

# Overview of the ImageCLEF 2017 Population Estimation (*Remote*) Task

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**Abstract.** Estimating population has many applications as planning disaster responses, communication infrastructure, or development activities. In 2017, ImageCLEF Lab introduced a new pilot task: the Population Estimation (or Remote) task which aims at estimating the population of an area of interest by exploring Copernicus earth observation data (i.e. free Sentinel-2 satellite images). In line with the goal of FabSpace 2.0 project, a European Unions initiative to bring Geo-Enthusiast together around the 6 European universities in collaboration with Business Incubation Centers, participated to this challenge. This paper presents the results that were obtained by the participants as well as a brief summary of some of the approaches that were used.

**Keywords:** Information Systems, Information Retrieval, Image Retrieval, Copernicus data, Automatic Population Estimation, FabSpace 2.0, CLEF

## 1 Introduction

Estimating population for the planning of communication infrastructure and any development activities is an important issue. Such accurate estimation is also crucial for NGOs before engaging any rescue operation or humanitarian action. Population estimation is indeed fundamental to provide any services for a particular region. While good estimates exist in many parts of the world through accurate census data, this is usually not the case in developing countries. Collecting new census is expansive and time consuming; it is not possible in case where decision has to be taken quickly. Moreover, census data are generally based on political areas such as cities or counties while humanitarian and rescue actions and/or communication activities are more geographically-based as they take place in the areas of catastrophe such as where hurricane, earthquake or flood happened and to combat epidemic diseases.

Alternatively, counting the number of buildings (given the fact they can be properly extracted) can provide a first estimate; however, it may not be enough since people in various places in the globe do not live the same way, the population may vary in summer and winter in different touristic places, or population may vary where there is easy access to public services or amenities.

Moreover, the distribution of population in the coast and the urbanized area is not similar in terms of building structures and spatial distributions, household sizes and topographical representations.

This pilot task is part of the imageCLEF 2017 Labs [13] and was introduced this year. It aims at investigating the use of non commercial satellite data as a free and quicker process to estimate the population of an area of interest. More specifically, this pilot task aims at exploring Copernicus<sup>1</sup> earth observation data (i.e. Sentinel-2 satellite images) which are available for free and in a good temporal and spatial resolution.

## 2 Population Estimation Pilot Task Overview

In this pilot task, participants had to estimate the population for different areas in two regions Lusaka and Uganda. To achieve this goal, organizers provided a set of satellite images (Copernicus Sentinel-2). The boundaries of the areas of interest were provided as shape files. The clipped satellite images were provided as well as the meta data of the original images (before clipping). This pilot task uses Copernicus Sentinel-2 multi-spectral images with 13 bands (resolution between 10 and 60 meters). However, participants were allowed to use any other resource they think may help to reach the highest accuracy.

The study area consist of 83 areas of interest in the city of Lusaka and 17 in west Uganda for which the population has to be estimated, for a total of 100 areas. For 90 of these areas ground truth is available thus evaluation considered these areas only.

This pilot task was initiated within FabSpace 2.0 project<sup>2</sup> in collaboration with CartONG, founded in 2006, CartONG is a French non-governmental organization committed to furthering the use of geographic information tools to improve data gathering and analysis for emergency relief and development programmes around the world.<sup>3</sup> The task is an open challenge in the ImageCLEF laboratory as well as in the 6 FabSpaces laboratory in Europe.

## 3 Dataset and evaluation protocol

### 3.1 Dataset

The data set<sup>4</sup> consists of topographic and geographic information as follows:

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<sup>1</sup> [www.copernicus.eu/main/sentinels](http://www.copernicus.eu/main/sentinels)

<sup>2</sup> FabSpace 2.0 is the open-innovation network for geodata-driven innovation by leveraging Space data in particular, in Universities 2.0. This project received funding from the European Unions Horizon 2020 Research and Innovation program under the Grant Agreement n°693210. More information at <https://www.fabspace.eu/> and [6]

<sup>3</sup> <http://www.cartong.org/fr>

<sup>4</sup> The dataset is available on Zenodo with the DOI 10.5281/zenodo.804602 or on demand

