File S1. Detailed methodology of the study.

The study methodology included collecting relevant literature and required datasets as follows:

Digital Elevation Model (DEM) SRTM v3 (30m resolution) and satellite images (Landsat 5TM and Landsat 8OLI/TIRS) were downloaded from the USGS website (https://earthexplorer.usgs.gov/) and Glovis website (https://glovis.usgs.gov/app).

Administrative areas geographical borders were obtained from the respective municipalities of Bab Amman and Jarash.

Census data for the years 1994, 2004, 2015 and 2020 were downloaded from the Department of Statistics in Amman, Jordan, website (http://dosweb.dos.gov.jo/).

Administrative areas (in km^2) data was obtained from the Department of Statistics in Amman, Jordan, website (http://dosweb.dos.gov.jo/).

Social services data were obtained from the Ministry of Education (schools), Ministry of Health (health centres) and Civil Defense (civil defence centres) in Jordan websites and the use of Google Earth Pro. Software.

Then, the data was pre-processed based on the intended further analyses, tabulated and saved in proper formats; Excel spreadsheets, shapefiles, etc., for further analyses.

3.1 Built environment parameters

Alongside population size and growth, wherein GIS spatial analysis tools such as choropleth maps, point density maps, heat maps and directional distribution ellipse are useful in understanding the spatial and temporal variability in population size and growth rates, remote sensing (RS) data, particularly obtained through satellite remote sensing (SRS), are important basis for mapping different built environment parameters [1-4].

Several indices have been developed to extract desired features and maps from the RS data, of which, the normalized difference vegetation index (NDVI) is the mostly used to extract vegetation cover [3,6]. In addition, built up land can also be observed and its changes can be monitored using image classification tools in ArcMap Software (e.g. [7]).

3.1.1 Population size and growth rate spatial and temporal variation over the period 1994-2020.

For this part, the researcher follows a descriptive, analytical approach as follows:

a. Obtain data about the administrative boundaries for the towns in the study area from the respective governmental directorates.

b. Obtain census data for the years 1994, 2004, 2015 and 2020 from the Jordan Department of Statistics for the towns in the study area.

c. The data was tabulated and inserted into Microsoft Excel software for:

i. Basic descriptive statistics.

ii. Calculation of the population growth rate based on the following equation:

$$R=Lnh\ (Pt/P0)/T*100, [8]$$

where; R= population growth, Pt=population in the next time period, P0= population in the previous time period, T= time period in question, Lnh=Lin to the power of (growth and time) rates.

d- The data was then input into a GIS environment (ArcMap10.8.1) to create maps that show the population temporal/spatial distribution, growth rate spatial distribution, population density, Mean Center Point of Population and the Directional Distribution-Standard Deviation Ellipse for the years 1994, 2004, 2015 and 2020 in the study area. This was accomplished using the spatial analysis tools in ArcMap10.8.1.

The results provides an understanding about the population growth, density and direction in the study area which is essential to understand whether the population and the consequence urbanization is well managed to avoid landslide prone zones or not.

3.1.2 Built-up lands change over the period 1994-2020.

Following [7], Landsat images were used to detect temporal and spatial changes in built-up areas and calculate their areas and percentages over the studied time periods.

Landsat data was inserted into ArcMap software and using digital image processing tools, the built-up lands were mapped by supervised classification. The colour combination of bands 4(Red), 3 (Green) and 2 (Blue) was used for this step (ESRI, 2011). In this colour combination the built up land appears in cyan colour, while vegetation appears in red and green colours and water in black [9]. Since the focus is on delineating built-up lands, the on-screen digital image processing focused the training sample points on identifying areas with cyan colour. Built-up (urban) areas typically comprise industrial and commercial buildings, residential development and transportation facilities [9].

