Remote Sensing Information for Urban Planning of Sirajganj Town and Surrounding

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Summary

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The products of this report aim to provide support for urban planning for the city of Sirajganj and its surrounding areas. Based on optical and radar satellite data, maps on recent land use and urban development, river course changes, rainy season inundation and ground motion are created.

Land-use in the Sirajganj study area is characterized by a relatively large central urban area surrounded by rural settlements and a large developing zone in the southeast, the future Sirajganj Economic Zone. Frequent inundation is visible close to the Jamuna River and in a lesser frequency in outlying areas west of Sirajganj. The city centre does not experience seasonal inundation. Significant urban development of former river parts can be identified using the river shifting change detection within the study area.

Ground motion maps are created using two different multi-temporal Interferometric SAR (InSAR) approaches, Persistent Scatterer Interferometry (PSI) and Small Baseline Subset (SBAS), and medium-resolution Sentinel-1 data. There are significant differences in the spatial coverage achieved by both methods. The PSI dataset is dense in the city centre and other urbanised areas but rather sparse in the more rural parts of the project area. SBAS delivers spatially coherent data that covers most of the project area, including the more rural parts, but at the cost of loss of detail. Nonetheless, the results are mostly coherent with each other and reveal that most of the city centre can be considered stable or moving only slightly over the observation period. Points of strong subsidence are mostly found on or around newly built structures as well as along the main embankments protecting the city centre of Sirajganj.

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List of Abbreviations

ASF	Alaska Satellite Facility
BBD	Bodenbewegungsdienst Deutschland (German Ground Motion Service)
BGR	Bundesanstalt für Geowissenschaften und Rohstoffe (Federal Institute for Geosciences and Natural Resources)
BWDB	Bangladesh Water Development Board
dB	Decibel (unit)
DEM	Digital Elevation Model
DOS	Dark Object Subtraction
ESA	European Space Agency
GNSS	Global Navigation Satellite System
GPAC	Geo-Information for Urban Planning and Adaptation to Climate Change
GPS	Global Positioning System
GSB	Geological Survey of Bangladesh
InSAR	Interferometric Synthetic Aperture Radar
Landsat MSS	Landsat Multispectral Scanner System
Landsat OLI	Landsat Operational Land Imager
Landsat TM	Landsat Thematic Mapper
LEDAPS	Landsat Ecosystem Disturbance Adaptive Processing System
NASA	National Aeronautics and Space Administration
NIR	Near Infrared
NDWI	Normalized Difference Water Index
PSI	Persistent Scatterer Interferometry
RADAR	Radio Detection and Ranging
SAR	Synthetic Aperture Radar
SBAS	Small Baseline Subset
SRTM	Shuttle Radar Topography Mission
SWIR	Shortwave Infrared
TIR	Thermal Infrared
UAV	Unmanned aerial vehicle
USGS	United States Geological Survey

1 Introduction to Remote Sensing

Remote sensing has been variously defined, but basically is the science that describes the collection of physical information, interpretation and extraction 3f information acquired over an object or area of interest without having physical contact, by the use of remote sensing instruments. The term information refers to a wide range of observable quantities, such as reflected solar radiation across the electromagnetic spectrum and emitted thermal radiation measured from handheld, unmanned aerial vehicle (UAV), airborne or spaceborne imaging sensors and received back-scattered microwave radiation equipment. Availability and effective exploitation of such data has facilitated advances in many applied fields (CHAMBELL, 1996; USTIN, 2004)

The availability and capacity of remote sensing data is comprehensive and huge, therefore the application of remote sensing data to identify and monitor land surfaces and environmental conditions has expanded enormously and remotely sensed data are an essential tool in natural resource management. Climatic changes, desertification processes, forest fires, glaciers melting, water pollution, land cover and vegetation status can be observed thanks to remote sensors onboard of aircraft or satellites orbiting around the earth. Remote sensors onboard of aircraft and satellites allow for a synoptic view of the earth surface at different wavelengths of the electromagnetic radiation at the same time (multi-spectral, -frequency), with (high-) frequent time interval and scale (multi-resolution).

Sensors can be divided into two groups: Passive sensors depend on an external source of energy, usually the sun. Sun radiation is reflected and emitted from the earth surface and collected by a wide variety of optical sensors. Active sensors have their own source of energy. These sensors send out a signal and measure the amount reflected back, and do not depend upon varying illumination conditions (PRASAD ET AL., 2011) (see Fig. 1).

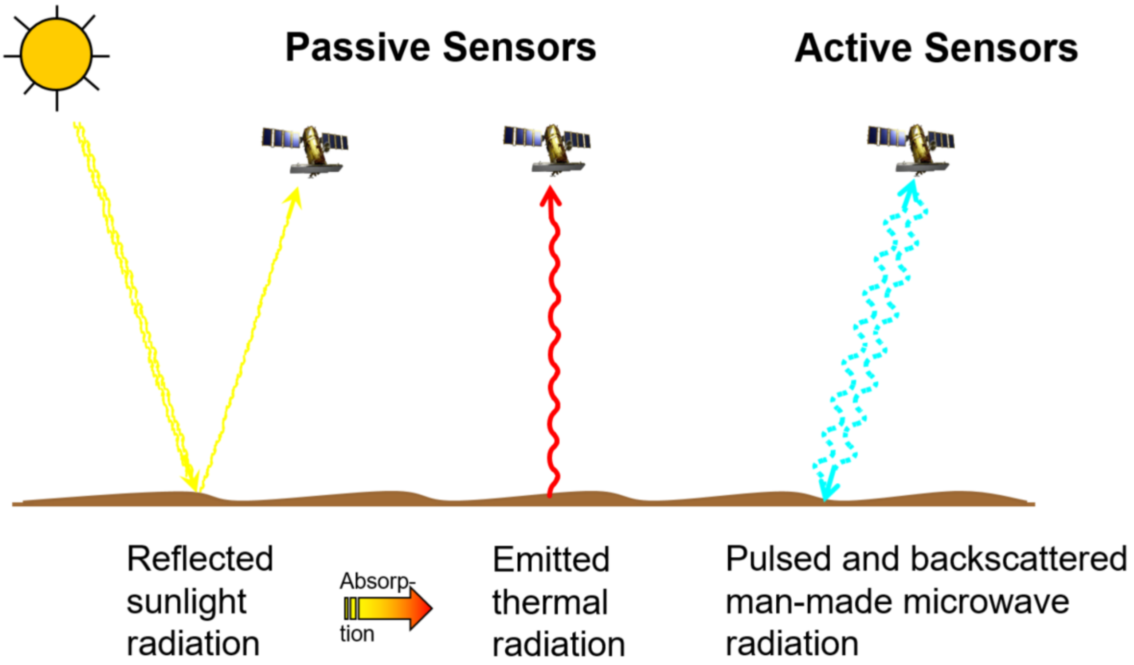

Figure 1: *Passive and active sensors (Source: BGR).*

1.1 Fundamentals of Optical Remote Sensing

Optical remote sensing involves acquisition and analysis of optical data, based on solar illumination and the detection of electromagnetic radiation reflected from targets on the ground. Optical Remote Sensing deals with those part of electromagnetic spectrum characterized by the wavelengths from the visible (from 0.4 µm) to the near infrared (NIR) and short wave infrared (SWIR) up to thermal infrared (TIR, 15 µm), collecting radiation reflected and emitted from the observed surfaces (see Fig. 1).

Optical remote sensing is a passive technique for earth observation, which is exposed to a strong interaction of the electromagnetic radiation within the atmosphere at its operating frequencies and to the presence of clouds. Both factors constitute important limitations on the potential observation of the earth's surface.

Analysis is based on the spectral differences of materials, as materials reflect and absorb differently at different wavelengths, resulting in a specific and unique "spectral footprint". Thus, the targets can be differentiated by their spectral reflectance signatures in the remotely sensed images (SABINS, 1996; RENCZ, 1999).

Optical remote sensing systems are classified depending mainly on the number of spectral bands used in the imaging process. Advances in imaging hardware enabled availability of high spatial, spectral and temporal resolution (PRASAD ET AL., 2011).

A wide range of applications is still based on multispectral imaging systems e.g. Sentinel-2, Landsat-OLI, even so hyperspectral sensors show rapid development on all platforms from UAV to spaceborne carriers.

1.2 Fundamentals of RADAR Remote Sensing

RADAR is an acronym for *RA*dio *D*etection *A*nd *R*anging and describes an object-detection and active imaging system using radio waves (see Fig. 1). The electromagnetic waves used for imaging radars have wavelengths in the order of several centimeters up to roughly one meter. Since earth's atmosphere has a high penetrability in this part of the electromagnetic spectrum, radar-imaging systems are highly independent from weather conditions in the atmosphere.

The accuracy of an imaging radar is defined by two measures: the resolution along the line-of-sight (range resolution) and the resolution along the flight path of the carrier platform (azimuth resolution). The azimuth resolution depends on the antenna aperture: the larger the distance to the area of interest, the larger the antenna must be. For space-borne missions this leads to unrealistic demands on the size of the antenna mounted on the satellite (WOODHOUSE, 2006). To overcome this obstacle, Synthetic Aperture Radar (SAR) exploits the Doppler Effect to synthesize a larger virtual antenna through the combination of several return signals (echoes).

The signal received at the sensor has a frequency variation induced as a result of the platform motion. This effect is known as Doppler shift, a well-known phenomenon in physics. Since the resolution depends on the time, a particular object on the ground is illuminated by the radar beam, making use of the Doppler shift to combine several backscattered echoes effectively results in increasing the duration of irradiation. As this is in effect equal to increasing the antenna aperture size of which the illumination time is a direct function, the term Synthetic Aperture Radar (SAR) is used to describe such an imaging system (RICHARDS, 2009).

SAR sensors are usually mounted on an airborne or space-borne platform and have a side-looking imaging geometry. While the carrier platform moves forward, the SAR system continuously emits and receives electromagnetic pulses. The emitted radiation interacts with objects on the surface that will then backscatter a portion of the signal to the sensor. How big that portion will be, depends on the physical and electrical properties of the objects (FORNANO & PASCAZIO, 2014). At the sensor, both amplitude and phase of the backscattered signal are received (MOREIRA ET AL., 2013).

While the amplitude is related to the object properties (material, roughness, dielectric properties, etc.), the phase is a function of the sensor-target distance.

Synthetic aperture radar (SAR) remote sensing is used today in a wide range of applications and offers a number of complementary and additional capabilities with regard to optical remote sensing. For instance, it can be used to acquire images at night and almost weather independent, to determine soil moisture, biomass or to measure terrain deformations. The ranging capabilities of SAR are used in various ways. Radar interferometry (InSAR) is one such application and allows the estimation of ground deformation and / or topography from (at least) two SAR acquisitions making use of the phase information contained in both images. Multi-temporal InSAR approaches such as Persistent Scatterer Interferometry (PSI) allow the precise estimation (with millimeter accuracy) of surface deformation for specific point targets over long time periods.

2 Products

2.1 Land-use Map

The fast growing population and the trend to move to urban areas leads to a dynamic change in land use. New urban areas are developed by filling agricultural land with river sand to make the building ground more resilient to flooding (see Fig. 2).

The overall goal of this analysis is the comprehensive mapping of the 2020 land-use in Sirajganj to derive information on existing and newly established filled areas. The resulting maps will be used in further analyses together with a geomorphological map as a basis for the regionalization of drilling points. Freely available optical satellite data and a supervised classification method allow for the mapping of the land-use.

Figure 2: *Filling of agricultural land with river sand in Faridpur. Photo: L. Wimmer, 11/2019.*

Land-use maps using the classes “Water”, “Bare Soil”, “Urban”, “Rural Settlements” and “Agriculture” are provided for October 2020. An overview map shows the land-use of the study area as well as the surrounding rural areas (Fig. A2). A map, focusing on the study area presents the land-use within the city of Sirajganj (Fig. A3).

The main focus of this analysis is the distribution of filled and non-filled areas from the land-use map by reclassification of the five above-mentioned classes. A third map presents these areas within the study area of Sirajganj (Fig. A4).

To process the land-use maps, a supervised classification method based on interactively selected training areas is used. These areas are interactively chosen from the original satellite image and represent the spectral properties of a certain land-use class. The supervised classification classifies the satellite image by comparing all the image values with the selected training areas.

Data

The land use classification is based on a cloud-free image from the Copernicus Sentinel-2 mission for the period of the Bangladesh dry season between October and April and the transition times before and after it. To be able to receive results on the most recent land-use and in order to map water areas comprehensively, a satellite image from the early dry season 2020/2021 is required. Different atmospheric conditions during the sensing times of the images can result in different image features of the same ground objects. Therefore, atmospheric corrected images are mandatory, to allow comparison with future land use maps based on Sentinel-2 data. An atmospheric correction eliminates the atmospheric effects in an image and results in a surface reflectance image that characterizes the spectral surface properties. The atmospherically corrected image, showing the overview area cloud-free, from October 16, 2020 is used for further processing (see Annexure C: Data).

As input for the land use mapping, all bands with the resolution of 10m and 20m of the image are used (Tab. 1). This selection enables the classification method to accurately characterize the land-use classes by using all available spectral properties of the ground objects.

Table 1: *Overview of the Copernicus Sentinel-2 satellite image used for the classification. Blue color represents the spectral band subset used in the analysis.*

Sensing Date	Bands		Wavelengths	Spatial Resolution
16.10.2020	1	Coastal Aerosol	417nm – 471nm	60m
	2	Blue	399nm – 595nm	10m
	3	Green	515nm – 605 nm	10m
	4	Red	627nm – 703nm	10m
	5	Near Infrared	685nm – 723nm	20m
	6		722nm – 758nm	20m
	7		754nm – 810nm	20m
	8		690nm – 980nm	20m
	8A		832nm – 898nm	20m
	9	Water Vapor	919nm – 971nm	60m
	10	Cirrus	1299nm – 1449nm	60m
	11	Shortwave Infrared	1471nm – 1757nm	20m
	12		1960nm – 2444nm	20m

Methods

The workflow of the classification is visualized in Fig. 3.

Preprocessing

To prepare the image for the classification, a spatial subset and a spectral subset are created. The spatial subset shows an overview of the study area of Sirajganj as well as the surrounding rural areas (Fig. A1). The spectral subset includes the above-mentioned (Tab. 1) Sentinel-2 bands (Band 2, 3, 4, 5, 6, 7, 8, 8A, 11, 12). Subsequent, all image bands with 20m resolution are resampled to a 10m spatial resolution to keep the information of the higher resolution 10m bands.

Classes and Training Areas

The purpose of the land-use classification is to derive information on urban settlement structures. Accordingly, the two classes “Urban" and "Rural Settlements" are used for the description of these structures. “Agriculture" and "Bare Soil" are chosen to describe the undeveloped areas in general. Water areas are represented by the class "Water".

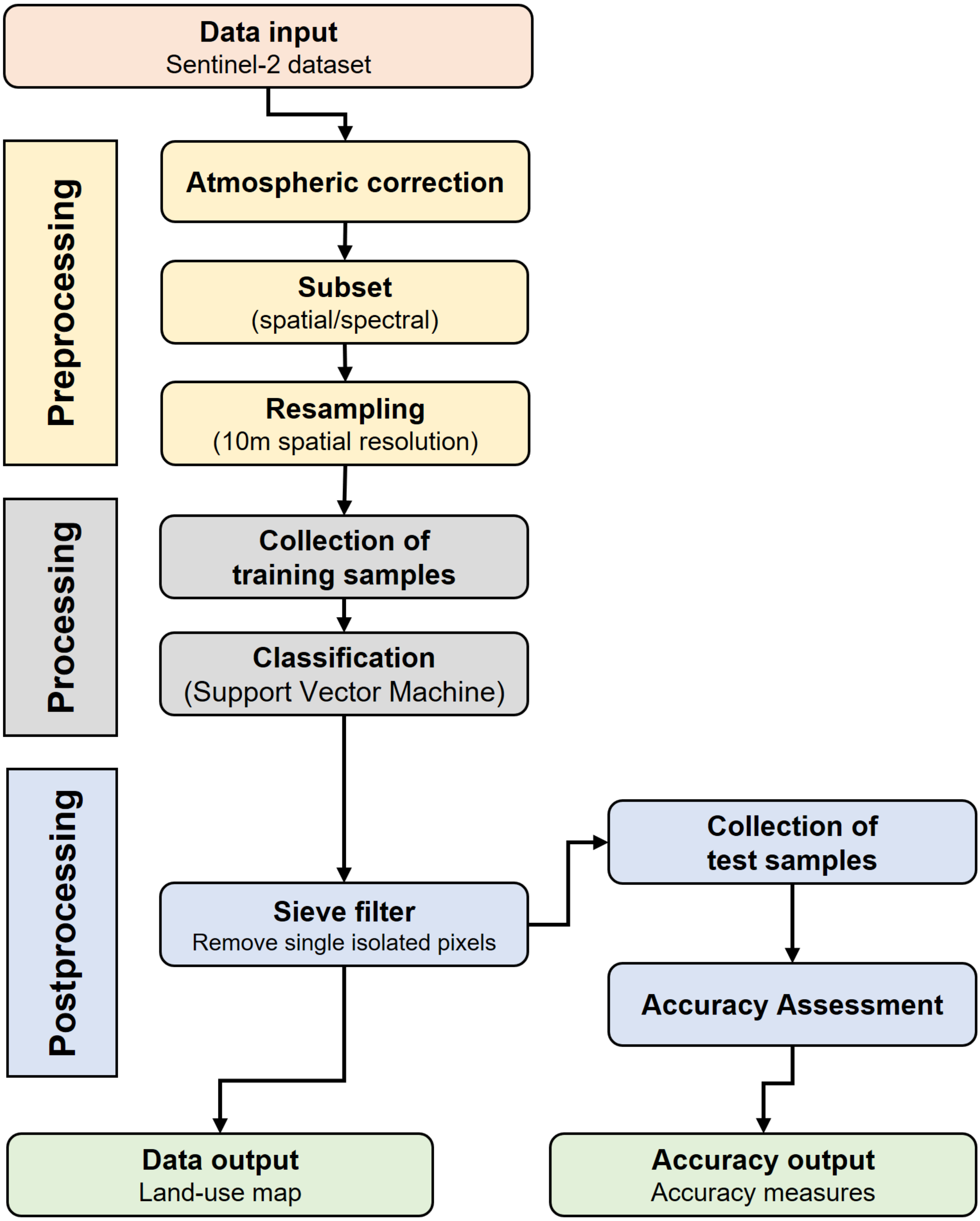

Figure 3: *Workflows of the Land-use classification.*

These classes are based on the CORINE Landcover (CLC) program (EUROPEAN ENVIRONMENT AGENCY, 2019). CORINE Landcover is a program of the European Commission to standardize the most important forms of land cover for environmental policy development. The standardized classes are based on biophysical characteristics of the Earth's surface (EUROPEAN ENVIRONMENT AGENCY, 2017).

"Water" includes all open water bodies, such as river, canals, channels, lakes and ponds. "Bare Soil" includes all surfaces of bright bare soil, such as riverbanks, pointbars and filled areas for urban development. "Urban" includes residential and industrial buildings without tree cover. Furthermore, it includes streets, railway lines and sealed surfaces. "Rural Settlements" include the city suburbs and rural villages that have tree coverage. "Agriculture" are all areas of farmland, such as cropland (rice, vegetables, etc.) or pasture land (for cattle, goats, etc.).

Training areas for all classes are selected from the Sentinel-2 dataset (see Tab. 2). To receive an acceptable classification result, the training areas must be both representative and complete for their land-use classes (LILLESAND ET AL., 2015).

All land-use classes have non-uniform spectral characteristics in common. For example, in the "Urban" class, the spectral characteristics of tin shacks and high-rise buildings differ. The "Agriculture" class includes spectral characteristics of different crops and in the "Water" class, different water qualities also differ spectrally. Different soil types in the "Bare Soil" class also have different spectral characteristics. The "Rural Settlements" class contains areas with different tree species, which result in different spectral characteristics.

The training areas of the land-use classes are required to represent these different spectral characteristics. The number of training areas therefore depends on the spectral variability within a land-use class (see Tab. 2).

The training areas are dispersed throughout the Sentinel-2 dataset to increase the representation of all variations in the land-use classes (LILLESAND ET AL., 2015).

__Table 2:__ Overview of the number of training areas per class.

Class	Number of Training Areas
Agriculture	20
Bare Soil	10
Rural Settlements	10
Urban	15
Water	15

To show the spectral variabilities of the individual classes, the spectral profiles of the classes are shown in Fig. 4. Each curve represents the averaged spectral signatures of all training areas per class, based on the Sentinel-2 data set of 16.10.2020. Fig. 4 shows the spectral separability of the classes over the whole band range (see Tab. 1).

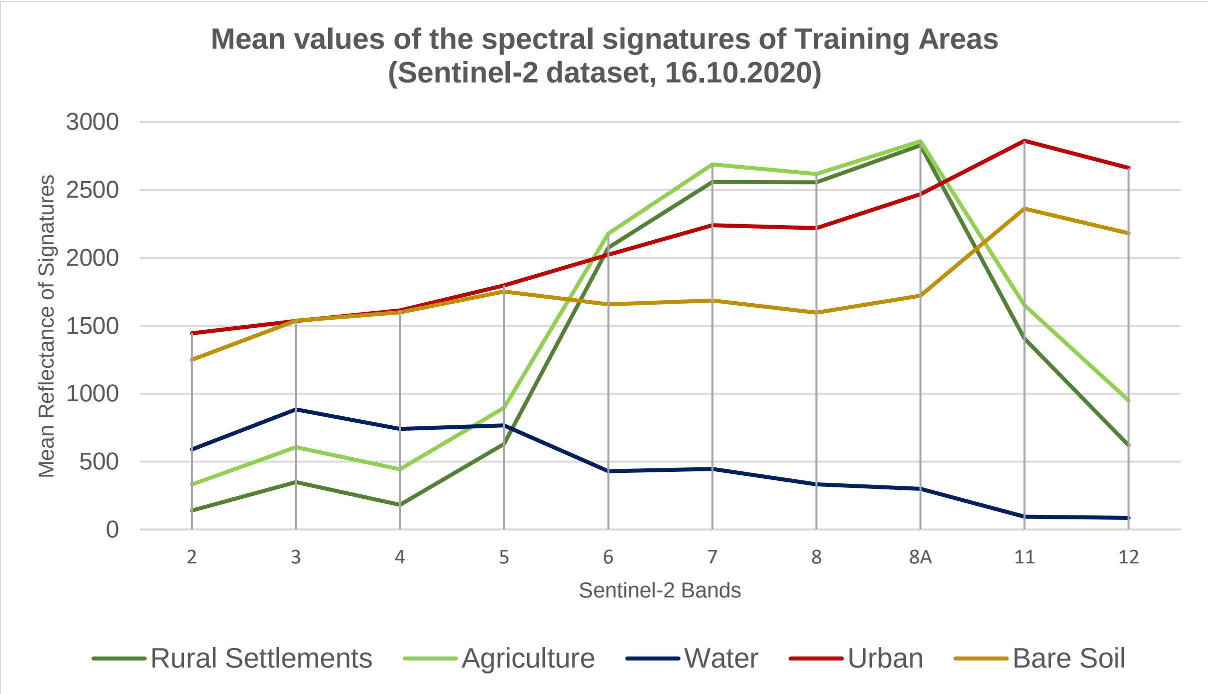

__Figure 4:__ Mean values of the spectral signatures of the training areas.

The spectral curves of the classes “Agriculture” and “Rural Settlements” have similar spectral signatures. The reason for these similarities is that the class “Rural Settlements” is dominated by tree coverage and therefore represents a strong vegetation signal.

Both classes show vegetation-typical characteristics, such as the "red edge" (a significant increase of reflection in the near infrared bands 5 and 6 compared to the visible bands 2 to 4). The main differences is an overall higher reflectance of the class “Agriculture” in comparison to the class “Rural Settlements”.
The spectral signature of “Water” shows higher reflection values around band 6 to 8A leading to the interpretation that the water class/signature contains impurities, such as sediments. Pure water would have zero reflectance in these longer wavelengths.
The spectral signature of the class “Urban” shows a relatively continuous increase and is similar to the signature of “Bare Soil”. The main difference between both spectral signatures is a higher “Urban” reflectance in the near infrared and the shortwave-infrared beginning with band 6 compared to a lower reflectance of “Bare Soil” in this wavelength range.

Classification

To perform the supervised classification, the Support Vector Machine (SVM) classifier is selected, a method based on statistical learning theory. Support Vector Machines are supervised learning models with associated learning algorithms that analyze data used for classification.
The classifier looks at spectral boundaries between individual classes in the multidimensional feature space. It aims to find an optimal margin (known as “hyperplane”) to separate the classes. The data values that constrain the width of the margin are known as “support vectors” (JONES & VAUGHAN, 2010).
In its simplest form, a SVM separates two classes (a binary classifier). Nevertheless, a classification with multiple classes is possible. Based on the training areas, several binary classifiers are calculated which separate the properties of each class from those of every other class (known as “one-versus-one” approach). The number of binary classifiers depends on the number of classes to be separated:

$$n_{classifier} = \frac{n_{class} * (n_{class} - 1)}{2}$$

The variable $n_{classifier}$ represents the number of classifiers; the variable n_{class} represents the number of classes.

Therefore, the properties of the five classes of this investigation are separated using 10 binary classifiers (Tab. 3 shows an example of possible connections of classes), as a result the classes are differentiated spectrally. Each classifier designates a class name to every pixel, the most frequent class name assigns the pixel to the final class (RICHARDS, 2013).

Table 3: *The table shows all possible connections of classes (cf. RICHARDS, 2013).*

Number of binary classifiers	Class name 1	Class name 2
1	Agriculture	Bare Soil
2	Agriculture	Rural Settlements
3	Agriculture	Urban
4	Agriculture	Water
5	Bare Soil	Rural Settlements
6	Bare Soil	Urban
7	Bare Soil	Water
8	Rural Settlements	Urban
9	Rural Settlements	Water
10	Urban	Water

Post-Processing

The same object feature may be classified in different classes due to spectral variabilities. The classification result might show single isolated pixels of one class in the area of another class (LILLESAND ET AL., 2015).

To remove the single isolated pixels in the classification image, a sieve filter is applied. This filter replaces all pixel patches that are smaller than twelve pixels by the value of the surrounding neighbor class. A pixel patch is a group of pixels that share their sides or have connected angles. The final classification result is shown in Fig. A2 and A3.

Calculation of filled and non-filled areas

Based on the knowledge of the GSB colleagues and the experience gained during fieldwork, all urbanized areas and settlement structures in Sirajganj are developed on filled areas. Therefore, those areas are considered as filled areas, the classes “Urban” and “Rural Settlements” are reclassified to “Filled” and the classes “Water”, “Bare Soil” and “Agriculture” are reclassified to “Non-filled” (see Fig. A4).

Accuracy Assessment

During the accuracy assessment, randomly distributed test samples are used to compare the classification result with an independent high-resolution reference dataset. As a high-resolution reference dataset, free accessible Google Earth satellite images are used. Thus, details for a more precise interpretation of the actual land use become visible and the classification result can be assessed visually without having the necessity to collect ground truth information during fieldwork.

LILLESAND ET AL. (2015) recommends using at least 50 test samples per class for accuracy assessment. Following this recommendation, 250 test samples are randomly distributed in the image, using 50 samples for each class (Tab. 4).

Table 4: *Accuracy Assessment, Sentinel-2 dataset (16.10.2020).*

Sentinel-2, 16.10.2020		Reference						
		Agriculture	Bare Soil	Rural Settlements	Urban	Water	Row Total	**User's Accuracy (%)**
Classification	Agriculture	49	1	0	0	0	50	98.0
	Bare Soil	0	48	0	0	2	50	96.0
	Rural Settlements	13	0	35	2	0	50	70.0
	Urban	0	25	0	25	0	50	50.0
	Water	0	0	0	0	50	50	100.0
	Column Total	62	74	35	27	52	250	
	Producer's Accuracy (%)	79.0	65.0	100.0	93.0	96.2		
	Cohen's Kappa per Class	0.97	0.95	0.64	0.48	1		
	Overall Accuracy (%)	**82.8**						
	Overall Kappa	**0.8**						

Since the images from Google Earth represent a compilation of different points in time, the Sentinel-2 dataset is used as an auxiliary dataset. Both data sets were acquired at different stages of flooding. Therefore, the visual impression of the Sentinel-2 dataset is given priority over the data from Google Earth when assigning water areas. Based on these datasets, land-use classes are interactively assigned to the test sample classes. Following this, the test areas are compared with the classification results to receive the accuracy measures (Tab. 4).

The overall accuracy of the classification is 82.8 %. The Kappa coefficient, a measure for the agreement between classification result and reference shows a good result of 0.8. The User's Accuracy shows how reliable the classified pixels represent actual land use, while Producer's Accuracy shows how well an object class has been correctly classified. In addition, the Kappa coefficients of each class are displayed in order to individually evaluate the reliability of the classification result.

The “Water” class shows a User’s Accuracy of 100.0 %.with a high corresponding Kappa coefficient of 1. The “Agriculture” (98.0 %) and the “Bare Soil” (96.0 %) also show a high User’s Accuracy, compared to the classes “Rural Settlements” and “Urban” with the lowest accuracies 70.0 % (“Rural Settlements”) and 50.0 % (“Urban”). This is also visible in the Kappa coefficients, so that the agreement between the classification result and the reference data is 0.97 (“Agriculture”) and 0.95 (“Bare Soil”) compared to 0.64 (“Rural Settlements”) and 0.48 (“Urban”).

The reason for lower accuracy values of the classes “Rural Settlements” and “Urban” (see Tab. 4) is related to different circumstances:

For example, the spectral signature of the class “Rural Settlements” shows similarities to the spectral signature of the class “Agriculture” (Fig. 4). Therefore, rural settlements having similar spectral characteristics as the agricultural areas may therefore be classified incorrectly and lead to a lower User’s Accuracy.

The lowest accuracy value (50.0 % User’s Accuracy) of the “Urban” class may be related to a mixed-pixel problem in the Sentinel-2 dataset. Individual residential or industrial buildings may be smaller than the resolution of the Sentinel-2 dataset (10m by 10m). As a result, a pixel represents a mixture of urban buildings and other surfaces (e.g. soil). This mixture can lead to misclassification. Due to the high-resolution reference image, it is possible to interactively determine the main content of a pixel (e.g. urban buildings) and to assign it to the test sample classes. The mixed pixels of the Sentinel-2 dataset can thus lead to a lower accuracy in the "Urban" class.

Another reason for the lowest User’s Accuracy value of class “Urban” (50.0 %) may be the spectral similarities to the spectral signature of the class “Bare Soil” (Fig. 4). Following that, urban areas having similar spectral characteristics as soil areas may therefore be classified incorrectly and lead to a lower accuracy (see Tab. 4).

The overall visual impression of the classification result (Fig. A2), as well as the overall accuracy and the overall Kappa coefficient (Tab. 4) show a good result and representation of the actual land-use.

