# The State of the Art in Leveraging Public Domain Remote Sensing Data for Development Purposes

Yashothara Shanmugarajah, Merl Chandana
LIRNEasia, 12 Balcombe Place, Colombo, Sri Lanka

LIRNEasia
Pro-poor. Pro-market.

LIRNE*asia* is a pro-poor, pro-market think tank whose mission is *Catalyzing policy change through research to improve people"s lives in the emerging Asia Pacific by facilitating their use of hard and soft infrastructures through the use of knowledge, information and technology.*

Contact: 12 Balcombe Place, Colombo 00800, Sri Lanka. +94 11 267 1160. info@lirneasia.net
www.lirneasia.net

This work was carried out with the aid of a grant from the International Development Research Centre (IDRC), Canada.

IDRC | CRDI
International Development Research Centre
Centre de recherches pour le développement international

Canada

## Introduction

High quality data is the foundation of successful planning, prudent policymaking and the efficient delivery of public services. Despite the proliferation of technology, the collection of development data around the world is far from uniform. In fact, it is the countries that most need data that find it the hardest to produce them. As noted in a World Bank paper, as of 2015, more than 75 countries still lacked data to adequately measure poverty [1]. The role of data has also been recognized in the 2030 Agenda for Sustainable Development and special initiatives are underway to help countries produce high-quality, timely, reliable and disaggregated data. However, National Statistical Offices which are already burdened with the burgeoning demand for the statistics they produce, are struggling to expand their operations to increase the coverage of their data collection efforts.

Traditional surveys, which are the primary means through which development data are collected, can be resource intensive and time-consuming. Therefore, the need to augment traditional methods with new and innovative sources have been emphasized in recent times. One such solution is satellite-based remote sensing, which can provide a synoptic, detailed and real-time picture of the earth's surface [2]. It allows for the collection of data on a range of key variables on environmental, economic and social dimensions. Sensors mounted on satellites can pick up the spectral differences between objects and phenomena on earth and these signals can be computationally manipulated to make inferences about the underlying phenomena.

## The growth of remote sensing

While the first successful launch of a satellite occurred in the 1950s, the era of modern remote sensing only began in 1972 with the launch of the Landsat Program: a joint NASA/ U.S. Geological Survey series of Earth Observation satellites aimed at capturing images of the earth's land surface, to help land managers and policymakers make informed decisions about natural resources and the environment [3]. However, until recently, the access to remote sensing data was limited and expensive, the tools to analyze the data were not widespread and the algorithmic techniques were not deemed mature enough to warrant widespread adoption. However, the situation has changed substantially over the last two decades.

The year 2008 marked a key milestone in satellite remote sensing when the U.S. Geological Survey Department decided to make its archive of four-decades worth of Landsat data free and open. The European Space Agency soon followed suit in 2014 by making data from its Sentinel Series open from the beginning. Meanwhile, recent advances in computational power and the development of algorithmic techniques such as machine learning and deep learning have given researchers unprecedented capabilities in analyzing remote sensing data.

## Applications of remote sensing in development

In the early days, most all applications of remote sensing revolved around the identification and management of natural resources such as forests and water bodies [4]. However, with the increasing availability of data and analytical tools, remote sensing techniques have been successfully applied in socio-economic domains such as population mapping, detecting patterns of economic equality and understanding disease propagation. This growing sphere of applications has been acknowledged in the

2030 Agenda for sustainable development where remote sensing has been recommended to measure a broad set of development indicators [5].

## Research methods and algorithmic approaches

The process of remote sensing involves relating the information captured by a sensor at a pixel level to a real phenomenon of interest. Even though most remote sensing studies are based on optical imagery captured within the visible light band of the electromagnetic spectrum, sensors also operate in the infrared, thermal infrared and microwave bands which provide different insights about a given phenomenon. Once the image is fed into a computer, programs can manipulate the digital information by carrying out a series of computations. The amount and the complexity of processing steps required to produce an output depends on the application in question, the source of satellite data, the desired level of accuracy and the availability of ancillary and reference data. While there are hundreds of techniques and algorithms available for image manipulation, some methods have been used more commonly due to their accuracy, maturity and ease of use and interpretation.

## Challenges of applying remote sensing development settings

Despite the many advantages presented by remote sensing technology and the vast amount of applications that come with it, the uptake of techniques in development applications – especially in developing countries - has been slow. This can be attributed to several reasons. Remote sensing presents an entirely new paradigm to producing development data. Not only are the techniques involved complex, but they are also fundamentally different to the survey-based methods which prioritize statistical rigor. Further, most countries do not have base resources and systems in place to successfully leverage the power of remote sensing techniques. Meanwhile, remote sensing also has certain methodological limitations that prevent more widespread adoption.

In this paper, we aim to list major remote sensing applications and data sources, explore different methodologies and algorithmic approaches for image analysis, and investigate the primary roadblocks that are standing in the way of wide-scale adoption. The output is presented in a series of tables for easy reference and retrieval.

**Table 1** lists out the applications of remote sensing. They are separated to the 3 pillars of development: economic, social and environmental. Instead of presenting a comprehensive list, it aims to cover use cases that have been proven through research.

