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A SOCIO TECHNICAL APPROACH TO SCHOOL INFRASTRUCTURE MANAGEMENT USING DEEP LEARNING BASED ASSET MAPPING AND CATCHMENT ANALYSIS IN TIRUPATI DISTRICT

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ABSTRACT

Schools are fundamental to social development and human capital formation and equitable access to educational facilities is essential for sustainable regional growth. Rapid population increase and unplanned spatial expansion often lead to uneven school distribution and accessibility gaps especially at fast growing district like Tirupati District. In India, traditional planning approaches depended on administrative boundaries lack the spatial details which effect decision-making. To address this problem proposed a socio-technical approach by integrating Deep Neural Remote Sensing (DNRS) with Geographic Information Systems(GIS) to support education infrastructure planning. For this school buildings, play grounds, surrounding campus assets were extracted in spectral-spatial hyperspectral image called Hyperion through deep neural model. These outputs were incorporated into QGIS to delineate catchment zones, assess accessibility and evaluate population pressure. Further a suitable analysis is done to identify priority locations for establishing future schools based on accessibility, population density and land use constraints. Thus this proposed method provides a scalable, data-driven decision-support tool for equitable school planning.

KEYWORDS: Deep Neural Remote Sensing, Hyperspectral Imaging, Hyperion, School, Catchment, Tirupati District.

1. INTRODUCTION

Schools are essential for growth of regional, social development and equity for supporting human. Mainly education is linked to school accessibility, capacity and spatial distribution. But in rapidly growing regions learning opportunities in schools reduced due to travel burdens, infrastructure and overcrowded classrooms because faster expansion of residential developments. However, the developing area like Tirupati district which is located in Andhra Pradesh exemplifies this challenge due to demand of schooling because newly divisional district.

The traditional approach for educational planning rely on ground/physical and administrative statistics surveys. Despite their importance, these methods need more laborious and do not provide enough spatial accuracy. The educational planners can assess and locate areas with the help of Geographical Information System (GIS) [15] very easily. This GIS framework provide spatial school location, roads, population distribution data. But their effectiveness relays on accurate catchment mapping.

The remote sensing image particularly Hyperspectral Image from sensors has high dimensionality and mixed pixels [19] and presents a significant challenge for feature extraction. This sensor image provides a detailed spectral-spatial data like infrastructure, environmental conditions and land use over vast area. For this classification the Hyperion hyperspectral image is used because this HSI has the ability to distinguish insignificant materials like plants, pavement and rooftops etc.

For extracting spatial-spectral features of Tirupati District Deep Neural Remote Sensing (DNSR) model is applied because it maybe a best and most powerful method to identify buildings, classify surfaces and map infrastructure assets of schools for powerful solution.

This research proposes an socio-technical approach by integrating DNRS and GIS model to predict school catchment in Tirupati District study area using hyperion hyperspectral image using deep neural model for mapping school buildings and associated campus feature. This outcome was combined with statistical datasets like population and road data in to QGIS for determine school catchments, identify underserved settlements and suitable areas for new schools. So, this proposed research provides a scalable, data-driven decision support system for equitable school infrastructure planning.

2. RELATED WORKS

Recent years have seen a proliferation of techniques and review articles that examine algorithm, data and application advancements as a result of fast expansion of Report Sensing Image Processing (RSIP) due to advancements in Deep Learning (DL). Without explicit human feature engineering need DL model learn feature representations directly from data in an end-to-end manner [1]. By using machine Learning model [3,4] which is a game changing with impressive results including object detection, semantic segmentation, image recognition and many other tasks. The expert-free automation and versatile feature representation of DL have made it popular choice in remote sensing research. While it comes to time-series classification DL's skills for handling temporal aspects are particularly promising. Several models have been developed to improve land-use/land-cover mapping. Notable examples include Temporal Convolutional Neural Network (TCNN), Deep Recurrent Neural Network (DRNN), Bidirectional Long Short-term Memory (Bi-LSTM) is one such model achieved for improving land use/land cover [5]. However, developing DL architectures that can accurately represent the lengthy and intricate temporal interactions found in remote sensing time series is still a difficulty [6]. Despite Convolutional Neural Network (CNN) models are superior for two-dimensional pattern recognition they are also capable of competitive classification on one-dimensional spectral and temporal inputs [2]. Nevertheless, attaining high performance frequently need meticulous architectural planning and rigorous testing, leading models progressively intricate and computationally demanding. As a general rule, deeper layers' extract more general temporal patterns whereas lower levels catch more specific variations over shorter time periods [6]. Although deeper structures typically provide better results with longer time series, they may mot be as effective with shorter or sparse time series.