2.2 River Shifting Change Detection Map

Rivers in Bangladesh are highly dynamic and underlie severe changes in location and intensity during a few years. During a few decades, rivers may change whole landscapes. The overall goal of this analysis is to provide information on the changes of the Jamuna river system course and the direction of shifting. The river system includes the water bodies and pointbars. A regional map covers these changes from the area of Tarakandi in the north-east to the area of Bera in the south-west (Fig. A5). Local changes inside this area are presented in a map showing only the city of Sirajganj (Fig. A16). The main focus is the mapping of present areas of the river system and former areas which were active in the past decades but are inactive recently. River course maps are provided for six time slices (1973, 1980, 1990, 2000, 2010 and 2019) (Fig. A8-A13). The change detection map shows data of the time slices with the highest difference in river system areas (1973, 2000 and 2019) (Fig. A8-A13, A15). A map focusing on the Sirajganj study area shows present and former river system areas using all six time slices (Fig. A16).

Data

To carry out the analysis, cloud-free optical images from Landsat Multispectral Scanner System MSS, Landsat Thematic Mapper TM and Copernicus Sentinel-2 missions are used. These are available during the period of the Bangladesh dry season between October and April, and images from January and February are used in the analysis. A comparison between images of different years is only possible when the target features (e.g. water) can be identified in all the images by similar response signal. This can be ensured by using images of the same month in every year of the analysis.

Starting 1973, one image per decade is used (1973, 1980, 1990, 2000, 2010 and 2019). To enable comparability between the final river shifting products, only bands from the Landsat and Copernicus Sensors with similar wavelengths positions have been chosen for processing (see Tab. 5 and Annexure C: Data).

Table 5: *Overview of the satellite images and their bands used for the analysis (EUROPEAN SPACE AGENCY 2017; UNITED STATES GEOLOGICAL SURVEY n.d.).*

Mission	**Sensing Date**	**Bands (B), Spatial Resolution/ Wavelengths**	
		Green	**NIR**
Landsat MSS	21.02.1973	B4, 60m 0.5-0.6 µm	B7, 60m 0.8-1.1 µm
	21.02.1980		
Landsat TM	30.01.1990	B2, 30m 0.52-0.6 µm	B4, 30m 0.76-0.90 µm
	11.02.2000		
	06.02.2010		
Sentinel-2	19.02.2019	B3, 10m 0.538-0.583 µm	B8, 20m 0.76-0.97 µm

Methods

The workflow of the analysis is visualized in Fig. 5.

Atmospheric Correction

Different atmospheric conditions during the sensing times of the images can result in a different image feature of the physically same ground objects. Therefore, to enable the comparison between all the images, an atmospheric correction is mandatory. An atmospheric correction eliminates the atmospheric effects in an image and results in a surface reflectance image that characterizes the surface properties.

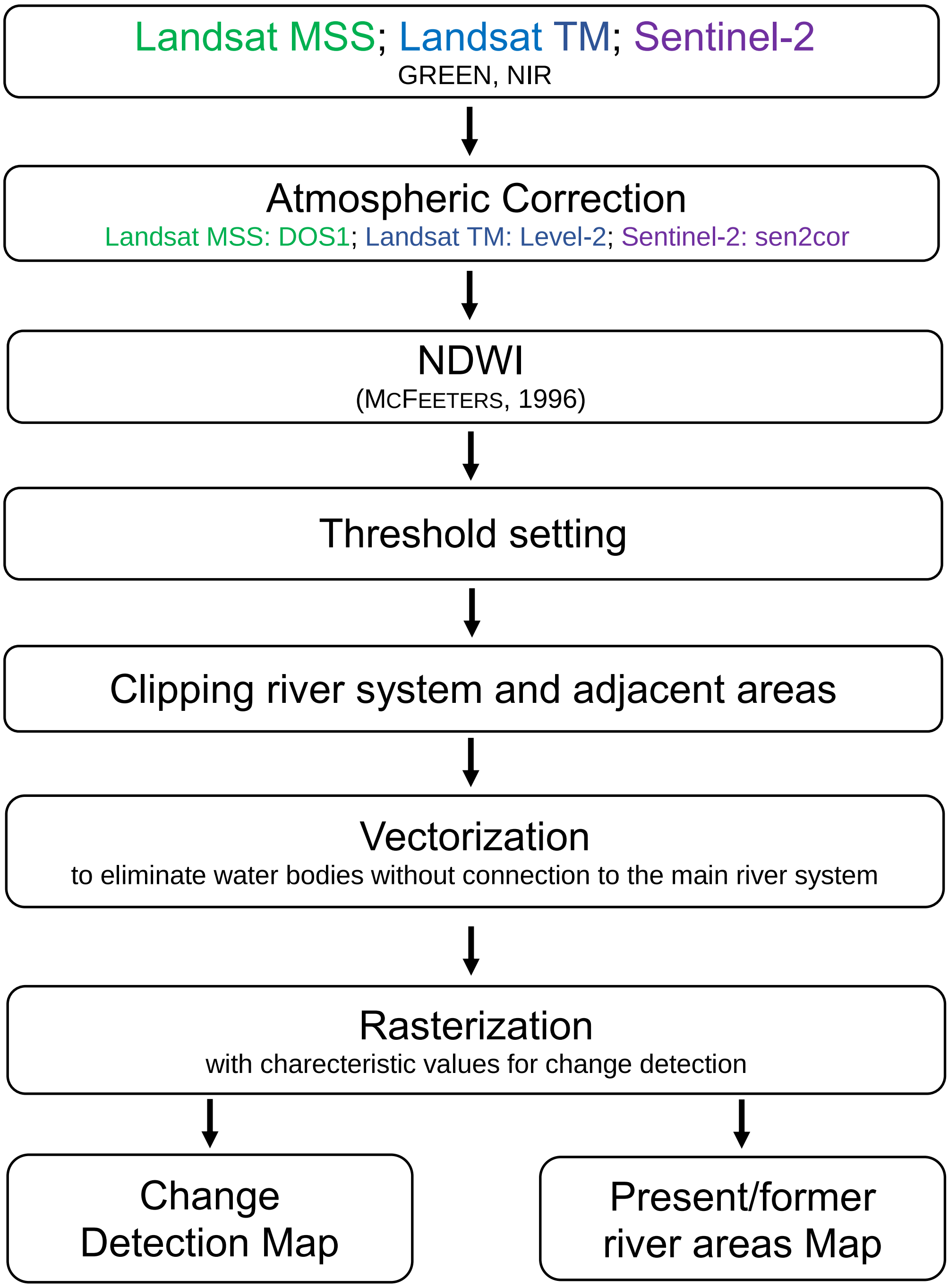

Figure 5: *Workflow of the River Shifting Change Detection analysis.*

Sentinel-2 and Landsat TM images are already atmospherically corrected and surface reflectance data are available for download (free Sentinel-2 download from Copernicus Open Access Hub and free Landsat TM download from USGS EarthExplorer).
The Sentinel-2 atmospheric correction is based on physical principals, physical-based algorithms use radiative transfer methods, which are simplified models of the radiation pathway from source to sensor, to model atmospheric scattering and absorption (LILLESAND ET AL., 2015). Auxiliary data such as water vapor data, atmospheric pressure or a digital elevation model are added to receive more precise information for the correction. The effects in the atmosphere are quantified by the model and used to calculate the surface reflectance values.
The Landsat TM surface reflectance "products are generated by a specialized software called Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS)" (LEDAPS PRODUCT GUIDE, 2020). Similar to the Sentinel-2 atmospheric correction, LEDAPS is also a physical-based algorithm that fits a radiative transfer model and includes auxiliary data to receive the atmospherically corrected surface reflectance product.
The Landsat MSS image is corrected by using the DOS1 (Dark Objects Subtraction) method. CHAVEZ (1996) describes that the methods "[…] basic assumption is that within the image some pixels are in complete shadow and their radiances [if above zero] received at the satellite are due to atmospheric scattering (path radiance). This assumption is combined with the fact that very few targets on the Earth's surface are absolute black, so an assumed one-percent minimum reflectance is better than zero percent." (CHAVEZ, 1996). The calculated radiance-value based on this assumption is used for the correction of the whole Landsat MSS image (image –based correction).
It is important to mention that the accuracy of an image-based correction technique is lower than a physically based correction (e.g. as applied for Sentinel-2) (CONGEDO, 2016). Nevertheless, CONGEDO (2016) states that image-based corrections "are very useful when no atmospheric measurements are available as they can improve the estimation of land surface reflectance" (CONGEDO, 2016).

Calculation of Normalized Difference Water Index (NDWI)

Using the respective bands of the images (Tab. 4), the NDWI is calculated (see Fig. A6). The Normalized Difference Water Index (NDWI) (MCFEETERS, 1996) uses the green and near-infrared bands to delineate open-water features.

Water surfaces show high reflections in the green and low reflections in the near-infrared wavelength region (see Fig. 6).

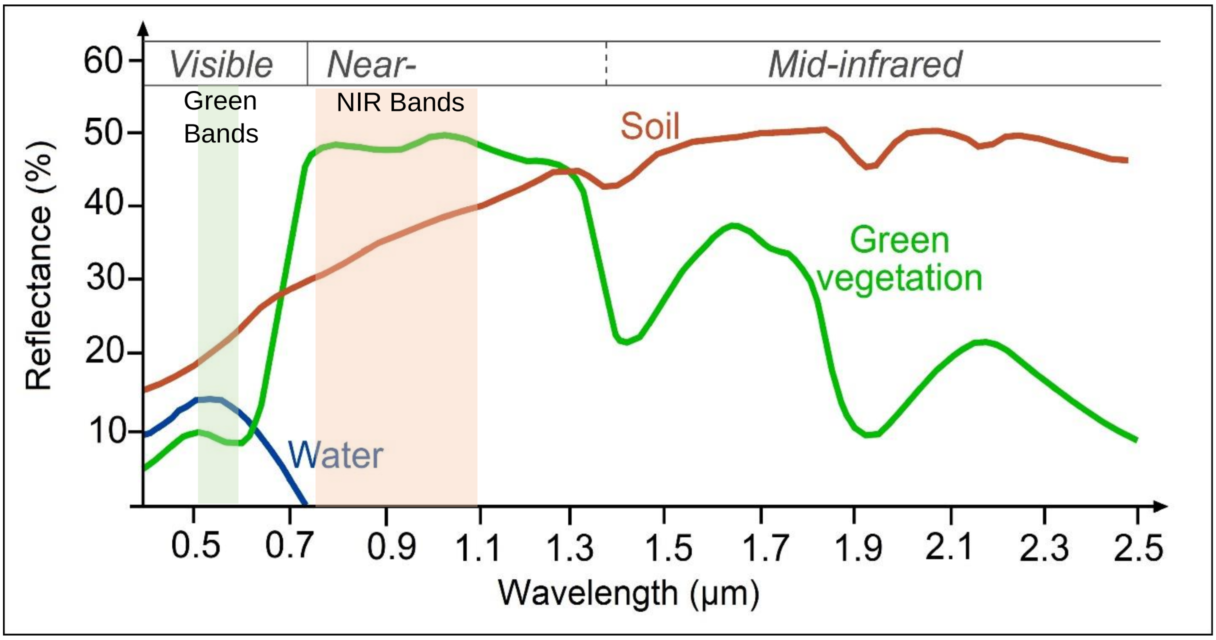

Figure 6: *Reflectance of water, soil and vegetation at different wavelengths; the wavelength areas used by the NDWI are highlighted in green (green bands) and red (NIR bands), modified after SEOS-PROJECT.EU, 2020.*

These differences are used to calculate an index that enhances the presence of open water features and suppresses the presence of soil and vegetation (MCFEETERS, 1996). The Waterindex is calculated as follows, using the respective bands of the satellite image:

$$NDWI = \frac{GREEN - NIR}{GREEN + NIR}$$

The generated index map contains values in the range of -1 to +1 (see Fig. A6), while excluding zero. Positive values are interpreted as water features. Soil and vegetation features have negative values (MCFEETERS, 1996).

Processing steps

At first, a threshold value is applied to discriminate between values that belong to the river system (water-bodies and pointbars) and all other values. This threshold value is defined manually by inspecting the pixels of the different NDWI images (see Tab. 6).

Table 6: Thresholds to discriminate between river system and other values.

NDWI image of the year	Threshold
1973	-0.15
1980	0
1990	-0.08
2000	-0.07
2010	-0.06
2019	-0.1

The application of the thresholds results in maps that only show water-body and pointbar areas differentiated from other areas (see Fig. A7 as an example).

Based on these threshold maps, an area is clipped interactively (due to computing limitations of QGIS regarding data quantity) that covers mainly the river system (including water bodies and pointbars) and adjacent areas. In the next step, all remaining pixels of the river system in the clipped images are assigned the value “1”, whereas the areas below the threshold (see Tab. 6) are assigned NA.

The resulting image still includes many small objects that lie outside of the main riversystem (e.g. small ponds, agricultural canals). To eliminate these water bodies having no connection to the main river system, the raster data are vectorized and single isolated polygons are automatically eliminated, based on the assumption that the main river area shows in one connected polygon.

The results of all processed years are overlain to visualize the different extents (Fig. A8-A13). The three results with the greatest differences in extent are selected interactively and then processed for the change detection map: years 1973, 2000 and 2019 (Fig. A15).

Change Detection Map

The goal of the change detection map is to provide information on the changes of the Padma river system course and the direction of shifting. The changes are visualized in a single map. The conversion of the vector map (polygons) back to a raster map enables to present different river areas with characteristic values in a single map.

A unique year-dependent characteristic value is assigned to the cells of each new raster image (see Tab. 7). The raster cell size is set to 20 m, as this is the pixel size, needed by the successive project analyses.

The yearly products are joined to receive the change detection map of the area of the Padma river system for the different years (see Tab. 8).

Table 7: *Overview of the characteristic values per year.*

	1973	**2000**	**2019**
Characteristic value	1	10	100

Table 8: *Legend of the raster values in the change detection map.*

Raster value	**Area of the Padma river system in**
1	1973
10	2000
11	1973, 2000
100	2019
101	1973, 2019
110	2000, 2019
111	1973, 2000, 2019

Mapping present and former river system areas

In the Sirajganj study area, the information of all results (1973, 1980, 1990, 2000, 2010, 2019) are included into a map that presents present and former areas of Jamuna river system.

Present areas are defined as the area of the Jamuna river system in 2019.

Former areas are defined as the area of the Jamuna river system in all years before 2019 but not in 2019.

The polygons of each year are rasterized. A unique year-dependent characteristic value is assigned to the cells of each new raster image (see Tab. 9). The raster cell size is set to 20 m, as this is the pixel size, needed by the successive project analyses.

The individual results are joined. The values of the map represent the area of the Jamuna river system in different years (see Tab. 10). To reduce the values to present or former areas, the raster is reclassified into two classes (see Tab. 10). Areas where the river is not classified in 2019, are defined as former and are assigned with a value of "1". Areas, which show the river system in 2019, are defined as present and are assigned with the value of "2".

Table 9: *Overview of the characteristic values per year for the mapping of present/former river system areas.*

	1973	**1980**	**1990**	**2000**	**2010**	**2019**
Characteristic value	1	10	100	1000	10000	100000

Table 10: *Legend of the raster cell values in the map of present/former river system areas.*

Characteristic value	**Area of the Jamuna river system in**	**Reclassified value (1=former/2=present)**
1	1973	1
10	1980	1
11	1973, 1980	1
100	1990	1
101	1973, 1990	1
110	1980, 1990	1
111	1973, 1980, 1990	1
1000	2000	1
1001	1973, 2000	1
1010	1980, 2000	1
1011	1973, 1980, 2000	1
1100	1990, 2000	1
1101	1973, 1990, 2000	1
1110	1980, 1990, 2000	1
1111	1973, 1980, 1990, 2000	1
10000	2010	1
10001	1973, 2010	1
10010	1980, 2010	1
10011	1973, 1980, 2010	1

10100	1990, 2010	1
10101	1973, 1990, 2010	1
10110	1980, 1990, 2010	1
10111	1973, 1980, 1990, 2010	1
11000	2000, 2010	1
11001	1973, 2000, 2010	1
11010	1980, 2000, 2010	1
11011	1973, 1980, 2000, 2010	1
11100	1990, 2000, 2010	1
11101	1973, 1990, 2000, 2010	1
11110	1980, 1990, 2000, 2010	1
11111	1973, 1980, 1990, 2000, 2010	1
100000	2019	2
100001	1973, 2019	2
100010	1980, 2019	2
100011	1973, 1980, 2019	2
100100	1990, 2019	2
100101	1973, 1990, 2019	2
100110	1980, 1990, 2019	2
100111	1973, 1980, 1990, 2019	2
101000	2000, 2019	2
101001	1973, 2000, 2019	2
101010	1980, 2000, 2019	2
101011	1973, 1980, 2000, 2019	2
101100	1990, 2000, 2019	2
101101	1973, 1990, 2000, 2019	2
101110	1980, 1990, 2000, 2019	2
101111	1973, 1980, 1990, 2000, 2019	2
110000	2010, 2019	2
110001	1973, 2010, 2019	2
110010	1980, 2010, 2019	2
110011	1973, 1980, 2010, 2019	2
110100	1990, 2010, 2019	2

110101	1973, 1990, 2010, 2019	2
110110	1980, 1990, 2010, 2019	2
110111	1973, 1980, 1990, 2010, 2019	2
111000	2000, 2010, 2019	2
111001	1973, 2000, 2010, 2019	2
111010	1980, 2000, 2010, 2019	2
111011	1973, 1980, 2000, 2010, 2019	2
111100	1990, 2000, 2010, 2019	2
111101	1973, 1990, 2000, 2010, 2019	2
111110	1980, 1990, 2000, 2010, 2019	2
111111	1973, 1980, 1990, 2000, 2010, 2019	2

Results and Discussion

The resulting maps are added in Annexure A (A5-A16) and described in this section. For better orientation, topographical information and some in Bangladesh well-known cities are included in the final map visualization of the remote sensing based products.

Extent of the Jamuna river system and its water body

As already mentioned, the NDWI values greater than the threshold lead to the classification of a larger area than just the water bodies as it includes water bodies and pointbars. All together is interpreted as full extent (maximum water coverage) of the Jamuna river system based on discussions with the GSB colleagues. As an example, Figure A14 shows the NDWI result for 2019 with a threshold greater than -0.06 overlain on the Sentinel-2 RGB 432 image from 2019. It is visible that the water body and pointbars are included into the result.

Figure A8 to A13 show in blue the extents of the Jamuna river system (based on NDWI) in the years of 1973, 1980, 1990, 2000, 2010 and 2019.

The different levels of details between the final maps are caused by the different spatial resolutions of the images. Due to the higher spatial resolution, Sentinel-2 shows more details than Landsat TM and Landsat MSS (Tab. 5).

It can be summarized, that the general shape of river system for the different years is visible in all decades.

Change Detection Map

Based on the NDWI evaluations, the change detection map is calculated (Fig. A15). This map includes information on the shifting direction of the river system, together with the locations of land-loss and possible land-gain. Furthermore, it shows which regions were part of the river system for the period between 1973 and 2019 (Fig. A15, dark blue).

In several regions of the river areas, changes in time are observable (Fig. A15):

Section A shows the westward shift of the main current of the Jamuna River (Fig. A15, section A). Light orange indicates the location of the river system in the year 2000, dark orange in both years of 2000 and 2019. Red color indicates the position of the river system in 2019 only. Large amounts of the section are colored dark orange and red. This shows the continuous erosion of the river towards the west. The red areas only in the western part of the Jamuna River show the newly eroded areas after 2000 until 2019.

East of the study area of the city of Sirajganj (see Fig. A15, study area), the dark blue color highlights regions that have been part of the Jamuna River system continuously since 1973. In the north-east of the study area, turquoise color indicates the location of the river system in 1973 and light green in 1973 and 2000. In this area, the river has shifted eastward since the year 2000. In the center of the western boundary of the study area, no shift is evident. This may be due to the protection of the riverbank of Sirajganj city with an embankment against river shifting and inundation. In the south-eastern area, a shift of Jamuna River towards the east is visible. The light orange colored area shows the location of the river system in 2000, light green areas show the location of the river in 1973 and 2000. After 2000, these areas are no longer part of the active river system. This area has been filled with sand for several years. The development of an economic used area is planned.

Section B shows the eastward shift of the river system within the study period between 1973 and 2019 (see Fig. A15, section B). The western half of Section B shows areas in light orange and turquoise representing the location of the river in the year of 2000 and the year of 1973. These areas are no longer part of the river system in 2019 and are used for agriculture.

Areas in dark orange show the location of the river in 2000 and 2019, red areas represent the location in 2019 only. The sequence dark orange to red running from west to east shows the shift of the river course towards the east.
When looking at the course of the river in 2019 (shaded area) (see Fig. A15, section B), a meandering bow developing to the east can be recognized. The development of that river form corresponds to the erosion of land in the east and land gain in the west of the Jamuna River.

Section C shows an eastward and westward expansion of river course within the study period from 1973 to 2019 (see Fig. A15, section C). Turquoise, light orange and light green colors in the center of the section represent the course of the river in the year 1973, the year 2000, and in both years of 1973 and 2000, respectively. In 2019, this area represents a river island (char) that is used for agriculture. Areas of red color are visible in both the western and eastern parts of the Jamuna River. These represent the river course in 2019 and developed after 2000. In summary, the Jamuna River system in Section C has evolved from a central river course in 1973 to a course with multiple branches during the study period from 1973 to 2019. Agricultural chars have developed between the branches.

In summary, the Change Detection Map in Figure A15 shows significant changes of the Jamuna river system between the years of 1973 and 2019.
Of particular note is that the main channel of the Jamuna River immediately adjoins the city of Sirajganj to the east. North of Sirajganj, the river has shifted westward during the study period. Events such as a collapse of the river embankment for a length of 100m in June 2021 indicate severe erosion on the western bank of the river at the location of the city of Sirajganj (NEWAGE Bangladesh, 2021).

Present and former river areas in Sirajganj study area

In the Sirajganj study area, the change detection map shows present and former areas (Fig. A16). The map allows locating areas of sedimentation processes (former areas) and provides indications on other geo-related processes (e.g. liquefaction-prone areas).
In particular, the former areas in the southeastern part of the study area are filled with sand for the development of an economically used area.

2.3 Inundation Map

Due to climate change, Bangladesh is experiencing an increase in rural-urban migration movements. Therefore, the demand for safe building ground is very high. One result is an increasing lateral growth of urban areas. However, urban growth is limited to suitable building ground and eligible areas are often low-lying and therefore prone to flooding during the yearly monsoon season between May and October. Planning agencies may benefit from geodata on inundation-prone areas that are reliable, available frequently and sustainable, easy to process and easily understandable.

The overall objective of this analysis is to receive a map that gives an overall impression on the frequency of inundation in areas that are at risk of flooding (Fig. A17) for the years 2015 to 2020. The analysis is carried out using 12 Sentinel-1 radar images from 2015 to 2020 and a threshold approach to differentiate between inundated and non-inundated areas. To ensure an easy processing of the large amount of multi-temporal radar data, the analysis is carried out using the online processing tool Google Earth Engine (see the programming code in Annex B).

The Bangladesh Water Development Board (BWDB) already established inundation mapping using Sentinel-1 datasets. In their annual flood reports, the BWDB is using an inundation map to verify the output of a flood-forecasting model (BANGLADESH WATER DEVELOPMENT BOARD 2018, pp. 92-93).

Data

The analysis is based on Copernicus Sentinel-1 images starting 2015, with operation of the Sentinel-1 sensor.

Google Earth Engine states to preprocess the images using the Sentinel-1 Toolbox to receive radiometrically calibrated images, terrain corrected and thermal noise removed (GOOGLE EARTH ENGINE DATA CATALOG, 2020).

A data selection from the rainy season in Bangladesh is required to map the maximum inundation. The selected images are acquired in “IW” (interferometric wide swath), the default acquisition mode of Sentinel-1 (EUROPEAN SPACE AGENCY, 2020). To differentiate between water and non-water pixels, the VH polarization is selected. Preliminary works in the study areas have shown that VH is the most suitable polarization for the detection of water. The respective spatial resolution of the VH polarization images is 10 meter.

The Bangladesh rainy season is roughly between May and October of each year. Depending on the year, the time of maximum inundation for the study area of Sirajganj is in the months between July and August (see Tab. 11). This assumption is based on the flood reporting by the BWDB (see e.g. BANGLADESH WATER DEVELOPMENT BOARD 2017, 2018, 2019) and by interactively assessing and selecting the images from a period that show the largest inundated areas. Since the exact dates of maximum inundation of a year are unknown, all available images of the respective months of each year are processed in this analysis.

Finally, using the above-mentioned benchmarks, 12 Sentinel-1 images of descending orbits are selected for the processing (Annex B, lines 9-23). Annex C lists the images in a table.

Table 11: *Months of maximum inundation in the years 2015-2020.*

Year	**Month(s) of maximum inundation**
2015	July
2016	July
2017	August
2018	July
2019	July
2020	July

Method

The workflow of the processing in Google Earth Engine is visualized in Fig. 7. The selected images of each year are combined and mean values are calculated. The mean-value images are subsetted to fit the extent of the study area (see Fig. A18; Annex B, lines 24-29).

Thresholding

Water surfaces appear in black and dark gray colors in the averaged amplitude images (see Fig. A18). In order to identify a threshold value, the values of assumed water and non-water image areas are identified interactively. Based on experience in the definition of thresholds discriminating between water and non-water surfaces, the identified threshold values in Bangladesh range from -20 dB to -22 dB.

For the Sirajganj study area, a threshold value including values smaller than -20.5 dB is chosen and applied to images from all years (Annex B, lines 109-118). The output image only shows pixels smaller than the threshold, representing the inundated areas of each year (see Fig. A19).

All areas that have been inundated between 2015 and 2020, are compiled by combining the threshold images of all years into one image (see Fig. A17; Annex B, lines 120-123). The result is exported with a 20m spatial resolution, which is a requirement for further analyses in the project (Annex B, lines 129-141).

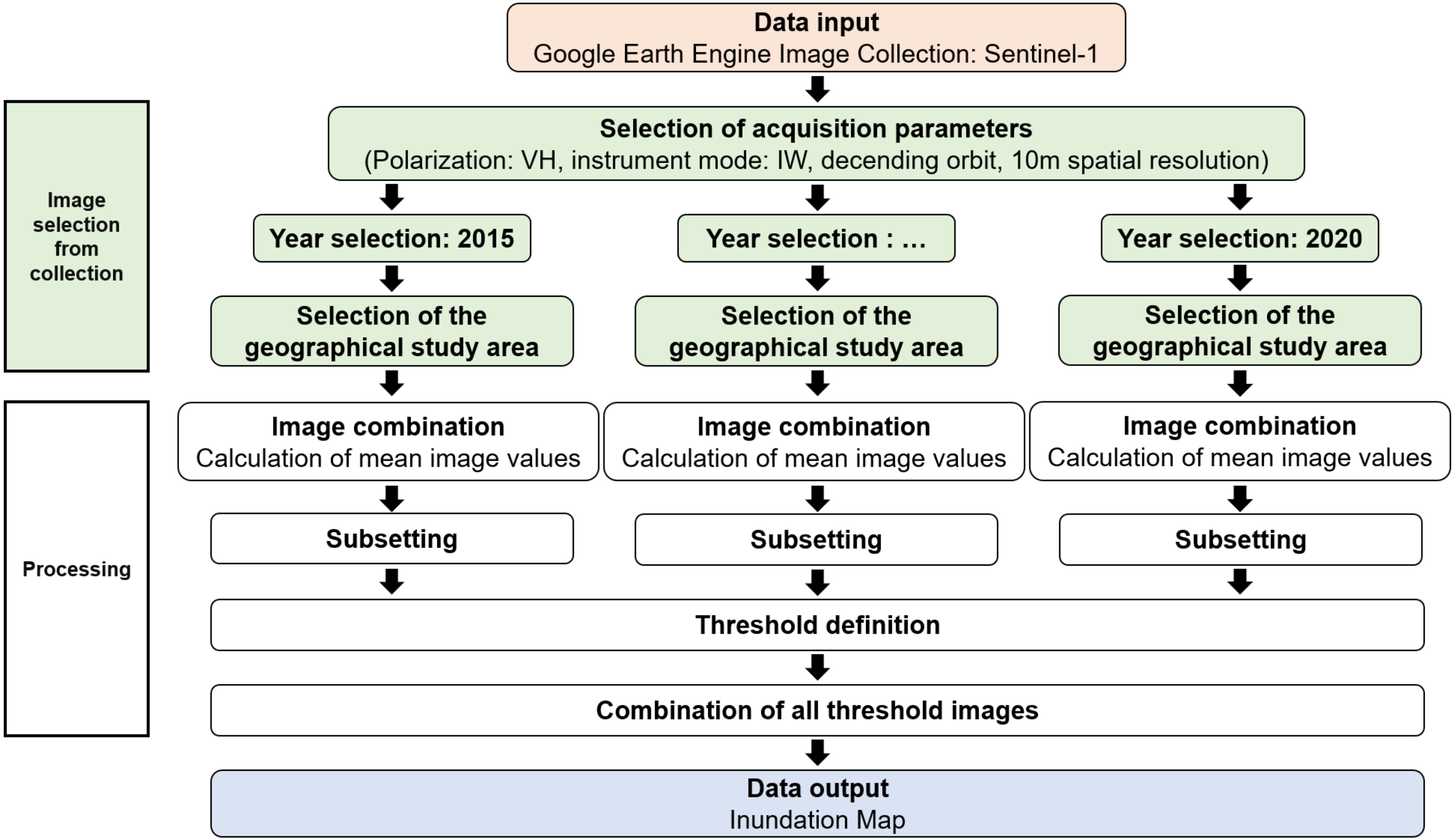

Figure 7: *Workflow of the Google Earth Engine processing of the inundation mapping method.*

Results and Discussion

The resulting map presents the areas and frequencies of inundation between 2015 and 2020 (see Fig. A17).

The map exhibits three major areas: (1) The city area of Sirajganj, west of the Jamuna River which only shows rarely inundated areas in the years from 2015-2020. (2) The rural area that stretches west of the city of Sirajganj in a north-south direction and shows large areas of frequent inundation. (3) Frequently inundated areas near the Jamuna River south of the city of Sirajganj which also show the filling with river sand which is the development for planned economic zone (see Fig. A20). Rural areas north of Sirajganj near Jamuna River are inundated frequently as well.

Many small areas in the Sirajganj city area are inundated yearly (e.g. around the landmark DC Office), representing ponds and lakes as they partially overlap with the water bodies in the topographic base map (data of the Survey of Bangladesh and OpenStreetMap). Nevertheless, the majority of frequently inundated areas is located in the outskirts of Sirajganj (see Fig. A17).

