The evaluations of Signal-to-Noise Ratio impacts on Sensor Data during the process of Data Analytics in a Satellite Imagery

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Abstract: The signal-to-noise ratio levels are used to estimate and validate the selected satellite image band and its feature image quality using the signal-to-noise ratio (SNR). The sensitivity of threshold levels of a satellite image gives in terms of the signal level threshold level of SNR. The acquisition of data from the sensor is affected by the signal strength, heat, distortion, lenses, and atmospheric conditions are created noise from the satellite sensor. The information and its feature depend on the Landsat-8 sensor datasets. The greater the SNR ratios, the improved the image quality, which impacts the satellite imaging system's anti-noise interference accuracy. Today's technology is challenged by satellite cost-cutting for sensor design, and SNR is still not supported by the desired limits in the current technology. The SNR result is influenced by atmospheric parameters such as aerosol, cloud formations, and other noise effects, as well as sensor design, mathematical models, and atmospheric conditions such as aerosol, cloud formations, and other noise effects. The objective of this research paper is to improve the feature of its satellite imagery and increase the signal noise threshold levels of the Multispectral and Hyperspectral imagery of the Landsat-8 sensor. The dataset of the Landsat-8 sensor is processed using average values of standard deviations in machine learning and wavelet algorithms. The results showed improvement of the SNR on each algorithm and its visualization effects on land cover, water quality, and forest area etc. is highlighted by the low SNR values in the satellite imagery.

Keywords: Signal-to-Noise (SNR), Noise detector radiance (NDR), Operational Land Imager (OLI), Thematic Mapper (TM),Enhanced Thematic Mapper plus (ETM +).

1. Introduction

The objective of remote sensing is to maximizing the signal-to-noise ratio and removing unwanted noise from the received signal through optics, spectral systems, and detectors from the sensor, etc. During the pre-processing of image modulation of the original signal adds noise due to electronic circuit converts radiant energy into electrical energy (Othman & Qian, 2008). To optimize this system, you make design, balance, or equalize the signal including sampling time, and spectral resolution so that the signal strength is greater than the noise. The signal-noise ratio (SNR) is used to maintain the sharpness of satellite imagery during the restoration process. The higher the (SNR) value, the increase the sharpening of the restoration back to the original image and the SNR is the parameter describing your original image. The results based on the high SNR value also risk for restoring noise signals to their originals. The SNR values are higher than 50 units are noise-free images and lesser than 20 as noise image shown (Muehlhauser, 2015 in Figure 1 a, b, c) and Figure 2 a and b).

The Landsat-8 satellite has a wider spectral range of TM and ETM+ satellites, and OLI is designed to measure surface reflected radiance with a 30m resolution. The list of bands with different spectral ranges is near, shortwave, visible, and infrared wavelengths. The noise level is based on the quality of the image, stability, and uniform radiation response of the signal noise(SNR) to smoothen the error in the signal noise from the onboard of the Landsat-8 sensor as shown in Table 1 (Schott et al.,2016).

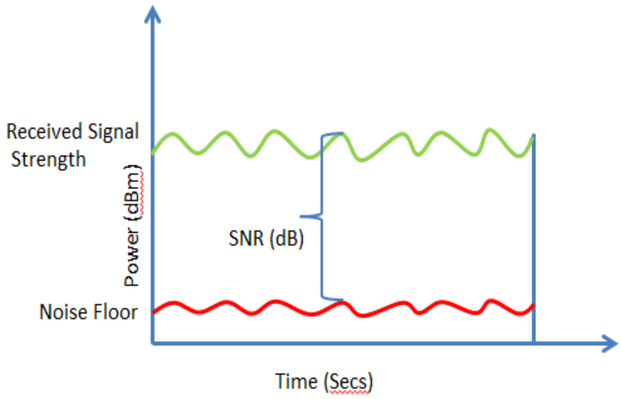

Figure 1. a) SNR Graph

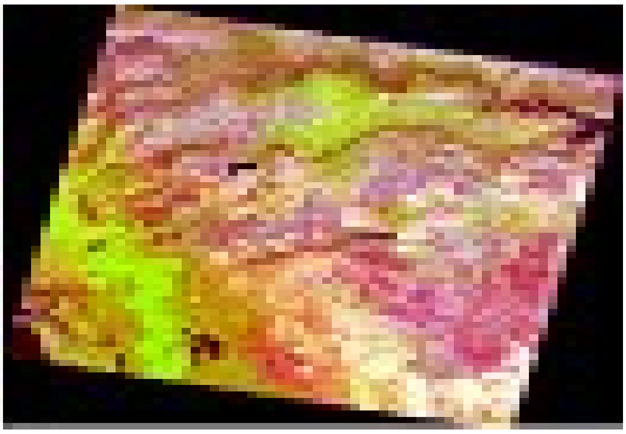
Figure 1. b) Satellite Image with noise <=20