**Table 2** outlines data sources, algorithmic techniques and research methodologies involved in remote sensing. It tries to cover both the well-established methods and the state-of-the art. Four major application areas, namely agriculture, urbanization, disaster management, and health have been selected to capture a wide array of data sources and methodologies

**Table 3** presents the major challenges in applying remote sensing techniques for development problems. They are divided into three main categories: resource and capacity-based, institutional, and data and technical.

*Table 1:Applications of Remote Sensing in Development*

| Pillar of Development | Subsection | Real life applications |
|---|---|---|
| Economic | Agriculture | 1. Crop cultivated area estimation [6]<br>2. Crop yield prediction [7]<br>3. Crop disease detection and monitoring [8]<br>4. Crop damage estimation due to natural disasters [9]<br>5. Monitoring soil parameters and vegetation health [10] |
| | Infrastructure | 1. Assessing infrastructure needs [11]<br>2. Monitoring the progress of infrastructure projects [12]<br>3. Evaluating the economic impact of infrastructure [13] |
| | Economic activity and growth | 1. Estimating Gross Domestic Product (GDP) [14]<br>2. Predicting GDP growth [15]<br>3. Measuring economic inequality [16]<br>4. Detecting urban marketplaces [17] |
| | Poverty | 1. The detection of slums [18]<br>2. The spatial distribution of poverty [19]<br>3. Understanding environment relationships of poverty [20]<br>4. Improving access to basic services [21] |
| | Resource exploration and monitoring | 1. Petroleum products [22]<br>2. Mineral exploration [23]<br>3. Fisheries and aquaculture [24] |
| Social | Urban studies | 1. Measuring urban extent [25]<br>2. Detection of urban change and their drivers [26]<br>3. Characterizing urban sprawl [27]<br>4. Forecasting urban growth [28] |
| | Demography | 1. Population estimates [29]<br>2. Large scale human settlement maps [30]<br>3. Spatial allocation of population [31] |
| | Health | 1. Spread of infectious diseases (disease vector tracking) [32]<br>2. Lifestyles factors and impact of non-communicable diseases [33]<br>3. Mapping the vulnerable areas for the spread of diseases [34] |
| | Rebuilding and reconciliation after war and conflict | 1. Analysis of impacts of violent conflict [35]<br>2. Understanding physical destruction after war [36]<br>3. Landmine detection [37] |
| | Migration | 1. Causes and effects of migration [38]<br>2. Monitoring refugee camps [39] |

| | | |
|---|---|---|
| | | 3. Predicting migration [40]<br>4. Coordinating humanitarian relief [41] |
| Environmental | Climate | 1. Spatial patterns of sea-level rise [42]<br>2. Urban Heat Islands [43]<br>3. Cooling effects of increased stratospheric aerosols [44]<br>4. Measuring ocean acidification [45]<br>5. Ozone measurements [46] |
| | Forestry | 1. Forest cover types [47]<br>2. Species identification [48]<br>3. Forest fire management [49]<br>4. Detecting deforestation [50]<br>5. Monitoring biodiversity [51] |
| | Disaster | 1. Measuring damage of natural disaster [52]<br>2. Disaster modelling [53]<br>3. Environment change assessment [54]<br>4. Early warning systems [55]<br>5. Vulnerability assessment [56] |
| | Air Quality | 1. Satellites to pinpoint greenhouse emissions and air pollution [57]<br>2. Measuring key air quality parameters [58]<br>3. Forecasting air pollution levels [59] |
| | Water management | 1. Delineate surface water bodies [60]<br>2. Large Scale irrigation management [61]<br>3. Measuring water quality parameters [62] |

*Table 2: Data Sources, Algorithmic Techniques and Research Methodologies in Remote Sensing for Development*

| Sector | Paper Details | Data Sources | Methodology | Reason for Choosing the Paper |
|---|---|---|---|---|
| Agriculture | Title: The use of Landsat data in a Large Area Crop Inventory Experiment (LACIE).<br><br>Authors: Macdonald, R. & Hall, Forrest & Erb, R. (1975)<br><br>Focus: Wheat | RS data – Landsat 1<br><br>Reference data – historical yield data | A stratified random sampling technique was used to select 637 sample wheat fields. LANDSAT digital data was converted to film image form, and analyst interpreters selected 40 to 50 training fields for wheat and other agricultural categories and provided a definition of the boundary of such fields to the analyst for the classification. Major wheat-growing regions were partitioned into smaller areas based upon crop calendars, meteorology, and soil color, as well as on the basis of trial classifications. The segment was classified with a maximum likelihood classifier into wheat and non-wheat classes. The initial models which were statistical in nature: i.e., expressions for yield as a function of critical meteorological parameters, were derived from regression analyses using historical yield and weather data over each of several yield strata. | One of the earliest applications of satellite data in agriculture |
| | Title: Use of Remote-Sensing Imagery to Estimate Corn Grain Yield<br><br>Authors: Shanahan, John & Schepers, J.s & Francis, D. & Varvel, G. & Wilhelm, Wallace & Tringe, James & Schlemmer, Mike & Major, David. (2001)<br><br>Focus: Corn | RS data – multispectral images mounted on aircrafts<br><br>Reference data – historical yield data | Image data were converted to vegetation indices (NDVI, TSAVI, and GNDVI using equations). Leaf Chlorophyll Content Assessment was done to assess variation in leaf chlorophyll content. Measurements were taken midway between the leaf tip and base and midway between the leaf margin and midrib from 30 representative plants selected from the center two rows of each plot. These measurements were then averaged for each plot. Damaged plants or those unusually close together or far apart were not sampled. Harvest Procedures and Statistical Analysis: Grain yield, vegetation index, and chlorophyll meter data were analyzed via ANOVA with a mixed model, using the SAS PROC MIXED procedure with a constant moisture basis. Linear correlation analysis was used to determine the association between the different vegetation indices at each date and final grain yield. | One of the most influential papers in crop yield prediction |

