**SPATIAL DATA QUALITY IN GIS DATA: A REVIEW**

**Abstract:**

Understanding spatial data quality is important in GIS applications. Spatial data are used in a variety of critical applications, including urban planning, environmental management, emergency response, and natural resource management where the accuracy and precision of spatial data can have a significant impact on the decision making, especially when used with predictive analysis. A review of the importance of spatial data quality in GIS data is necessary to understand the factors that affect the quality of spatial data and strategies used to interrogate and maintain spatial data quality. While there is no standard definition for spatial data quality, typically the term refers to the accuracy, completeness, consistency, and currency of the data. One of the key factors that affect spatial data quality is the data acquisition phase. The accuracy of spatial data can be compromised due to errors introduced during data collection, such as measurement errors or errors in data processing of raw data. Therefore, it is essential to ensure that data collection procedures are well-designed and accurately executed to minimise such errors. In this paper a review on various applications of spatial data quality is GIS is showcased.

1. **Introduction:**

Data quality plays an important role in any form of data analysis and predictive analysis. Over the years big data environments like cloud computing, geographic information (satellite images and other earth observatory data) and healthcare have attracted researchers. These fields have huge scope and findings that can be disclosed using data analysis but data quality plays an important role to conclude a strong finding, else it may result in error-prone analysis and predictions.

In the field of earth observatory, the data are generated by various agencies using different tools and techniques. This can result in an error or incomplete data. Such incomplete data or low quality data used for analysis may result in low accuracy or even misleading results. Data quality in GIS is important because accurate and reliable data is essential for making effective decisions. Poor data quality can lead to incorrect conclusions and poor decision-making. In GIS, data quality refers to the degree to which the data meets the requirements for its intended use. This includes factors such as accuracy, precision, completeness, and consistency. To ensure data quality in GIS, it is important to use high-quality data sources, properly maintain and manage the data, and regularly verify and validate the data to ensure it is accurate and up-to-date. Additionally, proper documentation and metadata are essential for understanding the quality of the data and for ensuring that it is being used correctly.

GIS data primarily consists of raster and vector data types. Both types of data sources and databases suffer from different types of data quality issues and can be assessed with different metrics. In the raster data type the database mostly suffers from the satellite image quality and the quality of data in the image source may be due to resolution, visibility or noise.

In this work, we survey of various works to demonstrate the importance of data quality in raster satellite image data sources for various application like cloud cover detection, ocean data, object detection in vector layer, data accuracy of time series data and structural accuracy of bridge, building and roads .

1. **Motivation**

Currently, a huge amount of satellite data is available from various sources varying from low to high resolution with various bands for vegetation and many other applications like ocean data, precipitation time series data, soil temperature data, object accuracy in vector layer. But the issue that exists in the current scenario is to evaluate and find the suitable dataset from existing satellites like sentinel 1 to sentinel 7 and landsat 1 to lansat 9. With such a huge data its becomes difficult to identify a useful data for a user defined application with a specific objective. In such case there is a need of a quality metadata and quality check to be attached to the datasets to make filtration and identification of datasets easier for a specific use cases. In this work our aim is to identify existing spatial data quality which can be generalized to check for data quality.

1. **Related Work:**

In this field many studies are being performed by various researchers to define the need and how data quality can be defined for earth observation data.

There exists various type of GIS data type and use cases where different data quality matrix plays an important role. In general, the GIS data can be divided into raster and vector data types, where raster data includes satellite images from various products like MODIS, Landsat, sentinel and many more. On the other hand, vector data are various layers over the map which are generated through the machine like road maps, river maps, location of hospitals and many more location-based information. Both type of data suffer from data Quality issues and resulting in poor results and analysis. In this section we introduce various quality indexes in raster and vector with some of the related work in that domain.

Data Quality in GIS is attached to various type of data types ranging from satellite data to vector data from sensor like soil temperature, precipitation data, ocean temperate and tides and many more. In [1] a work on data quality for watershed data which is a timeseries data. [1] Mauro et.al. presented a study on the importance of data quality in watershed streamflow and sediment data analysis. The work showcases the study of fine sediment yield in the Goodwin Creek watershed of 21.3 km. The work is a study on the effect of various spatial data, and geomorphology on land use and land cover maps. The work uses various existing models like Soil and Water Assessment Tool (SWAT) and AVSWAT to study the performance. The result shows that GIS data has a significant effect on the models to predict the streamflow and sediment data analysis where the data quality plays an important role to improve the accuracy of the model.