The agricultural areas in the west of Sirajganj city (north and south of the LGED Office landmark), which are not in close proximity to the rivers, have the lowest frequency of inundation (Fig. A17). These areas have been inundated from once up to three times during the study period between 2015 and 2020. The agricultural areas closer to the river north of Sirajganj (e.g. west of the landmark of Hard Point) show higher frequency of five to six times of inundation within the period between 2015 and 2020. (e.g. section A, Fig. A17).

In the November 16, 2020 Sentinel-2 satellite image (Fig. A20), the area around the landmark of the Sirajganj Economic Zone, south of the city of Sirajganj, is visible being filled with river sand (Fig. A20, section B). During the six years of the study, this area was inundated annually (Fig. A17). In the River Shifting Change Detection Analysis (see Chapter 2.2), it became visible that the currently filled area was part of the Jamuna River system in years prior to 2019. However, a bordering area in the south-eastern corner of the map was only inundated once or twice within the six-year period.

It can be concluded that between 2015 and 2020 for the rainy season mainly areas in the rural outskirts of Sirajganj were inundated. Additionally, rural areas and areas near the Jamuna River had a higher frequency of inundation during this period.

2.4 Ground Motion Map

2.4.1 Introduction

Within the project Geo-Information for Urban Planning and Adaptation to Climate Change (GPAC), a project of German-Bangladeshi technical cooperation and carried out by the Geological Survey of Bangladesh (GSB) and the German Federal Institute for Geosciences and Natural Resources (BGR), ground motion products based on Radar Interferometry (InSAR) were created for several study sites in Bangladesh. The goal of these analyses is to establish a workflow for the systematic integration of ground motion data into a climate change adapted urban planning in Bangladesh. The availability of free, medium resolution, radar satellite images through the European Copernicus program and the progress in computing capabilities, open up new opportunities for the wide-scale, multi-temporal and continuous ground motion analysis based on satellite data.

In the context of an advancing urbanisation and the resulting increased demand in suitable building space, in combination with the particular exposure of Bangladesh to climate change related risks, InSAR ground motion products enable the identification and monitoring of potentially stable areas and can be used in the prediction of inundation scenarios. In combination with other relevant geodata, InSAR can hence contribute to the assessment of building ground suitability.

In this section, the results of the InSAR analysis for the city of Sirajganj from January 2015 to December 2019 are presented and discussed.

2.4.1.1 SAR Interferometry (InSAR)

SAR interferometry (InSAR) is a technique for the precise measurement of topography and terrain movement in the range of several millimetres from two or more SAR images. The different methods used in this field have in common that they exploit the phase information contained in the images acquired from two or more different sensor positions (spatial baselines) and/or at different acquisition times (temporal baselines). Concretely, the phase difference between the different acquisitions (the so-called interferometric phase) implicitly contains information about the topography of the area of interest and – when data from different points in time is available – on any terrain movements during the observation period.

When terrain deformations are to be observed over a longer period, the issue of increasing loss of coherence - or decorrelation - between the different scenes arises. Coherence is estimated from the amplitude of the complex correlation coefficient of two SAR images. In the context of SAR interferometry, coherence is used as a measure to evaluate the quality of the phase difference; high coherence indicates high quality of the phase difference while low coherence indicates a highly noisy phase difference (LÓPEZ-MARTÍNEZ et al., 2004).

Decorrelation particularly affects areas with vegetation (forests, parks, farmland, etc.) where the backscatter to the radar sensor is subject to high temporal variations due to quick changes in geometry (e.g. leaves moving with the wind) and dielectric properties (moisture variations). It also affects areas with a low backscatter to the sensor such as smooth surfaces (water, roads, airstrips, etc.) or areas of radar shadow. In these areas, noise dominates the return signal (low signal-to-noise ratio). In essence, decorrelation occurs when the contributions of topography and deformation to the total phase difference are superimposed by random phase contributions and noise, and can no longer be isolated. As a rule of thumb, the longer the time gap between two acquisitions and the larger the spatial distance between the sensor positions (temporal and spatial baseline), the higher the degree of decorrelation (WOODHOUSE, 2006).

Therefore, if the goal is to examine deformation time series, one has to limit the analysis to image pixels that are less affected by decorrelation. That is, pixels that exhibit a strong and stable backscatter to the radar sensor even over long periods of time. These sort of targets are usually abundant in urban areas and correspond to man-made structures. In addition, natural targets such as rocks, gravel fields and even desert surfaces can be sufficiently stable over time to be considered for multi-temporal analyses. There are different approaches in this field of multi-temporal radar interferometry. Two approaches, Persistent Scatterer Interferometry (PSI, see Ferretti et al., 2001) and Small Baseline Subset (SBAS, see BERARDINO et al., 2002) are used in the frame of this work and are described briefly in the following section.

2.4.1.2 Multi-temporal InSAR (PSI and SBAS)

Persistent Scatterer Interferometry (PSI) is a technique that relies on point targets, which have a strong backscatter and are stable over time (so-called persistent scatterers, PS).

Within an image pixel, a PS has to be dominant while the backscatter contributions of the other objects (scatterers) within that resolution cell can be neglected. These conditions are normally fulfilled by artificial (i.e. man-made) objects which are particularly prevalent in urban areas. Examples include cell phone towers, roofs and edges of houses, bridges, metallic structures, utility poles, etc. These objects are referred to, in the context of radar interferometry, as *persistent scatterers* and can be identified within the image stack using different methods. Frequently, the amplitude stability over the observation period is considered for this purpose. PSI is particularly effective in urban areas with a high density of point targets. In rural areas on the other hand, the number of potential PS is considerably less.

The PSI algorithm initially selects a master image from the stack of available radar acquisitions based on a minimisation of the average spatial and temporal baseline with respect to the other images in the stack. Secondly, one interferogram is created between the master image and each of the secondary images. All images in the stack of acquisitions are then *zero baseline steered*, i.e. the measured interferometric phases are adjusted for the different imaging geometries of the different acquisitions with respect to the master image, using an external DEM like e.g. SRTM and precise orbit information. The next step is the identification of PS candidates. Here, the classical approach is to use the amplitude stability over time. Subsequently, and using an iterative approach, the atmospheric and topographic phase contributions are calculated and removed and the deformation velocity for the PS is calculated. To do so, a deformation model is applied. In the most common case, a linear deformation model is used (see FERRETTI et al., 2001).

Small Baseline Subset (SBAS) is another method for multi-temporal radar interferometry that uses a network of interferograms. Instead of choosing a single reference image for all interferograms, groups (subsets) of images are considered that have been acquired with a small temporal and spatial baseline. Subsequently, for each image combination within a subset, an interferogram is calculated respectively (as long as a user-defined maximum temporal and spatial baseline is not violated). For this reason, in SBAS the number of interferograms is usually much higher than the number of available SAR acquisitions. In order to achieve a continuous motion time series, the individual subsets are subsequently linked together (see BERARDINO et al., 2002).

Since SBAS tries to minimise the temporal and spatial baseline between the images of a particular subset, the resulting interferograms are less affected by decorrelation when compared to PSI. This leads to the detection of more stable points (scatterers) including natural objects such as rocks, gravel fields or desert surfaces. SBAS is also able to deal with disconnected subsets and can interpolate over points that are affected by a temporal loss of coherence.

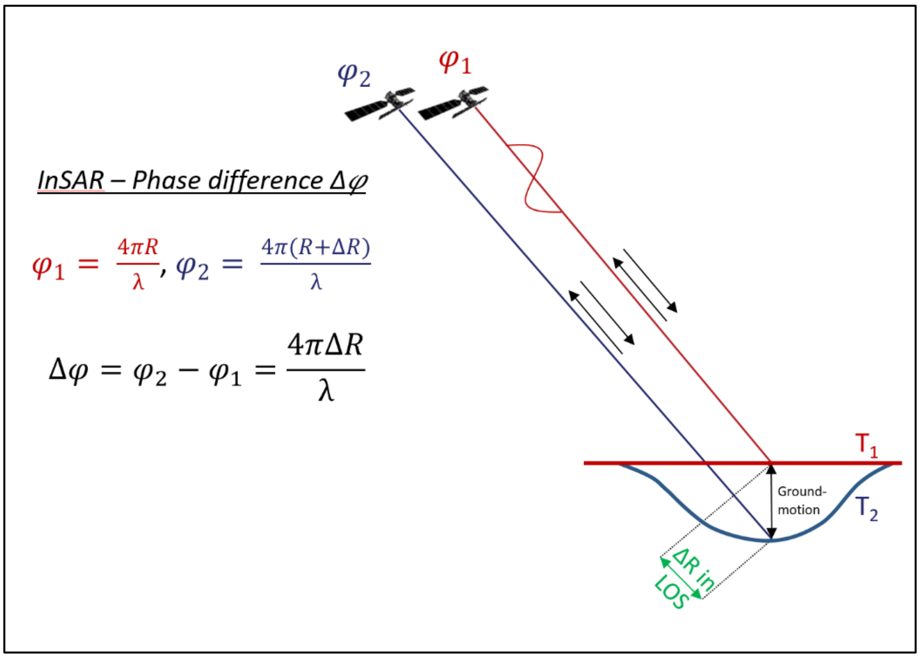

Figure 8: *Schematic representation of InSAR basic principle.*

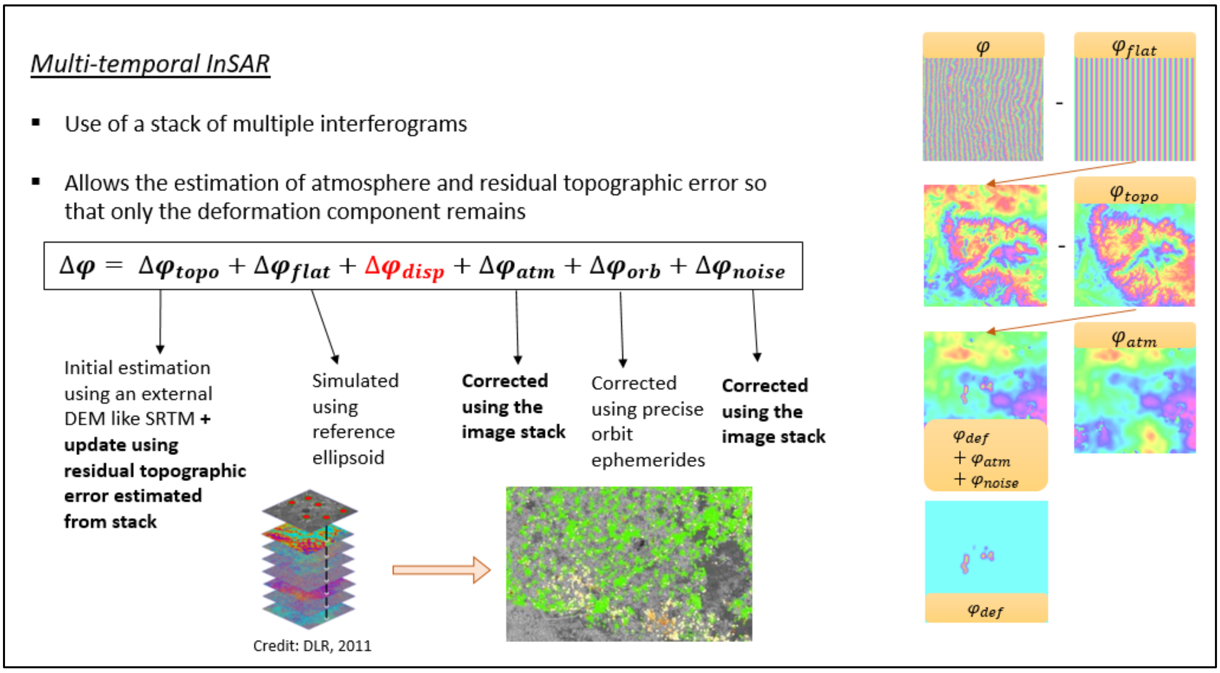

Figure 9*: Schematic representation of an interferometric stacking (multi-temporal InSAR) approach.*

2.4.1.3 Multi-temporal InSAR limitations

The deformation measured in radar interferometry is always along the line-of-sight of the imaging sensor/satellite and not the true vertical deformation. SAR sensors are not nadir looking but instead are looking at the ground obliquely with an incidence angle. For Sentinel-1 this angle is between 20 and 45 degrees with respect to nadir. However, the vertical deformation component can be estimated with a certain probability using adjustment calculation if acquisitions from both satellite orbit directions (ascending and descending) are available. In this case, two images acquired in different orbits with different look angles are used to estimate the vertical motion component and one horizontal motion component (usually the east-west component is estimated since the north-south component is not well constrained by most satellite imaging geometries). Furthermore, in radar interferometry all the estimated velocities and displacements are relative to one or several reference points. The principal reference point is assumed to be stable over the whole observation period, an assumption that is not always true. In order to get the absolute motion, GNSS or other survey data is required, to which the dataset can be referenced instead. For our analyses within the GPAC project, no external reference data is used, as no adequate GNSS are available.

Another aspect that needs to be considered is the ability to exactly assign a particular deformation measurement to an object on the ground. For the German Ground Motion Service (BBD) a mean geolocation accuracy of 3.5 metres for strong point targets was shown (KALIA et al., 2020). In the case of SBAS, assigning a particular object to an observation proves more challenging since SBAS applies spatial averaging of adjacent pixels, merging together signals from numerous individual scatterers.

The ambiguous nature of the phase information contained in SAR images (only displacements corresponding to fractions of a wavelength can be measured) means that InSAR is limited in its ability to measure fast displacements. In fact, the maximum theoretical displacement that can be measured between two scenes corresponds to one fourth of the wavelength. CROSETTO et al. (2016) described the maximum differential accumulated deformation rate measurable with Sentinel-1 with 42.6 cm/year. A final limitation that needs to be mentioned is the availability of coherent targets. While SBAS is able to detect a high density of targets even in rural areas, neither technique (PSI or SBAS) can provide information in areas where there are strong changes in ground cover over time (for example seasonally flooded fields).

The BGRs Remote Sensing Working Group is mainly using ENVI SARscape software for InSAR processing. This software is developed by the Swiss company sarmap S.A. and is entirely integrated into ENVI. For PSI, SARscape currently only supports linear deformation models while the SBAS implementation in SARscape also supports non-linear models.

2.4.2 Methods

2.4.2.1 Project area

Sirajganj is a city in the Rajshahi Division in north-central Bangladesh roughly 100 km north-west of Dhaka. The city is located on the western bank of the Jamuna River and had a population of around 160,000 in the 2011 government census. The topography of the city is flat with an average elevation of roughly 15 meters above sea level. The city is furthermore characterised by numerous waterbodies (ponds, channels, rivers) in particular the Jamuna River that forms the natural eastern border of the city. The city centre, which covers the largest part of the project area, is densely built-up with multi-storey residential buildings, shops and bazaars shaping the appearance of the city.

Suburbs and rural settlements that display a high vegetation component and are dominated by low-rise residential buildings surround the city centre to the north, west and south. To the east, the Jamuna River borders Sirajganj with the riverbank enforced by concrete embankments. To the south-east, two large areas filled up with sand in preparation for future construction work, can be found along the Jamuna riverbank. Further south, the *Bangabandhu Bridge* or *Jamuna Multi-purpose Bridge*, a combined road and rail bridge, spans the Jamuna river over a length of 4.8 km (see Figure 10). Just 300 metres further upstream, a new railway bridge is currently under construction. This area is also the location of a 225 MW combined cycle power plant operated by the company NWGCP and the new *Sirajganj Economic Zone*, an industrial development project currently under construction (see Figure 10).

As many Bangladeshi cities, Sirajganj has experienced intensive construction activities over the past two decades. The city centre in particular saw the construction of numerous new buildings. Outside of the city centre, several large-scale construction projects were realised or are currently under construction. Apart from the projects already mentioned, the *Shaheed M. Monsur Ali Medical College* (SMMAMC) is another large-scale construction project of the past years (see Figure 10). It is located west of the city centre and has been under construction since 2017.

Recent Sentinel-2 imagery shows that, as of March 2021, most of the construction work seems to be completed, while parts of the campus are still under construction. Along the river bank of Sirajganj, new embankments are also under construction with parts completed in 2016.

While the Sirajganj project area has a size of 43.19 km², for the InSAR analyses a larger area of 368.48 km² is chosen. This area covers the city of Sirajganj, its immediate suburbs and parts of the opposite (eastern) bank of Jamuna River. Even though the deformation dynamics within the city of Sirajganj are the main focus of this work, a larger area was consciously chosen for the InSAR processing, to enable a higher selection of potential reference points in the phase unwrapping part of the processing.

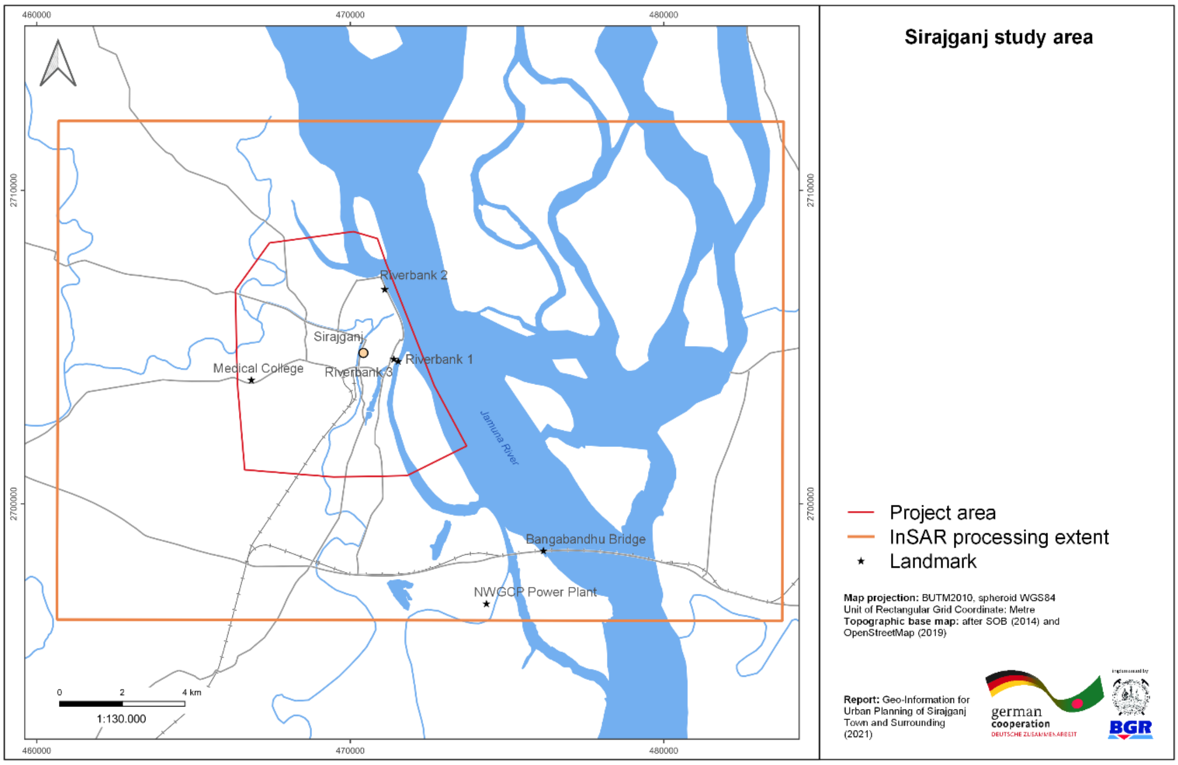

Figure 10: *Map of project area and InSAR processing area.*

2.4.2.2 Data and data download

The radar interferometry analyses carried out within the scope of the GPAC project are based on Sentinel-1 data. Sentinel-1 is a C-band radar satellite constellation operated by the European Space Agency (ESA) consisting of two identical satellites – Sentinel-1a and Sentinel-1b. The data is distributed free of charge by ESA.

For the Sirajganj area, Sentinel-1 data covering the period from January 2015 to December 2019 in the ascending and the descending orbit direction are used. Until April 2017 roughly one acquisition per month and orbit direction is available. Starting from April 2017, a repeat cycle of roughly 12 days is available for each orbit direction. In total, 224 Sentinel-1 scenes are downloaded for the Sirajganj analyses (see Annexure C: Data, Ground Motion Map).

Sentinel-1 data can be downloaded from the Copernicus Open Access Hub (https://scihub.copernicus.eu/) and from the Alaska Satellite Facility (ASF) (https://asf.alaska.edu/).

For this project, all Sentinel-1 data are downloaded through the ASF. For more details on the download process, please refer to the *Interferometric Stacking in SARscape Processing Guidelines.*

2.4.2.3 Orbit files download

In addition to the image files, it is necessary to download the so-called precise orbit ephemerides files. These are highly precise satellite position vectors, which are available online 20 days after the Sentinel-1 acquisitions are published. These vectors are necessary for InSAR processing, since the exact sensor position at the time of acquisition is needed for high quality InSAR results. The orbit files can be downloaded from the *Sentinel-1 Quality Control website* (https://qc.sentinel1.eo.esa.int/).

For an InSAR analysis only those Sentinel-1 scenes should be considered, which are older than 20 days at the time of the analysis. The accuracy of the satellite positions after the update using precise orbit information is given by ESA with 5 cm (3D RMS). For more information on the orbit file download, please refer to the *Interferometric Stacking in SARscape Processing Guidelines*.

2.4.2.4 SARscape PSI and SBAS workflow

ENVI SARscape is used in this project for InSAR processing. The PSI workflow within the software consists of five steps: Connection graph, Interferometric process, Inversion: First Step, Inversion: Second Step and Geocoding. Once both orbit directions are processed until the Geocoding step, the tool Shape Combination is used to combine both datasets and estimate the vertical deformation component.

SBAS processing was also done using ENVI SARscape. The SBAS workflow consists of seven iterative steps: Connection Graph, Interferometric Process, Ground Control Point Selection, Refinement and Re-Flattening, Inversion: First Step, Inversion: Second Step and Geocoding. As with PSI, both orbit directions were processed separately and then merged using the Meta Combination tool. In following, the processing steps are briefly explained.

The first step in the PSI and SBAS processing chain is the **Connection Graph** tool. For PSI, this function analyses the stack of SAR images and selects the best master image from the stack (based on temporal and spatial baseline). All differential interferograms are subsequently formed with this master image. For SBAS the tool creates a network of image connections based on a user defined maximal temporal and spatial baseline. For every image connection, an interferogram is formed in the following step. Not all images in the network need to be directly connected to each other. Ideally however, all images are connected at least *indirectly*.

The Connection Graph tool also creates a working directory in which the outputs of all the processing chain’s steps are stored and creates the auxiliary.sml file in the working directory. This file is needed as an input to all the following steps and it contains information about the data used and the progress of the processing chain.

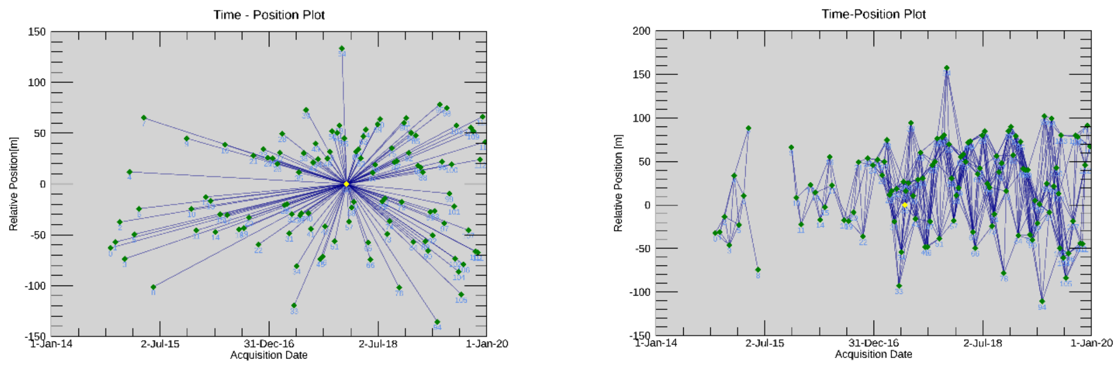

Figure 11: *Right: PSI connection graph with one master image and only one connection between master and each child; Left: SBAS connection graph showing multiple connections for each image and two disconnected blocks.*

In the **Interferometric Process**, the interferograms between all image pairs are generated. To do so, all images are first co-registrated, i.e. they are aligned in such a way that each pixel in the child image represents the corresponding object in the master image. This is achieved by locally matching the image intensity values using a maximisation of local cross-correlation between master and child image.

After co-registration, each master image is multiplied by the complex conjugate of the child image. The phase of the resulting complex interferogram corresponds to the phase difference between master and child image. This phase difference is retained, the so-called interferometric phase. This phase has multiple contributions of which the most important ones are the different atmospheric attenuation between the two acquisitions, the topography, the so-called flat earth contribution and the deformation that occurred between the two acquisitions. Since we are only interested in the latter contribution, the others need to be cancelled out as best as possible.

The flat earth phase is the phase contribution, which comes from the variation of range distance across the image due to the curvature of the earth. This contribution can be removed by using an ellipsoid in a process called interferogram flattening. The topographic phase contribution can be initially estimated using a digital elevation model (DEM) such as SRTM and the satellite orbit information. This estimate is further refined in the following steps of the workflow. Similarly, the atmospheric contribution is estimated in the following steps of the workflow.

For PSI, the Interferometric Process includes the steps co-registration, interferogram generation and interferogram flattening (which includes removal of flat earth component and topographic phase component). Contrary to “standard” InSAR processing, no spatial filtering is applied and point targets (individual objects with a strong backscatter to the sensor) are preserved.

For SBAS, the Interferometric process also includes coregistration, interferogram generation and interferogram flattening but also includes filtering of the flattened interferogram to reduce phase noise and an initial phase unwrapping (transformation of the interferometric phase from multiples of 2π to absolute values using appropriate reference points).

The next step in the SBAS workflow, **Refinement and Re-Flattening**, uses user defined reference points to correct for possible orbit inaccuracies and large-scale atmospheric influences.

In the **Inversion: First Step** an initial estimate of the model parameters (residual height and displacement information) is undertaken. In the case of PSI, the algorithm identifies a number of coherent targets (Persistent Scatterers, PSs) and analyses the phase history of these targets only.

Initially, only highly coherent targets are considered and their information is used to get a first estimate of the model parameters. In the case of SBAS, the input scenes are processed in whole, the residual height and displacement related information are estimated from the interferometric phases and the phase unwrapping is re-done to generate higher quality products.

In the **Inversion: Second Step** the atmospheric phase components are estimated. This step is identical for both PSI and SBAS. The atmospheric phase contributions are estimated, removed from the interferometric phase and the date-by-date displacements are estimated for all images in the stack. Finally, in the **Geocoding** step, the calculated displacement information is geocoded from SAR slant range geometry into a geographic coordinate system.

All steps are explained in detail in the document *Interferometric Stacking in SARscape Processing Guidelines*. The processing parameters are detailed in Annexure D: SARscape Processing Parameters.

2.4.3 Results

2.4.3.1 PSI processing

Using the SARscape PSI workflow, the Sentinel-1 data is processed in both orbit directions (ascending and descending) respectively. The results for each dataset are then combined (decomposed) to obtain the vertical and east-west motion component. Finally, the results are filtered such that only persistent scatterers with a temporal coherence value >= 0.7 are retained.

The decomposed Sentinel-1 PSI dataset contains more than 16,000 points (persistent scatterers) and covers the time period from January 2015 to December 2019. Figure 12 shows the vertical ground motion velocity for the Sirajganj project area obtained by the PSI multi-temporal InSAR approach for the observation period. Green colours correspond to points, which are stable, blue tones to points that have experienced an uplift during the observation period, and red points correspond to areas of subsidence. Most persistent scatterers are concentrated in the city centre with significantly fewer points found in the rural settlements surrounding the city. As expected, almost no points are found within the large agricultural areas that surround the city, as these areas are mostly free of stable targets.

Figure 12 shows that much of the project area is moving only slightly or is stable within the margin of error (+/-2 mm/year) during the observation period.

Within the city centre, the motion patterns are diverse. A number of isolated points of strong subsidence (<-8 mm/year) can be found here, and a larger cluster of points of (relatively) strong subsidence (<-5 mm/year) is found along the riverbank in the northeast of the project area. There are no points of strong uplift (>+5 mm/year) within the project area.

Figure 13 shows the PSI east-west ground motion velocity for the period January 2015 to December 2019. Here, blue tones represent an eastward motion, red tones a westward motion and green colours represent points that did not experience any horizontal motion during the observation period.

There are only a few scatterers with strong horizontal motion (>5 mm/year) for the observation period and almost all are found within the city centre. No large-scale horizontal motion patterns are discernible and most scatterers are exhibiting only slight horizontal motion in the range of +5 mm/year to -5 mm/year.