| Sector | Paper Details | Data Sources | Methodology | Reason for Choosing the Paper |
|---|---|---|---|---|
| | Title: Deep Transfer Learning for Crop Yield Prediction with Remote Sensing Data<br><br>Authors: Wang, Anna & Tran, Caelin & Desai, Nikhil & Lobell, David & Ermon, Stefano (2018)<br><br>Focus: Soybean | RS data – MODIS<br><br>Reference data – county level and province-level yield statistics | Harvest data obtained for county and province level were paired with a sequence of MODIS reflectance and temperature images from the months leading up to the harvest. In order to train deep learning models, the authors processed the MODIS imagery into the dimensionally reduced pixel histograms and grouped into matrices before stacking into a single three-dimensional tensor. Because the MODIS cropland mask does not distinguish soybeans from other crops, they ignored regions that contributed the bottom 5% of total production. A preprocessing step of ignoring the first month of the growing season in Argentina was needed by the transfer learning approach was to match the lengths of harvest image sequences between Argentina and Brazil. | Represents the state-of-the-art of machine learning techniques where large-scale predictions could be made with a relatively small amount of training data |
| Urbanization | Title: A cluster-based method to map urban areas from DMSP/OLS nightlights<br><br>Authors: YuYu Zhou; Steven J. Smith; Christopher D. Elvidge; Kaiguang Zhao; Allison Thomson; Marc Imhoff (2014)<br><br>Focus: United States and China | RS Data – Nighttime stable night data from The Defense Meteorological Satellite Program/Operational LineScan System (DMSP/OLS)<br><br>Reference Data – high resolution land cover data at cluster and regional levels | In this study, the authors developed a cluster-based method to estimate optimal thresholds and map urban extent from the DMSP/OLS NTL data in five major steps, including data preprocessing, urban cluster segmentation, logistic model development, threshold estimation, and urban extent delineation. In the method the optimal thresholds vary by clusters and are estimated based on cluster size and overall nightlight magnitude. The derived thresholds and urban extent were evaluated using a validation sub-sample of high-resolution land cover data at the cluster and regional levels. | A recent, influential paper which proposes an efficient methodology to use night lights to map urbanization |
| | Title: Outlining where humans live – The World Settlement Footprint 2015<br><br>Authors: Marconcini, Mattia & Metz-Marconcini, Annekatrin & Uereyen, Soner & Palacios Lopez, Daniela & Hanke, | RS data – Landsat 8, Sentinel 1<br><br>Reference data – Google Earth satellite/aerial Very High-Resolution imagery | First, from the images, the authors extracted key temporal statistics (i.e., temporal mean, minimum, maximum, etc.) of: i) the original backscattering value in the case of radar data; and ii) different spectral indices (e.g., vegetation index, built-up index, etc.) derived after performing cloud/cloud-shadow masking in the case of optical imagery. After automatically extracting candidate training samples for the settlement and non-settlement class, support vector machines were used for binary classification. The output was quantitatively assessed through | Global urban map with the highest resolution currently available (10m) |