- ESRI shape files: there is single shape file by region and the projected shape file of the region has the necessary attributes to represent the various areas the region is composed of.
- Sentinel-2 satellite images: The remote sensing imagery comes from the Sentinel-2 platform. The imagery is multi spectral, cloud-free satellite imagery downloaded from Sentinel Data Hub<sup>5</sup>. The images have been clipped to match the bounding box of the areas of interest. The bands for images have different spatial resolutions: 10 meters for bands B2 (490nm), B3 (560nm) B4 (665 nm) and B8 (84nm); 20 meters for bands B5 (705nm), B6 (749nm) B7 (783nm), B8a (865nm) B11 (1610nm) and B12 (2190nm). For the analysis, participants were encouraged to use Red, Green and Blue bands or in some cases near infrared bands which are 10 meters resolution.
- Meta-data associated to the images: Information regarding the original images is provided in XML files. These files contain information like capture time/date, sensor mode, orbit number, the id of quality files, etc. Further information regarding the Sentinel-2 products, as well as file structure can be found in the Sentinel 2 User handbook<sup>6</sup>.

In this pilot task two regions has been selected: city of Lusaka and West of Uganda. More specifically, the data set is composed of the following structure:

- City of Lusaka: The subareas are based on Operational Divisions, a unit defined by Médecins Sans Frontières in 2016. This organization divided the city of Lusaka in 83 units. For this region, the data set consists of: (1) ESRI shape file including locational and attributes information, (2) Two Sentinel-2 level-1C satellite images covering the area and for each image there are all 13 bands, (3) XML meta data associated to image files.
- West Uganda: In Uganda there is 17 subdivisions and for this region data sets consists of: (1) ESRI shape file including locational and attributes information, (2) Five Sentinel 2 level-1C satellite images covering the area and for each image there is all necessary bands, (3) XML meta data associated to image files.

The images from the data set are stored in zipped files with the following folder structure:

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<sup>5</sup> <https://scihub.copernicus.eu/dhus/#/home>

<sup>6</sup> [https://sentinel.esa.int/documents/247904/685211/Sentinel-2\\_User\\_Handbook](https://sentinel.esa.int/documents/247904/685211/Sentinel-2_User_Handbook)

[NAME OF THE STUDY REGION]: Lusaka or Uganda.  
[shp]: This folder contains a shapefile with the boundaries of the study areas.  
[sentinel2]  
[ID\_OF\_SATELLITE\_IMAGE]: Original id of the image as in the Sentinel Data Hub.  
[bands]: This folder contains the bands of the image. Each band is a Geo-Tiff file. Each band corresponds to a certain electromagnetic spectrum captured by the sensor.  
[xml]: This folder contains the XML files that contains metadata information regarding the images. The information applies to the original source (before image clipping). By using the information in this file a user can obtain the original dataset.

### 3.2 Evaluation

The evaluation method uses three metrics that compare the predicted values and the ground truth s: 1) Sum of the differences over the areas, 2) Root Mean Square Error, and 3) Pearson correlation.

The challenge comprise of geographically separated two areas, West Uganda, and Lusaka in Zambia. Because of this fact, it was decided to evaluate both areas separately but together in a single file. We evaluate the results considering two variables: 1) Population counts, and 2) Dwelling counts. Each run submitted by the participants has 12 possible metrics. However, not all the participants submitted results for both variables. All the submissions provided were estimation of the population, while only two of them provided estimates for both population and dwelling units.

The next subsections will provide a short description of the metrics used to evaluate the results.

**Sum of differences** This evaluation criteria estimates the differences between the predicted value and the ground truth. For each operational zone, we calculate the absolute value of this difference and summing up for the whole areas. The equation used is:

$$SumDelta = \sum_{t=1}^n |(d_t - s_t)|$$

Where  $n$  represents the total number of operational zones to evaluate,  $d_t$  represents the ground truth value, and  $s_t$  represents the estimation produced by the participant for the operational zone  $t$ .

**Root Mean Square Deviation** Root Mean Square Error (RMSE) (also known as Root Mean Square Deviation) is one of the most widely used statistics to compute the differences between a modeled output and the observed values.