Remote sensing has many potential uses in that geological mapping is one of them. It also helps with things like mineral prospecting and prospective mapping [7,9]. When faced with challenging terrain, political restrictions or safety issues, conventional field mapping can be expensive, time-consuming and impractical remote sensing provides a viable alternative [10]. Images are gathered by optical remote sensing systems installed on satellites using a wide range of electromagnetic frequencies from visible infrared spectrum [11]. Geologists can benefit from data collected by multispectral sensors, which measure light in visible, near infrared (VNIR, 400-1000 nm) and short-wave infrared (SWIR, 1000-2500 nm) bands. The distribution of rocks and minerals can be mapped using multispectral photography due to their unique spectral absorption properties [13,14]. Where mapping and classification methods based on spectra are founded. The ability to distinguish between rock units across vast areas is made possible by high spatial and spectral resolution of satellite images [15]. Problems with sin-pixel heterogeneity, sensor noise, mineral mixing, thick regolith cover, data gaps induced by vegetation and cloud cover and thick regolith cover continue to make geological mapping using remote sensing problems [8,15,17]. There have been several proposals for frameworks and methodological breakthroughs to address these difficulties [18-20].

A common component of conventional geological mapping methods is the comparison of absorption characteristics to reference spectra or training samples [12]. On the other hand, it is no easy task for collecting enough samples can be considered representative. Mineral composition, particle size, texture and structure variations are impacted by geological processes, which in turn affect spectral variability [21]. As a result of strong correlations between spectral bands lacks labelled samples and high spectral variability within rock units distinguishing between lithological classes is difficult [22]. So, improving geological discrimination performance [23] requires identifying informative features while suppressing redundant information.

Advancements in deep learning for remote sensing have been summarized in multiple reviews. Li et al. [25] analysed deep learning techniques for RSIP covering both scene level and pixel-wise procedures. Whereas Yao et al. [24] examined data sources and classification methods. Quote few noteworthy surveys emerged in 2019 when it comes to hyperspectral image scene categorization. Li et al. [26] went over some DL methods and how to make them work better. Hyperspectral classification algorithms, frameworks and normalization strategies were thoroughly reviewed by Paoletti et al. [27]. The work of Song et al. [28] outlined current difficulties and potential future directions in the use of CNN methods for remote sensing scene classification. The well-known models comparing including CNN, GAN and SAE by Cheng et al. [29] investigated difficulties, datasets, benchmarks and new possibilities. Alem et al [30] examined deep CNN architectures on various remote sensing datasets, whereas Vali et al [31] examined scene categorization methods using hyperspectral and multispectral viewpoints. Using CNN and Convolutional Recurrent Neural Network (CRNN) architectures as an example. Kuras et al., [32] examined data fusion methods that integrate hyperspectral and LiDAR data for urban land cover mapping. The methods of land-use mapping ae supervised, semi-supervised or unsupervised including pixel and object based approaches were reviewed by Zang et al. [33]. Lastly [34] provides a more comprehensive review of current DL models and hybrid RSIP approaches.

3. METHODOLOGY

This paper proposed framework for mapping asset of school catchment monitoring and catchment prediction in Tirupati District, Andhra Pradesh, using deep neural remote sensing model to map the school assets in hyperspectral image. The proposed method is visualised in figure 1.