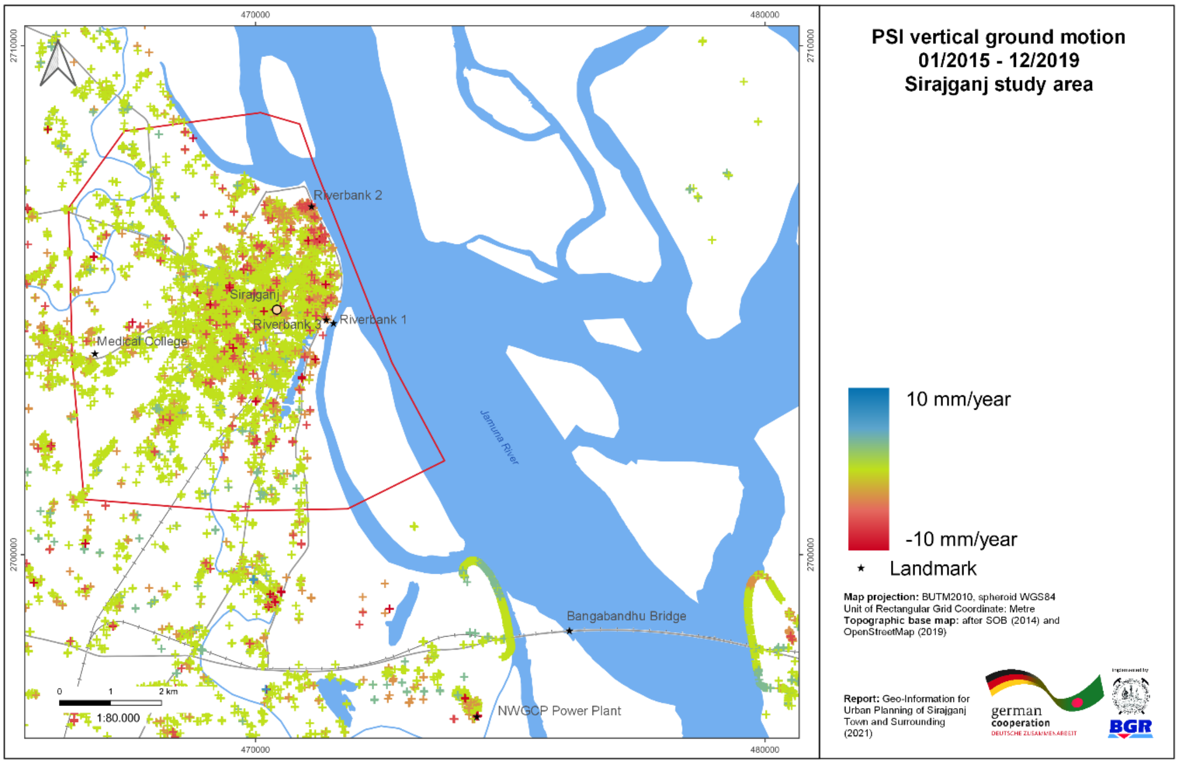

Figure 12: *PSI vertical ground motion velocity 01/2015-12/2019.*

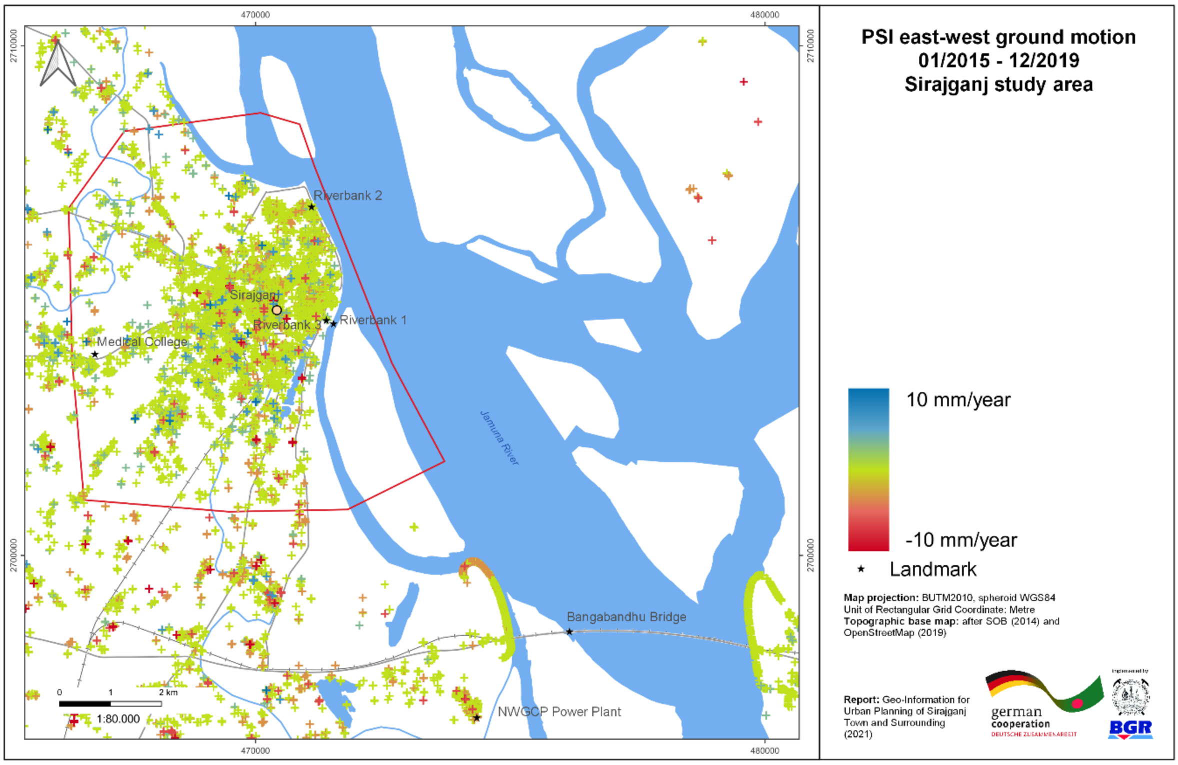

Figure 13: *PSI east-west ground motion velocity 01/2015-12/2019.*

2.4.3.2 SBAS

SBAS results are obtained using the SBAS workflow within the SARscape software. As with PSI, both orbit directions are processed separately and then merged to obtain the vertical and east-west motion components.

Figure 14 shows the SBAS vertical ground motion velocity in Sirajganj for the period January 2015 to December 2019 obtained using Sentinel-1 data. The dataset has a higher spatial density than the PSI dataset. The city centre and most of the rural settlements are well covered, but the dataset is showing gaps in areas that are subject to strong backscatter variations over time, such as agricultural fields.

Within the city centre, and where data from both datasets (PSI and SBAS) are available, the results seem to match well with the PSI results. Large parts of the city and its surrounding areas fall within the margin of error and can be considered stable during the observation period. However, the SBAS data also reveals that in the eastern part of the city a section of four to five kilometres length along the Jamuna riverbank is subsiding at a rapid rate (<-21 mm/year in the northern part).

This large-scale process is not visible in the PSI data due to the lack of persistent scatterers in this part of the city. The SBAS analysis further reveals strong subsidence on the *SMMAMC* campus, another area that where there are no measurement points in the PSI dataset. Within the city centre, a positive vertical movement (uplift) worth noticing of up to 7 mm/year can be found around the Quami Jute Mill.

South of the city, the SBAS data reveals areas of subsidence and uplift around the NWGCP power plant and *Jamuna Multi-purpose Bridge*. Using SBAS it is possible to extract information on the movements of the bridge itself which was not possible using the PSI approach due to the lack of sufficiently coherent scatterers. While both the bridge and the power plant lie outside of the project area, the motion patterns observed here are discussed in further detail in section 2.4.3.3 due to the significance of both facilities for the city of Sirajganj.

Overall, the SBAS dataset makes it easier to detect large-scale deformation patterns and enables the detection of several clusters of strong subsidence not visible in the PSI data. SBAS provides information in areas where the PSI method delivers no results or PSI point density is low. However, the SBAS dataset is also showing gaps in areas that are subject to strong changes in backscatter over time, such as agricultural areas or fields that are seasonally inundated. Furthermore, while the spatial coverage outside of the city centre is much larger using SBAS than using PSI, the small-scale motion patterns within the city centre and on individual buildings are lost.

Figure 15 shows the east-west ground motion velocity in Sirajganj for the period January 2015 to December 2019 obtained using the SBAS approach. Most of the city has not experienced any strong horizontal movements during the observation period. A notable exception is the area along the eastern riverbank of the Jamuna River. This area, which also experienced vertical motion rates of up to -21 mm/year, experienced an eastward motion of up to 11 mm/year over the observation period. This possibly relates to construction activities in this location that can be observed on recent Google Earth imagery. Other points of strong horizontal ground motion can be found on the SMMAMC campus, the Jamuna Multi-purpose Bridge and around the NWGCP power plant. All results are discussed in more detail in section 2.4.3.3.

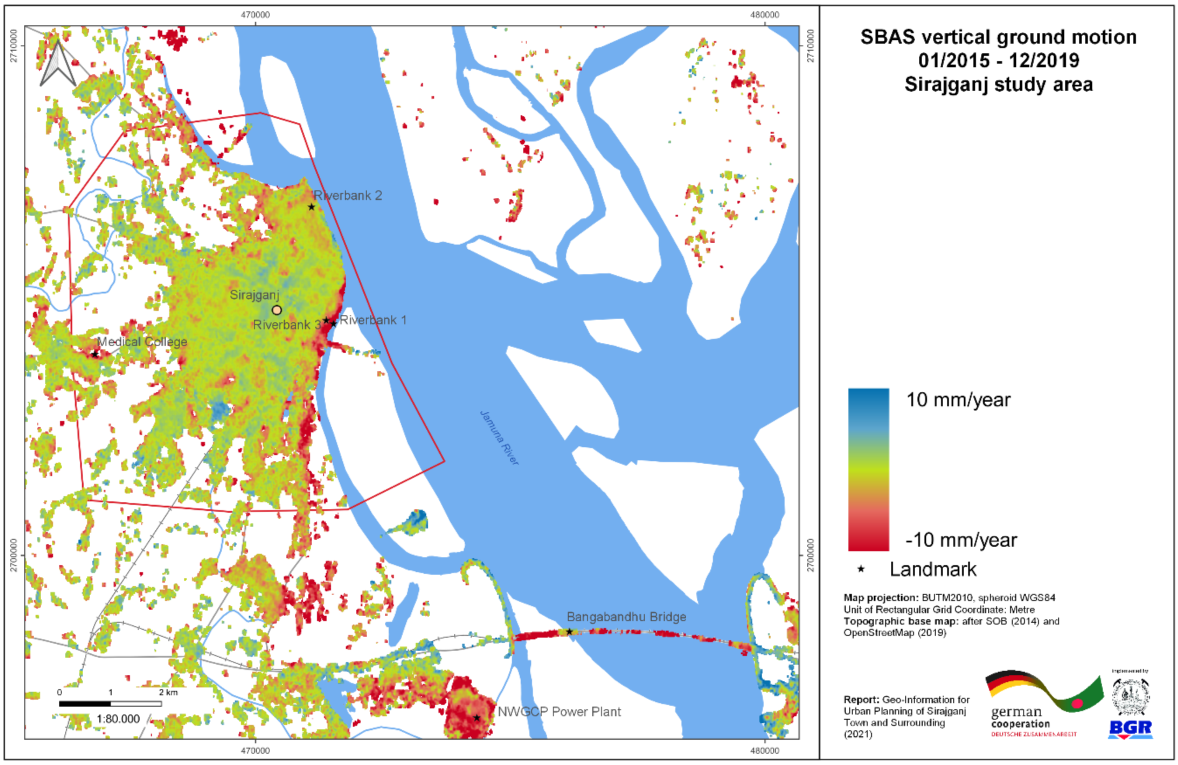

Figure 14: *SBAS vertical ground motion velocity 01/2015-12/2019.*

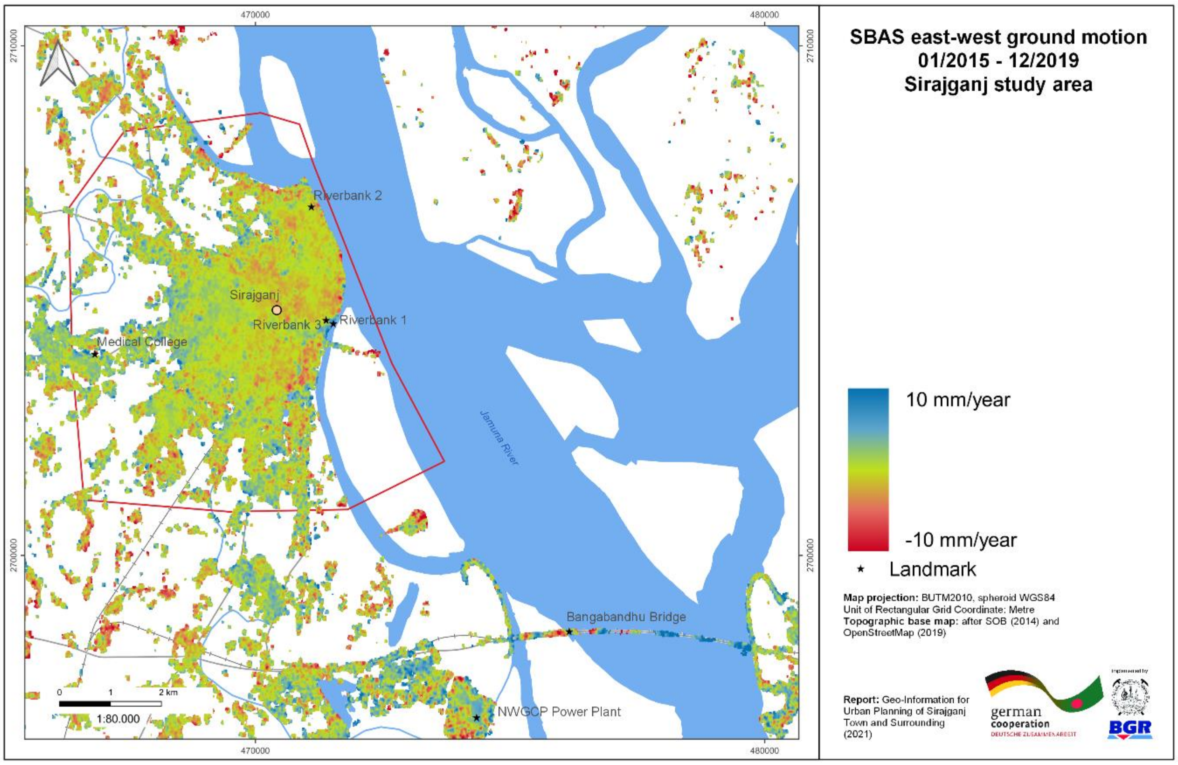

Figure 15: *SBAS east-west ground motion velocity 01/2015-12/2019.*

2.4.3.3 Comparison of PSI and SBAS results

When comparing both datasets, it is immediately evident that SBAS achieves a significantly higher spatial coverage than PSI. The difference is particularly striking in areas outside of the city centre. This is due to the ability of the SBAS approach to deal with so-called distributed scatterers (DS) like open fields, rocks and other geometrically not well-defined objects. The SARscape implementation of the SBAS algorithm is also able to handle objects affected by low coherence or even coherence loss for some part of the observation period.

On a visual inspection, there seems to be good agreement between the two vertical motion datasets in terms of the general ground motion trends. Where there is coverage in both the SBAS and PSI data, generally both show similar trends. Both datasets reveal that most of the project area can be considered stable within the margin of error (+/-2 mm/year) or moving only slightly. Within the project area, the largest observed vertical motion rates are -28.78 mm/year and +14.52 mm/year for SBAS and -13.44 mm/year and +6.08 mm/year for PSI. In the east-west direction, the values are -28.78 mm/year and +14.52 mm/year and -16.41 mm/year and +15.71 mm/year respectively (see Table 12). Slightly different deformation values are expected since both methods use different reference points during processing.

Table 12: *Basic statistics for PSI and SBAS datasets.*

Dataset	Minimum velocity [mm/year]	Maximum velocity [mm/year]	Mean [mm/year]	Standard Deviation [mm/year]
PSI vertical	-13.44	+6.08	-0.28	+1.77
SBAS vertical	-28.78	+14.52	-1.53	+3.76
PSI east-west	-16.41	+15.71	-0.38	+1.94
SBAS east-west	-14.86	+21.22	0.31	+3.30

In the following, a few points of interest and their respective vertical motion time series are presented to illustrate the relationship between both methods and exemplify their respective strengths and limitations. Figure 16 shows the vertical and horizontal velocity for SBAS and PSI on the eastern riverbank of the Jamuna River. Figure 21 shows the SBAS horizontal and vertical time series for a point along the riverbank (*Riverbank* 1 in Figure 10).

The point is located in an area of active land reclamation through infilling with sand, probably in preparation for future construction work. Unfortunately, there are no persistent scatterers in this location. PSI has difficulties in areas that experience temporal changes. SBAS, on the other hand, can deal with a temporal drop or even loss of coherence. Figure 21 shows a clear negative vertical displacement trend over the observation period (cumulative displacement of -80 mm) and a clear positive horizontal displacement (i.e. displacement towards the east). This possibly relates to the ongoing filling of this area with sand. As the sand settles over time, a vertical displacement can be observed while at the same time, the sand spreads out horizontally. Interestingly though, displacements can be observed all along the southern and northern riverbank of Sirajganj also in areas where no construction works are taking place. Another possible explanation for some of these displacements is ongoing river erosion.

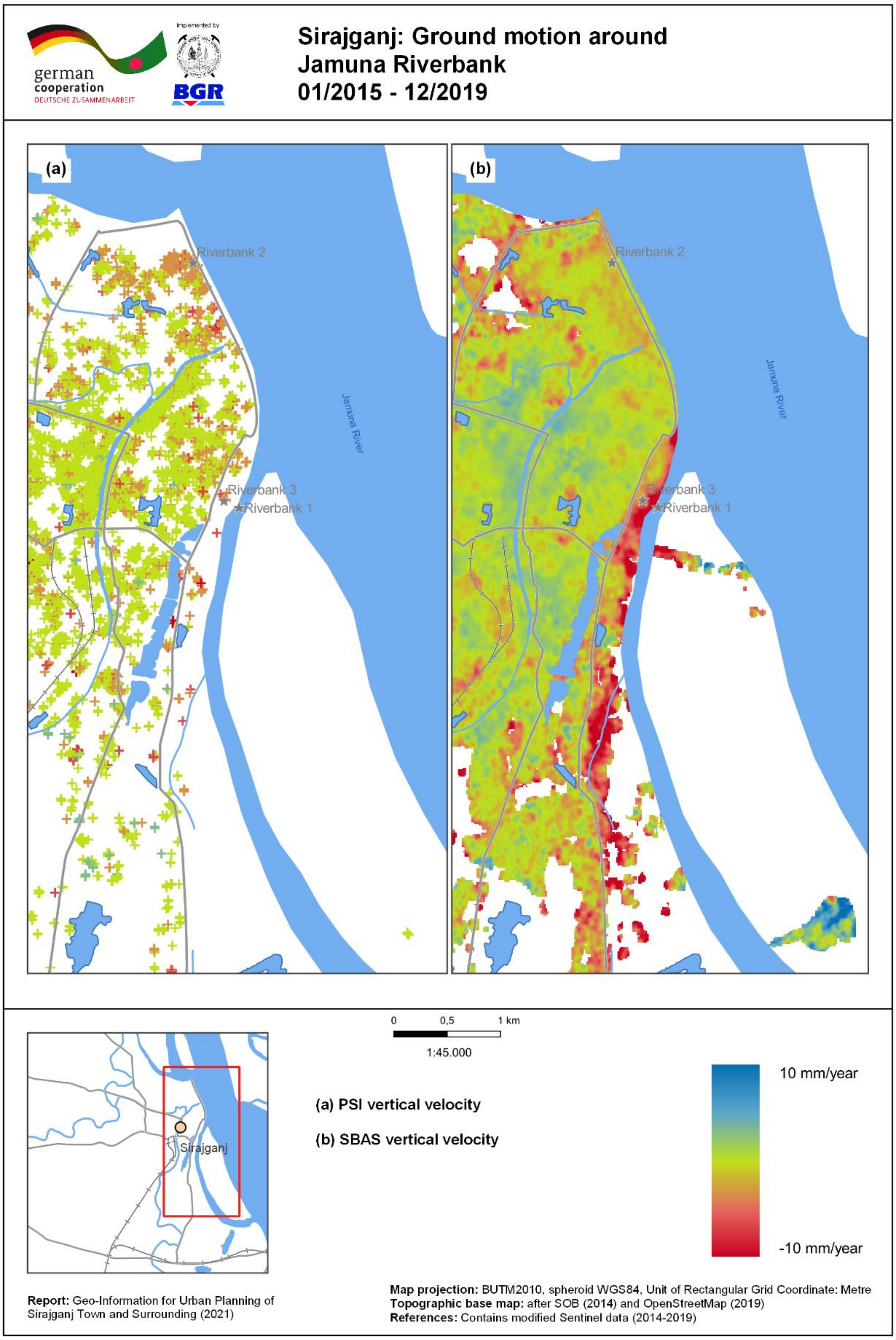

Figure 16: *Comparison of a) PSI and b) SBAS vertical ground motion velocity along Sirajganj riverbank.*

Figure 22 is the vertical and horizontal time series for a persistent scatterer roughly 100 meter north of *Riverbank 1* (*Riverbank 3* in 10) and the corresponding SBAS time series for that point. This point is located just outside the area of active land filling. The horizontal and vertical time series from both methods look almost identical. This is an indication to the validity of the results. The horizontal and vertical trends are similar to those observed in *Riverbank 1* (i.e. subsidence coupled with an eastward motion) though the total displacement is less (around -15 mm in the vertical direction and +15 mm in the eastern direction versus -80 mm and +60 mm respectively for point *Riverbank 1*).

Figure 23 shows both PSI and SBAS vertical time series for a point in the northern riverbank, close to the large embankment that protects the city centre of Sirajganj from Jamuna River (point is denoted as *Riverbank 2* in 10). While the PSI time series shows a clear negative trend (cumulative displacement of roughly -30 mm), the SBAS time series follows a cyclical trend with the cumulative displacement being close to 0 over the observation period. The PSI time series is also affected by a cyclical trend, superimposed on the dominant linear trend. In general, the SBAS algorithm is more flexible in mapping non-linear motion trends. The PSI algorithm on the other hand, tries to fit observed motions to the chosen trend model (linear model in this case). When such nonlinearities are present, SBAS is generally more reliable than PSI with a linear motion model.

Figure 24 is a comparison of both vertical displacement results in the city centre of Sirajganj. Here, the strengths of the PSI algorithm are visible: While SBAS achieves a higher spatial coverage, the PSI results give a more detailed picture. It is possible to identify individual buildings and on larger buildings and structures, often several points are available, allowing the detection of different displacement rates for different parts of a building. The comparison between both subfigures illustrates well the fact that SBAS is assuming a spatial correlation of the observed deformation phenomena while PSI is well suited to analyse uncorrelated motions.

A further important aspect to note, when working with SBAS results, is the fact that the SBAS algorithm includes a spatial averaging (multilooking) operation. This leads to an overall better spatial coverage and a smooth appearance when compared with PSI, but at the cost of "diluting" displacement signals.

A single pixel in the SBAS dataset includes contribution from various different objects on the ground while a persistent scatterer generally corresponds to a single object that has a dominant backscatter over the other objects in its resolution cell. The result of this spatial averaging can be seen in the numerous ponds, canals and other open water bodies present in the city centre of Sirajganj: These locations are not included in the PSI dataset, while the SBAS dataset (wrongly) suggests that it is possible to retrieve ground motion information from these features.

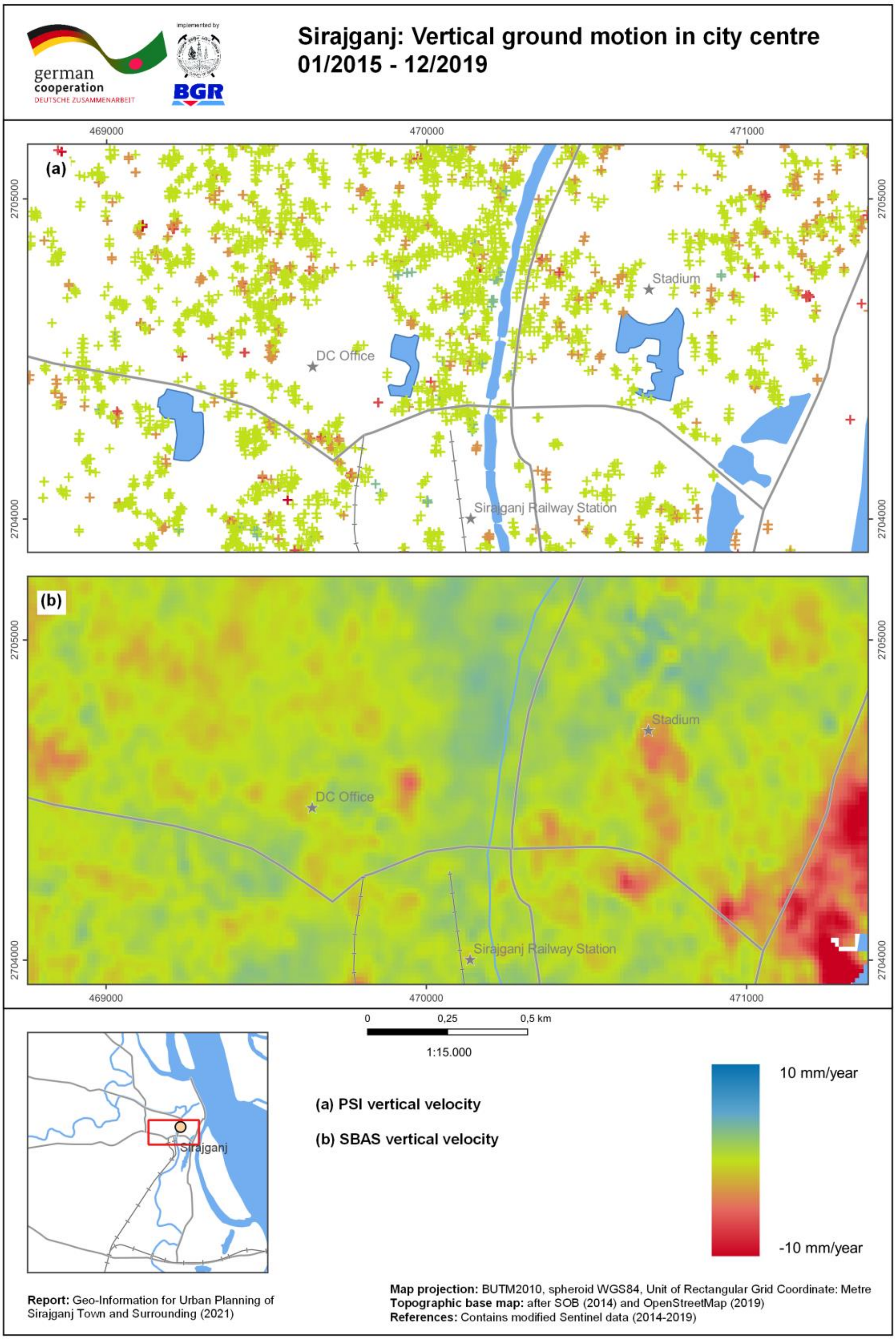

Figure 17: *Comparison of a) PSI and b) SBAS vertical ground motion velocity for city centre.*

Figure 8 is another example how SBAS can be used to observe ongoing dynamics. The figure shows the SBAS vertical velocity for the *SMMAMC* campus in the west of the project area. The campus has been under construction since 2017 and recent Sentinel-2 imagery suggests that parts of the campus are still under construction as of March 2021. Again, no PSI data is available for this location. As was explained earlier, PSI cannot deal well with targets that are undergoing change and are affected by a temporary loss or decrease in coherence. SBAS, on the other hand, can be used to monitor active construction sites provided the temporal changes are not too drastic. Figure 25 shows the SBAS vertical time series for a point on the medical college campus. The total displacement on this point for the observation period was around -70 mm. A slightly negative motion trend can be observed from 2015 to 2017. In 2017 the trend accelerates until June 2019 when the graph flattens. This fits well with the construction activity on the campus, which started in 2017. It is conceivable that the construction work immediately around this point was completed by 2019. Sentinel-2 data from around this time supports this interpretation.

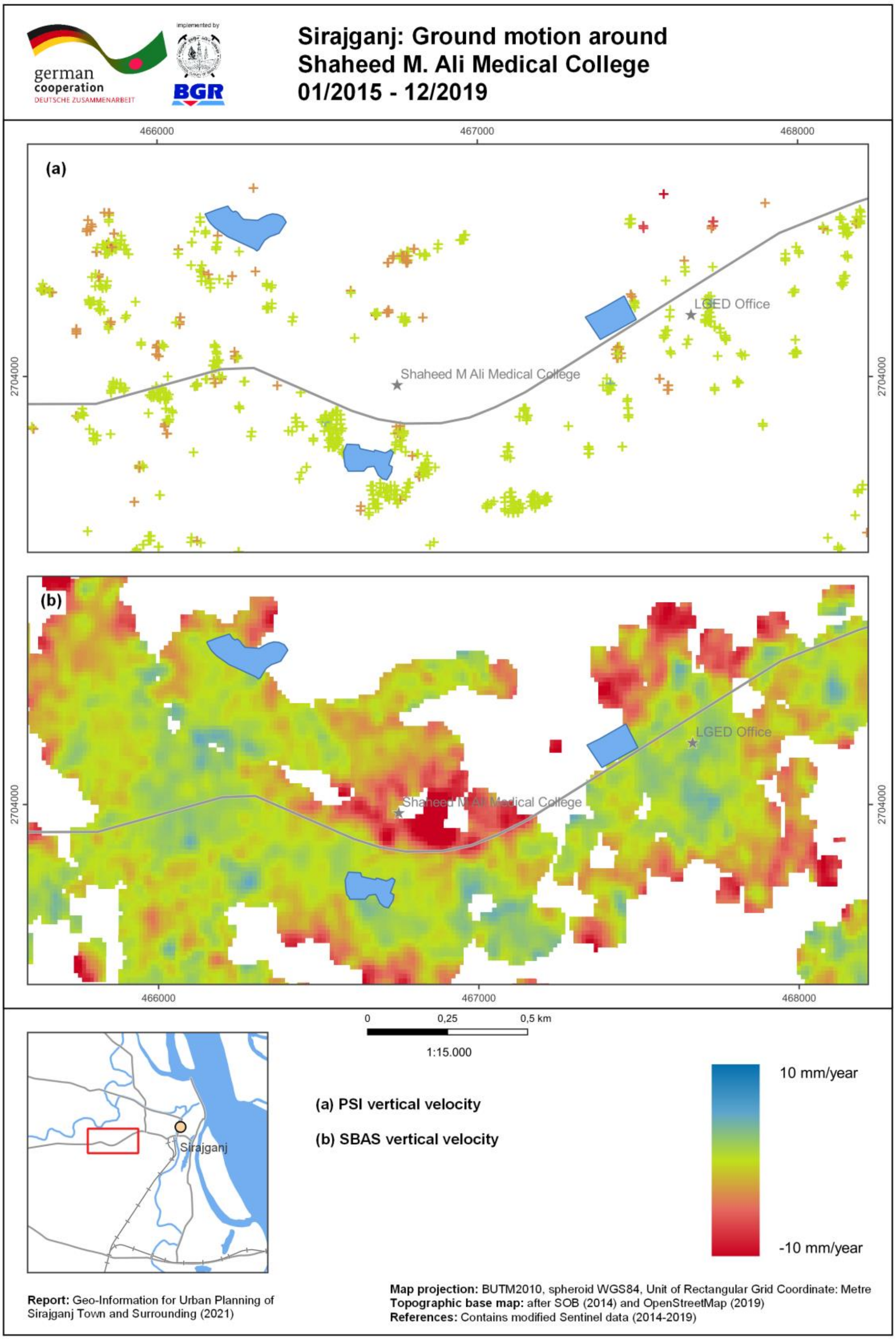

Figure 18: *Comparison of a) PSI and b) SBAS vertical ground motion velocity around SMMAMC.*

Figure 9 shows the PSI and SBAS vertical velocity on and around *Jamuna Multi-purpose Bridge* and the adjacent NWGCP power plant, located on the eastern riverbank of the Jamuna River. Figure 20 shows the horizontal velocities for PSI and SBAS at the same location. The bridge is not covered in the PSI datasets because no scatterers located on the bridge had a coherence larger or equal to the coherence threshold applied (0.7). The area shows varied ground motion dynamics. In particular the area around the power plant and parts of the Jamuna Bridge are subsiding at an accelerated rate during the observation period. The protective embankments located at both riverbanks at the bridge's endpoints on the other hand remained stable during the same period. Bridge and power plant also show strong horizontal movement during the observation period.