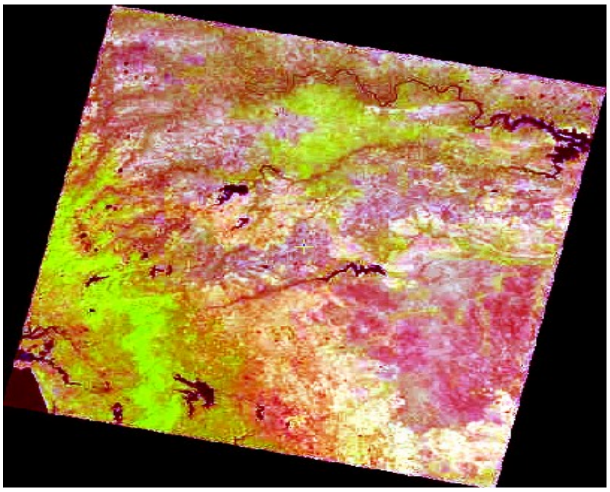

Figure 1. c) Original Image after SNR=50

Table 1. Required SNR and its characteristics

PRIMARY FEATURES USE	BAND	BANDWIDTH	SPECTRAL RADIANCE / REQUIRED SNR	
Land/Cloud/Aerosols Boundaries	1	620 - 670	21.8	128
	2	841 - 876	24.7	201
Land/Cloud/Aerosols Properties	3	459 - 479	35.3	243
	4	545 - 565	29.0	228
	5	1230 - 1250	5.4	74
	6	1628 - 1652	7.3	275
	7	2105 - 2155	1.0	110
Ocean Color/ Phytoplankton/ Biogeochemistry	8	405 - 420	44.9	880
	9	438 - 448	41.9	838
	10	483 - 493	32.1	802
	11	526 - 536	27.9	754
	12	546 - 556	21.0	750
	13	662 - 672	9.5	910
	14	673 - 683	8.7	1087
	15	743 - 753	10.2	586
	16	862 - 877	6.2	516
Atmospheric Water Vapor	17	890 - 920	10.0	167
	18	931 - 941	3.6	57
	19	915 - 965	15.0	250

2. Literature Review

The SNR is the key parameters and the ratio of signal power to the noise power of satellite sensor and it quantifies the signal corrupted by noise due to atmospheric conditions with datasets with high SNRs for better estimation of data analytics and its feature. To design a satellite sensor with a high SNR is an expensive and challenging technology to achieve better SNR value by increase the aperture or lens size to capture a signal strength, lowering the temperature for noise dissipation with larger pixel size. To solve the complex signals noise using advanced satellite signal processing to improve the SNR level and separate the noise coefficient values in the satellite images using machine learning and wavelet transforms and required SNR of the Landsat-8 as shown in Table 1. The noise-reduction or denoising for multispectral satellite image datasets corresponds to spatial and spectral wavelength in the wavelet domain for better results. The spectral derivative of elevating the noise level and wavelet separates the transform domain of signal noise and back to its original time domain by the integration of the spectral domain. The hybrid wavelet method is a feasible and cost-effective solution to improve the SNR of satellite sensor observed images by removing noise and retaining the original signal (Huazhong 2014).

3. Methodology

The OLI and TIS of the Landsat-8 images consist of nine spectral bands with a spatial resolution of 30 meters for Bands 1 to 7 and 9 and Band-8 (panchromatic) is 15 meters. Thermal bands 10-11 are used for accurate surface temperatures and received signals at 100 meters in Table 2 (Othman & Qian.,2006). The daily noise is created due to the following parameters based on SNR, absolute radiometric accuracy, uniformity, radiometric stability, relative and absolute gain calibration, absolute calibration concerning radiance and reflectance. During the night, noise related to Radiometric stability, impulse noise, white noise, coherent noise, and focal length noise and blackbody noise related to deep space collect Noise detector radiance (NDR) collects noise over the ocean, coherent noise, and focal length (1/f).

Table 2. Band descriptions with wavelength

BAND NO	DESCRIPTION	WAVELENGTH	RESOLUTION
Band 1	Coastal / Aerosol	0.433 to 0.453 µm	30 meter
Band 2	Visible blue	0.450 to 0.515 µm	30 meter
Band 3	Visible green	0.525 to 0.600 µm	30 meter
Band 4	Visible red	0.630 to 0.680 µm	30 meter
Band 5	Near-infrared	0.845 to 0.885 µm	30 meter
Band 6	Short wavelength infrared	1.56 to 1.66 µm	30 meter
Band 7	Short wavelength infrared	2.10 to 2.30 µm	60 meter
Band 8	Panchromatic	0.50 to 0.68 µm	15 meter
Band 9	Cirrus	1.36 to 1.39 µm	30 meter
Band 10	Long wavelength infrared	10.3 to 11.3 µm	100 meter
Band 11	Long wavelength infrared	11.5 to 12.5 µm	100 meter

The created noise from the OLI instrument caused by two main sources are: The noise associated with random error signals will reduce the image quality due to the darkness detection, scattering signal, and optical path of onboard circuit from the instrument that creates a noise signal.
Calculation of wavelength and SNR for the various radiance designs are

ETM+=12% and SNR 37% is required for the accuracy improvement in these bands are given below:

Coastal Aerosol (B1), Blue (B1), Green (B1), Red (B1), NIR (B5), SWIR1 (B6), SWIR2 (B7)

Radiance level vs SNR:
Classification accuracy improvements in Radiance Level and SNR (Designed and Achieved) = ETM + Noise Bands (2-7) = 12 %

SNR (Designed and Achieved) = OLI Required Bands (1-7) = 37 %

SNR (Designed and Achieved) = OLI Bands (1-7) = 59 %
Comparison between the noise levels and degraded noise implementation of algorithms after verification of both the images.

