Chapter

Remote Sensing Applications in Disease Mapping

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Abstract

Disease mapping utilizes disease maps as visual representations of sophisticated geographic data that provide a general overview of the disease situation in a defined geographic area. Epidemiology is concerned with investigating the causes of diseases, and often, these causes vary in frequency and in space. This variation in space gave a niche to remote sensing to find its way into the public health domain as disease researchers sought to investigate the explaining environmental and climatic factors. Studies have demonstrated the potential offered by remote sensing application to disease mapping and epidemiology and to support surveillance and control efforts. We used some examples from a case study conducted in Eswatini in Southern Africa. Remote sensing imagery when combined with GIS spatial analyses techniques could support and guide existing disease surveillance and control programs at local, regional, and even continental scales. Researchers have also studied factors influencing the patterns and distributions of vector-borne diseases at a variety of landscape scales. However, successful application of remote sensing technology depends on the ability of nonexperts' remotely sensed data and end users to access, retrieve, and analyze the data captured from satellites. The exploration of some of the opportunities presented by remote sensing to disease mapping and epidemiology is still unfolding as new opportunities are being presented.

Keywords: disease mapping, epidemiology, geostatistics, remote sensing, GIS

1. Introduction

Remote sensing could be described as the science of scanning the earth using sensors onboard a satellite platform launched into space or high flying aircraft to obtain information and also monitor land use and land cover changes on the earth surface [1]. Often, the monitored land use and land cover changes emanate from human activities and their interaction with the environment. The observation of the earth by the orbiting satellites is done at different geographic scales and at different intervals or revisit periods, which are both widely referred to as spatial and temporal resolutions, respectively. Over the years, there had been noticeable improvements in the spatial and temporal resolutions which had been accompanied by an interesting visibility and readability of the captured images. In addition, the number of spectral bands used by the sensors to capture images had also increased, aiding in an appealing appearance to the human eye. Consequently, even nonexpert remote sensing users had been drawn into remote sensing by the *beautiful pictures* and availability of some of the end products of remote sensing. There had been, therefore, an increase in the application of remote sensing products by other disciplines and fields of study. In public health, remotely sensed (RS) data products had been widely adopted and used in disease mapping and epidemiology. We used some examples from a case study conducted in Eswatini in Southern Africa.

Disease mapping referrers to the use of disease maps as visual representations of sophisticated geographic data that provide a general birdeye overview of the disease situation in a defined geographic area. On the other hand, epidemiology is a branch of medicine that deals with the incidence, distribution, and strategies for disease containment and control as well as other factors relating to human and animal health. Epidemiology is concerned with investigating the cause of disease, and often, these causes vary in frequency and in space. This variation in space is what gave a niche to remote sensing to find its way into the public health domain as disease researchers sought to investigate the explaining environmental and climatic factors. For this reason, remote sensing which provides a birdeye overview of the earth surface had continued to be applied in disease mapping for rapid risk assessment and monitoring efforts. As a result, remote sensing products have for quite a reasonable while been prolifically applied and used in disease mapping and epidemiology. Products of remote sensing include various vegetation indices and environmental proxies which are derived from satellite images and used to elucidate land use and land cover changes as well as to approximate environmental and climatic conditions on the earth surface.

Vegetation indices are mathematical combinations of different spectral bands that are designed to numerically separate or stretch the pixel value of different features in an image [2, 3]. RS data products had been used in a number of disease mapping and epidemiological studies such as in risk mapping of malaria [4, 5], soil-transmitted helminths [6], schistosomiases, and prediction of high risk areas for leishmaniasis in Brazil. Previous work include incorporation of RS data in human health studies and spatial targeting of trachoma control in Southern Sudan [7] by developing a national risk map and mapping tsetse fly habitat suitability among others [8]. In addition, identification of environmental risk factors for cholera using satellite-derived remotely sensed data products had been undertaken by [9]. Determination of population living in a city using remotely sensed data products was carried out in a study by Karume et al. [10], whereby a GeoEye satellite image at 50-m resolution was used, and population of the city was obtained by taking the number of houses times an average number of habitants per house. To date, an inexhaustible number of exploratory research studies in disease mapping and epidemiology had been undertaken using remote sensing vegetation indices as environmental and climatic proxies in combination with various modeling approaches.

One of the main advantages of using RS data products in disease mapping and epidemiology is its near real-time availability for rapid assessment of at risk areas and prediction of disease distribution, especially in inaccessible areas that may also lack baseline data [11]. The increase in the launch of higher resolution satellites sensors and advances in data processing techniques have enabled a wider adoption of RS data [12]. In economically disadvantaged areas with poor ground measurement meteorological station networks, RS data had often been preferred and used as environmental and climatic proxies in disease risk mapping and prediction. As new sensors with better spatial and temporal resolutions become available, new opportunities had been presented and explored in the application of remote sensing products in disease mapping and epidemiology [13].