Figure 25 shows the vertical time series for a persistent scatterer located in the south-eastern corner of the power plant and the SBAS vertical time series for that same point. Both graphs show a continuous subsidence over the observation period and are in good agreement with each other. The cumulative displacement estimated over the observation period is around -40 mm for both methods. Figure 26 is the SBAS vertical time series for a point located in the middle of the Jamuna Bridge. As mentioned before, no PSI data is available for the bridge. The time series shows a cyclical behaviour. This could relate to thermal dilation of the material in accordance with seasonal temperature changes.

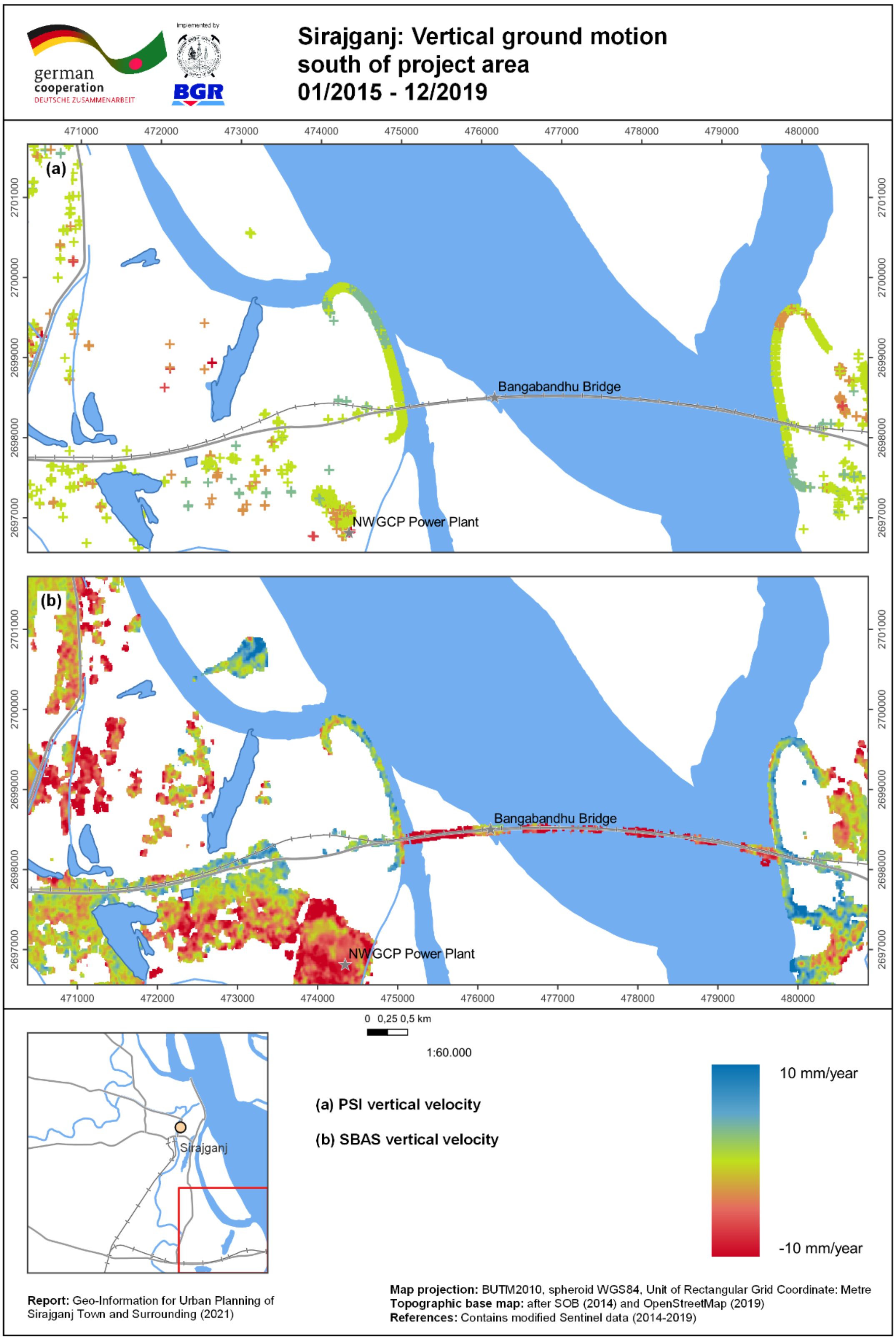

Figure 19: *Comparison of a) PSI and b) SBAS vertical ground motion velocity south of project area.*

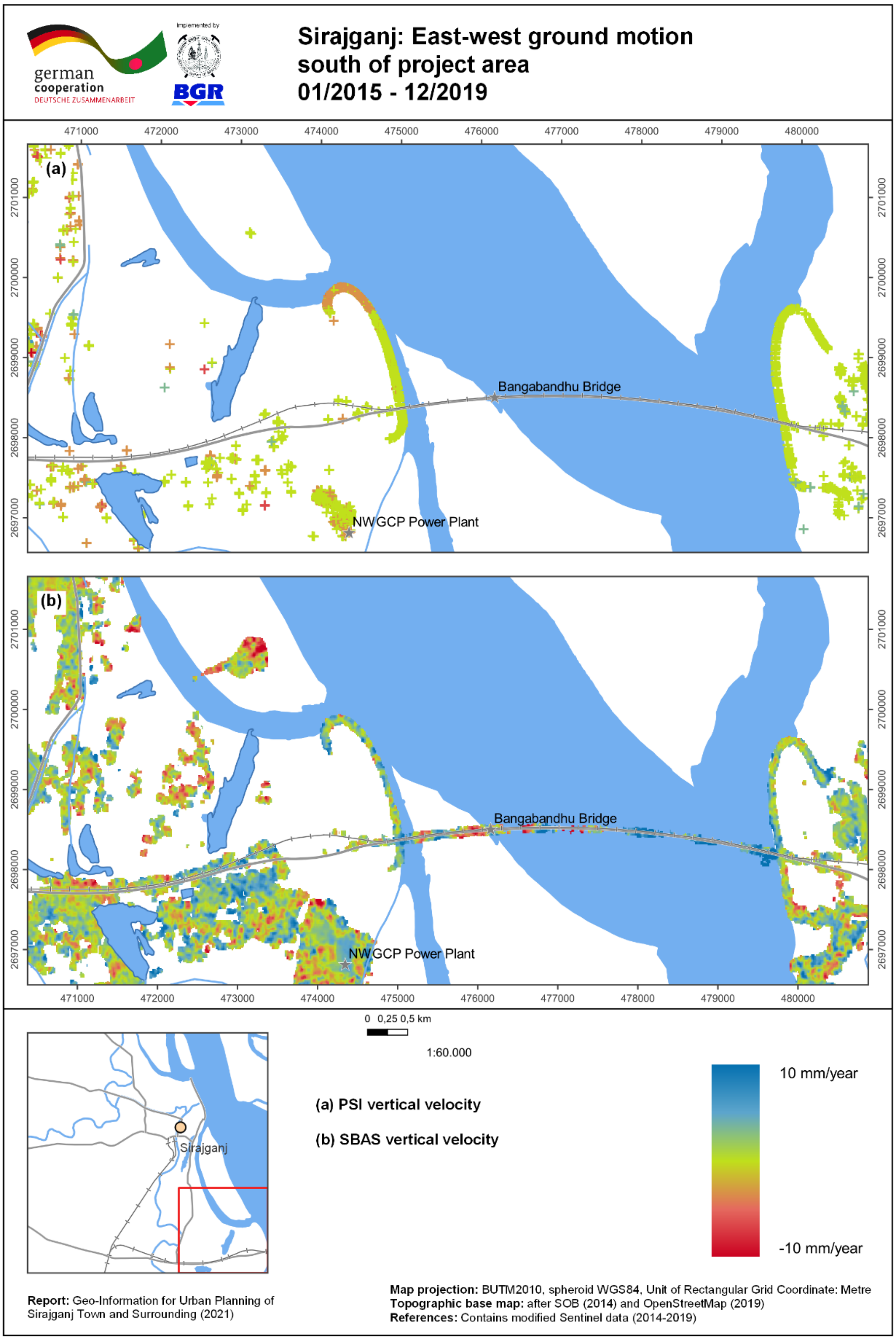

Figure 20: *Comparison of a) PSI and b) SBAS east-west ground motion velocity south of project area.*

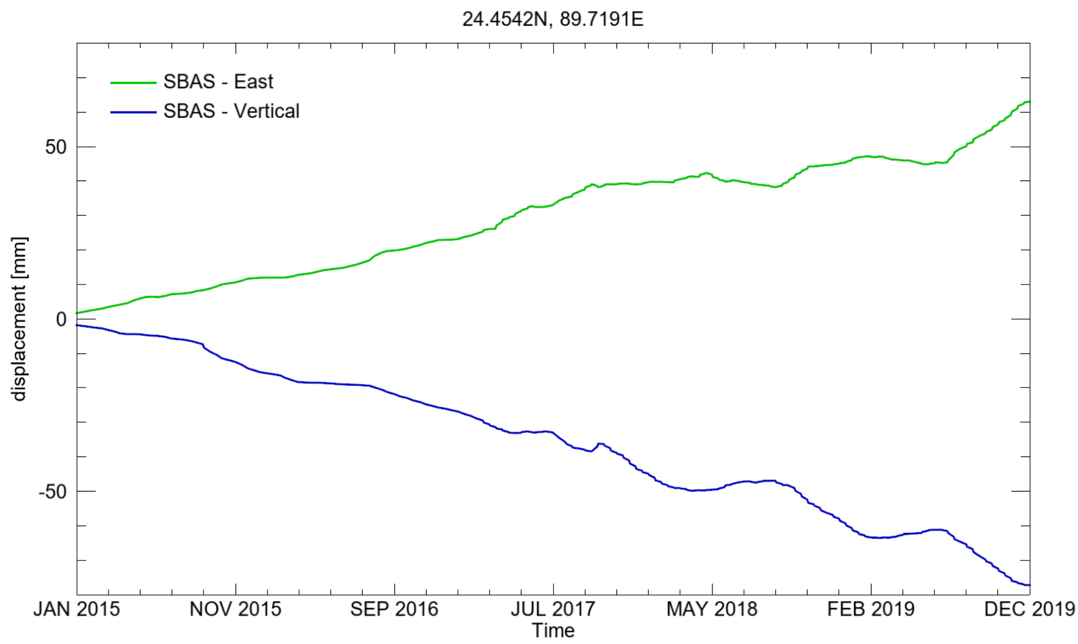

Figure 21: *SBAS vertical and horizontal (east-west) ground motion time series on landmark Riverbank 1.*

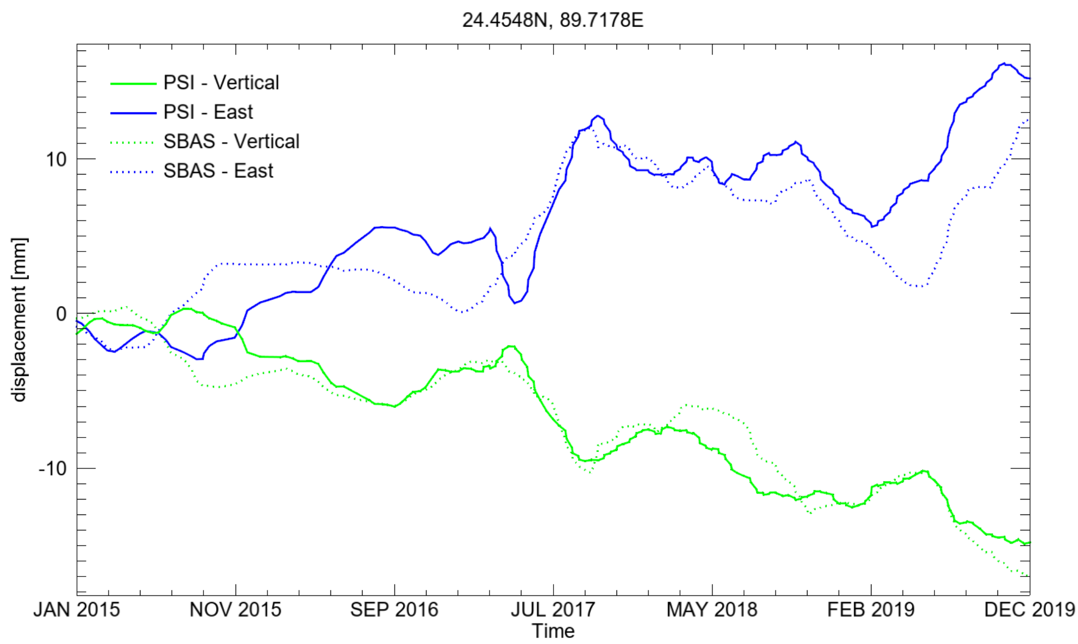

Figure 22: *SBAS and PSI vertical and horizontal (east-west) ground motion time series on landmark Riverbank 3.*

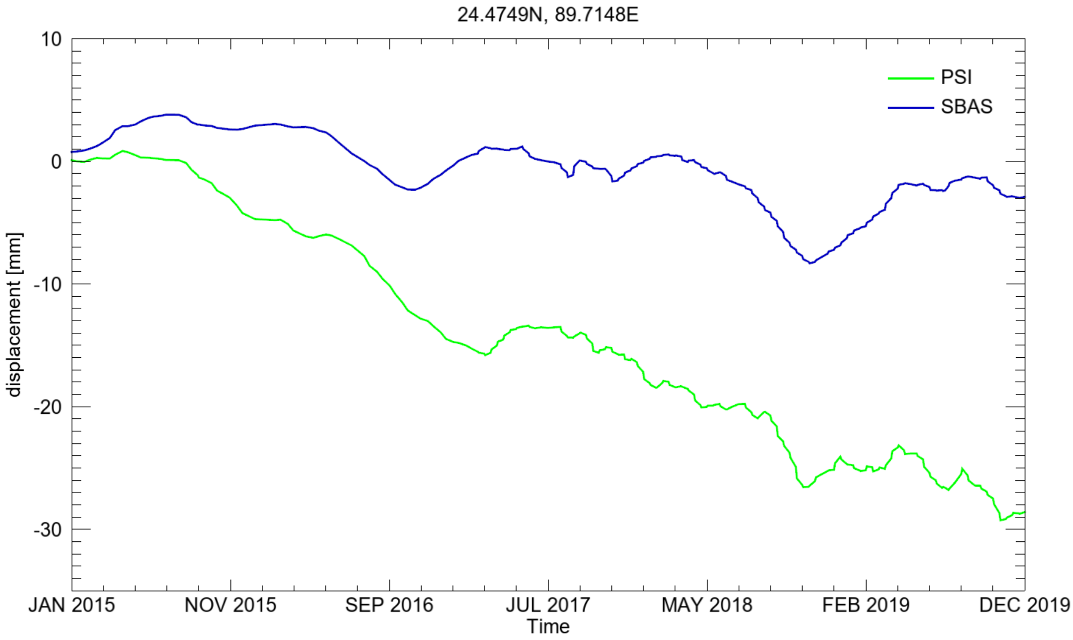

Figure 23: *SBAS and PSI vertical ground motion time series on landmark Riverbank 2.*

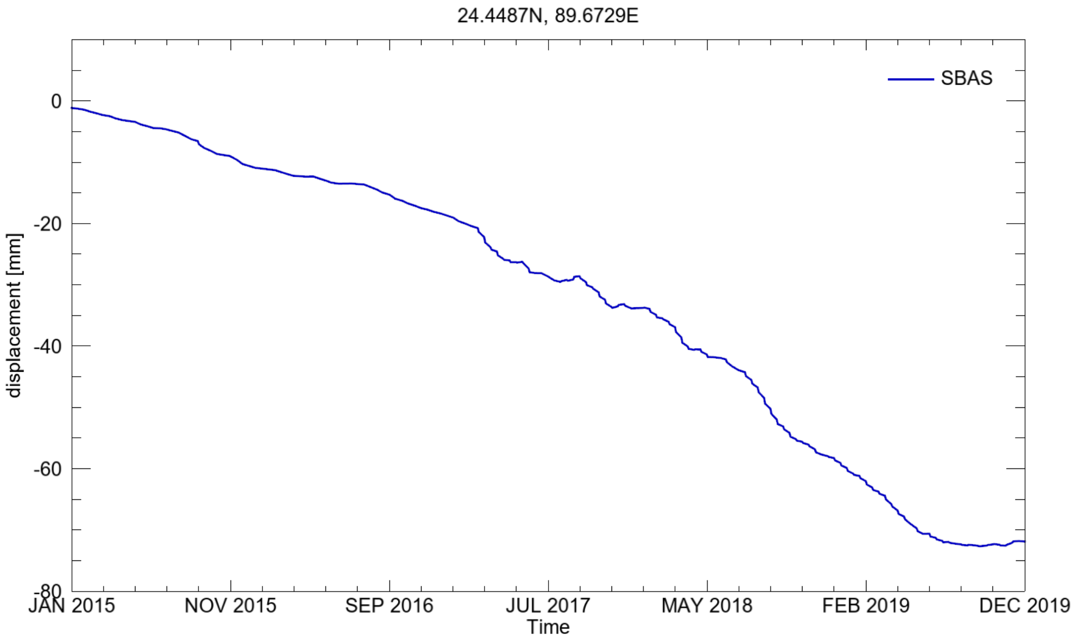

Figure 24: *SBAS vertical ground motion time series over Shaheed M. Monsur Ali Medical College campus.*

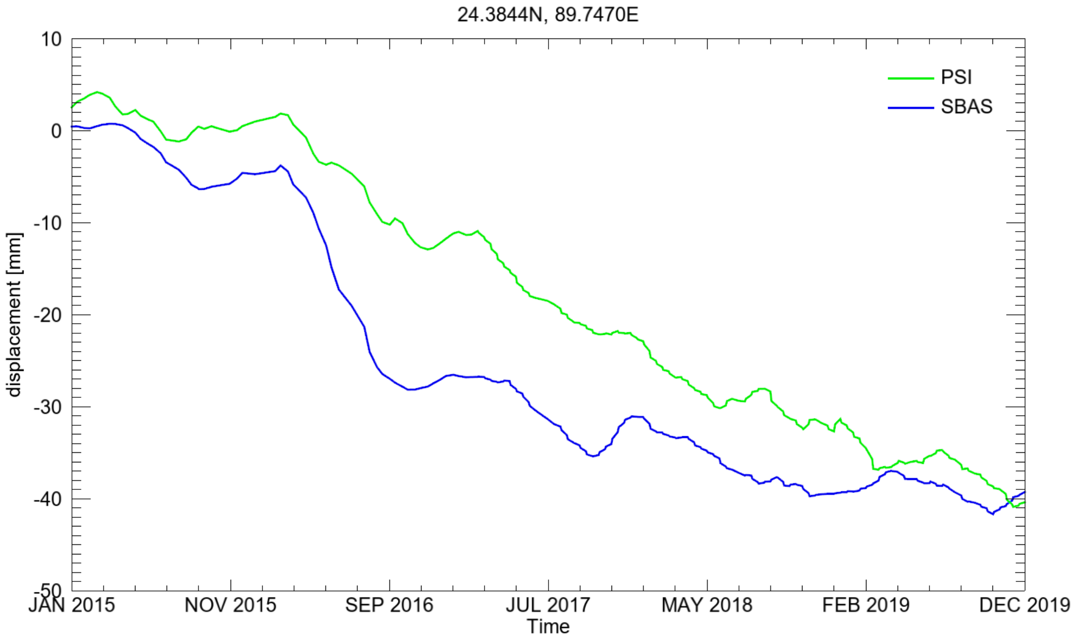

Figure 25: *SBAS and PSI vertical ground motion time series for NWGCP power plant.*

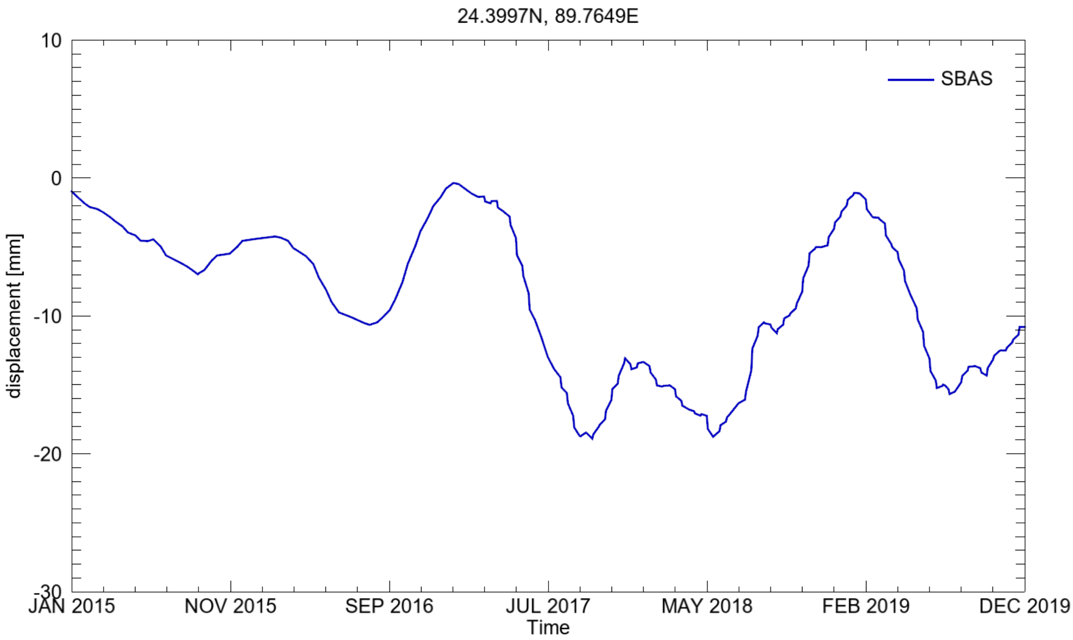

Figure 26: *SBAS vertical ground motion time series for Bangabandhu Bridge middle part.*

2.4.4 Conclusions

Four different ground motion datasets are calculated in the context of this study. A PSI and a SBAS dataset showing the vertical ground motion component and a PSI and a SBAS dataset showing the horizontal (east-west) ground motion component. The Sirajganj project area is mostly urbanised with a large number of potential targets (coherent objects) for multi-temporal InSAR analyses.

Both InSAR approaches used in this study have their unique strengths and drawbacks. SBAS achieves a higher spatial coverage at the cost of spatial resolution, whereas PSI delivers only punctual information but with high accuracy and spatial resolution. Due to the high share of urbanised land in the project area however, both methods lead to a similar spatial coverage. Significant differences in spatial coverage could be observed in areas where construction activities took place during the observation period. In these areas (which are quite numerous) SBAS performed significantly better than PSI.

While the overall motion trends obtained by both methods are largely consistent with each other, the exact magnitude of the observed motion differs in many cases. Nonetheless, the large degree of agreement between the two methods in both the vertical and horizontal direction can be seen as an indicator to the validity of the results. Strong subsidence can be observed along the riverbank. This trend is more pronounced in the SBAS data than in the PSI data. In particular, the south-eastern part of the Sirajganj riverbank forms a large cluster of subsidence, spanning more than 4 kilometres. Other (smaller) clusters of strong subsidence can be found on the SMMAMC campus in the east of the city as well as around the NWGCP power plant south of the city center.

It is expected that a number of factors contribute to the observed ground motion patterns and trends. Many of the observed subsidence clusters seem to be related to structures that were recently built or recently enlarged. Here, the building load of these structures seems to play a major role. From other project areas, it is also known that there is a link between the local geomorphology and ground motion. In particular, it could be shown in other project areas that constructions in floodplains are more likely to be affected by strong subsidence while constructions on natural levees tend to be more stable. The displacements observed along the riverbank seem in part related to ongoing construction activities, in particular the construction of new embankments. In addition, they seem to be caused by river erosion as visible in the recent collapse of parts of the embankments.

Both methods provide huge amounts of measurement points with high spatial and temporal information that can be acquired extremely fast and cost-efficiently when compared to other geodetic methods such as levelling or GPS/GNSS (even though permanent GPS stations might achieve a higher measurement accuracy and temporal density, they provide only punctual measurements). Both methods work particularly well in urban and vegetation free environments where there is a large amount of high coherent targets, while SBAS also performs well in more suburban or even rural environments. These two facts highlight the immense value of multi-temporal InSAR applications for urban planning.

Each of the two methods used within this work has its unique strengths and possible areas of application within urban planning. While SBAS enables a denser spatial coverage and the detection of large-scale motion trends related to large infrastructure, PSI enables a more detailed analysis of singular buildings, bridges and roads. On large buildings, we can often find several persistent scatterers, thus PSI can be used to detect different displacement rates for different parts of a building. PSI is also expected to be slightly more accurate than SBAS (PASQUALI et al. 2014, p. 236).

Both PSI and SBAS allow the extraction of ground motion information from satellite data with millimetre accuracy and at a high temporal resolution using freely available Sentinel-1 data. Due to the unique characteristics of each method, both methods complement each other well. For absolute ground motion data, external data needs to be used as reference (e.g. GPS/GNSS data from fixed stations).

It could also be shown, that InSAR methods can be used to observe existing infrastructure such as bridges, power plants or embankments. Even active construction sites can be monitored using these techniques. SBAS seems to be more suited for the latter purpose since it can deal with temporal drops or even a temporal loss of coherence. PSI has higher coherence requirements, which are apparently not fulfilled by a construction site that experiences some temporal change.

2.4.5 Recommendations

Multi-temporal InSAR can be used in urban planning to detect stable areas that are potentially suited as building ground. The combined analysis of InSAR and ancillary data (in particular geological, geomorphological, hydrological and land use data) possibly enables the detection of links and causalities for observed ground motion patterns. Furthermore, multi-temporal InSAR can also serve as a tool for the monitoring of existing infrastructure and buildings.

Two of the most commonly used methods in this field are Persistent Scatterer Interferometry (PSI) and Small Baseline Subset (SBAS). Overall, both methods have their unique strengths and complement each other well. SBAS provides an overview over the large-scale motion patterns within a study area while PSI enables a more detailed analysis of specific points of interest.

A possible constraint to be considered is the computational effort required. While both methods have high computational demands, SBAS is much more computationally intensive for the same data since the number of interferograms created is usually significantly larger than the number of input images. For PSI, the number of interferograms is N-1. Finally, a precondition for the use of any InSAR technique is the existence of enough coherent targets within the area of interest and over the observation period. In areas with seasonal flooding, the use of artificial targets such as corner reflectors or active transponders should be considered.

Where other ground motion data for example from GPS fixed stations or continuous levelling campaigns is available, this data can and should be used as reference for the InSAR results. While different studies have shown that both PSI and SBAS deliver high quality results much depends on the number of acquisitions used. To properly isolate phase influences due to atmosphere and topography from the actual deformation a large number of acqusitions should be used. In general, the more acquisitions are used, the better the results.