- Noise reduction
- Periodic noise removal
- SNR
- Minimum noise fraction

The SNR result is calculated by dividing the mean average signal by the standard deviation variance, and the higher noise is shown as scattered background dots from photon impacts. The calculation of SNR is based on the pixel value of a single photon hit and the computation of SNR:

- Extend the image to the viewer until the individual color pixels are visible. Finding the dark areas and positioning the cursor to respective locations and reading its pixel value in the row and column in the datasheet.
- The background with low-intensity dots with similar intensity by the result of a single photon hit scattered over two or three adjacent pixels. Finding the total intensity noise is the sum of the dot pixel values of a single photon hit.
- The spreading of the intensity in an asymmetric way depends on the design of the data acquisition system with Huygens image statistics.
- Obtaining the good values of :
- I_{SINGLE} and I_{MAX} = {(Black Level - (single hit intensity(I_S) + maximum intensity(I_M))}
- The number of photons (max pixel) = (intensity I_{MAX} / single hit intensity $_{ISINGLE}$).
- SNR = (Mean_signal_value / Standard Deviation) or
- SNR = (Useful_Image_Information) / NoiseorRandom_Information.

3.1 Measurement of Signal-to-Noise (SNR):
Here C refers to electrons but not photons because photons excite electrons in the detector (CCD Camera) that are measured by the circuit device by increase the grey-value of I_{Max} pixel. An ideal condition of the detector is the captured photons has a quantum efficiency and its factor C and the intensity value I_{Max} of the brightest pixel in the image, the SNR efficiency is given (Lingfeng et al., 2009) by :

$$SNR = \sqrt{} C_{Electrons\,,\,Max} = \sqrt{} I_{Max}\, C \qquad (1)$$

- The improvement steps and drawbacks of wrong estimations of results are
- The estimation of results is below the expected desired information of data will be considered as a noise in the high-frequency range and the resulting image is smooth but lacking detailed information.
- The estimation is more than expected the noise may not be removed properly and has a significant impact on satellite image quality.
- Some artifacts are generated like a noisy background and the appearance of tiny objects in the restored satellite image.

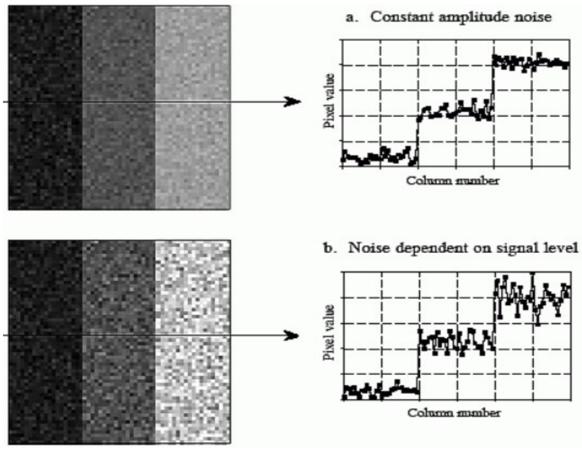

Figure 2. a) Image Noise Levels

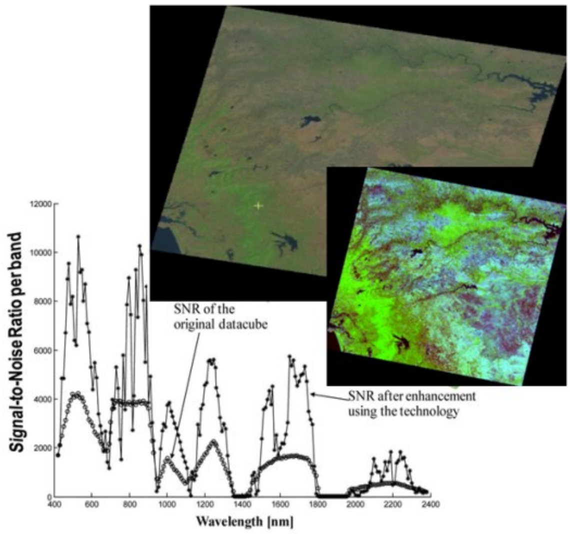

Figure 2. b) Signal-To-Noise Ratio (SNR) of a Satellite Data cube Pre and Post enhancement using advanced signal processing

3.1.1 Types of satellite imaging processing noise
Randomized Noise:
It is based on the intensity fluctuations of the actual image and it will generate some amount of random noise due to the circuit design of the imaging system for continuous exposure parameters.
Scattered-Pattern and band fixed noise: The pixels are related to columns and rows of pixel data and it is related to the sensor detections.
Simulation of SNR Model: It is the ratio of signal electrons number to noise electrons number, measured in decibel (dB) in scientific applications.

4. Multispectral Datasets for the case study

4.1 Satellite Data Products: Belgaum District is in Karnataka State (India's northwestern region).The Landsat-8 sensor having nine spectral bands of Datum WGS-84 and UTM-Zone-43 with an area of 170 km × 185 km each tile. This image has a spatial resolution of 15 meters by 15 meters and a resolution of 30 meters by 30 meters. In the Landsat-8 (OLI) and (TIRS) images. The satellite image (https://earthexplorer.usgs.gov) datasets product is 14th, April 2020 collected for the case study in the Belgaum region (VTU Campus). The soil feature is types of rocks, black soils, red loamy soils, etc.