From the early generation of ecological studies that demonstrated the capability of RS data products in disease mapping [13–16], there had been a sustained proliferation of such studies in disease mapping and epidemiology. The application of geostatistical techniques to identify spatial heterogeneities in disease distributions, patterns, and trends as well as forecasting for epidemic preparedness planning had been demonstrated in studies by Chilès and Delfiner [17]; and Tran et al. [18] *inter* *alia*. Geostatistics is a branch of statistics that is used to analyze and predict the values associated with spatial and temporal phenomena [17]. It is often incorporated into modeling through the use of coordinates attached to the data that are being analyzed. An almost similar terminology also commonly used in such analysis is the term "biostatistics," which also refers to a similar approach except that the data being analyzed would involve biological data. Such models are then referred to as space–time models, especially due to the fact that they also include the observation dates of the mapped data. The theory behind incorporation of RS data in disease mapping and epidemiology was based on the field-observed association between environmental conditions and some of the disease-causing vectors [18–20], in particular how they vary in geographic space. For instance, some studies have demonstrated the association between radiation reflectance as measured by satellites and certain land cover types which have been used as environmental and climatic proxies for measurement of presence or absence of a disease and its vectors [21].

Incorporating remotely sensed data products in spatial modeling had been common in most aspects of geographic analyses. From the early usage of aerial photographs taken onboard aircraft to the launch of satellite-based sensors, remotely sensed data products have been in the forefront of scientific research on the land use and land cover changes of the earth. Many other disciplines such as public health and epidemiology have until recently overwhelmingly taken up remotely sensed data products and utilized them in disease mapping and in improvement of their understanding of environmentally driven diseases. The utilization of RS data products, especially in disease mapping, for instance, in mapping vector-borne diseases, had been prolific over the years. As mentioned earlier, products derived from remote sensing had been widely used in models as environmental proxies to analyze various behaviors of observed spatial phenomenon. Furthermore, environmental proxies had been incorporated as covariates in statistical models aimed at mapping, analyzing, and predicting spatial phenomenon relating to disease epidemiology.

In statistical models, disease analysis had been pursued by adjusting models with spatial covariates derived from remote sensing and regressed with any outcome of interest. In such cases, spatial regression models had often been parameterized using data variables derived from remotely sensed products. As a result, there had been an unprecedented upsurge in the utilization of environmental variables and proxies derived from remote sensing in statistical analysis models attempting to map diseases such as vector-borne diseases, including malaria, dengue fever, chikungunya fever, zika virus, and leishmaniasis *inter alia* [22]. Studies mapping the spatial distribution of such vector-borne diseases had often applied remotely sensed data products as environmental proxies by approximating either environmental conditions or land use and land cover features. When the spatial covariates had been used in such a manner in models, they would often be referred to as predictors or risk factors since they tend to covary with the severity of the disease. This association of diseases with their environment was first noted in some of the early ecological studies that demonstrated the capability of remote sensing products in disease mapping, including authors such as Beck et al. [15]; Hay [16], and Thomson et al. [14] among others. As an example, malaria had on numerous cases been referred to as an environmental disease, and describing environmental risk factors associated with this disease had driven the research in malaria risk mapping [23].

Whereas, the early uptake of remotely sensed products was initially limited by the slow processing power of first-generation computers as well as the limited and cumbersome storage facility required to store remotely sensed and geographic information system (GIS) data sets; the advent of fast processing computer power had made it possible to include remotely sensed data in mapping studies. In addition, storage facilities of geographic data sets had improved from the large and difficult-to-handle cassettes to small, easy-to-carry hard drives and universal serial bus (usb) including portable external hard drives. Furthermore, the open access to remote sensing end products even for civilian usage had stimulated the interest of the scientific community and facilitated the uptake and application of remote sensing in disease mapping and epidemiology.

In areas with limited ground-based environmental data observation stations, remotely sensed data products became the only option available for mapping disease risk distribution. Such inaccessible areas included those with rugged terrain, areas in armed conflict, and those with limited resources which would not be enough to undertake field-based studies. Also, in cases where for example, ground-based weather stations had been used, they had often been limited by data discrepancies emanating from human interference, human error, instrument jamming, and in some cases, power failure. This would often result in missing data as observation could not be completed on those days when the weather station failed. During the processing and analysis of such data, the missing values in the data would often require sophisticated methods of data imputation which would not escape criticism from the scientific peer review community. Therefore, remote sensing products had been preferred because of the reliability of availability often in near real-time compared to other data sources which may require field surveys to be undertaken and thus too expensive to be repeated.