In [42] a study on SDQ for American Community Survey Data 2013 is been performed. This study showcased the data quality errors in the American census data in various parameters like age income where discrepancy in these parameters for some counties was very high using mean and median as data quality parameters.

[2]In this work, the authors have performed a study on the spatial data quality for data from various sources like maps, vector layers and satellite images. The work **showcases a mathematical model to study the data quality accuracy** parameter from various sources and product databases where each product does not fulfil all data quality parameters.

Graphical user interface

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Figure 1. Spatial data quality in GIS

* 1. **Data Quality in Raster data**

Data Quality in satellite images refers to the quality of the image and accuracy of the image in relation to the position and size of the object in the image. Several of the GIS products suffer image quality due to low visibility or resolution and most of the time due to cloud cover in the image. So from the huge data available it is very difficult to identify the useful and correct data for the use case. In order to resolve this data quality plays an important role to define the quality and refine the data using Spatial data quality metrics. Some of the work in the field of image visibility and cloud masking are listed below. In section 3.1.1 accuracy of the data is defined by the cloud cover in raster data from different satellites, where accuracy is defined as the precision of detecting clouds in image with cloud shadow and further classification. In section 3.1.2 the related work from the field of object detection in vector layers and object detection algorithms in raster data are discussed where accuracy is defined as how accurately the object are detected and miss classified which defined the accuracy of the data and algorithm. In section 3.1.3 the work related to accuracy of data in bands from various sourced of raster data is discussed where the quality and Accuracy of band varied from one satellite to other.

* + 1. **Cloud cover and masking**

Ackerman, S [10] has presented a cloud masking algorithm for (Moderate Resolution Imaging Spectroradiometer) MODIS database. The algorithm uses MODIS and LIDAR data from the Department of Energy (DOE) Atmospheric Radiation Measurement (ARM) Program Southern Great Plains (SGP) site in Lamont. The algorithm is trained to find the cloud mask in the image with high accuracy. It uses 3 years of MODIS data.

Kopp, T [11] has proposed a (Visible Infrared Imager Radiometer Suite) VRIIS model for detecting cloud masks. This model used VCM (visible cloud mask) model. This algorithm is used to classify the various land use like cloud, land, soil, water, coastal & snow. This is a product of the Joint Polar Satellite System program, the algorithm is defined for the MODIS database. The model can define multi-layered clouds, can separate clouds and aerosols and cloud shadows.

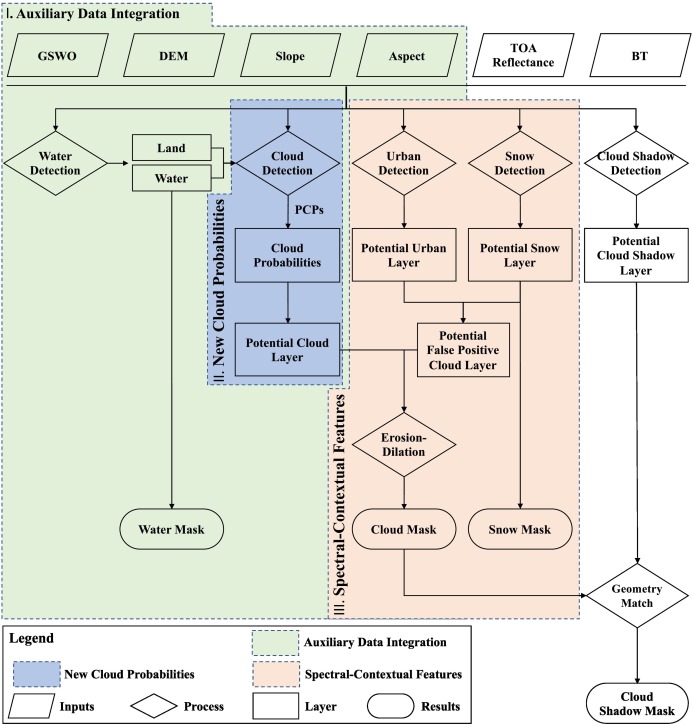
Cesar Aybar et.al. [12] has proposed a deep learning model for cloud detection for Sentinel-2. The model is called CloudSEn12 which is defined to detect cloud, cloud shadow and multi-layer clouds. The model is trained on 49400 image data. The main importance of this model as compared to other models is it can differentiate between thick and thin models. The work is also compared with other existing models like Fmask, Sen2Cor and UNetMob. The figure below shows the performance of CloudSEN-12 with various other existing models for cloud and cloud shadow classification.

