to direct sun light.

The second scenario was composed of a series of short duration measurements: four different times of day for approximately 1 hour, and nearby two alternative IMS stations. This scenario aims at determining the accuracy of the SG4 readings over short periods without having the need for data post-processing.

The SG4 measurements might be biased due to environmental conditions, which affect the measuring sensors. Therefore, it is essential to determine when do the SG4 readings are accurate without having to rely on external reference data. This is determined in the third scenario, which is composed from a series of five measuring sessions, where in each the SG4 was exposed for a short period to direct sunlight, which resulted in erroneous readings. Subsequently, the SG4 was moved from the sunlight to a shaded place until accurate measurements were obtained in comparison to the IMS data (with confidence level of 95%).

TABLE I. SHTC1 SENSOR OFFICIAL ACCURACY.

Data Accuracy	Meteorological Parameter			
	Relative humidity (%)		*Ambient temperature (°C)*	
	Range	*Accuracy*	*Range*	*Accuracy*
SHTC1	20-80	4.5	5-60	0.4
	<20 or >80	7.5	<5 or >60	1.2

TABLE II. IMS AMBIENT TEMPERATURE AND RELATIVE HUMIDITY ACCURACY.

Data Accuracy	Meteorological Parameter			
	Relative humidity (%)		*Ambient temperature (°C)*	
	Range	*Accuracy*	*Range*	*Accuracy*
IMS	<50	3-5	<40	0.1-0.2
	>50	3	>40	0.3

V. EXPERIMENTAL RESULTS AND EVALUATION

A. First Scenario

The results of the first scenario are displayed in Table III. The ambient temperature mean difference between the SG4 and the IMS measurements is 1.1°C, with Standard Deviation (SD) of 1.4°C. Assuming the data is normally distributed, the estimation interval of the mean with probability of 95% is 1.1°C ± 0.2°C. The relative humidity mean difference is 6.6%, with SD of 4%. The relative humidity confidence interval with probability of 95%, assuming the data is normally distributed, is 6.6% ± 0.7%.

Possible improvement of the measurements' accuracy can be achieved by eliminating outliers, which are caused by the surrounding environmental conditions affecting the sensor readings. Several outlier detection methods were implemented (IQR, boxplots, mean and SD methods). The outlier detection methods identified 6 to 9 outliers for the ambient temperature measurements, and 1 to 2 outliers for the relative humidity measurements; both, out of 134 observations, such that approximately 95% are considered as accurate and reliable. The mean and SD method was chosen to be used for eliminating outliers, since it was found to be more sensitive to outliers than the other methods.

After removing the outliers, the data were analyzed again, and the results are presented in Table IV. The ambient temperature mean difference was reduced to 0.8°C with SD of 0.7°C and confidence level of ±0.1°C. The relative humidity measurements were slightly reduced but remained of the same scale as prior to the outlier removal since not many outliers existed.

B. Second Scenario

The ambient temperature mean residual varies from minimal value of 0.3°C with SD of 0.1°C and similar confidence interval, to maximal value of 1.4°C with SD of 0.3°C and similar confidence interval, as can be seen in Table V. The average of overall mean residuals is 1°C, which is similar to the values obtained in the first scenario before the

TABLE III. RESULTS OF FIRST SCENARIO: MEASUREMENTS IN RESPECT TO REFERENCE DATA.

Statistical Analysis of Residuals	Meteorological Parameter	
	Ambient temperature (°C)	*Relative humidity (%)*
Mean	1.1	6.6
Standard Error	0.1	0.3
Standard Deviation	1.4	4
Minimal Residual	0	0.2
Maximal Residual	9.2	20.7
Count	134	134
Confidence Level (95.0%)	0.2	0.7

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TABLE IV. FIRST SCENARIO RESULTS AFTER OUTLIER REMOVAL.

Statistical Analysis of Residuals	Meteorological Parameter	
	Ambient temperature (°C)	*Relative humidity (%)*
Mean	0.8	6.4
Standard Error	0.1	0.3
Standard Deviation	0.7	3.7
Minimal Residual	0	0.2
Maximal Residual	3.1	15.4
Count	126	132
Confidence Level (95.0%)	0.1	0.6

outlier removal. The relative humidity means residuals range from 1% with similar SD and confidence interval of 1%, to 14% with SD and confidence interval of 1%.

The mean residuals in 6 out of 8 temperature measurements were better or similar to the data obtained in the first scenario before removing outliers. In the relative humidity measurements, 5 out of 8 mean residuals were smaller than the first scenario data after removing outliers. According to the analysis results obtained for the two different scenarios in controlled conditions, it is clear that the SG4 can be used for acquiring accurate and reliable meteorological data, even without eliminating outliers, since it serves with good quality measures and low bias of measurements.