$$SNR = 20\log_{10} (N_{Signal} / N_{Noise}) \quad (2)$$

$$[C / N_{0]T} = C / ((N_0)_U + (N0)_D + I_0)$$

T=Total
U=Uplink
D=Downlink
I_0= Interference noise

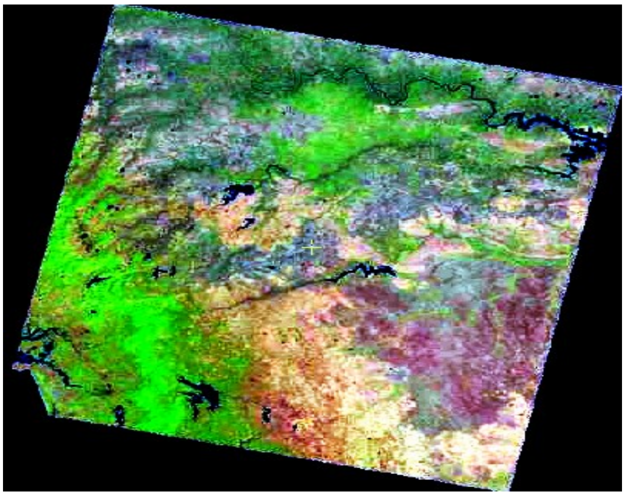

Figure 3. Data Product for Research Area

5. Case study experimental results and discussion

In satellite sensor design, the percentage of error (SNR) is high in the blue band and NIR band and relatively high impact in the blue band by the high atmosphere signal from the longer wavelengths. The relative error of bright lakes is a function of water clarity is below 50% for all bands and the highest errors in dark lakes. The results are based on the standard deviation$_s$ amplitude range and the spatial resolution Lake / Dam / River area (Wang et. al., 2019) as shown in Figure 3 and RGB Profile Graph and Image in Figure 4 a, b, c and d.

The pseudo code is given by

- imagery=imageread(Data Format');
- image = double(imagery(Data types));
- image = max(imagery(Data types));
- imagery = min(imagery(Data types));
- ims=std(img(Data types));
- snr=10 * log((image - ims) / ims);

The results of satellite imagery (red band) based on filtering are Majority, Gaussian, Bilateral, Edge aware, and anisotropic diffusion. Object-based voting is Crisp Voting and soft voting. The Relearning methods are relearning Histogram and Relearning PCM. The Random field is MRF.

5.1. Filtering: The anisotropic diffusion filtering is used in the post-computing problem to remove salt and pepper raw classification effect can see the pixel-wise classification. The mathematical model proposes a new equation-3 is given (Shen et.al., 2011) by

$$C(x) = \text{argmax } (P_{x,\, i}) \text{ where } i \in C \quad (3)$$

The intensity image provides a Gaussian smoothing with two intensity images that are

- Bilateral filter = $G_g(Ix - Iy) = Gg(Px,i - Py,i)$;
- Edge filter = I(x) and I(y)

The anisotropic diffusion is defined in eqnuation-4(Nair, et al., 2019) as:

$$\frac{\partial I}{\partial t} = d^t(x,y)\, \Delta I + \nabla d . \nabla I \quad (4)$$

5.2. Object-Based voting (OBV): The OBV is classified into crisp and soft voting in equation-5 (Nair et al., 2019) as:

$$\text{Crisp: } P_{s,\, i} = 1/N_s \sum T(C(y) = i) \quad (5)$$

$$\text{Soft: } P_{s,\, i} = 1/\, N_s \sum P_{y,\, i}$$

5.3. Markov random fields (MRFs): It improves the neighbor pixels and satisfactory results raw classification map is in equation-6 (Xiangyong et al., 2017) as:

$$E(X, C) = -\sum_{x \in X} \ln(p_{x,i}) + \beta \sum_{y \in N_x} [1 - \delta(C(x), C(y))] \quad (6)$$

Nx is a neighborhood cantered by pixel C(x,y).

5.4. Relearning: The primitive co-occurrence matrix (PCM) is called relearning and the frequency window and without loss of generality of PCMs is given by (Xin et al., 2014) the equations-7 as

$$PCM(w,dis) = \sum_{dir}(w,dis,dir) \quad (7)$$

$$\text{with dir} = \{0^\circ, 45^\circ, 90^\circ, 135^\circ\}$$

The noise removes all enhancements and displays the original image and noise is the result of errors in the image acquisition process that do not reflect the true intensities of the real scene. Linear filtering improves the overall contrast of an image by stretching the min-max values in the image to the normal distribution with DN units.

For each spectral band, OLI specifications and performance were compared to ETM+ performance for SNR (Landsat-8 Handbook, USGS-2019) at specified levels of Typical Spectral Radiance (Ltypical) (see Table 3 and Figure 5).