Chart, histogram

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Segal R M. et.al. [13] have proposed and improved S-2 cloud mask algorithm using the CNN model. The work provides better accuracy for cloud detection compared to the original S-2 cloud mask. The work uses sentinel-2 data for testing and training the model, with 13 spectral bands and bands of 10m. the testing was mostly conducted on images from Fiji island database.

Qiu.S. et.al. [14] in this work has proposed an improved version of FMASK algorithm for Lansat4, Landsat 8 and sentinel-2 images. This is one of the tools which allows cloud masking for multiple datasets available with high accuracy. This work demonstrates Fmask 4.0, a version of the algorithm integrated with separate models for cloud masking over land and water to maintain high accuracy. Fig X. shows the working of Fmask 4.0 where various auxiliary data are integrated for training purposes and detection of cloud, cloud shadow, urban detection and snow detection.



Additioanlly, there are various other models which are in TABLE X. This **model** proposes the feasibility and study of various other ML models that can be used for better performance.

Table1: cloud detection and masking techniques

|  |  |  |
| --- | --- | --- |
| **Reference** | **Model** | **Model used** |
| 15 | SEN12MS-CR-TS | SEN12MS-CR-TS |
| 16 | SECloud Mask | spectral-temporal classifiers |
| 17 | Fmask | fusion of Images and Auxilary data |
| 18 | dsen2-cr | deep residual neural network |
| 19 | DEcloud | Deep learning model |
| 20 | Luojia1-Cloud-Detection | Threshold-based cloud detection |
| 21 | Deep-gaofill | deep convolutional autoencode for cloud detection and gap filling |
| 22 | CloudFCN | Full CNN |
| 23 | Ukiscsmask | convolution neural network |
| 24 | STGAN | cloud removal using Spatiotemporal Generative Models |
| 25 | Cloud-Net | fully convolutional network (FCN) based cloud detection |
| 26 | CloudMattingGAN | GAN |
| 27 | ES-CCGAN | haze removal using cycle generative adversarial network |
| 28 | Cdnet | basic CNN with low dataset and low accuracy |
| 29 | GLNET | CNN based cloud and non cloudy classification |
| 30 | CDNetV2 | CNN based model cloud detection and removal |
| 31 | AISD | deep learning model for shadow detection |
| 32 | Cloud-GAN | Model used deeip learning GAN model |
| 33 | Mec-GAN | https://github.com/andrzejmizera/MEcGANs |
| 34 | CloudXNet | https://github.com/shyamfec/CloudXNet |
| 35 | SEnSEl | https://github.com/aliFrancis/SEnSeI |

In [15] this work is a comprehensive article that presents a new remote sensing data set aimed at cloud removal in multitemporal images. The authors start by highlighting the importance of remote sensing data in various applications, including land use and land cover classification, crop yield estimation, and urban planning. However, the presence of clouds in the images can significantly affect the accuracy of these applications. To address this issue, the authors introduce SEN12MS-CR-TS, a new data set that includes multimodal and multitemporal remote sensing data with and without clouds.

In another work a model was proposed to remove the noise from the images and new pixels were generated using geometric median. This authors in [16] propose an API name SECloud Mask to regenerate pixel and fill the noise in the image with high quality pixels where noise can be cloud and cloud shadow.

FMask[15] a tool kit and algorithm aimed to identify cloud, cloud shadow and snow in satellite images. The toolkit was released in 2015 which has been improved over the period of time with latest release of FMask 4.0. The tool is made for Landsat 4-8 and sentinel 2 satellite images. The model uses Haze Optimized Transformation (HOT) for prediction of cloud and snow in images. The tool is used to define Normalized Difference Snow Index (NDSI) and Normalized Difference Cloud Index (NDCI).

In this generation of artificial intelligence various work are been proposed using deep learning and neural networks. Various trained machine learning models are be produced using deep learning, artificial neural network, CNN, RNN and many more. In [18] a similar work in presented for cloud detection and removal from sentinel-2 images using deep neural network. The work showcases collection of huge satellite data and training the data for cloud detection using deep RNN which is neural network with large number of hidden layers and neurons. The work is useful to detect and remove cloud from image and regenerate the removed pixels using optical representation of near land structure.