| Sector | Paper Details | Data Sources | Methodology | Reason for Choosing the Paper |
|---|---|---|---|---|
| | Wiebke & Bachofer, Felix & Zeidler, Julian & Esch, Thomas & Gorelick, Noel & Kakarla, Ashwin & Strano, Emanuele. (2019).<br><br>Focus: Global urban mapping | | an unprecedented validation exercise based on 900,000 ground-truth samples collected by crowdsourcing photointerpretation and carried out in collaboration with Google. | |
| | Title: Utilizing publicly available satellite data for urban research: Mapping built-up land cover and land use in Ho Chi Minh City, Vietnam<br><br>Authors: Goldblatt, R., Deininger, K.W., & Hanson, G.H. (2018).<br><br>Focus: Ho Chi Minh City, Vietnam | RS data – Landsat 8, Sentinel 1, Sentinel 2<br><br>Reference data – administrative data, hand-labeled examples | Data from Landsat 8 and Sentinel 1&2 were obtained and preprocessed to remove noise, terrain inconsistencies and cloud cover. Then, five additional spectral indices, namely, Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Urban Index (UI), Enhanced Vegetation Index (EVI) and Normalized Difference Built-up Index (NDBI) were calculated as additional inputs for the classifier. Then Random Forest algorithm was used to conduct per-pixel supervised image classification. Finally, a k-fold cross-validation procedure was conducted to validate model using administrative data and hand-labeled examples. | Use of publicly available satellite data and open-access cloud-based computational platforms (Google Earth Engine) |
| Disaster Management | Title: Flood monitoring using microwave remote sensing in a part of Nuna river basin, Odisha, India<br><br>Authors: Kundu, Sananda & Aggarwal, Shiv & Kingma, Nanette & Mondal, Arun & Khare, Deepak. (2014<br><br>Focus: Nuna river basin, India | RS data – RADARSAT-1, Cartosat Dem, Cartosat 1<br><br>Reference data – field survey data | Remote sensing images from RADARSAT were pre-processed and used to obtain flood extent, depth and duration maps, vulnerability curves and damage maps. Cartosat DEM and Cartosat1 images were similarly pre-processed and used to obtain height information and permanent waterbodies respectively. The delineation of flood extent, which was obtained through a threshold method, was used to calculate the depth and the duration of the flood. To calculate the intensity of damage from the 2003 and 2008 floods the authors calculate the vulnerability of paddy crops in the area. The results were validated by a dedicated field survey. | A recent paper from the global south on a common natural disaster experienced by the other countries in the region |
| | Title: Detection of Urban Damage Using Remote Sensing and Machine Learning | RS data – Worldview-1 and Quickbird – 2 | The researchers obtained high resolution multispectral and panchromatic remote sensing data from the WorldView-1 satellite and post-disaster multispectral and panchromatic | Fairly influential recent paper |

| Sector | Paper Details | Data Sources | Methodology | Reason for Choosing the Paper |
|---|---|---|---|---|
| | Algorithms: Revisiting the 2010 Haiti Earthquake<br><br>Authors: Cooner, Austin & Shao, Yang & Campbell, James. (2016).<br><br>Focus: Haiti | Reference Data - United Nations Operational Satellite Applications Programme (UNITAR/UNOSAT) dataset | images from the Quickbird 2 satellite. All datasets were resampled to 0.6 meters using the nearest neighbor technique. Images were atmospherically corrected to top of atmosphere (TOA) reflectance and clipped to the study area of central Port-Au-Prince. The study evaluated the effectiveness of multilayer feedforward neural networks, radial basis neural networks, and Random Forests in detecting earthquake damage. Additionally, textural and structural features including entropy, dissimilarity, Laplacian of Gaussian, and rectangular fit, were investigated as key variables for high spatial resolution imagery classification. United Nations Operational Satellite Applications Programme (UNITAR/UNOSAT) dataset was used as validation. | |
| | Title: Assessing tropical cyclone impacts using object-based moderate spatial resolution image analysis: a case study in Bangladesh<br><br>Authors: Muhammad Al-Amin Hoque, Stuart Phinn, Chris Roelfsema & Iraphne Childs (2016)<br><br>Focus: Bangladesh | RS data – SPOT 5<br><br>Reference data – high resolution satellite imagery (Quickbird-2 & WorldView-1), reports and pictures taken after the cyclone | Pre- and post-cyclone images were obtained using the SPOT 5 satellite and pre-processed. A multi-scale object-based image classification was conducted based on a conceptual hierarchy. Reference data from Quickbird-2 and Worldview-1 were used to assess the accuracy of classification and develop pre- and post-cyclone classified maps. A cyclone impact assessment was conducted using a post-classification change-detection algorithm. Cyclone impact validation was conducted using reports and pictures taken after the validation. Impact was assessed for each land cover type. | One of the more recent papers to come out of South Asia on using remote sensing for cyclone assessment |
| Health | Title - Using remotely sensed data to identify areas at risk for hantavirus pulmonary syndrome<br><br>Authors: Glass, Gregory & Cheek, James & Patz, Jonathan & Shields, Timothy & Doyle, Timothy & Thoroughman, Doug & Hunt, Darcy & Enscore, | RS data – Landsat TM data<br><br>Reference data – HPS case data | A region of 105,200km2 in southwestern United States was used as the study area. Satellite imagery was used to characterize local environment conditions. Additional environment variables such as elevation, slope and aspect of the case and control sites were used as inputs. The spatial distribution of Hantavirus Pulmonary Syndrome (HPS) sites (cases) was compared with that of control sites to determine if cases were spatially aggregated within the study region. Then, the relationship between HPS and environmental factors measured by Landsat TM imagery was examined. The authors used logistic regression | Influential paper |