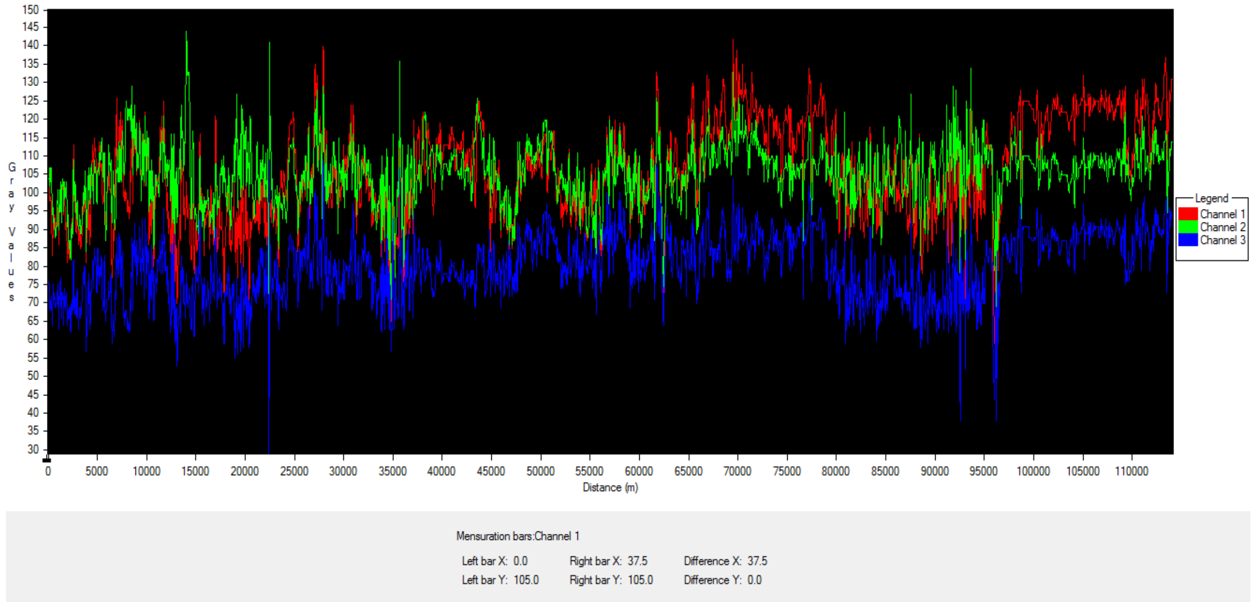

Figure 4. a) Satellite Image RGB Profile Graph

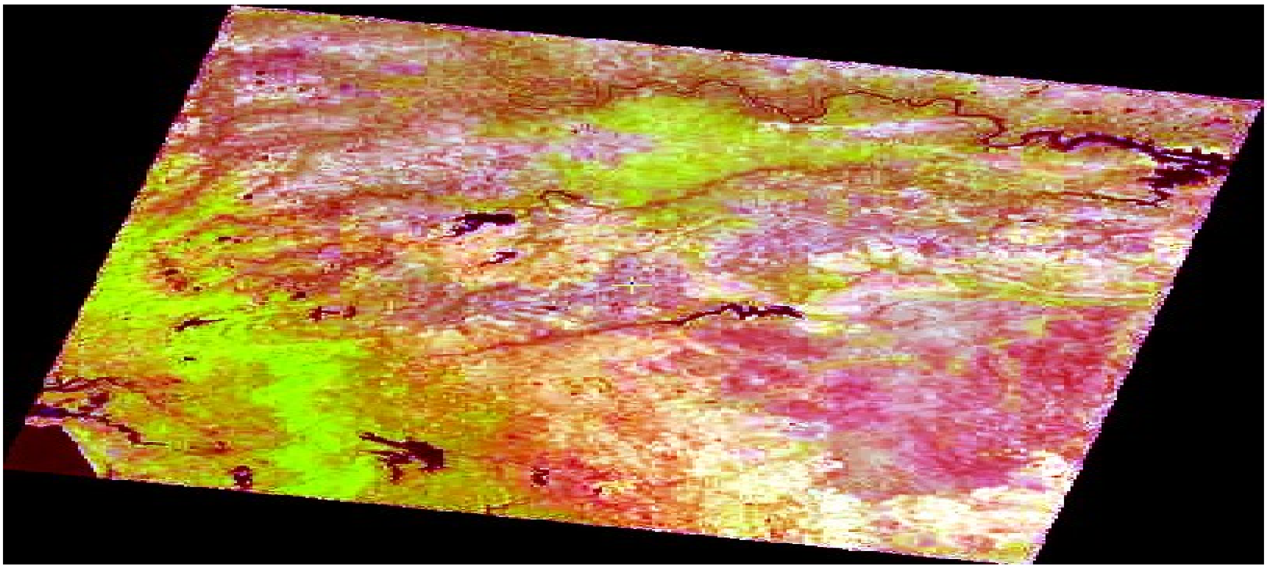

Figure 4. b) Satellite Image

Table 3. Landsat-8 OLI Specified and Performance of Signal-to-Noise (SNR) Ratios Compared to Landsat-8 ETM+.

ETM+ BAND	OLI BAND	ETM+ PERFORMANCE	OLI REQUIREMENTS	OLI PERFORMANCE
N/A	1	N/A	130	238
1	2	40	130	364
2	3	41	100	302
3	4	28	90	227
4	5	35	90	204
5	6	36	100	265
7	7	29	100	334
8	8	16	80	149
N/A	9	N/A	50	165

During the prelaunch of sensors measured in Signal-to-Noise (SNR) ratios specified by Landsat-7 ETM+ (Green Bar) and Landsat-8 OLI (Red Bar) and its respective bands. The Blue Bar graph is measured SNR values in units. The performance compared and representations in Statistical Bar Graph (Landsat-8 Handbook, USGS-2019) are given below:

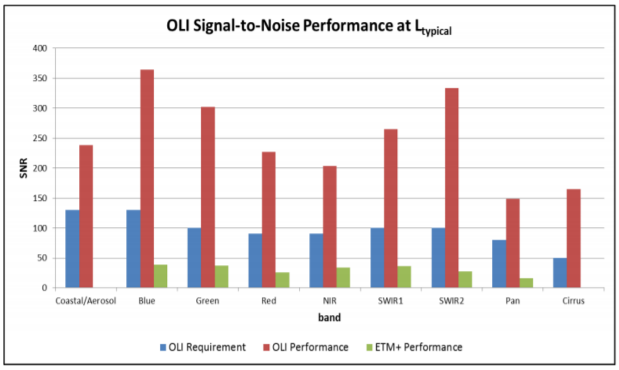

Figure 5. Statistical Bar Graph: Landsat-7 ETM+ and Landsat-8 OLI Signal-to-Noise (SNR) Performance measured before Pre-launch, after launch measured, and expected SNR.