2. Mapping environmental diseases in the twenty-first century

Most of the epidemiological studies that had mapped vector-borne diseases in the context of the environmental factors associated with those diseases [18–20] had based their assumptions on the established scientific evidence that those environmental factors were associated with the disease outcome of interest. To date an increasing number of disease mapping and epidemiology studies continue to use environmental and climatic data to map and predict disease distribution in defined geographic areas. Such studies would often be used to help guide and target the deployment of health interventions to those areas that had been identified to have high burden of the mapped disease. As the resolutions (both spatial and temporal) of remote sensing sensors had improved from the first generation of this technology, so has the interest and confidence in the use of their data products increased among the scientific community. As much as early studies were limited by computer processing power and storage, they were also limited by poor spectral bands of sensors which could not faithfully enhance delineation and demarcation of features. The spectral bands refer to the recorded wavelengths of the electromagnetic spectrum recorded by a sensor during image acquisition. Recently, sensor spectral bands have also improved and could now resolve and aid multicolor image display during feature analysis and identification. These advances in image processing, visualization and display have also supported and enabled the uptake and appreciation of research findings from mapping efforts as the resultant maps became more *beautiful* in addition to providing more information. **Figure 1** is an example of a high-resolution satellite imagery that had been used to develop a land cover classification map for part of Eswatini as shown in **Figure 2**.

In disease mapping, these advances in remote sensing and sensor technology meant that identification of spatial heterogeneities would be possible even at small geographic or local scales. These advances were pivotal for disease mapping as epidemiologist could identify important drivers of disease risk and thus be able to guide control programs more efficiently and with evidence-based decisions. Also, the costs of remotely sensed data products had been significantly reduced

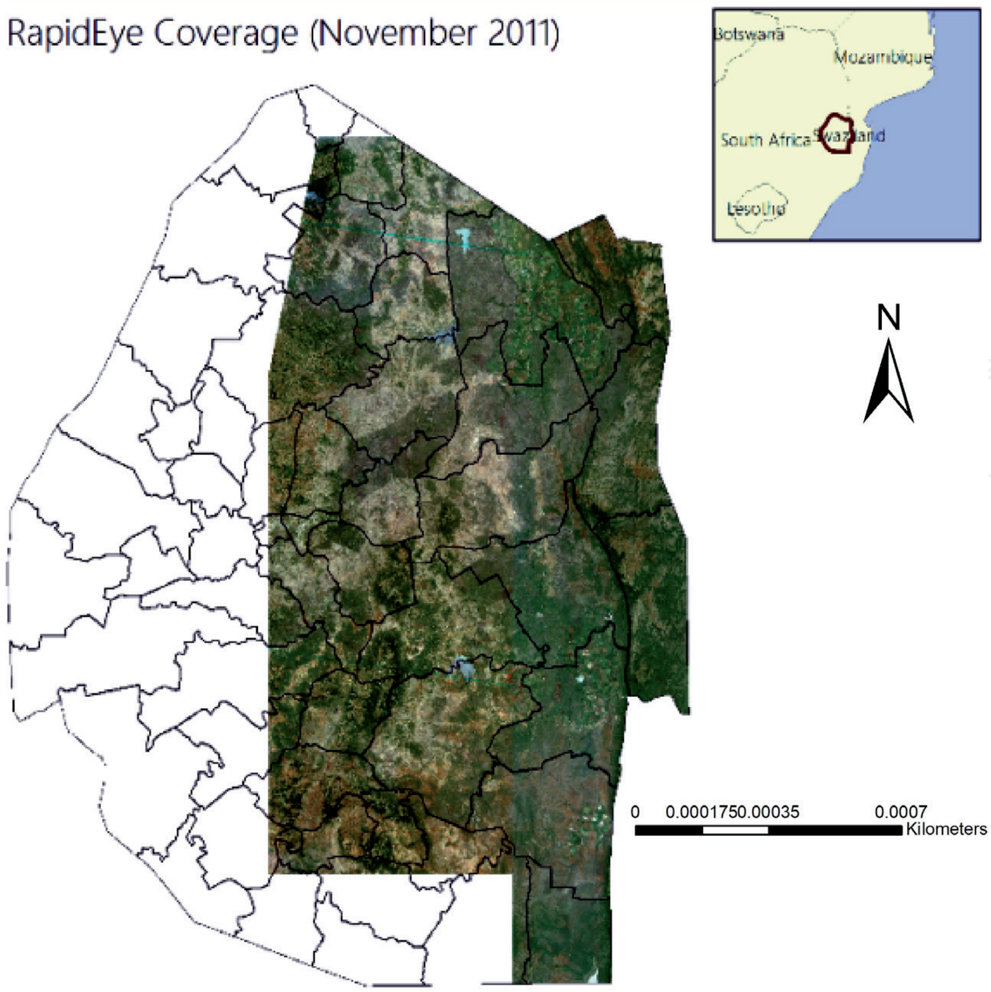

Figure 1.
An example of high-resolution true color image covering part of Eswatini used to develop a land cover classification.

as more sensors had been launched thus stabilizing the demand for data products and reliance in only a few remote sensing agents. More and more countries and private companies have launched satellites into space in the twenty-first century and the resultant imagery data products have been availed to the research community [24]. In addition, archived remotely sensed data products had often been offered to researchers free of charge and this have enabled spatial analysts to perform various analysis techniques such as time-series analysis, data mining and other data learning techniques. The RS data and other end products had also been customized in terms of the derivation and calculation of vegetation indices used in mapping studies. This customization had enabled direct incorporation of such indices into models as interpretation became possible to the research community even though not being experts in the remote sensing field. Common indices that had been widely adopted into disease mapping models because of their ease in interpretation include those of the Normalized Difference Vegetation Index (NDVI), temperature and rainfall. These indices had often been supplied or archived in their complete processed (derived) and customized form, thus enabling researchers to easily access them from the hosting agencies and websites and directly incorporate them into their mapping models as they had become interoperable.