C. Third Scenario

The aim of this scenario was to determine the environmental conditions in which the SG4 measurements are accurate and reliable; this is aimed to allow not to use external reference data. Since sensors calibration time (needed for obtaining reliable results) are not constant and cannot be predetermined, four parameters were defined, which are calculated dynamically from the SG4 measurements, that help determine when the sensor readings are stable (not biased) and accurate, hence sensor is calibrated: (1) gradient (of data); (2) SD; (3) number of observations, and (4) illumination. Using statistical analysis, threshold values for the aforementioned parameters were determined, depicted in Table VI; based on these parameters a calibration algorithm was developed, depicted in Figure 1. Implementing the algorithm makes it possible to identify when the sensor readings are biased and/or erroneous, while correctly detect when readings are reliable - without having to use any external reference data.

Validation of the algorithm is depicted in Figure 2, showing a comparison of the IMS temperature data (reference) with VGI readings. It can be noted that the ambient temperature readings from both data sources are similar at the calibration point, characterized in the graph by horizontal slope of both indicators (SD and gradient of data), that was determined automatically by the algorithm.

VI. POTENTIAL OF VGI FOR REAL-TIME WEATHER DATA

The potential of using crowdsourcing for the collection of weather data is illustrated by the use of the crowdsourced weather map created by 'Weather Signal' (WS). WS is an application used for voluntarily collecting weather data (along with other available sensor data) from sensors mounted on portable devices (such as smartphones). The map depicted in Figure 3 demonstrates the high density VG data have in respect to the static network which is comprised of weather stations that are part of the IMS network used by KKL-JNF (Keren Kayemeth LeIsrael-Jewish National Fund) to monitor meteorological data nearby forests, thus on the augmentation potential of using crowdsourced weather data. It is clear that the VGI ambient temperature readings are filling the gaps in areas having no coverage of weather stations, densifying the impact zones, which are sparsely

TABLE VI. CALIBRATION THRESHOLD VALUES.

Calibration Threshold	Calibration Parameters			
	No. of Observations	*SD*	*Gradient*	*Illumination*
Ambient Temperature	30	0.5 (°C)	5%	<50,000(Lux)
Relative Humidity	30	1(%)	5%	<50,000(Lux)

TABLE V. RESULTS OF THE SECOND SCENARIO: MEASUREMENTS IN RESPECT TO REFERENCE DATA.

Meteorological Parameter	Time of Measurement	*GMT+3 [01:00-02:00]*		*GMT+3 [08:00-09:00]*		*GMT+3 [13:00-14:00]*		*GMT+3 [19:00-20:00]*	
	IMS Station Name	*Oil refinery*	*University*	*Oil refinery*	*University*	*Oil refinery*	*University*	*Oil refinery*	*University*
Ambient Temperature Residuals [°C]	Mean	0.3	0.9	1.4	0.9	1.2	1.5	1.1	1.1
	Standard Error	0.1	0.1	0.2	0.1	0.2	0.1	0.1	0.1
	Standard Deviation	0.1	0.1	0.4	0.3	0.5	0.3	0.2	0.1
	Minimal Residual	0.2	0.7	0.8	0.6	0.5	1.2	0.9	1
	Maximal Residual	0.4	1	1.9	1.6	1.8	1.8	1.3	1.3
	Confidence Level (95.0%)	0.1	0.1	0.4	0.3	0.5	0.2	0.1	0.1
Relative Humidity Residuals [%]	Mean	7	1	14	10	1	3	4	2
	Standard Error	1	1	1	1	1	1	1	1
	Standard Deviation	1	1	1	2	1	1	1	1
	Minimal Residual	7	0	12	8	0	2	1	1
	Maximal Residual	7	1	15	13	2	5	5	2
	Confidence Level (95.0%)	1	1	1	1	1	1	1	1

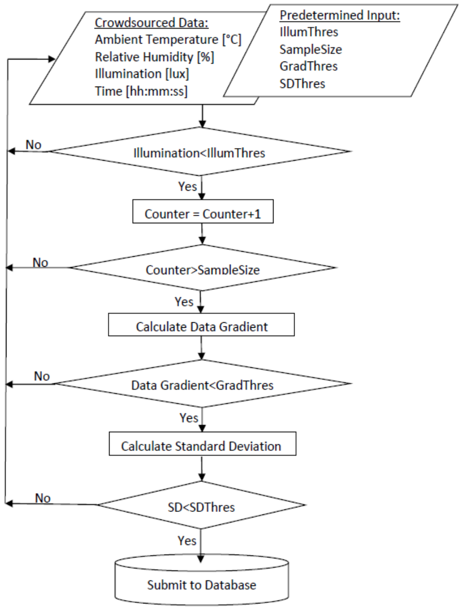

Figure 1. Calibration algorithm workflow.

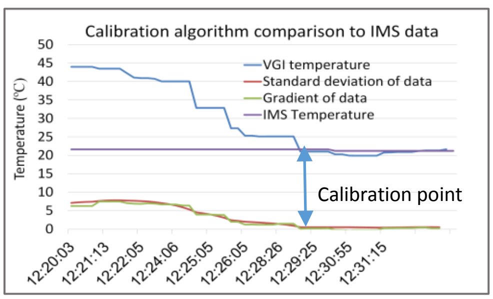

Figure 2. Algorithm indicators with IMS and VGI ambient temperature measurements.

represented by a single static IMS station. Moreover, it can be noticed that using crowdsourced data, areas currently not having any IMS station in their vicinity (south, center) now have several readings, which greatly contribute to a better assessment of physical conditions.