After processing satellite data, Landsat-8 OLI offers a reference, as well as higher sensitivity to chlorophyll and other suspended components in coastal waters and improved atmospheric features and the initial baseline for coastal resource management, Landsat 7 ETM+ data was used. In satellite signal communications, the carrier-to-noise ratio is the measure of received carrier strength (Relative) signal to the strength of the received noise signal. The Signal-to-Noise ratio (SNR) is a parameter that controls the sharpness of the restoration or sharper of the image results based on the SNR value. The SNR is a parameter describing the original image based on the number of iterations and it quantifies how much the signal has been corrupted by noise.
The ranges of the good quality images are

- 15 dB to 25 dB is an acceptable level due to poor connectivity
- 25 dB to 40 dB is a good Signal.
- 41 dB or higher is considered to be an excellent signal.

The calculating the Signal to Noise Ratio (SNR) = The Peak signal (PS)-Background signal (BS) / the square root of the Background signal (BS).
For power spectrum of SNR = (Avg. signal power) / Avg noise power)
Its units in dB are given by (SNR_{dB}=10 $\log_{10}$(SNR)) (8)

5.5. Adaptive filtering applies is using the wiener filter (linear filter), local image variance, and performing more smoothing. It preserves edges with the high frequency of an image with more computation time.

5.6. Equalization Applies is a histogram equalization enhancement of the original image as shown in Table 4 and Histogram display in Figure 6.

Table 4. Channel Statistics

	Sample Min	Sample Max	Sample Avg	Weighted Avg
Channel 1	35.000	142.00000	106.31965	106.31811
Channel 2	57.000	144.00000	105.51302	105.51256
Channel 3	29.000	109.00000	080.00041	080.00776

5.2 Adaptive Functions

The adaptive filtering techniques are used in multidimensional signals, image processing enhancement or restore data, or removing noise with good results. MMSE was used to estimate the input data by calculating the noise from the mean of all the local variances. The estimation of additive noise in the presence of multiplicative noise is used to remove noise from images without blurred edges of images as shown in equalization Figure 7.

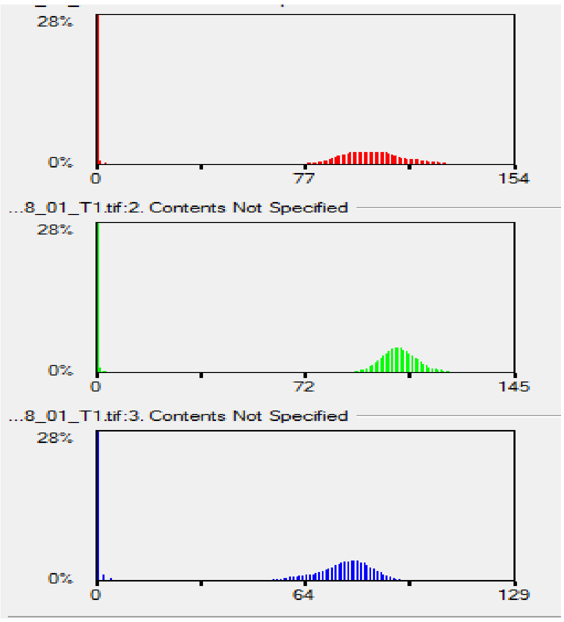

Figure 6. Histogram Display

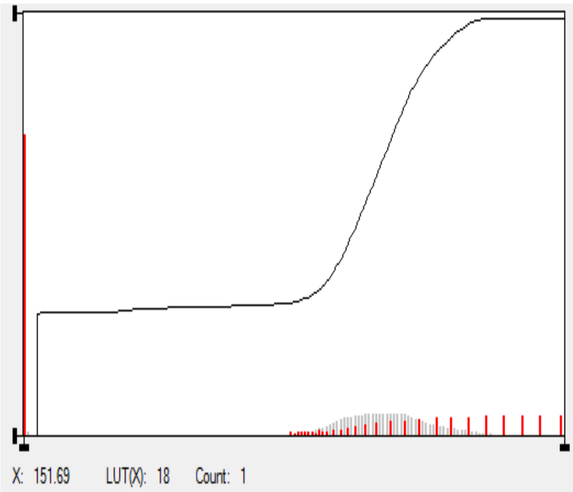

Figure 7. a) Equalization Graph

5.3 Infrequency Function

Infrequency Applies is an image enhancement and it maps a gray level's frequency of occurrence as shown in Figure 7 a and b).