Another work using deep CNN [21] is been presented in a tool called Deep-gaofill. The tool is a image gap filling model using deep convolutional neural network which is trained for filling the pixels in radar images. This work is just a demo since it is not trained with huge dataset.

CloudFCN [22] is a CNN based detection machine learning model for any raster images. The model is aimed to identify thing and thick cluster of cloud and its shadow over the area. The model is trained with Landsat and sentinel images for training purpose. The work uses RGB band images for training purpose. The work is compared with SVM , PCA and single-pixel neural networks (NNs) [39,40,41]

Similar work for cloud detection using fully convolutional network [23, 25] is proposed and used in tool named Cloud-Net and Ukiscsmask for cloud detection. Ukiscsmask is trained using Landsat OLI dataset over U-Net CNN model for cloud detection the work is an extension of existing work where this model extends the cloud classification to five classes (“shadow”, “cloud”, “water”, “land” and “snow/ice”). Where prior to this only 3 classes exists (Cloud, land , no cloud).

On the other hand Cloud-Net [25] is trained machine learning model using CNN for cloud detection in Landsat 8 data. The model is very specific in nature due to its training data restrictions. The work is compared with existing FMask model to compare the accuracy of cloud detection. The proposed cloud-Net model proved provide better accuracy in term of detection of cloud in landsat 8 data.

Some of the similar proposed ML based toolkit for cloud and cloud shadow detection are Cdnet and GLNET [27,28,29]. These are some simple CNN based model for cloud detection and classification into thick and thin cloud. For cloud shadow detection using deep learning is shown in AISD [31] where deep Deeply Supervised convolutional neural network for Shadow Detection (DSSDNet) is used to improve the cloud shadow detection raster Landsat data. In [32] a Distortion Coding Network method is proposed for cloud detection. In [33] another cloud detection algorithm is proposed using GAN which is an unsupervised model with higher accuracy than any other model but need huge data for training. Similar work using machine learning are proposed in [34,35] for cloud detection for various satellite datasets. Since the accuracy in GIS models depends on the quantity of dataset trained and the variety of datasets, so new developments are taking place to make the model more accurate.

After cloud detection and removal the empty pixels need to be filled/generated for this some of the work using mathematical modles [16,21] are proposed. In some of new research Machine learning models and deep learning models are used to improve the accuracy and quality of the pixels. In [26] author has proposed a Generative adversarial network to use deep neural network to generate similar pixel for replacing cloud pixels.

* + 1. **Accuracy of the object in GIS data**

Zhan, Q [4] has showcased a study on accuracy in object identification and placement in **vector maps**. The work showcases the study on the error and changes in accuracy in object detection to find the exact object like streets, buildings, trees and many more. The author has given a model to match the vector data which is a combination of lines and points which allows finding the changes like missing objects or errors in the data. On comparison of different data, the accuracy was found to 81.8%. The study area is in Amsterdam and the Ravensburg site.

Barazzetti et.al. [6] studied the accuracy using RMS(root-mean-square error) of the **images** between sentinel 2 and Landsat-8 images where the comparison of the image registered at 10 m and 15 m are taken into consideration. The work also studies the accuracy of various bands B1-B11 using RMS (root-mean-square error). The study showcases that error in various reference bands 4(10m), 5(20m) and 9(60m) where RMS error was recorded in each image which varies from 0.19-0.55. This can also be used to define the correctness of the data. The study was conducted for images of various countries where the RMSE value for each country was evaluated and where a variation in RMSE value of various locations was recorded.

Marangoz, A. M [7] has studied the accuracy of land use classification between Sentinel-2 and Landsat-8 images. The work aims to first define the land use classification using Sentinel images and compare the accuracy using RGB and NIR bands. In the second phase, the same process is done with Landsat images to find the land use and classification in the image. The work has showcased the lower accuracy in both sentinel and Landsat data with an accuracy of 0.74 and 0.66 correspondingly for RGB and NIR bands. The work also studies the accuracy of object-based classification where the accuracy of the sentinel and Landsat was recorded to be 80.7% and 73.4%. This showcases that for land use and object-based classification sentinel images have high accuracy than lansat-8.

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Frantz, D.[8] proposed a system called FORCE which is a tool to generate images with high accuracy for land use that combines the images from sentinel, Landsat, NANA and ESA. The tool is designed to take multiple images and fuse them into one to generate a single image and bands which has high-accuracy data. FORCE is a data fusion tool to improve the spatial resolution of land surface images using Landsat and Sentinel ARD.