The crowdsourced weather data, downloaded from WS database for a specific date and time (22/3/2014, 13:00-14:00 GMT+2), were processed using spatial and attributional queries for eliminating measurements with incomplete data or characterized as indoor, which are irrelevant for this analysis. The algorithm used for this process was implemented using ArcGIS model-builder. Figure 4 depicts Kriging interpolation of the VGI ambient temperature readings, with and without existing IMS data for that specific date and time. Inspecting the interpolation results, it is clear that they are continuous and similar in values - VG data in respect to reference data (IMS) with no anomalies detected – supporting the fact that VGI measurements are reliable. More importantly, as depicted in the lower image, it is clear that some physical conditions are revealed and made clear and

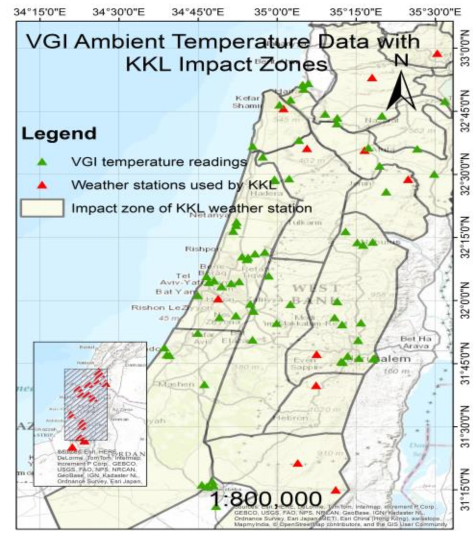

Figure 3. Map of VGI ambient temperature readings superpositioned with IMS weather stations used by KKL and their impact zones.

local (mainly in the center) thanks to the data densification – a direct result of using VGI.

VII. Conclusions and Outlook

The feasibility of collecting reliable and accurate VGI metrological observations (ambient temperature and relative humidity) via smartphones (SG4 in this case study) was verified. Consequently, as presented in the previous section, the use of crowdsourced volunteered meteorological measurements is made possible, enhancing the input weather data collected from the surrounding. Although the accuracy of the 'SHTC1' sensor might decrease due to environmental conditions, the algorithm developed for this research is capable to detect such situations, thus having the possibility to filter out erroneous observations. This proves that with relatively small post-processing, and without having the need to use reference data to analyze the correctness of the data, the collection device can function as a reliable and accurate 'dynamic geosensor station' that serves as supplementary data source that is external and independent to the static network. Though other devices - other than the SG4 - should be analyzed, first inspection made with available WS data showed that alternative portable devices are also reliable.

The next phase of this research will be focused on the collection and analysis of crowdsourced VG data from wider areas, and on the development of a fusion algorithm designed for observations from crowdsourced VGI and IMS. These are aimed for densifying the static geosensor network, while the output of such process will augment and improve the input data required for forest fire models.

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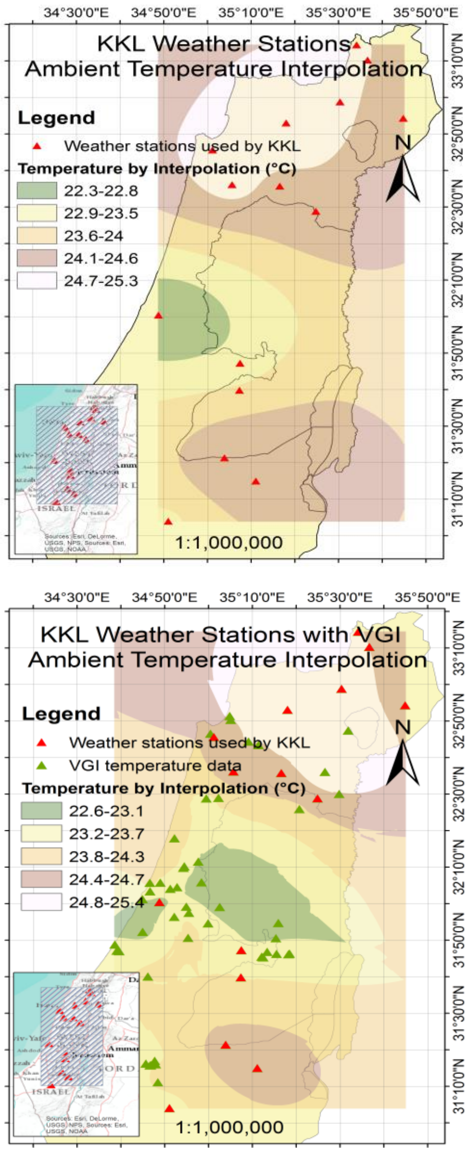

Figure 4. Kriging interpolation map of IMS stations ambient temperature measurements (top), and together with VGI readings (bottom).

delivered with valuable information and assistance regarding their WS web service and data.

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