Advances made in mapping software, particularly geographic information system (GIS) software, had seen interest being stimulated among disease researchers and epidemiologist. Whereas, earlier software was mostly geared toward solely remote sensing experts, the availability of customized mapping platforms for spatial epidemiology meant that these software programs could be utilized even by

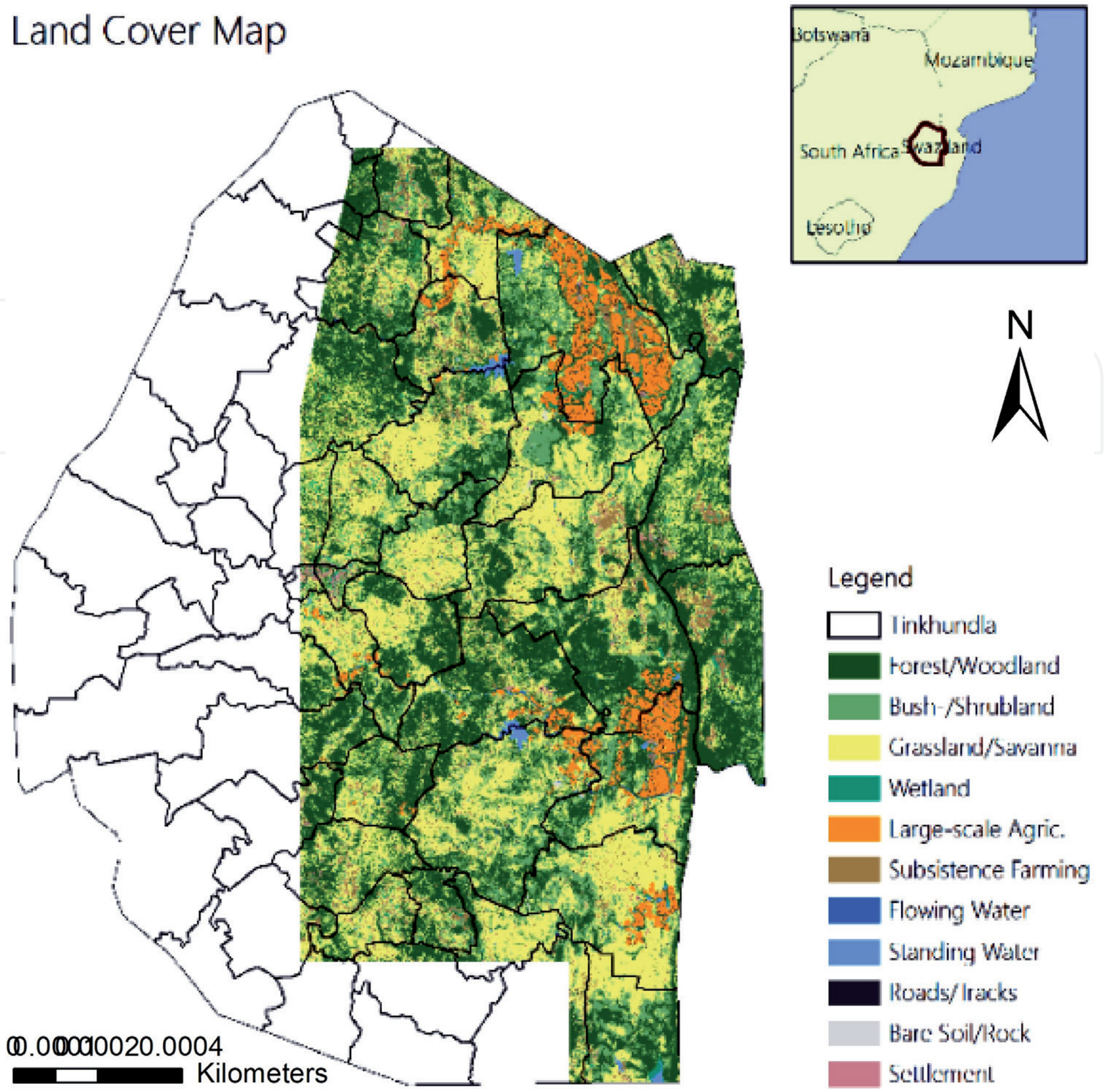

Figure 2.
An example of high-resolution land cover classification in Eswatini.

non-remote sensing experts. For instance, the public health community had been able to facilitate the development and customization of disease mapping software programs like; Health Mapper, Epi-Info, etc. Other GIS software programs such as ESRI ArcGIS had over the years added more customized mapping tools and extensions meant to support disease mapping and epidemiology efforts. Again, the high costs which were often associated with some of the commercial software had been reduced as more open source software became available. For example, GIS software programs such as QGIS had been availed as open source and could be directly downloaded and installed into any GIS capable computer. Also, true color visualization web-based software such as Google Earth which had even given mapping novices some level of confidence due to the fact that it had been made without any associated sophistication had contributed to the hype about disease mapping, rapid risk assessment, and prediction among epidemiologists. No mapping experts could leverage on such web-based imagery software programs and be able to identify, analyze, and interpret spatial phenomenon explicitly as it appears on the zoomed imagery on a computer screen. This way, disease experts had been able to explain some of the identified trends and patterns and also directly answer some of the pertinent questions associated with disease epidemiology such as clustering, severity variation and disease presence or absence *inter alia*.