| Sector | Paper Details | Data Sources | Methodology | Reason for Choosing the Paper |
|---|---|---|---|---|
| | Russell & Gage, Kenneth & Irland, Charles & Peters, Clarence & Bryan, R.T. (2000)<br><br>Focus – HPS in the South Western United States | | analysis to identify the best combination of TM bands and environmental variables associated with HPS status. The analysis was then repeated by using the remaining HPS and control sites to validate the model. Identifying the same model in the two analyses would indicate that the HPS risk model was robust for that period. | |
| | Title - Climate and infectious disease: use of remote sensing for detection of Vibrio cholerae by indirect measurement.<br><br>Authors - Lobitz B, Beck L, Huq A, Wood B, Fuchs G, Faruque AS, Colwell R. (2000)<br><br>Focus – Cholera in Bangladesh | RS Data - (NOAA's) Advanced Very High-Resolution Radiometer (AVHRR) sensor<br><br>Reference data – Cholera case data | The data set for this study included SST (Sea-surface temperature), SSH (Sea-surface height), and cholera case data. First, obtained remote sensing images for pre-processed. Then for each time and date, the values for SST and SSH were calculated at a pixel level from one point off the coast of Bangladesh. SST data were examined for a 6-year period, 1989–1995, whereas SSH data were available for a 3-year period, 1992–1995. These point data were compared with cholera case data by superimposing the data plots to detect patterns. Statistical analyses were done, and the patterns were found to be significant. | A highly influential paper |
| | Title - Remote sensing-based time series models for malaria early warning in the highlands of Ethiopia<br><br>Authors - Madelia, Alemayehu & Senay, Gabriel & Henebry, Geoffrey & Semuniguse, Paulos & Wimberly, Michael. (2012).<br><br>Focus – Malaria in Ethiopia | RS Data - MODIS instruments on-board the Terra and Aqua satellites<br><br>Reference data – Malaria case data | In this study seasonal autoregressive integrated moving average (SARIMA) models were used to quantify the relationship between malaria cases and remotely sensed environmental variables, including rainfall, land-surface temperature (LST), vegetation indices (NDVI and EVI), and actual evapotranspiration (ETa) with lags ranging from one to three months. Predictions from the best model with environmental variables were compared to the actual observations from the last 12 months of the time series. | Fairly influential recent paper |

*Table 3: Challenges in applying remote sensing data for development* [63] [64] [65]

| **Resource and capacity-based challenges** | **Institutional challenges** | **Data and technical challenges** |
|---|---|---|
| Remote sensing and GIS infrastructures do not exist - lack of consistent up-to-date base mapping, fundamental geographic datasets such as geodetic control, elevation, drainage, transport, land cover, geographic names, land tenure, etc. | Getting the data products into the hands of the appropriate decision makers, in time frames reasonable for action | Explainability – with modern machine learning methods it is extremely difficult to document how specific classifications were made |
| Domain expertise is not available in many at-risk areas in developing countries to pair with remote sensing scientists | Remote sensing research can be at times removed from practice, focusing more on methodological improvements as opposed to practical applications | Quality ground truth is difficult to obtain. The problem is maginified within the context of deep learning techniques which require a lot of training data |
| Modern very-high resolution satellite imagery cannot be processed at scale in individual computers or regular research labs due to high computational demands | Linking model outputs to the formulation of environmentally sound policies that are effective at the grass-roots level. This often requires multiple iterations of a model with many stakeholders working together | Need of multi-resolution sensors at multiple spatial and temporal resolutions to monitor a range of phenomena (e.g. especially sensors that can detect conditions in urban areas with complex mixtures of vegetation, buildings, and roads) |
| High and very high-resolution data is still quite expensive. | The lack of understanding among the decision makers about the utility of remote sensing and the possible applications | Maintaining the continuity of current satellite coverage so that change of environmental conditions and their effects on health can be monitored over extended time frames. Most satellites have limited life spans and are retired |
| Lack of funding for both primary and applied research | The unwillingness of domain experts to collaborate remote sensing scientists' issues of importance | The inability to obtain high-quality images due to cloud cover (especially in tropical countries) |
| The dearth of qualified remote sensing scientists and researchers | The resistance to change due by existing government bodies due to the fundamentally different paradigm of remote sensing | The lack of disaggregated ancillary data (such as census data) which complement remote sensing data in modelling. |

# References


[1] "Data for development impact: Why we need to invest in data, people and ideas." [Online]. Available: https://blogs.worldbank.org/voices/data-for-development-impact-why-we-need-to-invest-in-data-people-and-ideas. [Accessed: 20-May-2020].

[2] P. S. Roy, M. D. Behera, and S. K. Srivastav, "Satellite Remote Sensing: Sensors, Applications and Techniques," *Proceedings of the National Academy of Sciences India Section A - Physical Sciences*, vol. 87, no. 4. Springer India, pp. 465–472, 01-Dec-2017.

[3] A. P. Cracknell, "The development of remote sensing in the last 40 years," *Int. J. Remote Sens.*, vol. 39, no. 23, pp. 8387–8427, Dec. 2018.

[4] G. K. Moore, "What is a picture worth? A history of remote sensing / Quelle est la valeur d'une image? Un tour d'horizon de télédétection," 1979.

[5] "Big Data for Official Statistics." [Online]. Available: https://unstats.un.org/unsd/bigdata/taskteams/si-gsd/default.asp. [Accessed: 20-May-2020].

[6] S. Pradhan, "Crop area estimation using GIS, remote sensing and area frame sampling," *ITC J.*, vol. 3, no. 1, pp. 86–92, Jan. 2001.