The colour bands were input into ArcMap 10.8.1 software and image analysis tools were used to generate a composite image. The image was cropped to the Area of Interest (AOI) and the on-screen digital image processing was carried out using Image Classification Tools and the Training Sample Manager. After collecting the training sample points, the Merge option was used to create a class. Scatter plots were then generated in order to test the distribution and separability of the training samples. If the training samples do not overlap this means that they represent different classes that are well separated. Having prepared the signature file of the training samples, Maximum Likelihood method was used for supervised classification which assigns every pixel to a distinct class based on the means and variances of the class signatures (ESRI, 2011).

To calculate areas and percentages, the resultant raster data were reclassified and converted to feature classes and the calculate geometry option (in the attribute table) was used for the subsequent time periods 1994-2004, 2004-2015 and 2015-2020 to estimate the temporal and spatial variability in built up areas in the study area.

3.1.3 Green surfaces change (using NDVI) over the period 1994-2020

NDVI [10] depends on the chlorophyll absorption of visible light and the reflectance of near-infrared by the plant leaves and cellular structures. Since satellite images are composed of bands reflecting different parameters of the image collection, accordingly, measuring the difference between near infra-red (NIR) and RED bands in a satellite image is an indication of chlorophyll presence, and thus vegetation [6, 11]. In ArcMap, the formula can be applied using the spatial analysis tool "Raster calculator". In this study, satellite images captured during the months of March to May of every year were downloaded to avoid any disturbance in the images, such as clouds.

The NDVI is calculated using the "raster calculator" tool in ArcMap software as the difference between near infrared (NIR) and red (RED) reflectance divided by their sum:

$$NDVI=NIR-RED/NIR+RED$$

The resultant index has values ranging from -1 to 1. Values <1 indicate water or snow, values <0.1 and >0 reflect empty areas, rocks and sand. Values about 0.1-0.3 indicate meadows and shrubs, while high values >0.3 indicate vegetation.

For the NDVI calculations, Landsat images were downloaded from the USGS earth explorer website (https://earthexplorer.usgs.gov/) and Glovis website (https://glovis.usgs.gov/app).

For the years 1994 and 2004 Landsat 5 images are used, while the 2015 and 2020 NDVI calculations are based on Landsat8 imagery. The importance of understanding the version of the Landsat image is significant as different sensors record bands in different ways and this affects the calculation of the NDVI and the required bands. Where the NIR is the near infrared band and RED is the red band. Which are Bands 4 and 3 in Landsat 5 and Bands 5 and 4 in Landsat 8 data, respectively [6]. The NDVI images were created using ArcMap 10.8.1 and spatial analysis tools. The raster NDVI maps were then reclassified and the areas for the index values were calculated as pixel area and then transformed into %.

The NDVI maps and calculated areas were measured for the subsequent time periods 1994-2004, 2004-2015 and 2015-2020 to estimate the temporal and spatial variability in green surfaces in the study area. Change detection in NDVI was calculated using the “Combine Tool” from the spatial analyst in ArcMap 10.8.1 software.

2.1.4 Satellite images pre-processing

Due to the presence of different satellite imagery sources over space and time, imagery pre-processing is a substantial part of the indices calculations [11, 12]. Data downloaded from the USGS website, are corrected for terrain, radiometric, and geographic corrections, nonetheless, the data were formatted into an 8-bit number (from 0-255) and are referred to as digital number (DN) data. Thus, prior to using these bands for indices calculation, the data should be converted into reflectance data for Landsat 5TM (1994 and 2004 data) and 8 OLI/TIRS (2015 and 2020 data) imagery. All the imagery data were obtained during the months of May and June with 0-5% cloud cover.

Thus, prior to the NDVI calculations, the Landsat 5TM satellite images were pre-processed following the process reported by [13], as follows:

1. The Landsat data is re-projected using “Project Raster” tool in ArcMap software to project the data into a common geographic coordinate system. WGS1984 world Mercator is used in this research.

2. The Landsat data is then reclassified to ensure that all “0” values are re-mapped as “no-data” using ArcMap software spatial analysis tool “reclassify”. This step ensures that all missing data pixels are removed.