Again, a number of statistical software programs have also added mapping extensions which have enabled the analysis of environmental and climatic data to be undertaken using such software. This has resulted to a new field of research called geostatistics, which combines both geography and statistics during spatial analysis. For example, statistical software programs such as STATA, R, WINBUGS, and others have been used to process and analyze climatic data derived from remote sensing. In disease risk mapping, space and time analysis had often been conducted using these statistical software programs and they had been widely used as research methods in epidemiology and disease risk prediction in addition to the usage of mathematical models which attempt to explain the underlying factors and quantities in disease risk modeling. Geostatistics therefore had been pivotal in the application and incorporation of remotely sensed data products into disease mapping and epidemiology. The capability of Geostatistics to incorporate technical algorithms that could be used to forecast disease burden in space and time had also contributed to the wide adoption of such approaches as it meant that control programs could *a priori* be informed about disease risk and thus be better prepared to deal with disease outbreaks.

As already mentioned, advances in computer processing power had enabled the integration of computing methods based for instance on Bayesian inference approaches which had been previously limited due to poor computer performance. Data simulation methods such as Markov Chain Monte Carlo (MCMC) and the integrated Laplace approximation (INLA) had been widely used to estimate posterior distribution of geographic data in space and time. The results of which had been obtainable within reasonable time frames compared to earlier computation efforts of similar data. In statistics MCMC are methods comprised of a class of algorithms that sample from a probability distribution. MCMC uses simulation techniques to find a posterior distribution and sample from it. On the other hand INLA relies on analytical combinations that approximate and efficiently integrate numerical schemes to achieve highly accurate deterministic approximations of posterior quantities of interest [25, 26]. As a result of these statistical and computational advances, the integration of environmental and climatic data derived from remote sensing technology into disease mapping models had over the years markedly increased.

Recently, the capability of big data, machine learning and other location intelligence methods to handle a large array of data sets have contributed to the awareness about the application of geographic data as often models using these methods would be performed on geographic software. Big data refers to extremely large data sets that may be computationally analyzed to reveal patterns, trends, and associations relating to human behavior. Machine learning approaches focuses on computer programs that can assess data and use them to learn and improve from experience of them without being explicitly programmed [27]. These analysis methods are often conducted on GIS capable computers and they also rely on remote sensing products such as satellite imagery to analyze and reveal any patterns, trends and associations coming from the data. In disease mapping and epidemiology such analysis approaches are important in understanding risk of disease spread due to human behavior and their interaction with the environment. As a result, most of the diseases mapping efforts currently applied have either practically or theoretically ended up either utilizing remotely sensed data or its associated geographic data products into spatial analysis models as often the resultant modeling outputs would be displayed in a mapping environment.

2.1 Remote sensing data application in vector-borne disease surveillance

Mapping of vector-borne diseases began around 1950 with the use of aerial photography and cartographic techniques. Early studies included those that focused on eradicating malaria, dengue fever and yellow fever whereby climatic factors were used to identify areas at risk of higher transmission. The Malaria Atlas Project founded in 2006 took over from previous mapping efforts and demonstrated the application of geography based variables to map and disseminate accurate information on malaria endemicity. Identifying and mapping vector habitats using climatic suitability was used to guide surveillance and control efforts. Different approaches were used to improve visualization and to produce detailed maps such as high-altitude color-infrared photography and also incorporating high-resolution images [28]. Mapping of vegetation types associated with some of the vector breeding habitat had been carried out since 1973. The techniques used in such analysis had been very important for surveillance support and for identification of vector oviposition habitats. The visualization and interpretation techniques used were based on tone and texture and were used to identify habitats associated with tick-borne disease in some areas based on the concepts of landscape epidemiology of disease [29].

In early 1970s, multispectral scanner data was first used to monitor and map environmental parameters required for the breeding of disease vectors. A combination of remote sensing data acquired from satellites as well as aircraft platforms was used for this task. Later in 1976, some studies demonstrated that computer processing techniques could be used to classify airborne multispectral scanner data for mapping and identifying vegetation types associated with certain disease-causing mosquitoes. Around 1984, remote sensing techniques were applied to describe and map geographic characteristics associated with schistosomiasis [30]. Temperature and precipitation data obtained from remote sensing was also used to estimate the probability of disease occurrence at unsampled locations. These data were also used to identify and map mosquito larval habitats and their association with certain environmental variables in space and time. A study by [31] identified tick habitats on the island of Guadeloupe using derived vegetation and moisture indices.