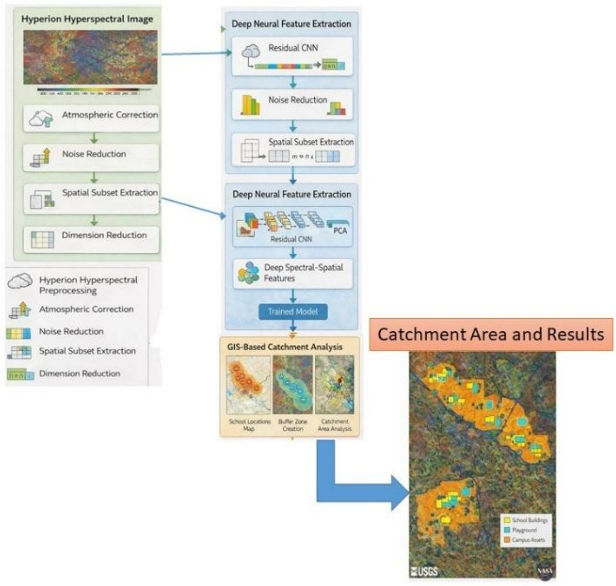

Figure 1. Workflow of the proposed methodology

3.1. Deep Neural Network Remote Sensing

Deep Neural Remote Sensing (DNRS) refers to the application of deep learning architectures to automatically learn spectral, spatial, and contextual information from remotely-sensed images [35]. Unlike traditional pixel-based or handcrafted feature approaches, DNRS allows the model to extract hierarchical features directly from raw data, improving object detection, classification, and feature extraction accuracy.

In this study, DNRS was used to extract school buildings, playgrounds, and campus assets from Hyperion hyperspectral imagery. The method integrates both spectral variability (across hundreds of bands) and spatial structure (shape, texture, and neighborhood relationships).

3.2. Model Architecture

A spectral–spatial deep neural network was implemented in three stages:

1. **Spectral feature learning (1-D CNN / PCA**

compressed bands) High-dimensional Hyperion bands were first compressed using PCA/MNF to reduce redundancy, and then fed into convolutional filters to capture discriminative spectral responses.

2. **Spatial feature learning uses 2-D CNN patches** to learn about school's physical layout and land use patterns in the area by capturing geometry, edges and texture of object in images.
3. **Feature fusion and classification using Fully connected layers and Softmax**: combined with spectral and spatial characteristics to get final class probabilities for every pixel..

$$\widehat{Y} = Softmax(f_{fusion}\left(f_{spectral}(x), f_{spatial}(x)\right))$$

3.3. Training and Validation

- School location data and visual interpretation were used to build reference samples.
- Data augmentation was applied to improve generalization.
- The model was trained using cross-entropy loss and Adam optimizer.
- Accuracy was evaluated using overall accuracy, user's/producer's accuracy, and Kappa index.

3.4. Study Area

The Tirupati District in Andhra Pradesh, India, encompasses a wide variety of landscapes from densely populated urban pilgrimage area and has remote rural area. Administratively, several mandals with diverse demographics and socio economic characteristics. Rapid urbanization around Tirupati city has improved educational infrastructure in central regions. The Tirupati had Area of 8229 Sq. Km., Population: 31.1 lakhs, Villages: 1051, Male: 10.98 lakhs, Female: 10.98 lakh. The tirupati district outlet map is displayed in figure 2.

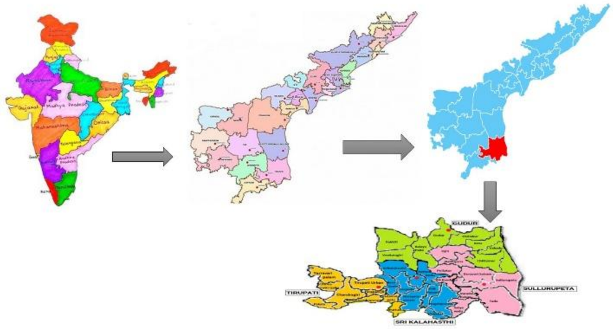

Figure 2: Study Area

3.5. Dataset Description

This study employed multiple spatial, spectral, and demographic datasets to support school asset extraction, catchment analysis, and suitability assessment in Tirupati District, Andhra Pradesh. The datasets used are summarized below.