3. The Landsat 5 TM data is converted to Landsat 7 ETM+ data, when using Landsat 5 data for the years 1994 and 2004. This step is important to enable using the tasseled cap of Huang et al. (2002). This is done based on the equation and using the “raster calculator” in ArcMap software:

$$DN7 = (\text{slope } \lambda * DN5) + \text{intercept } \lambda$$

Where, DN7 is the Landsat 7 ETM+ equivalent DN data, DN5 is the Landsat 5 TM DN data, and the slope and intercept are band-specific numbers given by the inverse of those found in [14] (Table 1).

Table S1. Slope and intercept data [14]

Band	Slope	Intercept
1	0.943	4.21
2	1.776	2.58
3	1.538	2.50
4	1.427	4.80
5	0.984	6.96
7	1.304	5.76

4. Converting the DN data to radiance data through the equation:

$$L\lambda = (gain\lambda * DN7) + bias\lambda$$

Where, $L\lambda$ is the calculated radiance [in Watts / (sq. meter * um * ster)], DN7 is the Landsat 7 ETM+ DN data (or the equivalent calculated in step 3), and the gain and bias are band specific numbers. The latest gain and bias numbers for the Landsat 7 ETM+ sensor are given in [12] and are shown in the following table.

Table S2. Gain and bias data [12]

Band	Gain	Bias
1	0.778740	-6.98
2	0.798819	-7.20
3	0.621654	-5.62
4	0.639764	-5.74
5	0.126220	-1.13
7	0.043898	-0.39

5. Converting radiance data to reflectance data. This step is important as the radiance data is the actual quantity measured by the Landsat images, but the reflectance data enables using this data to compare with other scenes. This correction removes the differences of sun position during the recording of different scenes and bands, thus corrects for the fraction of the sun's energy reflected by the surface. This correction can be estimated based on the following equation:

$$R\lambda = (\pi * L\lambda * d2)/(ESun,\lambda * \sin(\Phi SE))$$

Where, $R\lambda$: reflectance (unitless ratio), $L\lambda$: radiance calculated in step 4, d: earth-sun distance (in astronomical units), Esun, λ: is the band-specific radiance emitted by the sun, and ΦSE: solar elevation angle. Some of these values are given in Chander et al. (2009) (Table 3).

Table S3. Esun, λ data [12]

Band	$E_{sun,\lambda}$ [Watts / (sq. meter * µm)]
1	1997
2	1812
3	1533
4	1039
5	230.8
7	84.9

Whereas to find "d", the earth-sun distance, and ΦSE, the solar elevation angle, we need to look up the the day of the year and the time of day when the scene was recorded. These can be found in the metadata of the scene acquired and the values are based on Earth-sun distance (d) in astronomical units based on the day of year. A final step here is converting the solar elevation angle from degrees to radians as required by ArcMap through the equation:

$$\text{Radians} = (\text{degrees} * \pi)/180°$$

6. Enforcing positive values of reflectance. This step is the final step in pre-processing the required bands. It involves removing any calculated negative reflectance values using the "raster calculator" in ArcMap and the function:

"Corrected reflectance = CON ([reflectance] < 0.0, 0.0, [reflectance])"

7. The band is ready to be used for indices calculations.

While, the correction of the Landsat 8 OLI/TIRS images was undertaken based on the USGS Landsat 8 data Users Handbook (www.usgs.gov) to convert the bands to TOA reflectance using the image-specific rescaling coefficients in the MTL file and based on the equation:

$$\rho\lambda' = M_\rho Q_{cal} + A_\rho$$

Where: $\rho\lambda'$= TOA planetary reflectance, without correction for solar angle. Note that $\rho\lambda'$ does not contain a correction for the sun angle. M_ρ=Band-specific multiplicative rescaling factor from the metadata (REFLECTANCE_MULT_BAND_x, where x is the band number) A_ρ=Band-specific additive rescaling factor from the metadata (REFLECTANCE_ADD_BAND_x, where x is the band number) Qcal = Quantized and calibrated standard product pixel values (DN).