The individual differences between the produced estimation and ground truth and/or the standard deviation of residuals are called prediction errors ( $d_t - s_t$ ). If the ground truth is  $d_t$  and the estimated values is  $s_t$  are standardized (resulting in zero means and unit standard deviation) then the RMSE between  $d_t$  and  $s_t$  can be calculated by following equation [4].

$$RMSE = \sqrt{\frac{\sum_{t=1}^n (d_t - s_t)^2}{n}}$$

The variables depicted in this equation are the same as the one previously described in the previous section for the equation *Sum of differences*.

**Pearson Correlation** this evaluation process calculates the Pearson correlation between the run estimates and ground truth values. Pearson correlation is between +1 and -1, where +1 represents absolute positive linear correlation, 0 represents no correlation, and -1 represents negative correlation [17].

$$r = \frac{\sum_{t=1}^n (d_t - \bar{d}) \sum_{t=1}^n (s_t - \bar{s})}{\sqrt{\sum_{t=1}^n (d_t - \bar{d})^2} \sqrt{\sum_{t=1}^n (s_t - \bar{s})^2}}$$

**AvgRelDelta** We considered an additional measure we called the average of the relative deltas which is defined as follows/

Let us consider the *relative delta* as  $\frac{(d_t - s_t)}{d_t}$ . The range of values is from  $-\infty$  to 1. Negative values indicate overestimation, while positive values indicate underestimation.

We can then calculate the *relative delta in percentage* as  $\frac{(d_t - s_t)}{d_t} * 100$

The range of values would be  $-\infty$  to 100. This measure will be used for the maps depicting the results in the next section. We can calculate this value at the operational zone level. In this way we can indicate in which operational zone the proposed algorithm failed, how much and in which way (overestimation/underestimation).

However, to obtain an overall estimation for all the operational zones, it is necessary to use the absolute value of the relative deltas as  $\frac{|(d_t - s_t)|}{d_t} * 100$ . Otherwise, the delta values could cancel among themselves.

Then we obtain an average of the relative deltas which is defined as:

$$AvgRelDelta = \frac{\sum_{t=1}^n \frac{|(d_t - s_t)|}{d_t} * 100}{n}$$

where  $n$  is the number of operational zones considered for the estimation. The lower the value of *AvgRelDelta* the more accurate the approach is.

## 4 Participants and results

Although the pilot task was opened to anyone, the actual participants came from local events (i.e. Hackathon, Idea contest etc.) that were organized within

FabSpace 2.0 project in the 6 local FabSpace laboratories. Although different teams started working on the pilot task, four teams only managed to send a run (See Table 1 in the next section). Details can also be found in [2].

The methodologies and the background of the members of the participating teams was heterogeneous. For instance, in the case of Italy, the participating team was composed of two students from the university Tor Vergata, one is a Management Engineering student while the second one is a Computer Science Engineering student [18]. In the case of Greece, the background of the participants included domains such as electrical and mechanical engineering as well as business studies [15]. From Germany three participants participated where one is a graduate student of Environmental Engineering, second is a student of Physical Geography and the third one is a PHD student [14]. Also a couple of participants from diverse background were participated at Poland.

The approaches used were also diverse. In the case of Italy, the participants used an approach based on a convolutional neural network (CNN) that makes use of Sentinel-2 Imagery as well as built up estimates provided by the Center for International Earth Science Information Network (CIESIN) [18]. While in the case of Germany, the approach was based on supervised and unsupervised image classification with the inclusion of not only optical but also radar imagery [14]. The classification also includes supervised as Minimum Distance and Maximum Likelihood Classification algorithm and unsupervised as K-Means Cluster analysis algorithm. To run the classification algorithm different software as QGIS - SCP plugins, Sentinel Toolbox and Python platform have been used. The team from Greece used satellite imagery based on classification techniques coupled with a statistical forecast on historical data [15]. At the Poland participants used Railways approach to estimate the number of buildings using radar imagery i.e. Sentinel-1 images [2].

## 4.1 Results

Table 1 presents the results for the population estimation for the 4 official runs from participants, using the 4 measures presented above and both on the individual regions (Uganda and Zambia) and overall. Table 2 presents the results for the house estimation for the two runs using the same measures.