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Annexure A: Maps

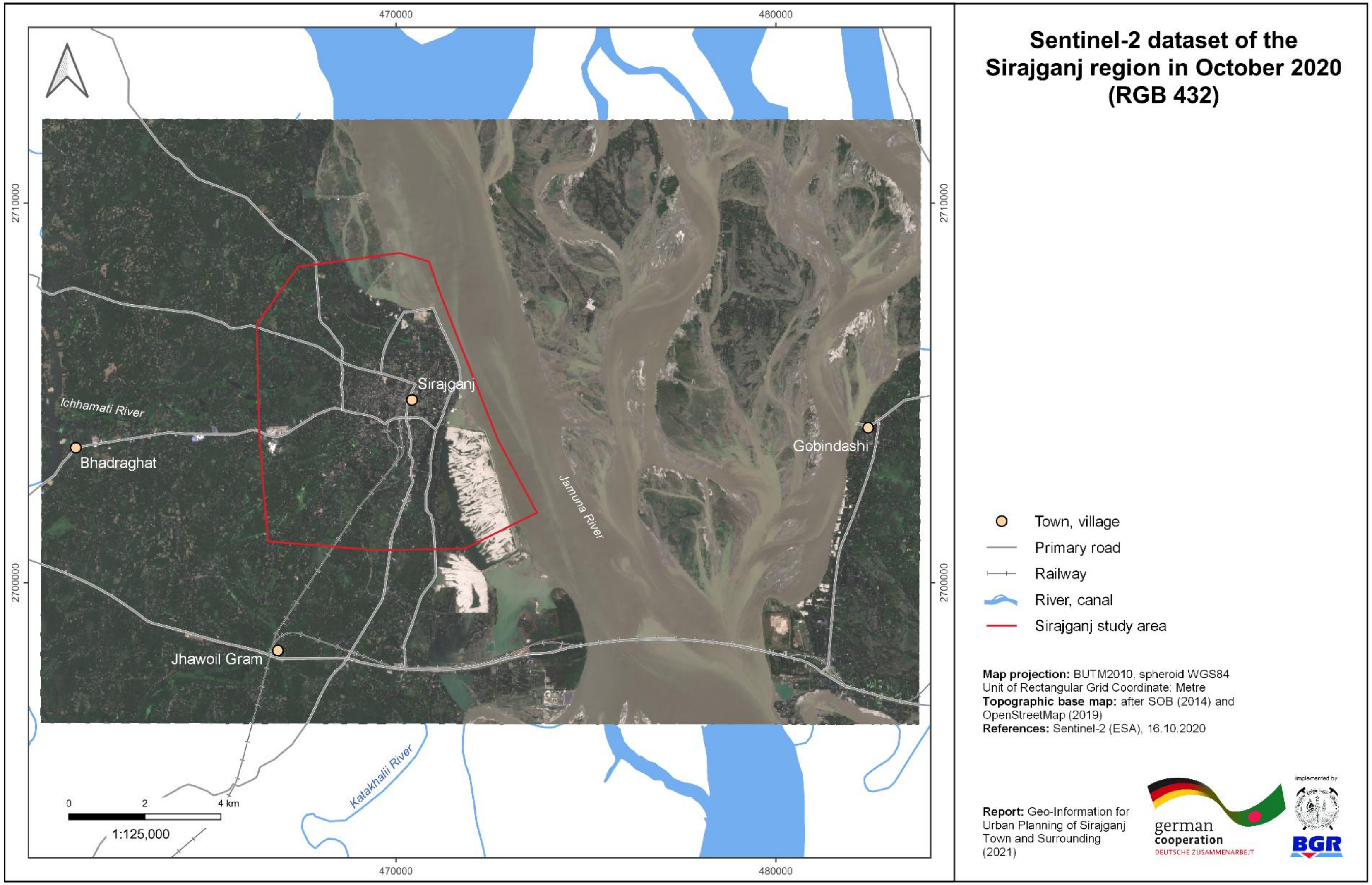

Figure A1: *Sentinel-2 Dataset of the Sirajganj Region, 16.10.2020 (RGB 4-3-2).*

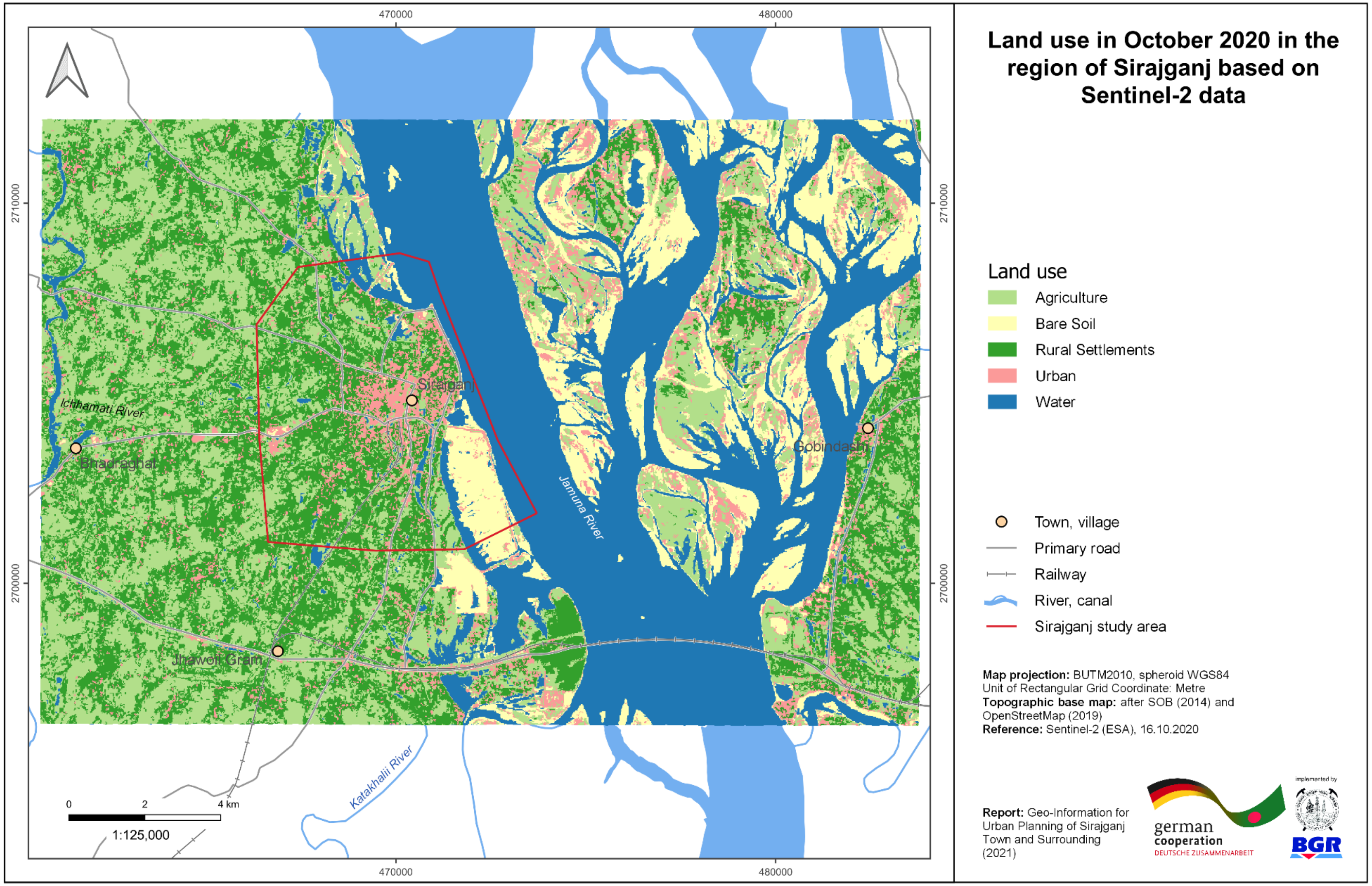

Figure A2: *Land use in October 2020 in region of Sirajganj based on Sentinel-2 data.*

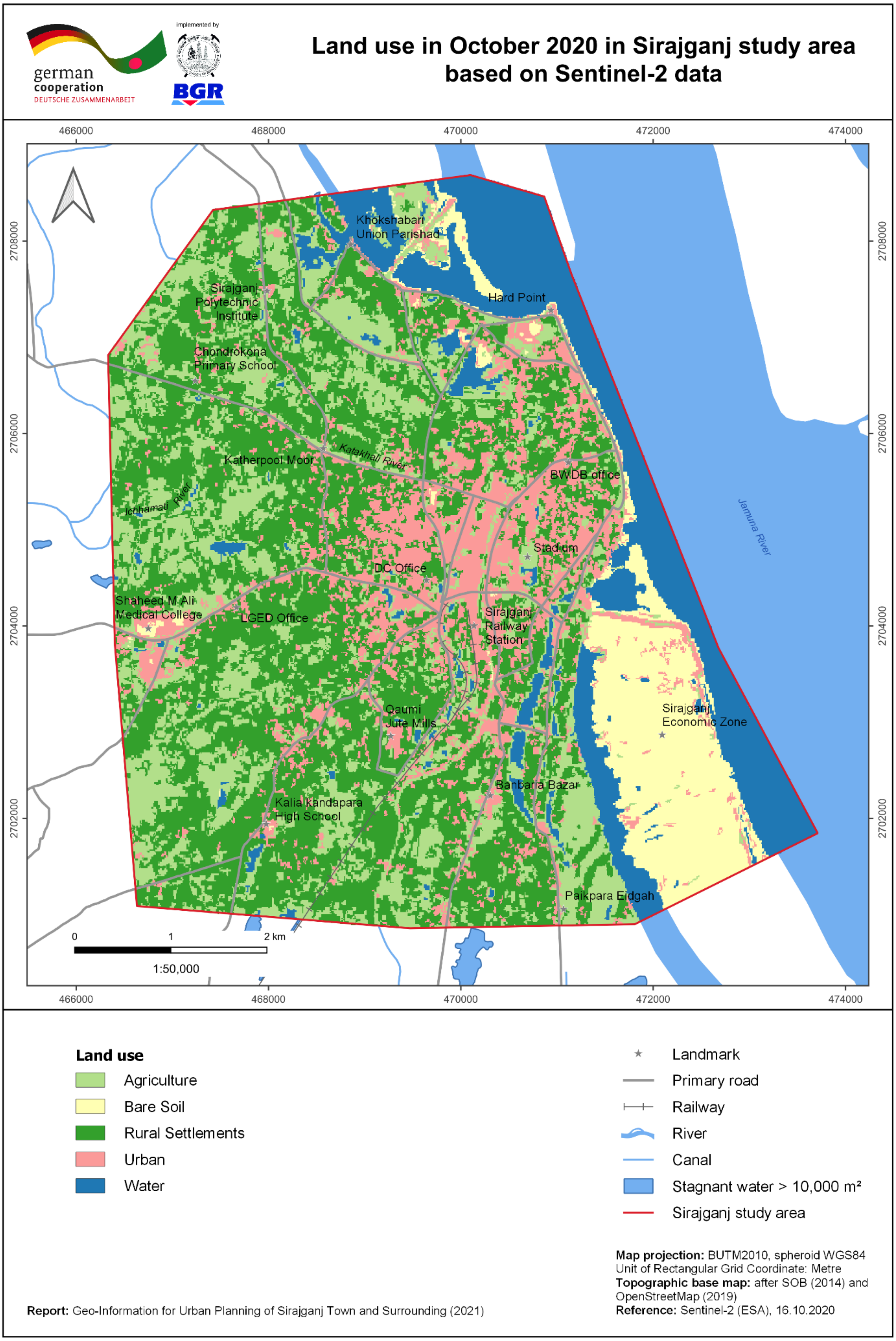

Figure A3: *Land use in October 2020 in Sirajganj study area based on Sentinel-2 data.*

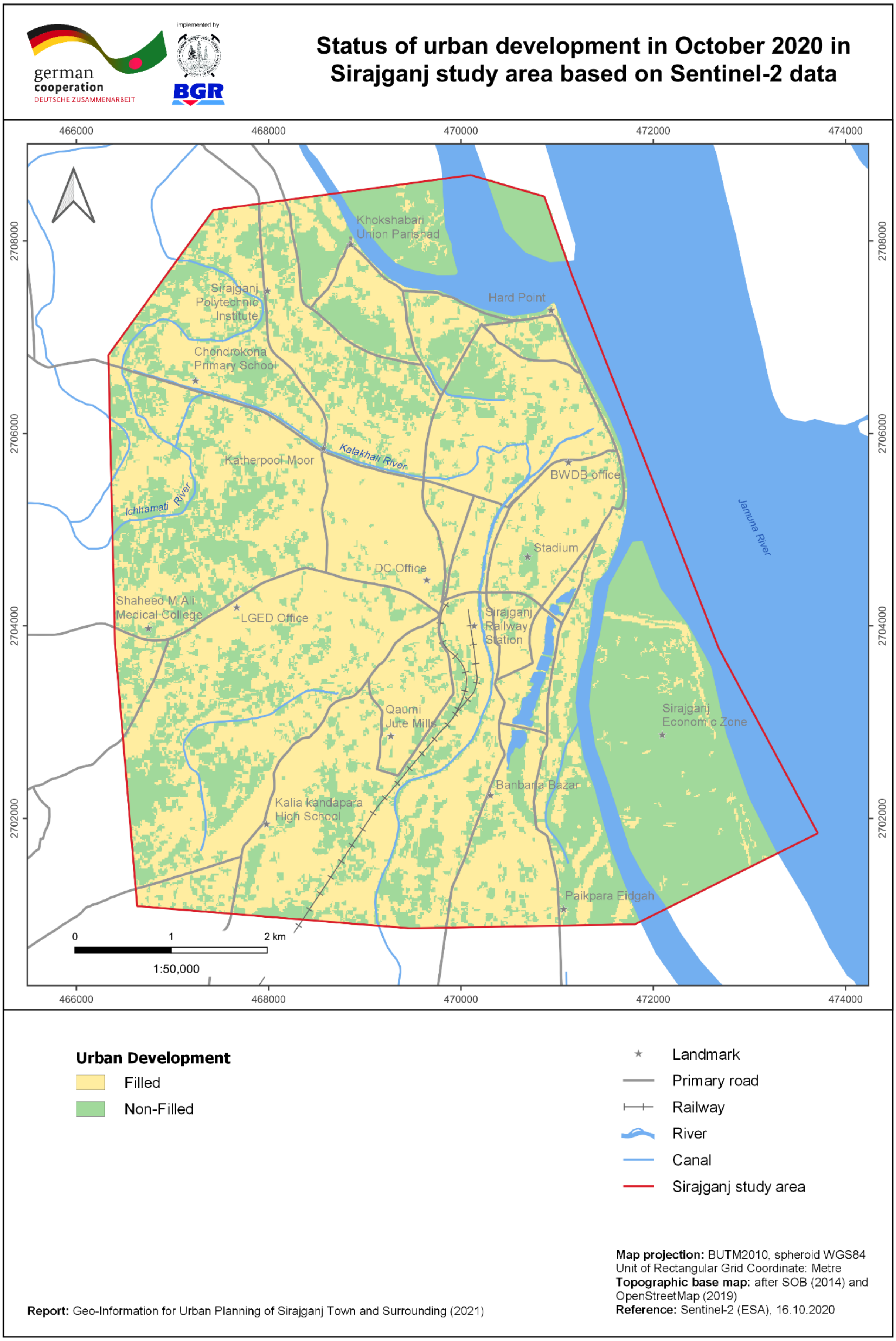

Figure A4: *Status of urban development in October 2020 in Sirajganj study area based on Sentinel-2 data.*

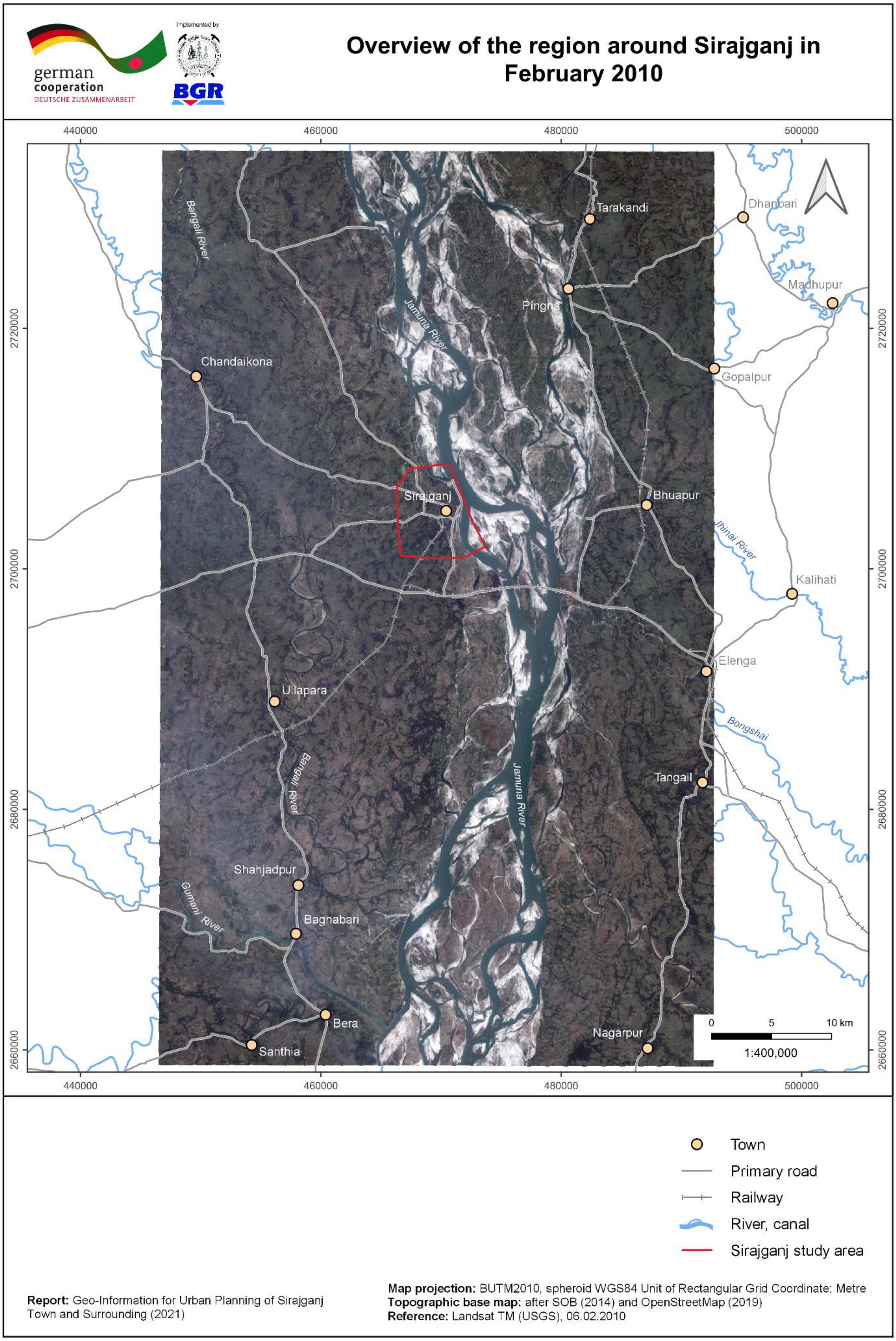

Figure A5: *Overview of the region around Sirajganj (Landsat TM, RGB 321, 06.02.2010).*

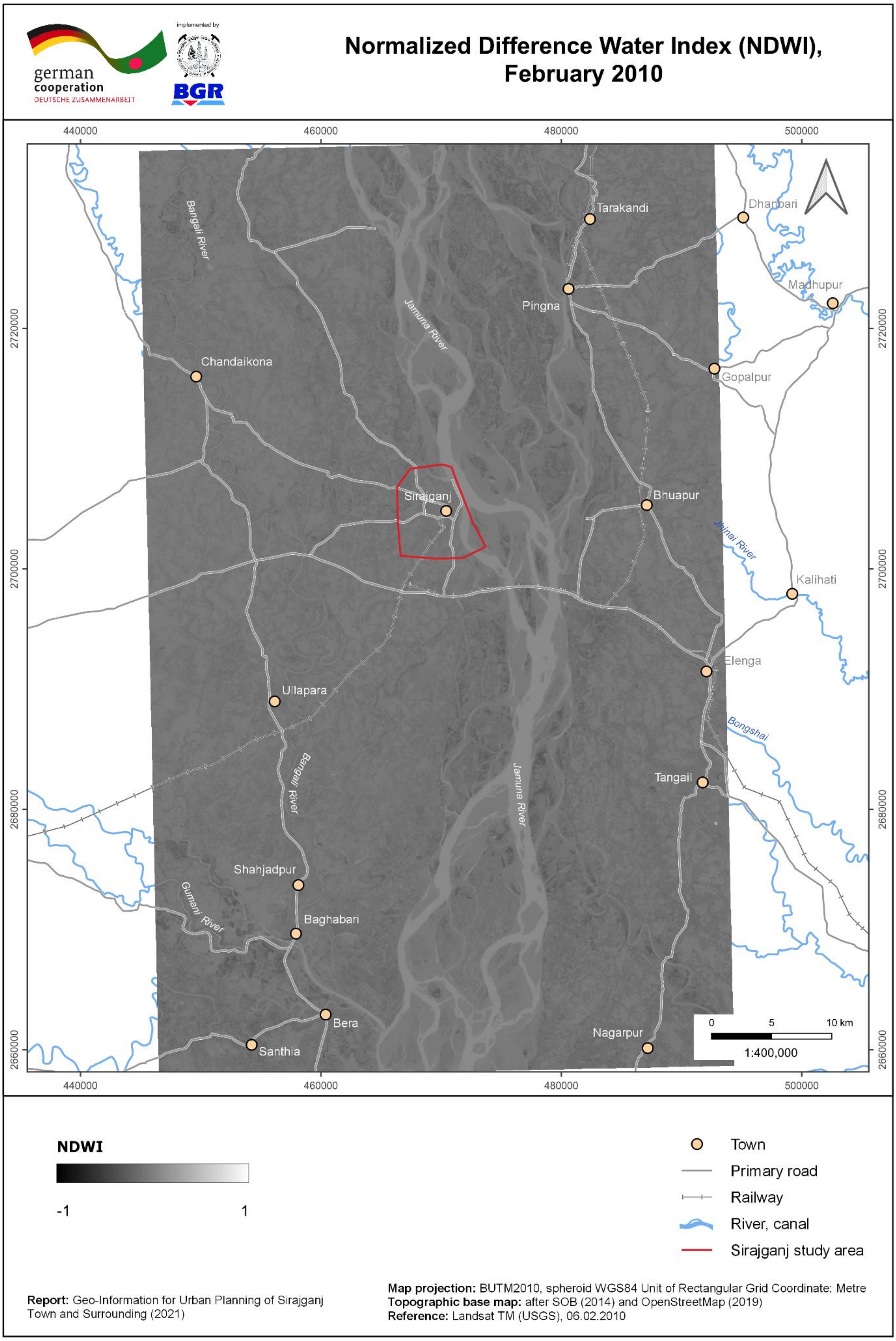

Figure A6: *Normalized Difference Water Index (NDWI), based on Landsat TM imagery (06.02.2010).*

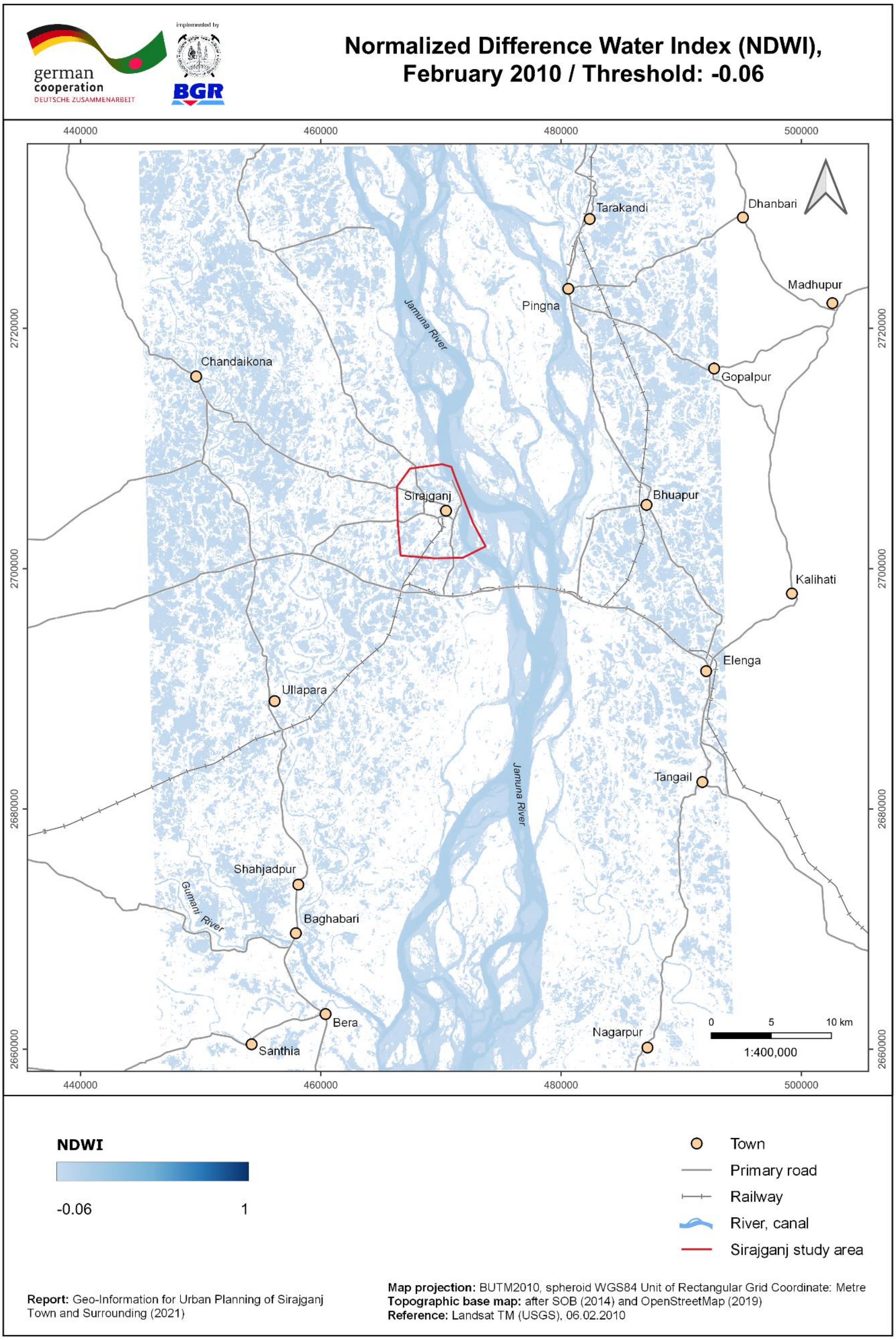

Figure A7: *Normalized Difference Water Index (NDWI), based on Landsat TM imagery (06.02.2010), threshold of -0.06.*