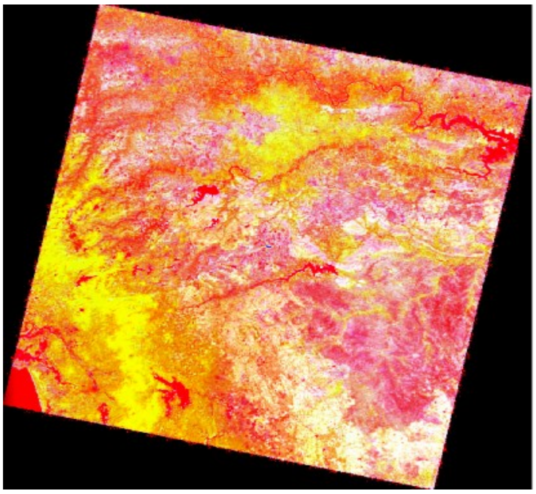

Figure 7. b) Using Infrequency Function

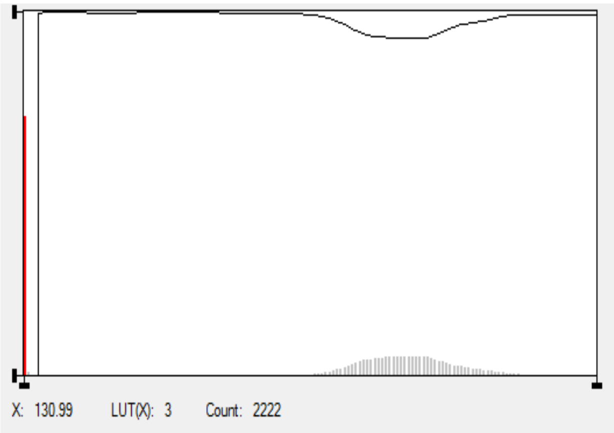

Figure 7. c) Infrequency Function Graph

5.4 Linear Function

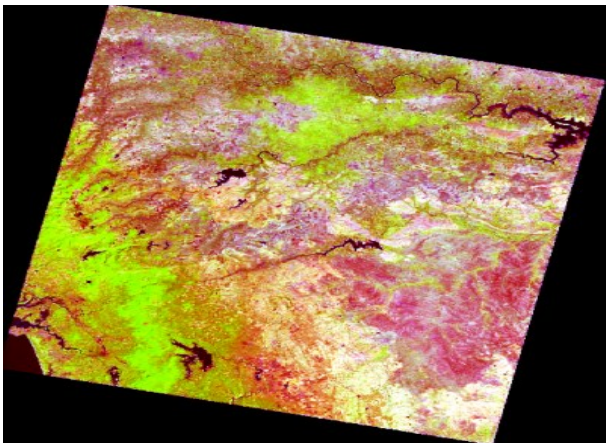

Figure 8. a) Using Linear Function

The noise signals of a satellite image having a bad or wrong setting of the sensor, vibration, heat generated electrons, and mean square estimations(cloud)is calculated by the square of the difference between the noise-free image and the denoised image[14] as shown in Figure 8 a) and b).

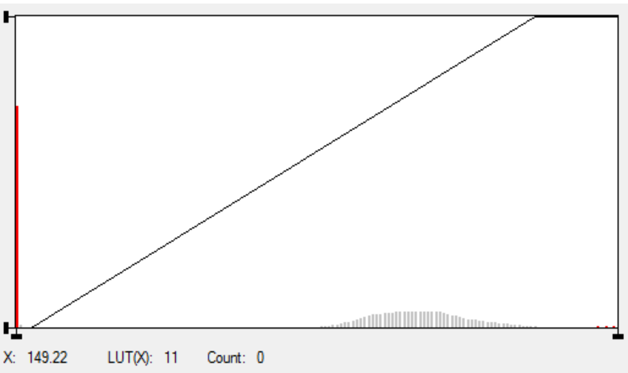

Figure 8. b) Linear Function Graph

5.5 Noise Function

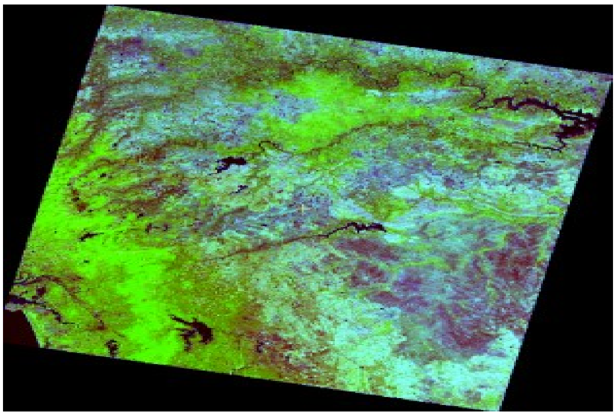

Figure 9. a) Using Noise Function

Noise Function which processes data for visual interpretation, removal of atmospheric effects, or automated analysis can be divided into sensor-related, calibration, geometric correction, and noise removal graphs as shown in Figure 9 a) and b).

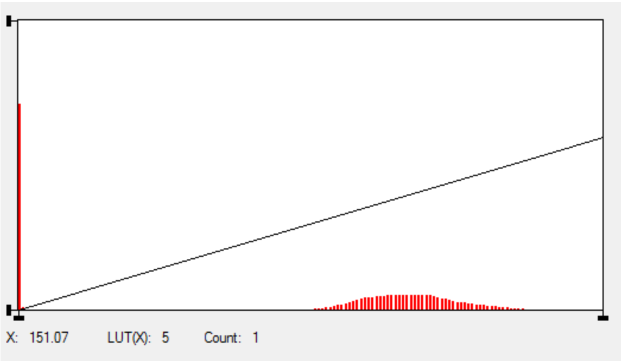

Figure 9. b) Noise Function Graph

5.7 Square Function

Square root or logarithmic Function stretch enhancement, which compresses higher DN values in an image, and Original darker values in the image are given more contrast than the original bright (high-DN) values with disproportionately expanding the darker values as shown in Figure 10 a) and b).