Most of the studies discussed above were primarily focused on the application of remote sensing to identify and map potential vector habitats and breeding sites based on vegetation, water, and soil. Identifying existing or potential habitats and breeding sites would not be enough to adequately guide surveillance and control efforts unless all possible affected areas were identified and mapped. Therefore most studies have also incorporated predictive techniques as part of their support of surveillance and control efforts. Consequently, it had been necessary for studies to go beyond mere habitat and potential breeding sites mapping and to make predictions of vector distributions in space and time often for the entire geographic area of interest. This often included identification and mapping areas where vector production and disease transmission risk would be greatest in defined time and space thresholds. **Figure 3** is an example of the spatial distribution of malaria vector breeding sites and their distance to subsistence farming in Eswatini.

2.2 Predicting diseases using remotely sensed data variables

An important aspect in the application of RS data in disease mapping and epidemiology is their use as predictor variables in modeling. Disease mapping studies had often used environmental and climatic proxies derived from remote sensing in statistical regression models aiming to predict disease risk in both its spatial and temporal dynamics. These studies predict disease distributions, vector populations and disease transmission risk within the affected populations in specific areas. Common climatic variables used in disease predictive modeling studies often combine remote sensing measurements of vegetation, precipitation, and temperature to identify when and where conditions would be favorable for disease propagation. Other studies have attempted to use remote sensing to predict the temporal as well

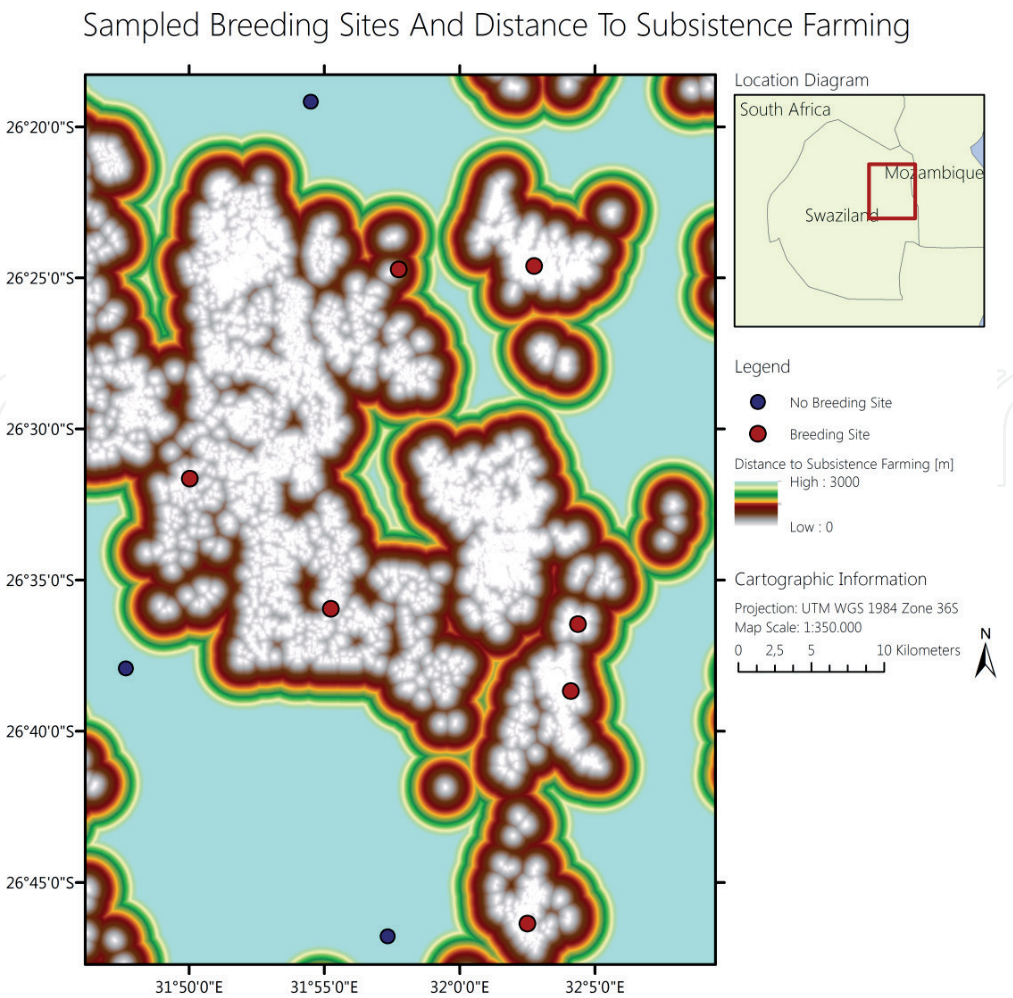

Figure 3.
Example of mapped breeding sites and their distance to subsistence farming.

as spatial patterns, of habitat development, vector populations, and disease transmission risk [32, 33].