[7] I. Ahmad, A. Ghafoor, M. Iftikhar Bhatti, I. Hassan Akhtar, and M. Ibrahim, "Satellite Remote Sensing and GIS based Crops Forecasting & Estimation System in Pakistan," *Crop Monit. Improv. Food Secur.*, pp. 95–109, 2015.

[8] W. Huang *et al.*, "Crop Disease and Pest Monitoring by Remote Sensing," in *Remote Sensing - Applications*, InTech, 2012.

[9] F. O. Tapia-Silva, S. Itzerott, S. Foerster, B. Kuhlmann, and H. Kreibich, "Estimation of flood losses to agricultural crops using remote sensing," *Phys. Chem. Earth*, vol. 36, no. 7–8, pp. 253–265, 2011.

[10] Y. Ge, J. A. Thomasson, and R. Sui, "Remote sensing of soil properties in precision agriculture: A review," *Frontiers of Earth Science*, vol. 5, no. 3. Higher Education Press, pp. 229–238, 2011.

[11] C. N. Thomson and P. Hardin, "Remote sensing/GIS integration to identify potential low-income housing sites," *Cities*, vol. 17, no. 2, pp. 97–109, Apr. 2000.

[12] D. C. Wickramasinghe, T. T. Vu, and T. Maul, "Satellite remote-sensing monitoring of a railway construction project," *Int. J. Remote Sens.*, vol. 39, no. 6, pp. 1754–1769, Mar. 2018.

[13] "Roads through tough places: Using remote sensing for impact evaluations of infrastructure investments in conflict-affected settings." [Online]. Available: https://blogs.worldbank.org/developmenttalk/roads-through-tough-places-using-remote-sensing-impact-evaluations-infrastructure-investments. [Accessed: 19-May-2020].

[14] W. Yue, J. Gao, and X. Yang, "Estimation of gross domestic product using multi-sensor remote sensing data: A case study in zhejiang province, east China," *Remote Sens.*, vol. 6, no. 8, pp. 7260–7275, 2014.

[15] N. Zhao, Y. Liu, G. Cao, E. L. Samson, and J. Zhang, "Forecasting China's GDP at the pixel level using nighttime lights time series and population images," *GIScience Remote Sens.*, vol. 54, no. 3, pp. 407–425, May 2017.

[16] D. Ehrlich, M. Schiavina, M. Pesaresi, and T. Kemper, "Detecting spatial pattern of inequalities from remote sensing – Towards mapping of deprived communities and poverty," 2018.

[17] K. Baragwanath, R. Goldblatt, G. Hanson, and A. K. Khandelwal, "Detecting urban markets with satellite

imagery: An application to India," *J. Urban Econ.*, p. 103173, Jun. 2019.

[18] D. Kohli, R. Sliuzas, and A. Stein, "Urban slum detection using texture and spatial metrics derived from satellite imagery," *Journal of Spatial Science*, vol. 61, no. 2. Mapping Sciences Institute Australia, pp. 405–426, 02-Jul-2016.

[19] "(PDF) Analysing the spatial heterogeneity of poverty using remote sensing: typology of poverty areas using selected RS based indicators." [Online]. Available: https://www.researchgate.net/publication/228862754_Analysing_the_spatial_heterogeneity_of_poverty_using_remote_sensing_typology_of_poverty_areas_using_selected_RS_based_indicators. [Accessed: 19-May-2020].

[20] G. R. Watmough, P. M. Atkinson, A. Saikia, and C. W. Hutton, "Understanding the Evidence Base for Poverty-Environment Relationships using Remotely Sensed Satellite Data: An Example from Assam, India," *World Dev.*, vol. 78, pp. 188–203, Feb. 2016.

[21] S. Shekhar, "Improving the slum planning through geospatial decision support system," in *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives*, 2014, vol. 40, no. 2, pp. 99–105.

[22] S. Shengwei, "The Exploration and Evaluation of Petroleum Resource based on Remote Sensing Technology," *Phys. Procedia*, vol. 33, pp. 1119–1123, Jan. 2012.

[23] H. M. Rajesh, "Application of remote sensing and GIS in mineral: Resource mapping - An overview," *Journal of Mineralogical and Petrological Sciences*, vol. 99, no. 3. pp. 83–103, 2004.

[24] S.-I. Saitoh *et al.*, "Some operational uses of satellite remote sensing and marine GIS for sustainable fisheries and aquaculture," *ICES J. Mar. Sci.*, vol. 68, no. 4, pp. 687–695, Mar. 2011.

[25] R. Goldblatt, W. You, G. Hanson, and A. K. Khandelwal, "Detecting the boundaries of urban areas in India: A dataset for pixel-based image classification in google earth engine," *Remote Sens.*, vol. 8, no. 8, 2016.

[26] P. J. Howarth and E. Boasson, "Landsat digital enhancements for change detection in urban environments," *Remote Sens. Environ.*, vol. 13, no. 2, pp. 149–160, May 1983.