2.1.5 Social Services mapping and spatial analysis for the year 2020

For the facilities and institutions mapping, the researcher used online resources as follows.

a. For the mapping of the schools, data were downloaded from the Jordan Ministry of Education (https://www.moe.gov.jo) and mapped on Google Earth Pro. 2020 software. The data was then input into ArcMap 10.8.1 and transformed into shapefiles as part of a database for the year 2020.

b. For the health centers, data were data were downloaded from the Jordan Ministry of Health (http://moh.gov.jo) and mapped on Google Earth Pro. 2020 software. The data was then input into ArcMap 10.8.1 and transformed into shapefiles as part of a database for the year 2020.

c. For the Civil Defence centers, data was digitised using Google Earth Pro. Software. The data was then input into ArcMap 10.8.1 and transformed into shapefiles as part of a database for the year 2020.

d. The data from this step was used as input on the final map to show the present day locations of the important social services in the study area relative to the green surfaces, built-up land, population patterns and recorded landslides.

e. Following to this, the researcher used GIS techniques to spatially illustrate the social services distribution in the study area and used the nearest neighbor tool in ArcMap 10.8.1 to investigate the nature of the services distribution.

3.2 Landslide spatial and temporal variability

To estimate the landslide variability over the period 1994-2020, the researcher follows the next approach:

a. The documented landslide events location in the literature from 1994 up to the year 2018 [15-21].

b. The raw data was entered into ArcMap.

c. The locations were digitized and transformed into shapefiles and landslide maps were generated for the years 1994, 2004, and 2015.

d. Using the data published from 2015 to 2018, a base map for the landslides was generated and then the landslide events recorded in the media for the years 2019, 2020 and 2021 were added to the map to generate the final landslide map for the year 2020. A field trip was conducted to visit the landslide locations and document them on the ground, using GPS readings and photographs to validate the 2020 landslide map.

e. Using Google Earth (GE) Pro, and based on landslide locations in the literature, the landslide changes were delineated to show their spatial and temporal changes for the years 2010 and 2020 (based on available temporal data in GE).

f. The landslide data was then superimposed on the resultant maps of the built environment and population to show the spatial relationships where present.

3.3 Topographical investigation

Topography plays a significant role in the distribution and changes in land cover and population [22]. Thus, this study used DEM data and GIS techniques in order to calculate the elevation and slope in the study area. Based on DEM data, the slope was calculated using Slope Tool from the spatial analyst tools in ArcMap software. Then the raster data were converted to feature class (polygons) to calculate their areas and to estimate the elevation and slope spatial distribution.

The Union tool form Arc Toolbox was then used to combine the different layers from previous analyses with the elevation (based on elevation scales used by [22]) to investigate the effect of topographic features on the built-up environment changes and landslide events.

3.4 Fieldwork

During this research two fieldtrips were conducted in March and April, 2021 in order to validate the landslides located using GE and to show their impact, if present, on populated areas.

During the fieldwork, the localities mapped on GE were visited and verified with photographs and GPS readings. The verification was based on the deformation caused by the landslide, e.g. soil erosion or trees inclination. Notes were also recorded where settlements were present and the relative extent of the effect of the mapped landslide. Thus, the author conducted a fieldtrip and a Google Earth survey to detect landslides in the study area located away from the highway that can be observed for the years 2010 and 2020. In addition, the author collected the media reports about landslide events that have occurred since 2018 and compiled a "landslide map" for the year 2020 and the new incidents of the year 2021. The survey resulted in locating 10 new landslide locations, most of which are away from the highway and close to the populated settlements. All the located landslides are accompanied by either deforestation, increased built-up land (residents) or both in some instances. This indicates the importance of having green surfaces and the impact of building residents and the associated cut and fills especially along slopes in the area.

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