Among the most common disease mapping studies where predictions had often been used included those of malaria. These studies also use remote sensing to predict which populations or villages are at risk of transmission. In these cases risk would often be defined by the proximity of a village to areas of heightened transmission as well as the breeding, feeding, and resting habitats required by the malaria vector *Anopheles* mosquito. In addition recent studies have focused on assessing the issue of predictive modeling and disease transmission risk based on the application of remote sensing and GIS technologies. To date, there have not yet been an alternative to disease mapping and prediction in space and time and to identify, characterize, and map the patterns of vector habitats other than using products derived from satellite imagery and remote sensing. For instance, identification and location of areas where vector survival rates are highest had been done using vegetation indices derived from remote sensing. **Figure 4** is an example of predicted potential malaria vector breeding sites in the northeastern part of Eswatini.

Also remote sensing data and GIS techniques had been used to identify and map landscape features associated with disease transmission risk. Landscape features such as brush, woodland and grassland and areas cleared for housing, roads, or trails and other similar locations identified through remote sensing had often been used for detecting intercept areas between human hosts, vectors and parasites. Other landscape features such as coniferous forest, deciduous forest, mixed forest,

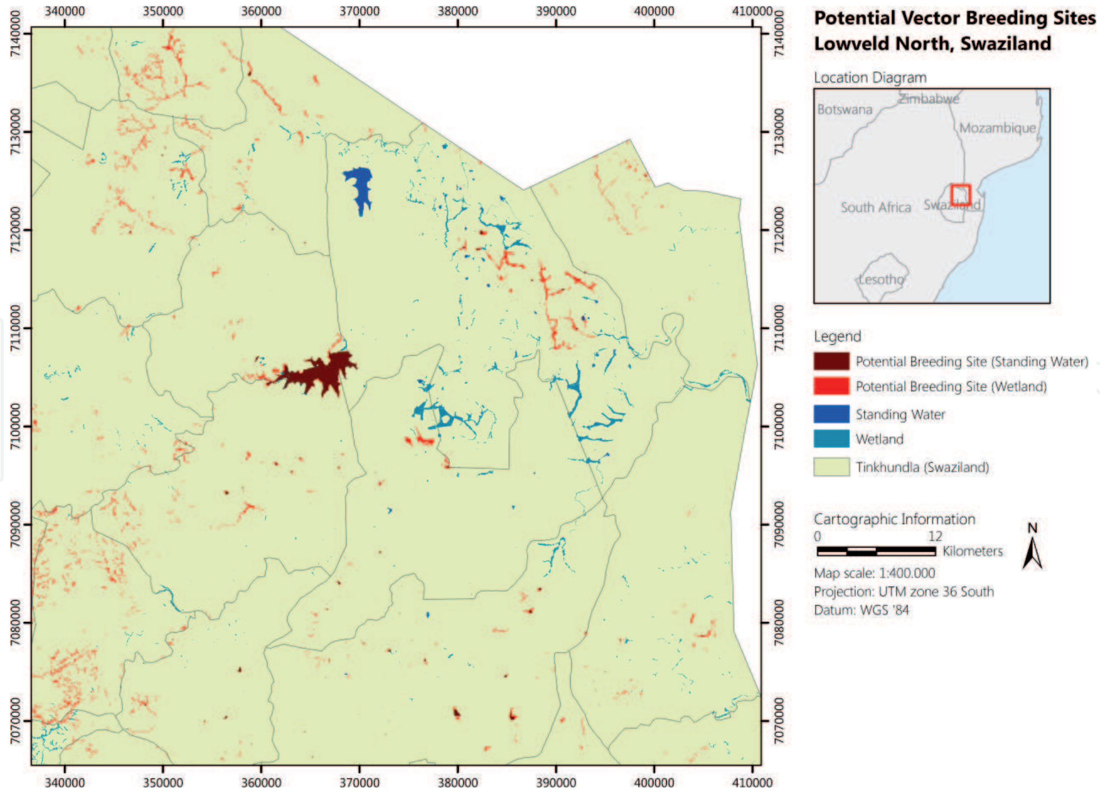

Figure 4.
An example of identified potential malaria vector breeding sites in Eswatini.

water bodies, glades, and housing developments had also been identified via remote sensing. Some studies have assessed these landscapes for their association with the presence of certain disease vectors and the proximity of housing as a measure of human exposure to those diseases. Such landscape epidemiology had therefore been used to identify areas where transmission risk is greatest by characterizing the mixture of deciduous forest and residential developments that bring diseases, vectors, and humans into contact.

Field studies had often been used to train spatial models that make use of remote sensing to map the distribution of disease and predict transmission risk areas. These studies also use GIS to capture groundtruthed coordinates or Global Positioning System point (GPS) which would then be used to assess the accuracy of predictive models. For instance, GIS and remote sensing had been used to investigate the adjacency of certain landscape features and residential properties with dense vegetation as a potential measure of human-vector contact. In this case, regression models would be used to assess general correlations between landscape and disease transmission risk. Evidently, remote sensing and GIS had been combined to study, for instance, the structure and composition of a landscape as it relates to the epidemiology of a disease. Again some studies have combined remote sensing and GIS analysis techniques, to assess various associations between diseases, vectors and human contacts.