In [9] Kocaman. S et.al. have studied the image quality and geometric quality of Landsat 7 & 8 where various issues were highlighted in the global database at zoom levels and in the histogram which was further improvised by histogram and other techniques. The work presents that the data suffer from the colour difference. The study also studies the advantages and disadvantages of the various data sources as shown below.

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* + 1. **Accuracy of bands in GIS data**

Albanai et.al .[5] has showcased a model to evaluate the thermal accuracy of Landsat in the band on the sea surface. This study allows checking the computational accuracy of satellite images with live data as compared to the vector data available from sea beakers. The work uses bands 10 and 11 from Lansat-8 and compares the accuracy which comes out to be a deviation in accuracy with a mean standard deviation 0.03 over the year. Figure 1 and 2 shows a similar deviation over various seasons for band 10 and 11. The work showcased a deviation is vector data when it was compared with real data from sea beakers

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| --- | --- |
| Chart, bar chart, histogram  Description automatically generated | **Chart, bar chart, histogram  Description automatically generated** |
| Figure1 . Mean-variance in band 10 | Figure2 . Mean-variance in band 11 |

**Structural Accuracy in GIS data**

In this section, some of the work of structural data quality in GIS data and its role is showcased. In [36] author has demonstrated the use of GIS data to measure the accuracy of a bridge deformation. This refers to the evaluation of degradation of data accuracy which allows you to evaluate any error in a structure like bridges, buildings and high-rise structures. This work uses a ground-based radar system to collect the structural data and then further comparison and evaluation The wark was able to evaluate the accuracy of deformation in bridge.

Similar work was done [37] to measure the change in land use spread in urban are using GIS where the accuracy of the data has an important role to play. The accuracy of such data needs to evaluate to measure the consistency in the data collected and the data showcased. This work uses thematic accuracy to evaluate the correctness of the data. In another work [38] Another standard for data positioning in GIS data [38] is National Standard for Spatial Data Accuracy (NSSDA) which is used in the US for positional accuracy of data in GIS data using a normal distribution. Where the normal distribution defines the spread of position error at a specific location.

**Data Completeness**

This data quality refers to the amount of useful data out of the whole data set. In the case of earth observatory data where various platform provides satellite images based on AOI( Area of Interest) in such cases polygon drawn may not provide complete data in such cases the data completeness data quality need to be checked upon.

Similarly other factors the affect data completeness are cloud cover, haze or fog in the atmosphere. As discussed in section 3.1.1 various cloud detection and classification algorithms are been proposed including machine learning models. This allows you to know the useful or visible data that can be used for analysis. Similarly, classification algorithms allow you to know the degree of the visible area, partially visible or cloud-covered area.

Data completeness plays an important role in various applications like landcover, forest cover and sea or water bodies. In these specific GIS applications users are interested in knowing the quality of data in terms of useful data for their need like land cover or sea cover without processing the data. In such case data completeness allows you to know the data completeness in terms of land cover and sea cover which allows the user know the data quality without computing the data which allows the user to select the high-quality data for analysis.

Table 1. Summary of work on data quality

|  |  |  |
| --- | --- | --- |
| **Data Quality parameter** | **GIS data quality** | **Related Work** |
| Percission | Image Resolution,  Quality of Bands,  Number of Bands | [3,5-7,13] |
| Consistency | Logical consistency | [1-2] |
| Completeness | Useful Land data, Useful Sea data,  Useful Forest data | [10-33] |
| Accuracy | Structural Accuracy,  Accuracy of bands ,  Accuracy of the object,  Spatial accuracy,  Temporal accuracy,  Thematic accuracy | [4-9] [36-38] |

// review of

**Conclusion:**

The work **showcases the need for data quality in GIS data for various applications**. Many researchers have showcased the need for data quality in GIS applications like land use, forest application and various other studies on climate and farming. But there do not exist any standard for evaluating data quality of GIS data. This raises an issue where selecting a correct dataset that is useful and on the other hand dataset with low data quality may result in low accuracy and even incorrect assumptions. Various European earth observatories reported that data quality of machine-generated GIS data is low quality when tested. **Thus this work aims to identify a generalized data quality benchmark**. The work can identify some of the parameters for SDQ as shown in table 1, where precision, consistency, completeness and accuracy are some of the parameters which should be evaluated for each data before usage. Table 1 also highlights some of the parameters which are clustered under specific data quality assessment. These generalized parameters will be useful for most of GIS data applications.

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