[27] M. K. Jat, P. K. Garg, and D. Khare, "Monitoring and modelling of urban sprawl using remote sensing and GIS techniques," *Int. J. Appl. Earth Obs. Geoinf.*, vol. 10, no. 1, pp. 26–43, Feb. 2008.

[28] K. C. Seto, B. Güneralp, and L. R. Hutyra, "Global forecasts of urban expansion to 2030 and direct impacts on biodiversity and carbon pools," *Proc. Natl. Acad. Sci. U. S. A.*, vol. 109, no. 40, pp. 16083–16088, Oct. 2012.

[29] S. S. Wu, X. Qiu, and L. Wang, "Population estimation methods in GIS and remote sensing: A review," *GIScience and Remote Sensing*, vol. 42, no. 1. V.H. Winston and Son Inc., pp. 80–96, 2005.

[30] M. Marconcini *et al.*, "Outlining where humans live -- The World Settlement Footprint 2015," Oct. 2019.

[31] S. Leyk *et al.*, "The spatial allocation of population: a review of large-scale gridded population data products and their fitness for use," *Earth Syst. Sci. Data*, vol. 11, no. 3, pp. 1385–1409, Sep. 2019.

[32] S. Kalluri, P. Gilruth, D. Rogers, and M. Szczur, "Surveillance of Arthropod Vector-Borne Infectious Diseases Using Remote Sensing Techniques: A Review," *PLoS Pathog.*, vol. 3, no. 10, p. e116, Oct. 2007.

[33] "Using remote sensing technology to measure environmental determinants of non-communicable diseasesLetters to the Editor | International Journal of Epidemiology | Oxford Academic." [Online]. Available: https://academic.oup.com/ije/article/46/4/1343/3056758. [Accessed: 19-May-2020].

[34] P. Dambach, A. Sié, J. P. Lacaux, C. Vignolles, V. Machault, and R. Sauerborn, "Using high spatial resolution

remote sensing for risk mapping of malaria occurrence in the Nouna district, Burkina Faso," *Glob. Health Action*, vol. 2, no. 1, 2009.

[35] F. D. W. Witmer, "Remote sensing of violent conflict: eyes from above," *International Journal of Remote Sensing*, vol. 36, no. 9. Taylor and Francis Ltd., pp. 2326–2352, 03-May-2015.

[36] A. Lubin and A. Saleem, "Remote sensing-based mapping of the destruction to Aleppo during the Syrian Civil War between 2011 and 2017," *Appl. Geogr.*, vol. 108, pp. 30–38, Jul. 2019.

[37] I. Makki, R. Younes, C. Francis, T. Bianchi, and M. Zucchetti, "A survey of landmine detection using hyperspectral imaging," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 124. Elsevier B.V., pp. 40–53, 01-Feb-2017.

[38] B. KC, T. Wang, and P. Gentle, "Internal Migration and Land Use and Land Cover Changes in the Middle Mountains of Nepal," *Mt. Res. Dev.*, vol. 37, no. 4, p. 446, Dec. 2017.

[39] G. Laneve, G. Santilli, and I. Lingenfelder, "Development of automatic techniques for refugee camps monitoring using very high spatial resolution (VHSR) satellite imagery," in *International Geoscience and Remote Sensing Symposium (IGARSS)*, 2006, pp. 841–845.

[40] X. Chen, "Nighttime Lights and Population Migration: Revisiting Classic Demographic Perspectives with an Analysis of Recent European Data," *Remote Sens.*, vol. 12, no. 1, p. 169, Jan. 2020.

[41] J. A. Quinn, M. M. Nyhan, C. Navarro, D. Coluccia, L. Bromley, and M. Luengo-Oroz, "Humanitarian applications of machine learning with remote-sensing data: Review and case study in refugee settlement mapping," *Philos. Trans. R. Soc. A Math. Phys. Eng. Sci.*, vol. 376, no. 2128, 2018.

[42] W. Han *et al.*, "Spatial Patterns of Sea Level Variability Associated with Natural Internal Climate Modes," *Surveys in Geophysics*, vol. 38, no. 1. Springer Netherlands, pp. 217–250, 01-Jan-2017.

[43] D. Zhou *et al.*, "Satellite remote sensing of surface urban heat islands: Progress, challenges, and perspectives," *Remote Sens.*, vol. 11, no. 1, pp. 1–36, 2019.

[44] W. M. F. Grey and P. R. J. North, "Aerosol optical depth from dual-view (A)ATSR satellite observations," in *Satellite Aerosol Remote Sensing over Land*, Springer Berlin Heidelberg, 2009, pp. 161–192.

[45] R. Sabia, D. Fernandez-Prieto, J. Shutler, C. Donlon, P. Land, and N. Reul, "Remote sensing of surface ocean PH exploiting sea surface salinity satellite observations," in *International Geoscience and Remote Sensing Symposium (IGARSS)*, 2015, vol. 2015-November, pp. 106–109.

[46] A. P. Cracknell and C. A. Varotsos, "Satellite systems for atmospheric ozone observations," *International Journal of Remote Sensing*, vol. 35, no. 15. Taylor and Francis Ltd., pp. 5566–5597, 2014.