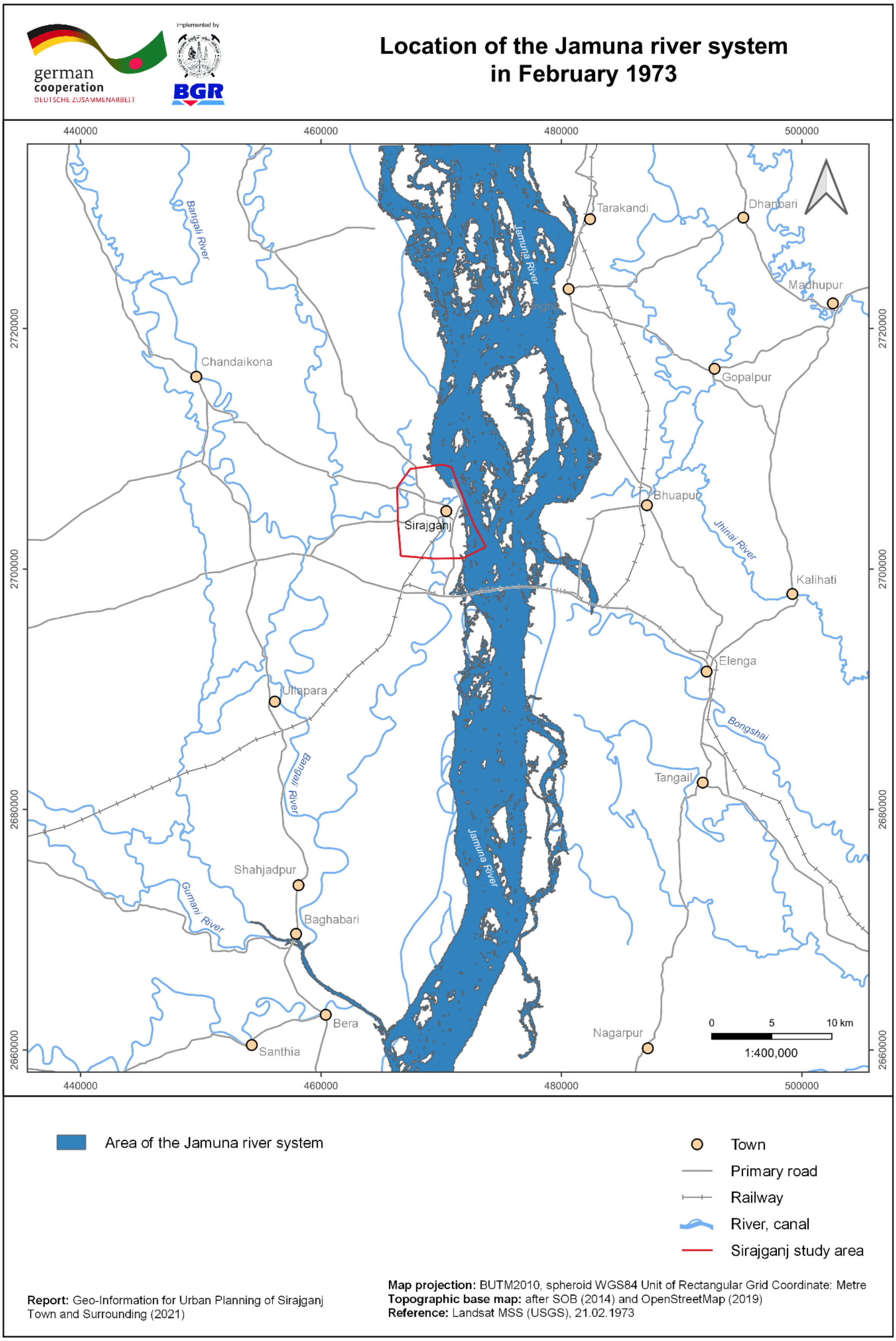

***Figure A8**: Location of the Jamuna river system based on NDWI from 1973.*

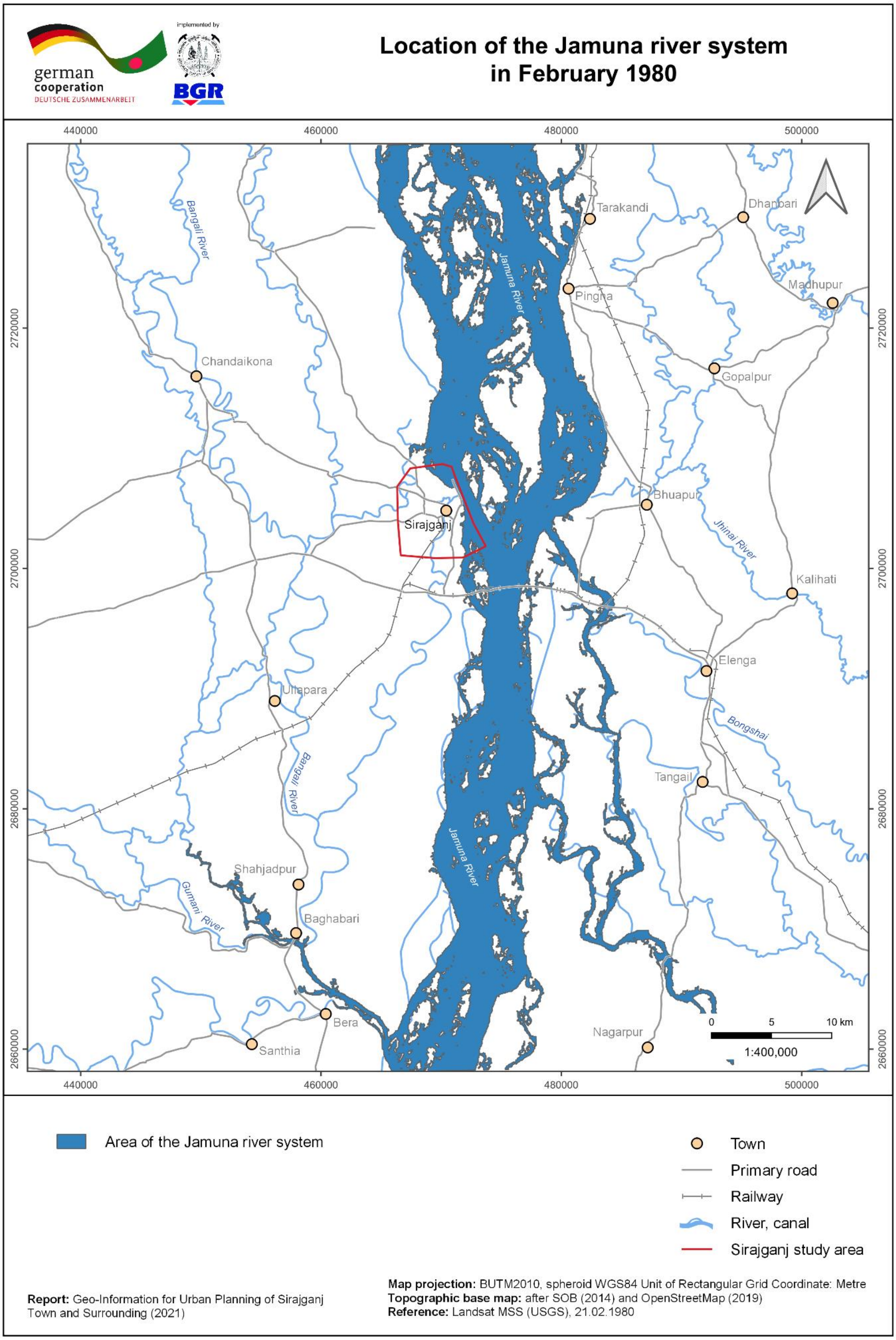

Figure A9: *Location of the Jamuna river system based on NDWI from 1980.*

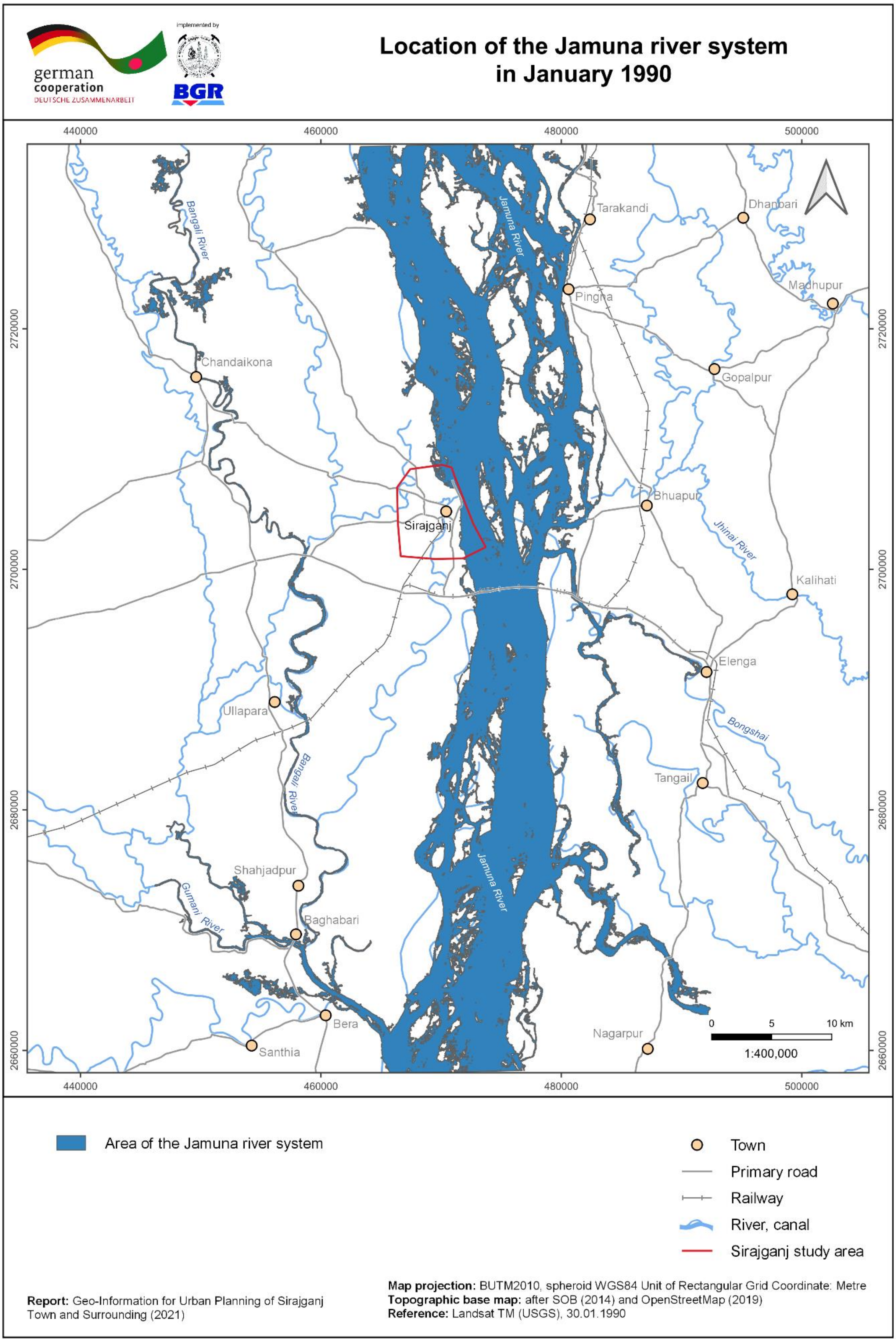

Figure A10: *Location of the Jamuna river system based on NDWI from 1990.*

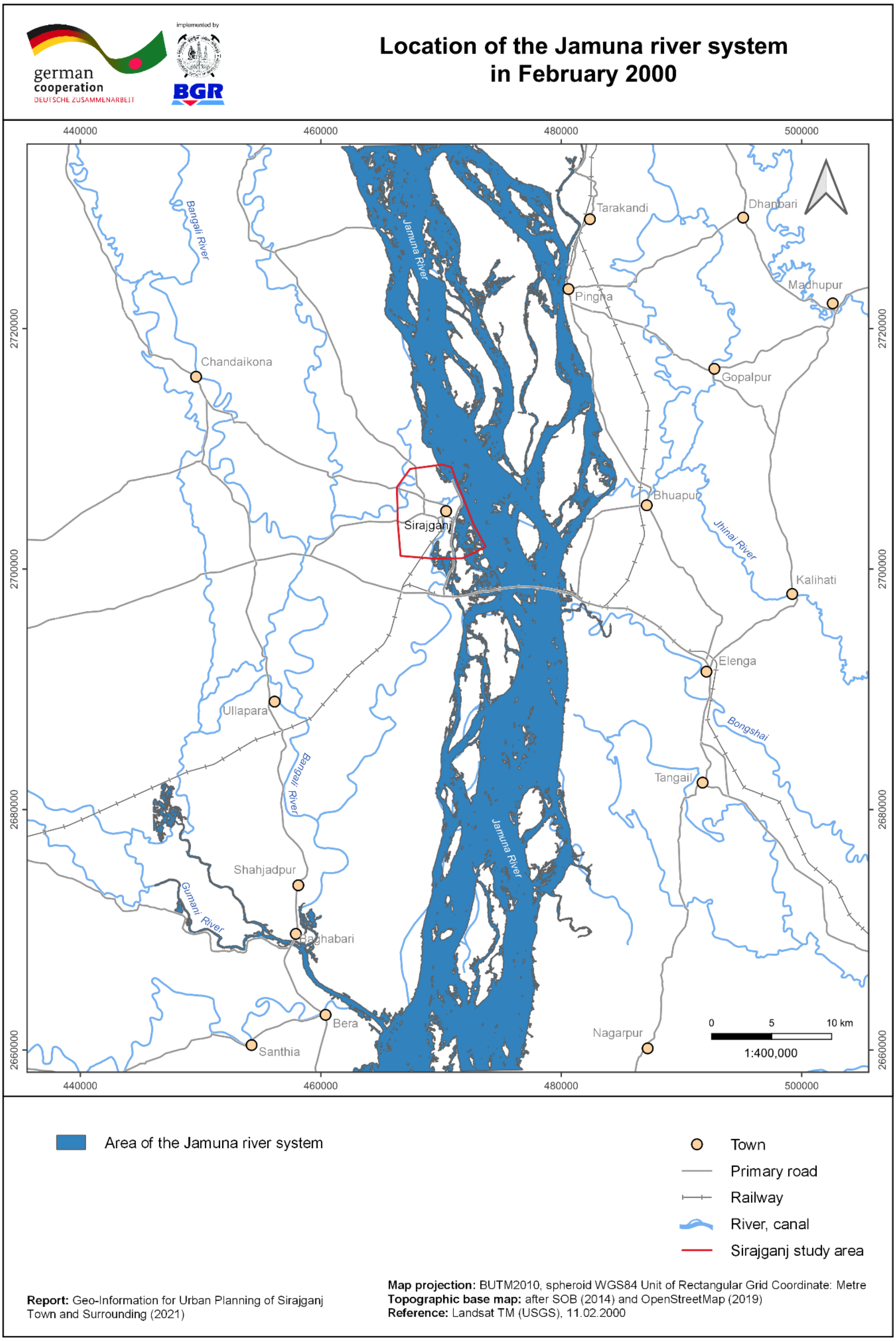

Figure A11: *Location of the Jamuna river system based on NDWI from 2000.*

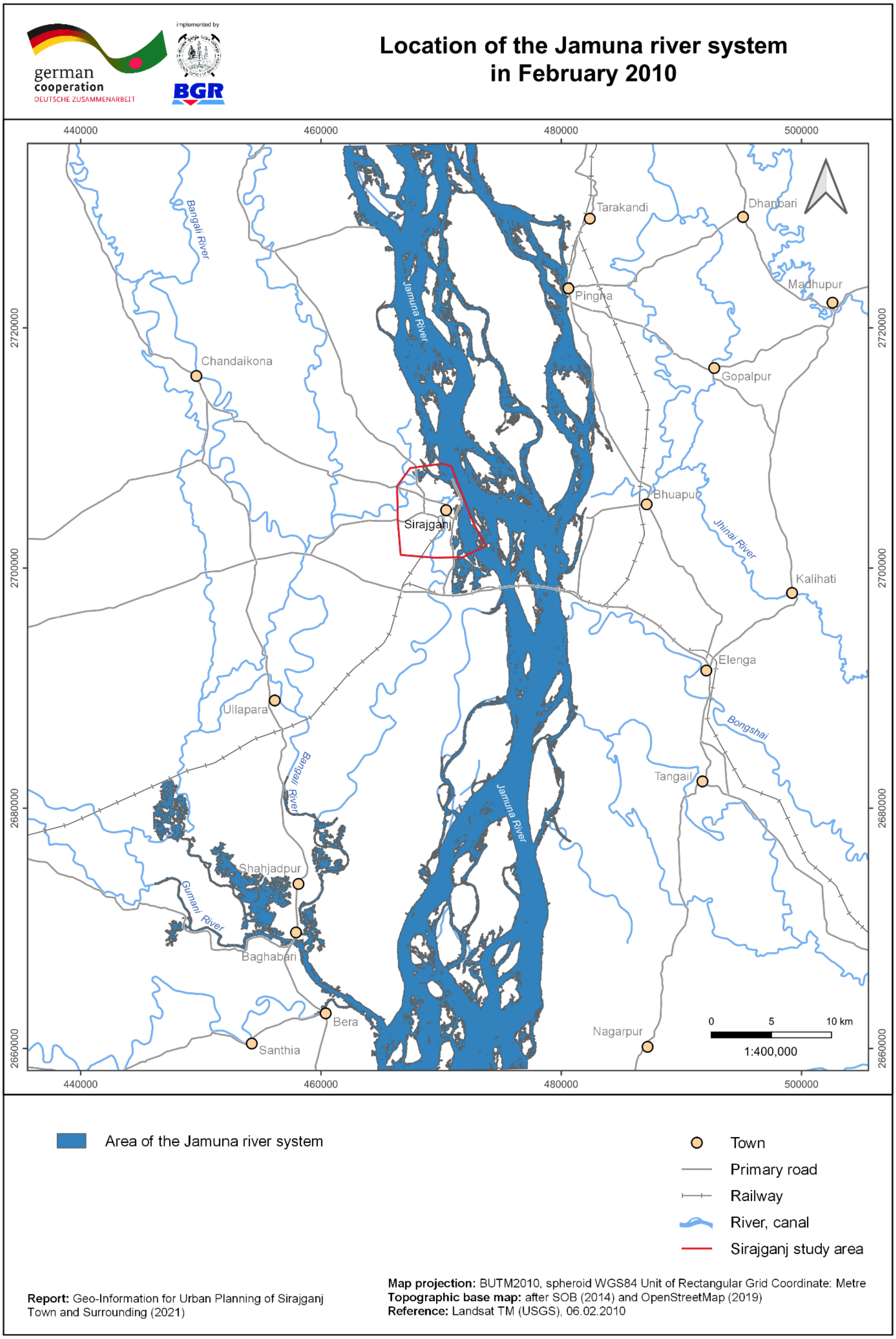

Figure A12: *Location of the Jamuna river system based on NDWI from 2010.*

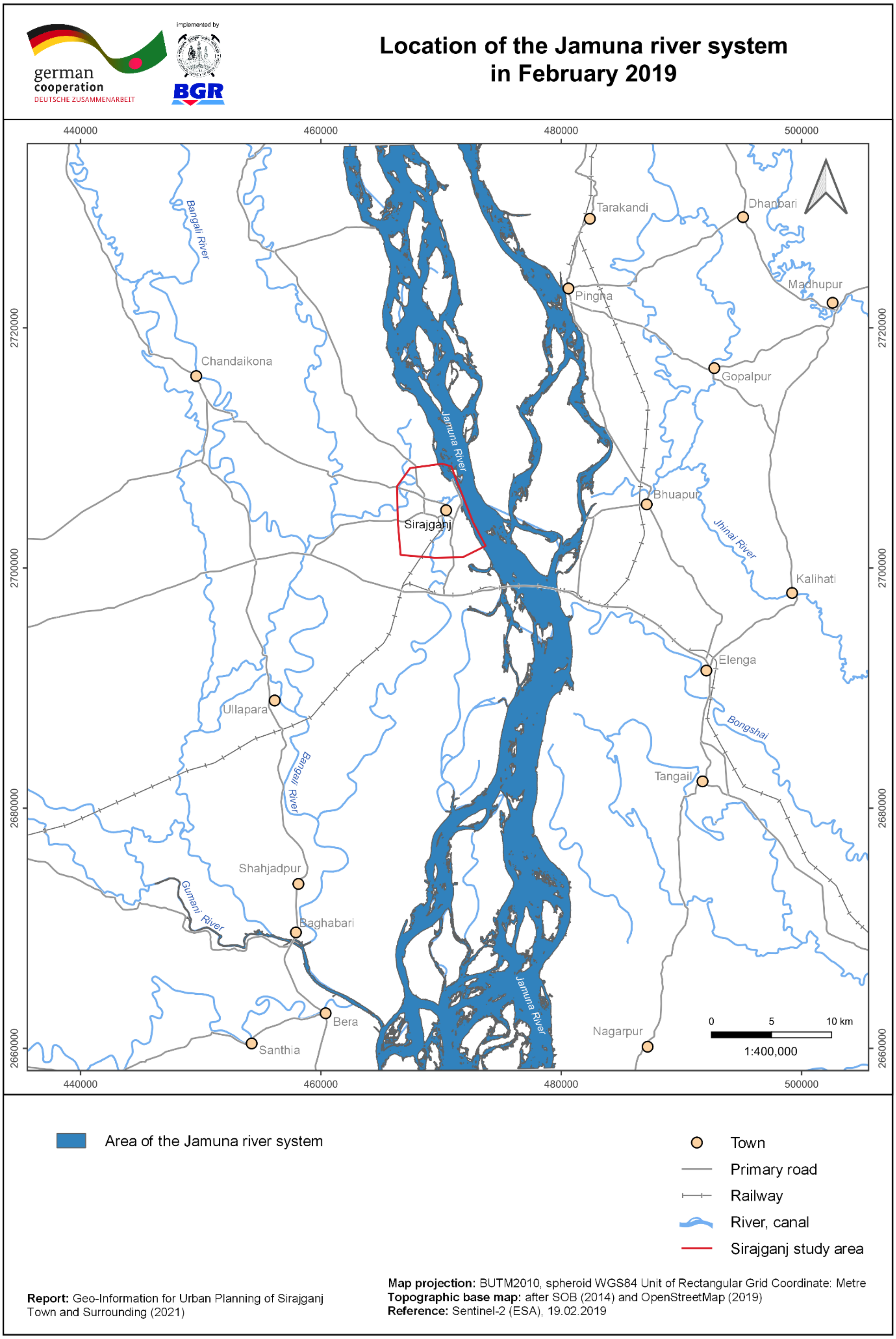

Figure A13: *Location of the Jamuna river system based on NDWI from 2019*

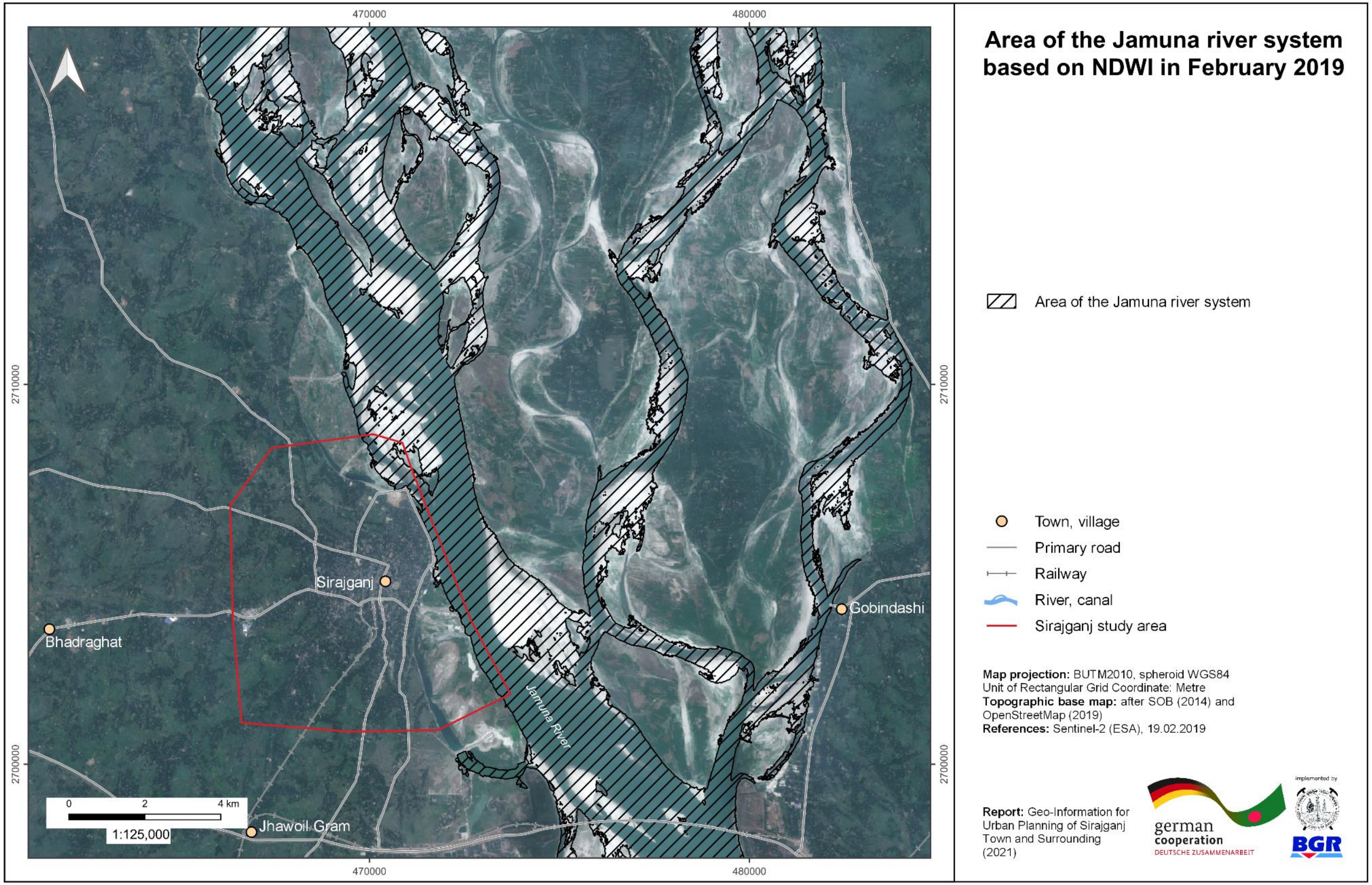

Figure A14: *Area of the Jamuna river system based on NDWI from 2019.*

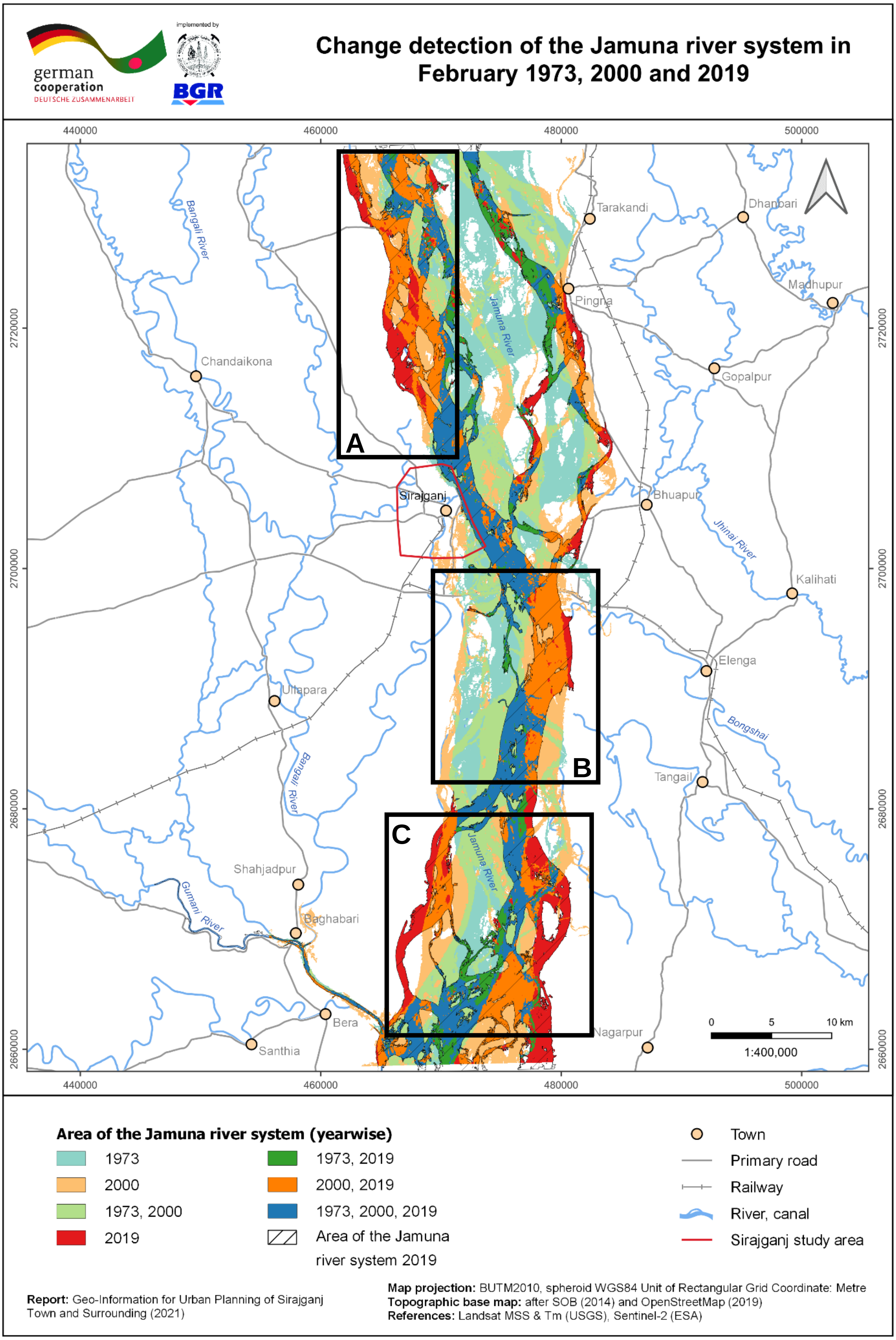

Figure A15: *Change detection of the Jamuna river system of February 1973, 2000 and 2019.*

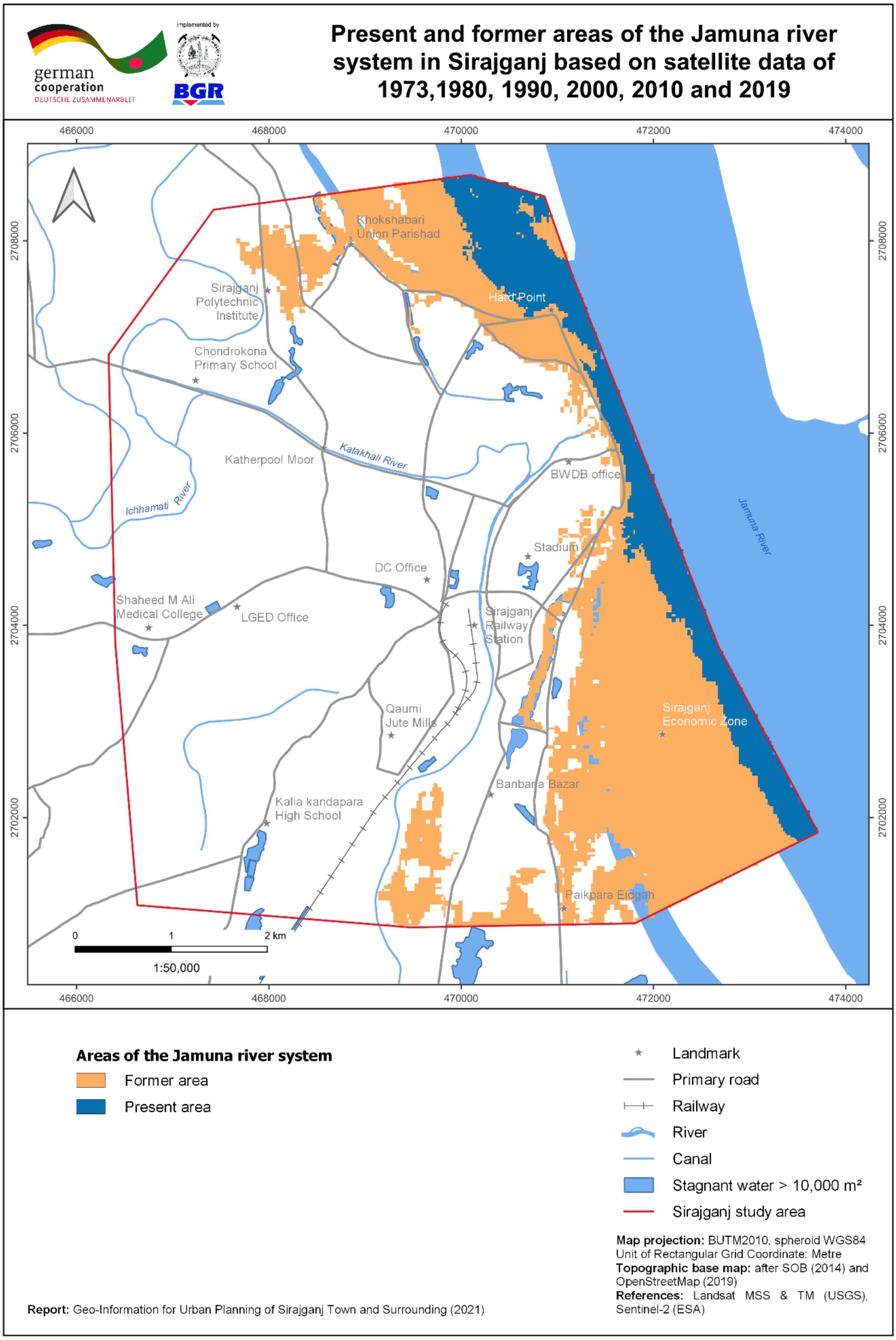

Figure A16: *Present and former areas of the Jamuna river system in Sirajganj, based on satellite data of 1973, 1980, 1990, 2000, 2010 and 2019.*

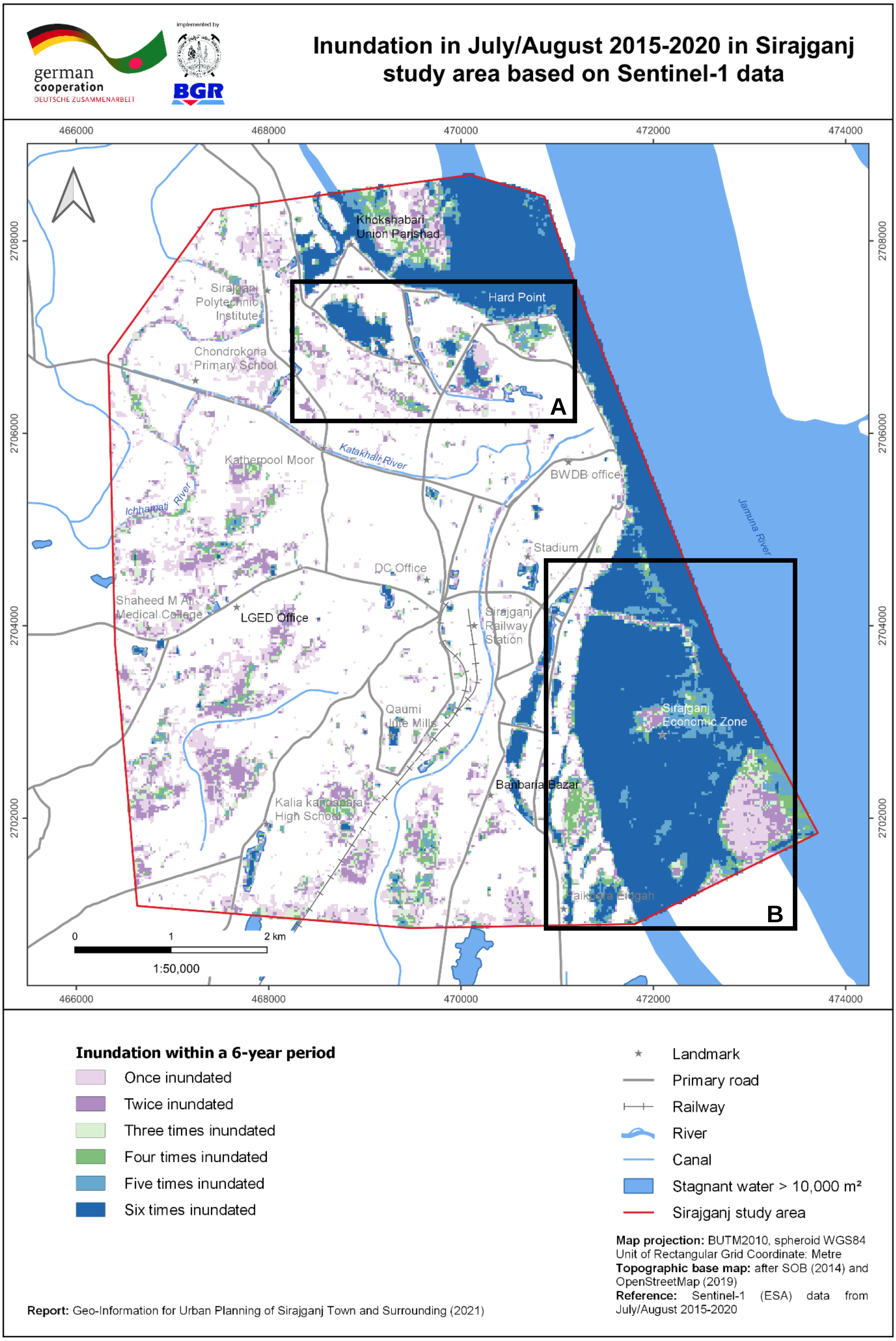

Figure A17: Inundation in July/August 2015-2020 in Sirajganj study area based on Sentinel-1 data.