Models based on remote sensing data and GIS techniques have also been used to study certain disease vector population dynamics using remote sensing and GIS technologies. Such studies use satellite imagery and GIS modeling techniques to distinguish between areas with either high or low disease-causing vectors. In these cases, ground data on vector populations are used jointly with remote sensing data combined via either a statistical or a GIS software. Ground data variables on vector presence or absence are analyzed in relation to the remotely-sensed spectral data captured via satellite imagery. The groundtruthed field measurement data, that were observable using GPS, would then be used to evaluate the accuracy of the remote sensing based predictive models.

2.3 Current applications of remote sensing in epidemiology

Current research is focusing on the capabilities of remote sensing and GIS data to perform various spatial analyses. The goal is to describe the landscape, or land cover, composition that explains better the distribution of diseases. In this regard spatial models mounted on different software platforms are being developed and validated with observed data to predict spatial phenomenon and in particular diseases that are of public concern. The approaches used to process, analyze and fit data into models are also constantly evolving as new software programs and tool extensions and functionalities become available. There is also an increase in exploratory research involving mathematical and statistical models which aim to capture both the deterministic and the stochastic components during data analyses. In such cases dynamic models involving Susceptible Infectious and Recovered models (SIR) used to model highly infectious diseases such as COVID-19 are being extended by adding probabilistic based components in order to model uncertainty in the behavior of the diseases among the affected population. In these instances, environmentally determined infectious diseases rely on climatic and weather data derived from remote sensing for effective modeling. Furthermore, Satellite imagery could be used to analyze the socioeconomic changes that are currently taking place as a result of COVID-19. This could also be useful in identifying the impacts that measurers such as the national lockdowns are having on the environment. Depending on the resolution of the RS data product being utilized, frequency of data capture and timeliness of the data capture, there is a high potential for remote sensing to be used a tool for deployment and monitoring the effects of health interventions implemented to fight COVID-19.

Point process models such as Log-Gaussian Cox Process had been developed are also being used to model climatic and environmental data on fine geographic scale. These models combine a Poisson process in the first level with a Gaussian Process at the second level and are used to analyze point patterns. In such cases very high-resolution remotely sensed data would be used to enhance boundary delineation during mapping especially at local scales. Tools like spatial scan statistics had also been used to identify and map disease clusters and to determine the key driving factors resulting in the identified clusters. Spatial scan statistics defined as the maximum likelihood ratio statistics over a collection of scanning windows had also been widely used to determine clustering in space and time. Research studies applying remote sensing in disease mapping and epidemiology are currently being undertaken at various degrees of complexity as new methods and techniques become available. The primary focus had been on the use of remote sensing and GIS capabilities to quantify various disease determining factors and to estimate the probability that vector-borne diseases will be more abundant in some of the identified habitats as well as to determine the factors necessary for transmission, survival and reproduction.

3. Conclusions

As already discussed, over the past 30 years, prolific research studies demonstrating the potential opportunities offered by the use of remote sensing, GIS, and statistics in disease mapping and epidemiology had been undertaken. Most of such studies aimed to analyze and measure some of the presumed associations between environmental factors and human diseases. The results of the studies mentioned above had been used to guide the public health community during health intervention planning and decision-making. The studies had also been used to demonstrate the potential offered by remote sensing application to disease mapping and epidemiology and to support surveillance and control efforts. They have illustrated the diversity of potential remote sensing applications in disease surveillance and control programs. However, successful application of remote sensing technology depends on the ability of nonexperts' RS data and end users to access, retrieve, and analyze the data captured from satellites. The preprocessing steps involved before such data could be added as covariates into models also determine their uptake and usage by nonexperts. The ability to develop near real-time monitoring spatial models in order to timely predict the spatial and temporal patterns of vector-borne diseases, and transmission risk is also a motivation for the use of RS data in disease mapping and epidemiology.

Clearly, the dynamics of vector-borne diseases at any location are influenced by processes that operate at a variety of landscape and geographic scales. For instance, malaria transmission is a result of spatial interaction between hosts, vectors, and parasites. Remote sensing imagery involving both high and coarse resolutions when combined with GIS spatial analyses techniques could be used to support and guide existing vector surveillance and control programs at local, regional, and even continental scales. The findings of some the studies cited above had been used to illustrate and cement how remote sensing and GIS technologies can provide epidemiologists with a new perspective in as far as determining the environmental drivers of the diseases concerned. Researchers had been able to study the multiple factors influencing the patterns and distributions of vector-borne diseases at a variety of landscape and geographic scales. The exploration of some of the opportunities presented by remote sensing to disease mapping and epidemiology is still unfolding as new opportunities are being presented.

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Conflict of interest

The author declares no conflict of interest.

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