[47] A. Isabel and T. Sotomayor, "A SPATIAL ANALYSIS OF DIFFERENT FOREST COVER TYPES USING GIS AND REMOTE SENSING TECHNIQUES," 2002.

[48] J. Holmgren, Å. Persson, and U. Söderman, "Species identification of individual trees by combining high resolution LiDAR data with multi-spectral images," in *International Journal of Remote Sensing*, 2008, vol. 29, no. 5, pp. 1537–1552.

[49] T. Xiao-rui, D. J. Mcrae, S. Li-fu, W. Ming-yu, and L. Hong, "Satellite remote-sensing technologies used in forest fire management," *J. For. Res.*, vol. 16, no. 1, pp. 73–78, Mar. 2005.

[50] "(PDF) Monitoring of Deforestation and Forest Degradation Using Remote Sensing and GIS: A Case Study of Ranchi in Jharkhand (India)." [Online]. Available: https://www.researchgate.net/publication/216406007_Monitoring_of_Deforestation_and_Forest_Degradation_Using_Remote_Sensing_and_GIS_A_Case_Study_of_Ranchi_in_Jharkhand_India. [Accessed: 19-May-2020].

[51] Z. Bochenek, D. Ziolkowski, M. Bartold, K. Orlowska, and A. Ochtyra, “Monitoring forest biodiversity and the impact of climate on forest environment using high-resolution satellite images,” *Eur. J. Remote Sens.*, vol. 51, no. 1, pp. 166–181, Jan. 2018.

[52] Y. Fan, Q. Wen, W. Wang, P. Wang, L. Li, and P. Zhang, “Quantifying Disaster Physical Damage Using Remote Sensing Data—A Technical Work Flow and Case Study of the 2014 Ludian Earthquake in China,” *Int. J. Disaster Risk Sci.*, vol. 8, no. 4, pp. 471–488, Dec. 2017.

[53] D. C. Mason, P. D. Bates, and J. T. Dall’ Amico, “Calibration of uncertain flood inundation models using remotely sensed water levels,” *J. Hydrol.*, vol. 368, no. 1–4, pp. 224–236, Apr. 2009.

[54] “(PDF) Monitoring of shoreline changes using remote sensing (case study: coastal city of Bandar Abbas).” [Online]. Available: https://www.researchgate.net/publication/263318867_Monitoring_of_shoreline_changes_using_remote_sensing_case_study_coastal_city_of_Bandar_Abbas. [Accessed: 19-May-2020].

[55] “Contribution of Remote Sensing to Drought Early Warning | Request PDF.” [Online]. Available: https://www.researchgate.net/publication/253598539_Contribution_of_Remote_Sensing_to_Drought_Early_Warning. [Accessed: 19-May-2020].

[56] H. Taubenböck, A. Roth, and S. Dech, “Vulnerability assessment using remote sensing: The earthquake prone mega-city Istanbul, Turkey.”

[57] “Using Satellites to Pinpoint and Predict Pollution - Scientific American.” [Online]. Available: https://www.scientificamerican.com/article/using-satellites-to-pinpo/. [Accessed: 19-May-2020].

[58] C. Clerbaux, S. Turquety, and P. Coheur, “Infrared remote sensing of atmospheric composition and air quality: Towards operational applications,” *Comptes Rendus - Geosci.*, vol. 342, no. 4–5, pp. 349–356, Apr. 2010.

[59] S. Michaelides, P. Evripidou, and G. Kallos, “Monitoring and predicting Saharan Desert dust events in the eastern Mediterranean,” *Weather*, vol. 54, no. 11, pp. 359–365, Nov. 1999.

[60] N. Mueller *et al.*, “Water observations from space: Mapping surface water from 25years of Landsat imagery across Australia,” *Remote Sens. Environ.*, vol. 174, pp. 341–352, Mar. 2016.

[61] S. J. Zwart and L. M. C. Leclert, “A remote sensing-based irrigation performance assessment: A case study of the Office du Niger in Mali,” *Irrig. Sci.*, vol. 28, no. 5, pp. 371–385, Nov. 2010.

[62] M. H. Gholizadeh, A. M. Melesse, and L. Reddi, “A comprehensive review on water quality parameters estimation using remote sensing techniques,” *Sensors (Switzerland)*, vol. 16, no. 8. MDPI AG, 16-Aug-2016.

[63] Y. Ban, S. Marullo, and L. Eklundh, “European Remote Sensing: progress, challenges, and opportunities,” *International Journal of Remote Sensing*, vol. 38, no. 7. Taylor and Francis Ltd., pp. 1759–1764, 03-Apr-2017.

[64] M. K. Jha and V. M. Chowdary, “Challenges of using remote sensing and GIS in developing nations,” *Hydrogeol. J.*, vol. 15, no. 1, pp. 197–200, Feb. 2007.

[65] “PROBLEMS IN USING REMOTE SENSING AND GIS IN THE PHILIPPINES.” [Online]. Available: http://www.fao.org/3/XII/0261-B1.htm. [Accessed: 19-May-2020].