The best results estimating the population for one particular geographic area (Uganda or Zambia) were submitted by the Greek team for Uganda (AvgRelDelta:38.75). However, their approach failed for the region of Lusaka (AvgRelDelta:Zambia), giving them an overall (AvgRelDelta:177.55). The Italian team provided the second best result (AvgRelDelta:50.5), also for the region of Uganda. While, their approach provided fair results for the region of Lusaka (AvgRelDelta:96.31), resulting in the best overall approach (AvgRelDelta:87.57). If we consider the values of *Sum Delta* and *RMSE* the Italian team has also the best values.

In the case of the Pearson value, in general the submitted results did not resulted in high overall values. They only obtained high values for the region of

Table 1: Population estimation. UGD stands for Uganda while ZMB is for Zambia region. Overall is when considering both regions all together. Bold font highlights the best value and italic the best second value.

Participant	Country	Geographic Zone	Sum	Delta	RMSE	Pearson	AvgRelDelta
Darmstadt	Germany	UGD	26,755	2,199	<i>0.87</i>	115.93	
Darmstadt	Germany	ZMB	1,466,397	30,510	0.11	93.69	
Darmstadt	Germany	Overall	1,493,152	27,495	0.22	<i>97.89</i>	
Grapes	Greece	UGD	10,160	770	<b>0.95</b>	38.75	
Grapes	Greece	ZMB	1,476,753	38,072	0.25	209.87	
Grapes	Greece	Overall	1,486,913	34,290	0.33	177.55	
AndreaDavid	Italy	UGD	18,485	1,816	0.76	50.05	
AndreaDavid	Italy	ZMB	1,465,603	30,480	0.08	96.31	
AndreaDavid	Italy	Overall	1,484,088	2,7462	0.21	<b>87.57</b>	
FABSPACE PL	Poland	UGD	22,730	2,103	0.11	115.99	
FABSPACE PL	Poland	ZMB	1,535,909	35,294	0.29	186.08	
FABSPACE PL	Poland	Overall	1,558,639	31,799	<b>0.37</b>	172.84	

Participant	Country	Geographic Zone	Sum	Delta	RMSE	Pearson	AvgRelDelta
Darmstadt	Germany	UGD	7,272	638	0.87	146.37	
Darmstadt	Germany	ZMB	290,197	6,055	0.11	104.71	
Darmstadt	Germany	Overall Houses	297,469	5,460	0.22	112.58	
FABSPACE PL	Poland	UGD	4,546	420	0.11	115.99	
FABSPACE PL	Poland	ZMB	270,007	5,494	0.44	100.58	
FABSPACE PL	Poland	Overall Houses	274,553	4,952.17	0.51	103.49	

Uganda. Again the best value was obtained by Greece (Pearson:0.95), the second best value was of the German team (Pearson:0.87).

Considering the *AvgRelDelta* we can say that in general the best population estimation approach is the one submitted by the Italian team (AvgRelDelta: 87.57).

## 4.2 Summary of participants' approaches

The aim of this work was to estimate the population for selected areas in Uganda and Zambia with Sentinel-2 data.

The approaches used by the participants to tackle this challenge were diverse.

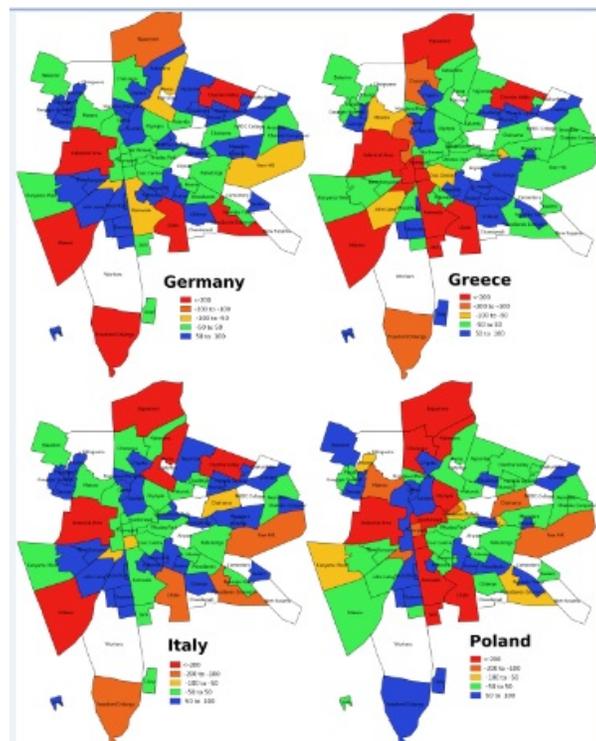
In the case of Italy, the participants used an approach based on a convolutional neural network (CNN) that makes use of Sentinel 2 Imagery (bands 2,3,4,8) as well as LDS built up estimates provided by the Center for International Earth Science Information Network (CIESIN). The LDS Built up estimates have a resolution of 30m and provide build up information as recent as 2014. The most recent estimates are based on Landsat 8.

