**ROLE OF SPARTIAL DATA QUALITY IN GIS DATA**

**Introduction:**

Data Quality plays an important role in any form of data analysis and predictive analysis of the data. 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 the data quality plays an important role to conclude a strong finding, else it may result in error-prone analysis and predictions.

Especially in the field of earth observatory where the data is generated by various agencies using different tools and techniques, which result in an error or incomplete data. Such incomplete data pr low quality data used for data 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 is mostly divided into raster and vector data types where the product for raster and vector data type. Both types of data sources and databases suffer from different types of data quality metrics. In the raster data type the database mostly suffers from the satellite image quality and the quality of data in the image source that may be due to resolution, visibility or noise.

In this work, we showcase a survey of various works to demonstrate the importance of data quality in raster in vector image data sources.

**Related Work:**

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

[1] Mauro et.al. has showcased 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.

[2]In this work, author has 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.

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 suffers 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 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.

**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.

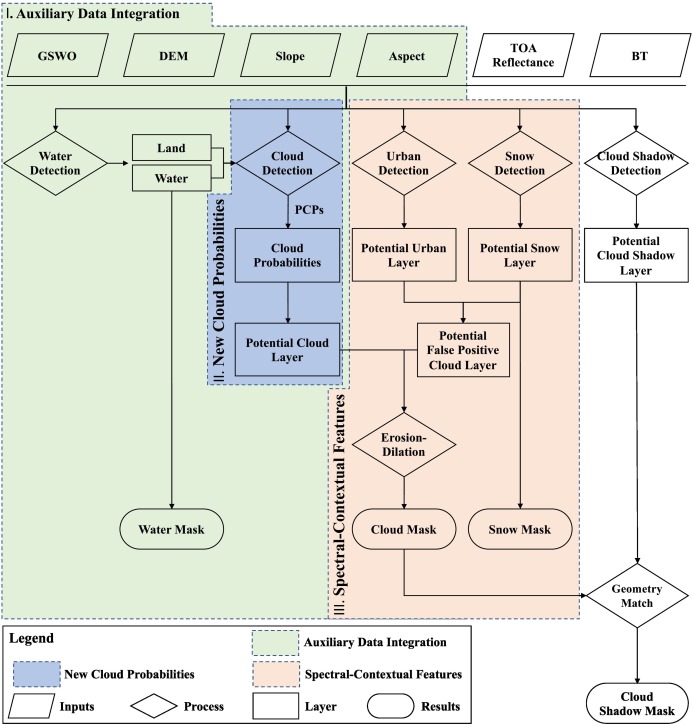
Cesar Aybar et.al. [12] has proposed a deep learning-based model for cloud detection for Sentinel-2. The model is name CloudSEn12 which is defined to detect cloud, cloud shadow and multi-layer clouds. The model is trained on 49400 image data. The main importance of this model as compared to other models 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

Description automatically generated

Segal R M. et.al. [13] have proposed and improved S-2 cloud mask algorithm using the CNN model. The work proves to provide better accuracy for cloud detection as compared to 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.



Other than above-discussed tools there are various other models which are listed below. 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 |

**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 mistakes 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] in this author has studied the accuracy 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 is 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. 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.

Table

Description automatically generated

Frantz, D.[8] has proposed a system called FORCE with is a tool to generate images with high accuracy for land use that combines the images from the sentinel, Landsat, NANA and ESA. The tool is designed to take an image and fuse them to generate a set of 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 showcase that the data suffer from the colour difference. The study also studies the advantages and disadvantages of the various data sources as shown below.

Table

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**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.

|  |  |
| --- | --- |
| Chart, bar chart, histogram  Description automatically generated |  |

Figure1 . Mean variance in band 10

**Chart, bar chart, histogram

Description automatically generated**

Figure2 . Mean variance in band 11

**Structural Accuracy in GIS data**

**Data Completeness**

**Data Accuracy**

**timeliness**

**Data Quality in Vector data**

**GIS-> actua data**

**Conclusion**

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