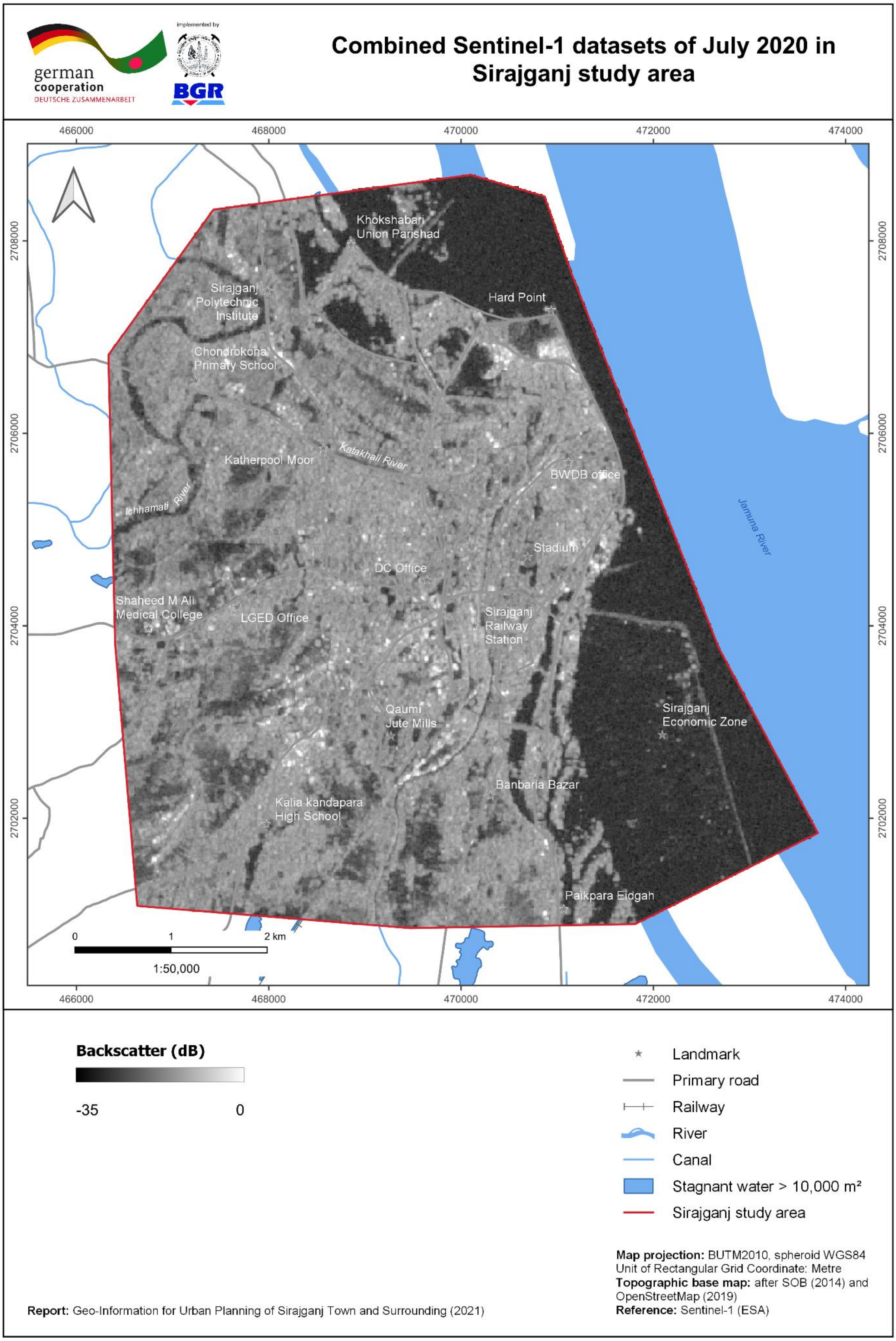

Figure A18: Combined Sentinel-1 datasets of July 2020 in Sirajganj study area.

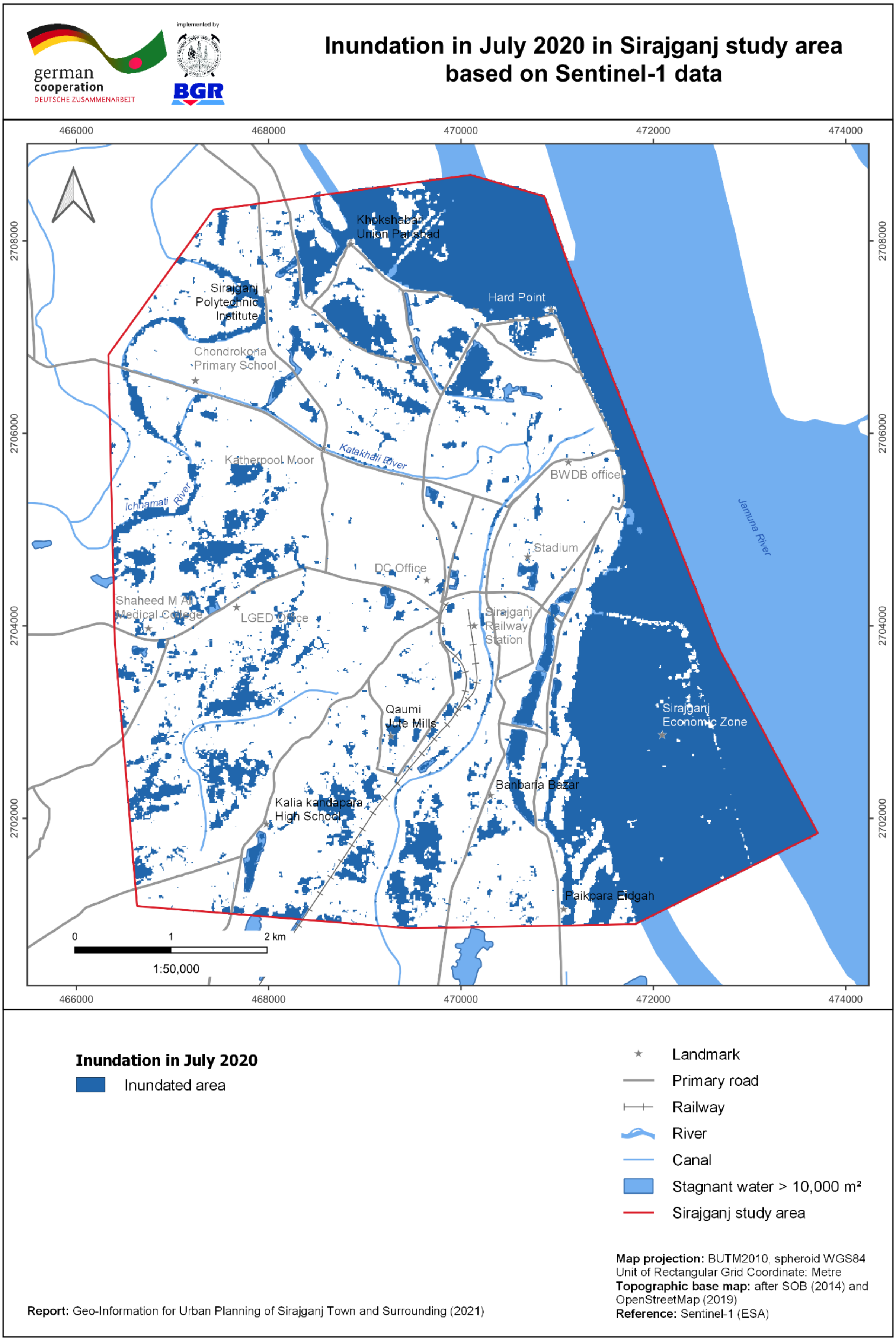

Figure A19: *Inundation in July 2020 in Sirajganj study area.*

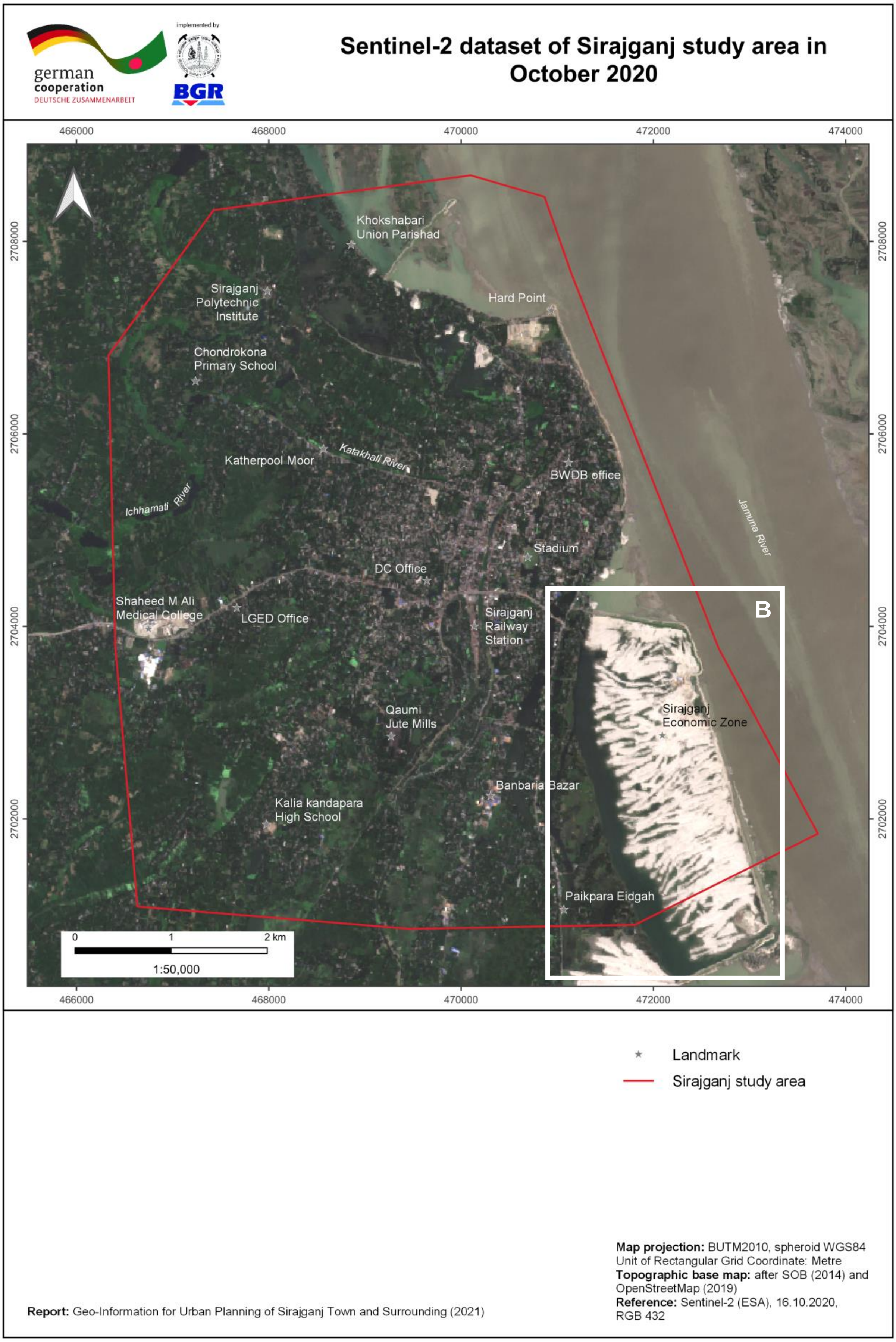

Figure A20**:** Sentinel-2 dataset (RGB 432) of the Sirajganj study area (16.10.2020).

Annexure B: Google Earth Engine Code

```
// Select Area of Interest (pa = uploaded SHP of Sirajganj study area)
pa = pa.geometry();
// Center the map with focus on the study area
Map.centerObject(pa);


// 2015
// Define start and end date of the study period
var start_wet = '2015-07-01';
var end_wet = '2015-07-31';

// Load the Sentinel-1 image collection
var S1_wet15 = ee.ImageCollection('COPERNICUS/S1_GRD')
// Filter: Return only Vertical-Horizontal (VH) polarization images
.filter(ee.Filter.listContains('transmitterReceiverPolarisation', 'VH'))
// Filter: Return only images with the main acquisition mode IW
.filter(ee.Filter.eq('instrumentMode', 'IW'))
// Filter: Return only descending orbit images
.filter(ee.Filter.eq('orbitProperties_pass', 'DESCENDING'))
// Filter: Return only images with a 10 m resolution
.filterMetadata('resolution_meters','equals',10)
// Filter: Return only images within the study period
.filterDate(start_wet, end_wet)
// Filter: Return only images within the study area
.filterBounds(pa)
// Calculate the mean of all remaining images
.reduce(ee.Reducer.mean())
// Clip the mean-image to the study area
.clip(pa);
// Print the image information to the console
print(S1_wet15)


// 2016
var start_wet = '2016-07-01';
var end_wet = '2016-07-31';

var S1_wet16 = ee.ImageCollection('COPERNICUS/S1_GRD')
.filter(ee.Filter.listContains('transmitterReceiverPolarisation', 'VH'))
```

```
.filter(ee.Filter.eq('instrumentMode', 'IW'))
.filter(ee.Filter.eq('orbitProperties_pass', 'DESCENDING'))
.filterMetadata('resolution_meters','equals',10)
.filterDate(start_wet, end_wet)
.filterBounds(pa)
.reduce(ee.Reducer.mean())
.clip(pa);
print(S1_wet16)

// 2017
var start_wet = '2017-08-01';
var end_wet = '2017-08-31';

var S1_wet17 = ee.ImageCollection('COPERNICUS/S1_GRD')
.filter(ee.Filter.listContains('transmitterReceiverPolarisation', 'VH'))
.filter(ee.Filter.eq('instrumentMode', 'IW'))
.filter(ee.Filter.eq('orbitProperties_pass', 'DESCENDING'))
.filterMetadata('resolution_meters','equals',10)
.filterDate(start_wet, end_wet)
.filterBounds(pa)
.reduce(ee.Reducer.mean())
.clip(pa);
print(S1_wet17)

//2018
var start_wet = '2018-07-01';
var end_wet = '2018-07-31';

var S1_wet18 = ee.ImageCollection('COPERNICUS/S1_GRD')
.filter(ee.Filter.listContains('transmitterReceiverPolarisation', 'VH'))
.filter(ee.Filter.eq('instrumentMode', 'IW'))
.filter(ee.Filter.eq('orbitProperties_pass', 'DESCENDING'))
.filterMetadata('resolution_meters','equals',10)
.filterDate(start_wet, end_wet)
.filterBounds(pa)
.reduce(ee.Reducer.mean())
.clip(pa);
print(S1_wet18)

//2019
var start_wet = '2019-07-01';
var end_wet = '2019-07-31';
```

```
var S1_wet19 = ee.ImageCollection('COPERNICUS/S1_GRD')
.filter(ee.Filter.listContains('transmitterReceiverPolarisation', 'VH'))
.filter(ee.Filter.eq('instrumentMode', 'IW'))
.filter(ee.Filter.eq('orbitProperties_pass', 'DESCENDING'))
.filterMetadata('resolution_meters','equals',10)
.filterDate(start_wet, end_wet)
.filterBounds(pa)
.reduce(ee.Reducer.mean())
.clip(pa);
print(S1_wet19)

//2020
var start_wet = '2020-07-01';
var end_wet = '2020-07-31';

var S1_wet20 = ee.ImageCollection('COPERNICUS/S1_GRD')
.filter(ee.Filter.listContains('transmitterReceiverPolarisation', 'VH'))
.filter(ee.Filter.eq('instrumentMode', 'IW'))
.filter(ee.Filter.eq('orbitProperties_pass', 'DESCENDING'))
.filterMetadata('resolution_meters','equals',10)
.filterDate(start_wet, end_wet)
.filterBounds(pa)
.reduce(ee.Reducer.mean())
.clip(pa);
print(S1_wet20)

// Set threshold to distinguish between water and non-water
var threshold = -20.5

// Filter every image collection to the defined threshold
var S1_wet_threshold15 = S1_wet15.select('VH_mean').lt(threshold);
var S1_wet_threshold16 = S1_wet16.select('VH_mean').lt(threshold);
var S1_wet_threshold17 = S1_wet17.select('VH_mean').lt(threshold);
var S1_wet_threshold18 = S1_wet18.select('VH_mean').lt(threshold);
var S1_wet_threshold19 = S1_wet19.select('VH_mean').lt(threshold);
var S1_wet_threshold20 = S1_wet20.select('VH_mean').lt(threshold);

// Combining all images to get one image with six classes
var final_img =
S1_wet_threshold15.add(S1_wet_threshold16).add(S1_wet_threshold17).add(S1_w
et_threshold18).add(S1_wet_threshold19).add(S1_wet_threshold20);
```

```
// Visualize the final result
Map.addLayer(final.updateMask(final_img),{palette:"0000FF"},'Water
extent’,1);

// Export the image to the Drive
Export.image.toDrive({
// Definition of the image
  image: final_img,
// Description
  description: 'Sirajganj_Inun_Map',
// Resolution in meter
  scale: 20,
// Study area
  region: pa,
// Format of the raster
  fileFormat: 'GeoTIFF'
});

Export.image.toDrive({
  image: S1_wet20.select("VH_mean"),
  description: 'Sirajganj_2020_image',
  scale: 10,
  region: pa,
  fileFormat: 'GeoTIFF'
});

Export.image.toDrive({
  image: S1_wet_threshold20,
  description: 'Sirajganj_2020_inundation',
  scale: 10,
  region: pa,
  fileFormat: 'GeoTIFF'
});
```

Annexure C: Data

Optical satellite images

Landsat naming convention

Image name: LXSS_LLLL_PPPRRR_YYYYMMDD_yyyymmdd_CC_TX

<table>
<tr><th>Group</th><th colspan="4">Meaning</th></tr>
<tr><td>LXSS</td><td>L: Landsat</td><td colspan="2">X: Sensor
“M” (MSS), “T” (TM)</td><td>SS: Satellite
“01” (Landsat 1), “03” (Landsat 3), “05” (Landsat 5)</td></tr>
<tr><td>LLLL</td><td colspan="4">Processing correction level: “L1TP”, “L1GT”, “L1GS”, “L2SP”</td></tr>
<tr><td>PPPRRR</td><td colspan="2">PPP: WRS path</td><td colspan="2">RRR: WRS row</td></tr>
<tr><td>YYYYMMDD</td><td colspan="4">Acquisition year, month, day</td></tr>
<tr><td>yyyymmdd</td><td colspan="4">Processing year, month, day</td></tr>
<tr><td>CC</td><td colspan="4">Collection number: “01”, “02”, …</td></tr>
<tr><td>TX</td><td colspan="4">Collection category:
“RT” (Real-Time), “T1” (Tier 1), “T2” (Tier 2)</td></tr>
</table>

Source: usgs.gov/faqs/how-can-i-tell-difference-between-landsat-collections-data-and-landsat-data-i-have-downloaded (Accessed on 20-07-2020).

Data (Landsat MSS, Level-1)

Year	Image name	Product
1973	LM01_L1TP_148043_19730221_20200909_02_T2	River Shifting Change Detection Analysis
1980	LM03_L1TP_148043_19800221_20200905_02_T2	River Shifting Change Detection Analysis

Data (Landsat TM, Level-2)

Year	Image name	Product
1990	LT05_L2SP_138043_19900130_20200916_02_T1	River Shifting Change Detection Analysis
2000	LT05_L2SP_138043_20000211_20200907_02_T1	River Shifting Change Detection Analysis
2010	LT05_L2SP_138043_20100206_20200825_02_T1	River Shifting Change Detection Analysis

Sentinel-2 naming convention

Image name: MMM_MSIXXX_YYYYMMDDHHMMSS_Nxxyy_ROOO_Txxxxx_<Product Discriminator>

Group	Meaning
MMM	Mission ID: “S2A”, “S2B”
MSIXXX	Product level: “Level-1C”, “Level-2A”
YYYYMMDDTHHMMSS	Sensing start time, date and time separated by character “T”
Nxxyy	PDGS processing baseline number
ROOO	Relative orbit number
Txxxxx	Tile number

Source: sentinel.esa.int/web/sentinel/user-guides/sentinel-2-msi/naming-convention (Accessed on 20-07-2020).

Data

Year	Image name	Product
2019	S2B_MSIL2A_20190219T043829_N0211_R033_T45QYG_20190222T154438	River Shifting Change Detection Analysis
	S2B_MSIL2A_20190219T043829_N0211_R033_T45RYH_20190222T154438	River Shifting Change Detection Analysis
	S2A_MSIL2A_20201016T043801_N0214_R033_T45RYH_20201016T070414	Land-Use Classification

RADAR satellite images

Sentinel-1 naming convention

Image name: MMM_BB_TTTR_LFPP_YYYYMMDDTHHMMSS_ YYYYMMDDTHHMMSS_OOOOOO_DDDDDD_CCCC

<table>
<tr><th>Group</th><th colspan="6">Meaning</th></tr>
<tr><td>MMM</td><td colspan="6">Mission Identifier: “S1A”, S1B”</td></tr>
<tr><td>BB</td><td colspan="6">Mode/Beam: “S1/S2/S3/S4/S5/S6”, “IW/EW/WV”</td></tr>
<tr><td>TTTR</td><td colspan="3">TTT: Product Type
“RAW”, “SLC”, “GRD”, “OCN”</td><td colspan="3">R: Resolution Class
“F” (Full), “H” (High), “M” (Medium)</td></tr>
<tr><td>LFPP</td><td colspan="2">L: Processing Level
“0”, “1”, “2”</td><td colspan="2">F: Product Class
“S” (Standard), “A” (Annotation)</td><td colspan="2">PP: Polarization
“SH” (single HH)
“SV” (single VV)
“DH” (dual HH+HV)
“DV” (dual VV+VH)</td></tr>
</table>

YYYYMMDDTHHMMSS	Product start time, separated by the character “T”
YYYYMMDDTHHMMSS	Product end time, separated by the character “T”
OOOOOO	Absolute orbit number at product start time
DDDDDD	Mission data-take identifier
CCCC	Product unique identifier

Source: sentinel.esa.int/web/sentinel/user-guides/sentinel-1-sar/naming-conventions (Accessed on 20-07-2020).

Data: Inundation Mapping

Year	Image Name
2015	S1A_IW_GRDH_1SDV_20150706T235524_20150706T235549_006697_008F55_E0E4
2016	S1A_IW_GRDH_1SDV_20160724T235529_20160724T235554_012297_013213_0790
2017	S1A_IW_GRDH_1SDV_20170812T235532_20170812T235557_017897_01E03B_AF9D
	S1A_IW_GRDH_1SDV_20170824T235533_20170824T235558_018072_01E586_DA73
2018	S1A_IW_GRDH_1SDV_20180714T235537_20180714T235602_022797_0278AA_2752
	S1A_IW_GRDH_1SDV_20180726T235538_20180726T235603_022972_027E33_C265
2019	S1A_IW_GRDH_1SDV_20190709T235543_20190709T235608_028047_032AE1_1F4E
	S1A_IW_GRDH_1SDV_20190721T235544_20190721T235609_028222_033027_264C
2020	S1A_IW_GRDH_1SDV_20200703T235549_20200703T235614_033297_03DB97_B775
	S1A_IW_GRDH_1SDV_20200715T235550_20200715T235615_033472_03E0EC_41A1
	S1A_IW_GRDH_1SDV_20200727T235551_20200727T235616_033647_03E64C_0433
	S1B_IW_GRDH_1SDV_20200721T235458_20200721T235523_022576_02AD94_32D8

Data: Ground Motion Map

Descending Sentinel-1 scenes for InSAR analyses

S1A_IW_SLC__1SDV_20141015T235522_20141015T235549_002847_003367_F5C6
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S1A_IW_SLC__1SDV_20150119T235519_20150119T235546_004247_0052B2_7043
S1A_IW_SLC__1SDV_20150212T235518_20150212T235545_004597_005A90_4D92
S1A_IW_SLC__1SDV_20150308T235519_20150308T235546_004947_0062FA_5343
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S1A_IW_SLC__1SDV_20150612T235522_20150612T235550_006347_0085AA_6E0A
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Ascending Sentinel-1 scenes for InSAR analyses

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Annexure D: SARscape processing parameters

SBAS processing parameters from parameters.sml file generated by ENVI SARscape:

**Parameter settings used for the process **

Min Normal Baseline is 0.000000 ** Max Normal Baseline is 2.000000 ** Min Temporal Baseline is 0 ** Max Temporal Baseline is 90 ** Redundancy is high ** Criteria is min_normal ** Only Forward Pairs is FALSE ** Allow Disconnected Blocks is TRUE ** Delaunay 3D is FALSE

Initialization From Orbit is TRUE ** Estimate From Amplitude is TRUE ** Estimate From Coherence is TRUE ** Range Looks is 4 ** Azimuth Looks is 1 ** Range Dependency is 3 ** Azimuth Dependency is 3 ** Range Res Dependency is 2 ** Azimuth Res Dependency is 1 ** Range Window Number is 12 ** Azimuth Window Number is 3 ** Range Window Size is 256 ** Azimuth Window Size is 128 ** Cross Correlation Threshold is 0.250000 ** Fine Range Window Number is 25 ** Fine Azimuth Window Number is 8 ** Fine Range Window Size is 32 ** Fine Azimuth Window Size is 32 ** SNR Threshold is 3.200000 ** Coregistration with DEM is TRUE

Spectral Shift Filter is TRUE ** Doppler Filter is FALSE ** Range Looks is 4 ** Azimuth Looks is 1

Orbit Interpolation is 100 ** Optimal Resolution Approach is TRUE ** Window Size Mean Filter size is 5 ** Window Size Interpolation is 11 ** DEM Resampling Factor is -1.000000

Goldstein filter ** Interferogram Window Size is 64 ** Window Overlap Percentage is 80.000000 ** Low Pass Percentage is 5.000000 ** Intensity Window Size is 5 ** Alpha Min Value is 0.300000 ** Alpha Max Value is 2.500000 ** Coherence from Fint is TRUE ** Coherence Rg Window Size is 5 ** Coherence Az Window Size is 5 ** Low Frequency Removal Rg is 0 ** Low Frequency Removal Az is 0

EMPTY

Unwrapping Method is MCF_DELAUNAY ** Unwrapping Coherence Threshold is 0.300000 ** Decomposition Levels is 1 ** Range Scale Factor Decomposition is 3 ** Azimuth Scale Factor Decomposition is 3 ** Use 3D Unwrapping FALSE ** 3D Velocity Step Nr is 200 ** 3D Height Step Nr is 200 ** 3D Velocity Step Size is 5.000000 ** 3D Height Step Size is 10.000000 ** 3D Interferogram Valid Percentage is 60.000000 ** Tile Size in Range is 800 ** Tile Size in Azimuth is 800 ** Range Overlap is 300 ** Azimuth Overlap is 200 ** Minimum Cost Coherence is -1.000000

** Refinement Method is RemoveResidualPhase ** Residual Phase Poly Degree is 3

Estimate residual height is OK ** Displacement model type is linear ** Weighted Solution is TRUE ** Inversion SVD type is jacobi ** Min Valid Interf Percentage is 60.000000% ** Interpolate Disconnected Blocks is TRUE ** Reject outliars H [m] is -1.000000% ** Reject outliars D [mm] is -1.000000% ** Coherence Threshold is 0.300000 ** Wavelet LP size is 1200.000000

Unwrapping Method is MCF_DELAUNAY ** Unwrapping Coherence Threshold is 0.200000 ** Decomposition Levels is 1 ** Range Scale Factor Decomposition is 3 ** Azimuth Scale Factor Decomposition is 3 ** Use 3D Unwrapping FALSE ** 3D Velocity Step Nr is 200 ** 3D Height Step Nr is 200 ** 3D Velocity Step Size is 5.000000 ** 3D Height Step Size is 10.000000 ** 3D Interferogram Valid Percentage is 60.000000 ** Tile Size in Range is 800 ** Tile Size in Azimuth is 800 ** Range Overlap is 300 ** Azimuth Overlap is 200 ** Minimum Cost Coherence is -1.000000

Refinement Method is RemoveResidualPhase ** Residual Phase Poly Degree is 3

Refinement poly degree is 3 ** Estimate residual height is OK ** Displacement model type is linear ** Weighted Solution is TRUE ** Inversion SVD type is jacobi ** Min Valid Interf Percentage is 60.000000% ** Interpolate Disconnected Blocks is TRUE ** Min Valid Image Percentage is 80.000000% ** Reject outliars H [m] is -1.000000% ** Reject outliars D [mm] is -1.000000% ** Coherence Threshold is 0.300000

Refinement poly degree is 3 ** Atmosphere Low Pass Size is 1200.000000 ** Atmosphere High Pass Size is 365.000000

X Dimension is 15.000000 ** Y Dimension is 15.000000 ** Precision Height threshold is 5.000000 ** Precision Velocity threshold is 8.000000 ** Temporal coherence threshold is 0.100000 ** Water body mask threshold [dB] is -10.000000 ** Generate results in raster format is TRUE ** Generate results in shape format is TRUE ** Add time series in shape is TRUE ** Max number of points in shape is 200000 ** Interpolation Window Size is 3 ** Mean Window Size is 3 ** Generate Vertical Direction Results is FALSE ** Generate Max Slope Direction Results is FALSE ** Max Slope Direction Files is NotOK ** Generate User Direction Results is FALSE ** Azimuth Angle is 0.000000 ** Inclination Angle is 0.000000

PSI processing parameters from parameters.sml file generated by ENVI SARscape:

**This Tool Implemet the PS Module ** First Version 10.02.2011 AC ** Copyright by Sarmap SA ** Based on F.Rocca, A.Ferretti ** A New Algorithm for Surface Deformation Monitoring Based on persistent scatterers **

Initialization From Orbit is TRUE ** Orbit Accuracy is TRUE ** Estimate From Amplitude is TRUE ** Estimate From Coherence is TRUE ** Range Dependency is 3 ** Azimuth Dependency is 3 ** Range Window Number is 12 ** Azimuth Window Number is 3 ** Range Window Size is 256 ** Azimuth Window Size is 128 ** Cross Correlation Threshold is 0.250000 ** Fine Range Window Number is 25 ** Fine Azimuth Window Number is 8 ** Fine Range Window Size is 32 ** Fine Azimuth Window Size is 32 ** SNR Threshold is 3.200000

Range Looks is -2 ** Azimuth Looks is 1 ** spectral Shift Filter is FALSE ** Doppler Filter is FALSE

Sub-Area size(sqkm) is 25.000000 ** Overlap(%) is 30 ** Coherence used for Merging all Sub-Areas is 0.660000 ** min velocity[mm/year] is -100.000000 ** max velocity[mm/year] is 100.000000 ** sampling rate velocity[mm/year] is 1.000000 ** min height[m] is -70.000000 ** max height[m] is 70.000000 ** sampling rate height[m] is 2.000000

Low Pass Filter Size[m] is 1200.000000 ** High Pass Filter Size[days] is 365.000000 ** min velocity[mm/year] is -100.000000 ** max velocity[mm/year] is 100.000000 ** sampling rate velocity[mm/year] is 1.000000 ** min height[m] is -70.000000 ** max height[m] is 70.000000 ** sampling rate height[m] is 2.000000

Coherence Threshold is 0.700000 ** Geocode using Mu/Sigma Threshold is FALSE ** Mu/Sigma Threshold is 0.000000 ** Water Body Mask is 0.000000 ** Refinement GCP File Is NotOK ** Geocoded Shape Products is TRUE ** Geocoded Raster Products is TRUE ** X Dimension is 15.000000 ** Y Dimension is 15.000000