In the case of Germany, the approach was based on diverse techniques of image classification. The participants used a subset of the bands provided by Sentinel 2 (bands 2,3,4 and 8) and also tested using only near infra-red band. The classification techniques used were supervised and unsupervised, using tools

as QGIS and Sentinel Tool Box (SNAP). As part of the approach, additional information from Sentinel 1 radar imagery was used.

In the case of Poland Railways approach to the number of buildings was done using radar images. The results obtained by estimating the number of buildings from radar imagery was more applicable. Optical data has been used to divide areas by type of building. The results obtained and their comparison to the number of buildings was very promising.

### 4.3 More evaluation



**Fig. 1.** Overview of the results submitted by the participating teams Team for the operational zones in Lusaka- Zambia.

Figure 1 depicts an overview of the results submitted by the participating teams. The maps depict the prediction errors divided by the ground truth population for each operational zone. We divide the prediction errors in order to consider the great range of population counts among the operational zones. We used the relative delta as described in Section 3.2.

Operational zones in which the models have severely overestimated the population (the models suggest more population than the real one) are depicted in red or orange. We consider severely overestimated results when the population estimation is more than 50% of the actual population. Areas in which the estimation is  $\pm 50\%$  are depicted in green, while areas in which the models severely underestimated the population are depicted in blue. For this paper, a population estimation would be considered severely underestimated if it is less than 50% of the actual population.

We can see that there are areas overestimated by all the models: The Industrial area (West), Ngwerere (North) and Libala (South). In the case of the industrial areas, it seems that the proposed algorithms confused industrial buildings for residential areas. In the case of Ngwerere, and Libala, the residential areas have low density which was incorrectly evaluated by the algorithms.

On the other hand, we can see that there are other areas that have been underestimated by all the models: George, Lilanda, Desai, (at the West of the city), Chelston at the East, Chawama and Kuoboka at the South.

Most of the models underestimated the population in Makeni, except for the Polish team. This team also differentiated from the rest in an area comprised by Ngombe, Chamba Valley, Kamanga and Kaunda square (North East of the city), providing good estimates with the exception of Chudleigh, which was overestimated by all the teams, except for the Italian team.

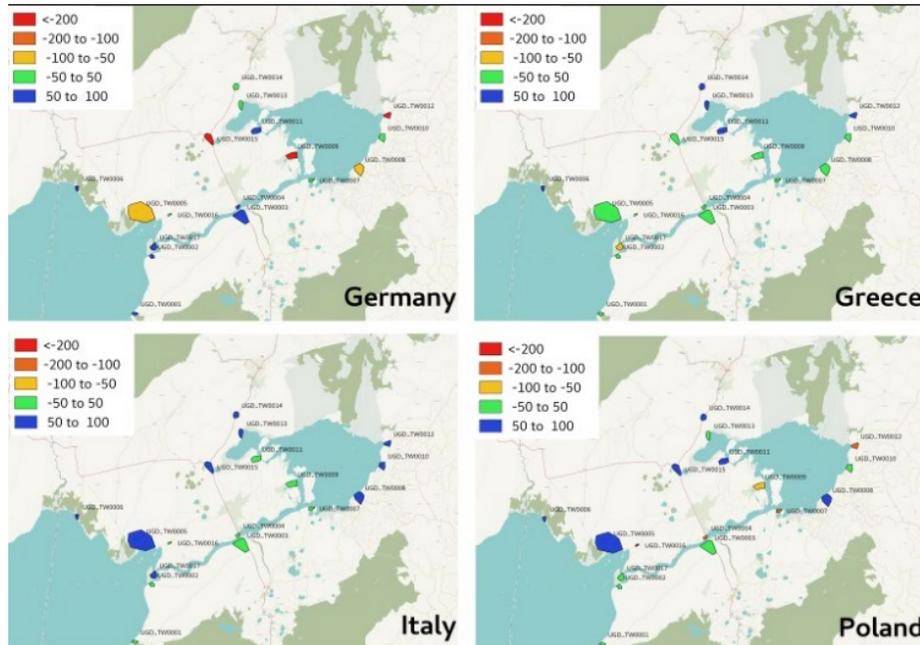
In general, all the teams got their best results in an area near the center of the city, an area roughly defined by the Operational zones, Civic Centre, Rhodes Park, and in most cases Northmead (except for the Polish team who did not provide a good result for this zone).