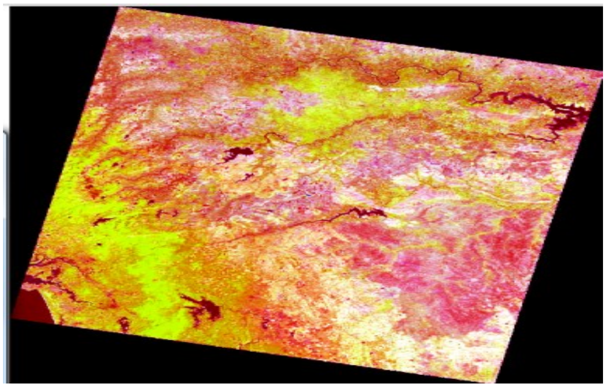

Figure 10. a) Using Square Function

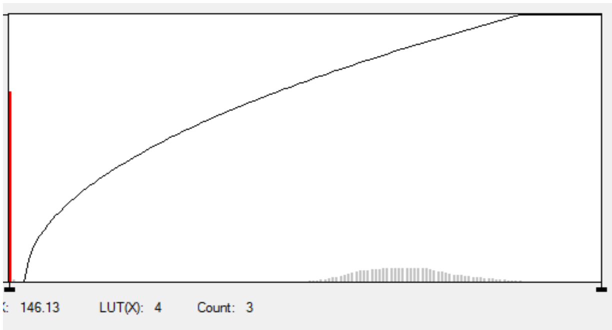

Figure 10. b) Square Function Graph

After applying SNR Functions like Linear, Adaptive, Square, etc. are given the good results of SNR value. There might be a risky for restoring noisy originals images due to more enhancing the noise levels. The SNR values greater than 50 indicate a noise-free image, therefore the ideal way for estimating SNR is to use the Standard Deviation (STD) method. The maximum noise levels around exists in the image pixels noise and after applying standard deviation is measured as shown in Figure 11 a) and b).

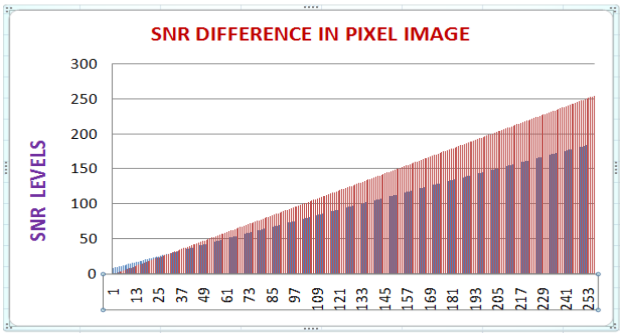

Figure 11. a) SNR Difference in Pixel Image

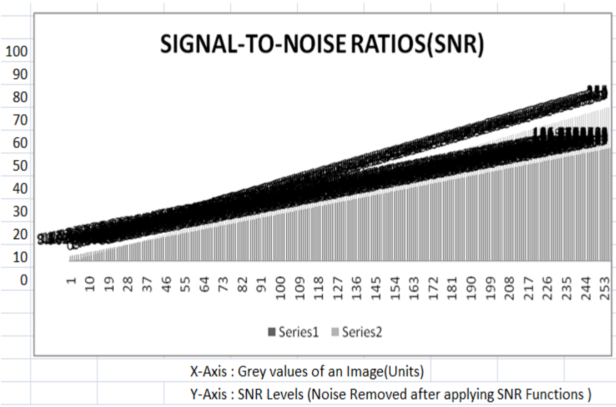

Figure 11. b) VTU Campus Satellite Image Vs Signal To Noise Ratio in Levels

In optical sensing systems, there are seven types of inaccuracy errors are: sensor drift, irradiance fluctuation, sensor calibration error, sensor radiometric resolution, signal digitization, atmospheric attenuation, and atmospheric path radiance. By using the Root Mean Square Error (RMSE) measures the error rate between the two data sets or classes. It compares the predicted value and an observed value (with known Reference Values) is given (Simon et al., 2018) in equation-9 is:

$$\mathrm{RMSE} = \mathrm{SQRT}\sum_{i=1}^{n}(\mathrm{Predicted}_i - \mathrm{Actual}_i) \qquad (9)$$

Cross-Validation of using RMSE using with two class (Bands) is given by
Accuracy = 0.5120 Precision = 0.0025 Correlation = 0.0354 Error Rate = 0.4880

RMSE = 3.492849 and Bias = -2.44

The RMSE displays concentrated noise data surrounding the line of best-fit equations, and it is a measure of how to spread out these residuals of noise are shown in Figure 11 b). The Signal to Noise Ratio (SNR) used to correlate the image quality and radiometric performance of the satellite imagery to be calculated to assess the image quality of the optical imaging system.

5.8 Scope and advantages of using AI & ML in Sensor Technology

The use of Signal-to-Noise (SNR), Artificial Intelligence, and Machine Learning to reduce the cost of satellites for sensor design is testing today's technology. The desired limitations in the datasets support satellite data communications technology. In this case study of the research area, the SNR results are influenced by atmospheric correction, sensor design, mathematical models, and atmospheric circumstances such as aerosol, cloud forms, and other noise effects. The results showed features improvement using the Signal-to-Noise (SNR) and AI & ML on each algorithm and its visualization effects of all the features classification to help to find accurate assessment of classifications on land cover, water quality, and forest area, etc. is highlighted by the low/high SNR values in the satellite imagery using Radiance level Vs SNR, Filtering, Equalization, Adaptive Functions, and Frequency Functions, etc.

6. Conclusions

The conclusion of this research case study is to use Filtering, Denoising Techniques, Adaptive Frequency Functions, Equalization, Artificial Intelligence, and Machine Learning Algorithms to improve the feature of its satellite imagery and increase the signal noise threshold levels of the Landsat-8 sensor's Multispectral and Hyperspectral Imagery. The characteristics of the illuminance of ground objects are low and vary day and night, transition to the signal-to-noise (SNR) test method based on time-sequence images for low-resolution cameras. It established the radioactive transfer model between night-light cameras and ground objects. The combing with radiometric calibration results calculated the theoretical SNR on-orbit with sequence images captured by a satellite. The traditional method cannot be used for low-resolution images for reliable solutions for on-orbit SNR calculation of night-light cameras by the sensitivity analysis of actual theoretical SNR and on-orbit SNR results. Concerning the results, the errors are acceptable for night-light image applications. The simulation predicts an algorithm calibration, perfect atmospheric correction, and error-free in datasets. The major sources of noise are clouds or cirrus clouds, which could be confused with proper classification in time series analysis with lower thresholds.

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