Figure 2 depicts the results of the participating teams for the operational zones in Uganda. As in the map depicting the operational zones located in Lusaka, the map depicts the zones with severe overestimation in red and orange (less than -50%), while it depicts the areas with severe underestimation in blue (more than 50%).

In the case of German team, they overestimated 5 of the 17 operational zones (depicted in orange and red) and underestimated 7 of the zones depicted in blue. The solution proposed by the Greek team has less overestimation, only one of the zones was overestimated. However, it severely underestimates 5 zones, while it has a good estimation for 11 zones. The submission of the Italian team, does not have any overestimation. However, it severely underestimates the population in 9 of the zones. The approach followed by the Polish team, produces mixed results. It severely underestimates the population in 5 zones while it underestimates it in 6.

## 5 Related work

Emerging technologies including mobile application, global positioning system and satellite images can create changes in development. Estimation of population using earth observation and geospatial technologies can ease emergency ser-



**Fig. 2.** Overview of the results submitted by the participating teams, for the operational zones in Uganda.

vices and humanitarian actions. For instance, providing emergency relief, tackling post-earthquake situation and tracking epidemic diseases like cholera needs up-to-date and geographically specific information. The accurate information a governmental organization and/or NGOs and/or other aided organization can have, the more they can save lives.

A couple of related works has been done to estimate population and make it atomize to avoid unnecessary expenses and time required in conventional census methods of estimating population. In their studies Florence A. Galeon [10] and Almeida et al. [1] underline the potentials of using high resolution Quick-bird images to estimate population in informal and semi-informal settlements in urban area. In another study, United Nations Statistics Division DESA [9] integrated GPS, digital imagery and GIS technology to make the census mapping more accurate and efficient. Li and Weng [16] integrated Landsat ETM+ data with census data for estimation of population density of Indianapolis, Indiana USA. They incorporated spectral signatures, principle components, vegetation indices, fraction images, textures and temperature as predictive indicators to make a correlation analysis between remote sensing parameters and population. In the studies of Cheng et al. [5], Prosperie, [19] and Sutton [21] [22], the authors used “night satellite” imagery to estimate population according to the local densities of light sources. Dittakan et al. ’s studies [7] [8] used satellite images

from GeoEye 50m ground resolution data publicly available by Google Earth. In another studies Ilka et al. [20] used TM/Landsat5 and ETM+/Landsat7 data to estimate population of Belo Horizonte city in Brazil by generating statistical model.

There are also plenty of other studies that used high to moderate resolution satellite imagery to estimate population. There are relatively few studies on estimating population based on radar satellite data such as Henderson, F. and Xia, Z. elaborated radar applications in Urban Analysis, settlement detection and population estimation [11] [12], Balz, T. and Haala, N., interpreted high resolution SAR data using existing GIS data in urban areas to estimate population [3].

There are lots of other new satellites providing either commercial or free satellite images which can be also evaluated in the task of estimating the population of an area. However, Sentinel-2 optical and Sentinel-1 radar satellites are free and moderately high resolution satellite imagery. In this ImageCLEF 2017 pilot task the prime objective was to precisely identify how powerful are Sentinel-2 imagery of 10m resolution.

## 6 Conclusion

This paper summarizes the pilot task introduced this year at image CLEF 2017 and that aims at estimating the population of a zone. Participants encountered various difficulties mainly linked to the nature of the images they had to use. The results that were obtained show that there is room for improvement using low resolution images for estimating the population in a zone although these images have the huge advantage of being free of use.

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