- **School-level data**, detailing geographic coordinates (latitude and longitude), school names, types (e.g., primary, secondary).
- **Administrative boundary layers** (districts, wards, blocks), typically in shapefile or GeoJSON format.
- **Demographic datasets** such as child population by age and gender, useful for estimating demand in each school's catchment area.
- **Hyperion Hyperspectral Dataset** The remote sensing dataset consisted of **EO-1 Hyperion hyperspectral imagery**. Because Hyperion provides narrow, contiguous bands that enable detailed spectral characterization of urban and rural surfaces and also allows discrimination between school rooftops, paved surfaces, playgrounds, vegetation, and other campus features. The **Spectral range**: 400–2500 nm, **Number of bands**: 242 (after removing noisy bands, ~180–200 usable), **Spatial resolution**: 30 m, **Radiometric resolution**: 12-bit, **Swath width**: 7.5 km. The **Acquisition source**: USGS Earth Explorer. **Coverage**: Tirupati District and surrounding areas.

4. EXPERIMENTAL ANALYSIS

For classification of school asset mapping, catchment delination and suitability evaluation for future school development with in Tirupati District at first python based processing and QGIS integrated deep neural hyperspectral feature extraction with spatial decision support modelling in GIS tools are used for final decision making.

To that Hyperion hyperspectral dataset of tiruapti District is downloaded from USGS earth explorer website. So, initially image correction is done to improve radiometric quality and geometric consistency. Due to hyperion image contains several noisy bands especially those affected by water-vapour absorption therefore these bands were carefully identified and removed. In first step, atmospheric correction is applied to convert input raw digital data numbers into surface reflectance values and to mitigate the influence of atmospheric absorption and scattering. Following with clipping the administrative boundary image of Tirupati District using QGIS for minimizing computational load and focus analysis strictly within the study area. The dimensionality reduction is appled using

Minimum Noise Fraction and Principal Component Analysis (PCA) to retain dominant spectral information for supressing noise and reduncy and to improve deep neural model. The pre-processed Hyperion hyperspectral dataset of tiruapti District is as viualised in figure 3.

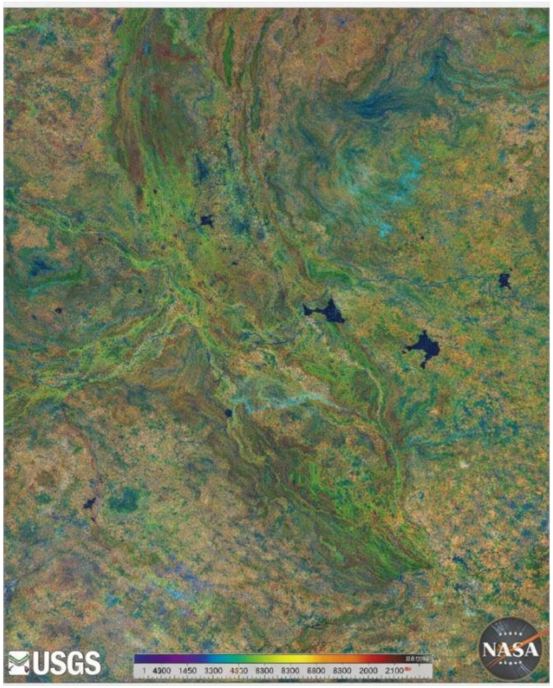

Figure 3. Tirupati District Hyperion Hyperspectral Image

Then feature extraction is done using Dep Neural Remote Sensing (DNRS) to that spectral spatial patches were generated around each sample pixel enabling the model to capture both spectral characteristics of each land cover class and its spatial context. Then training samples were developed through visual interpretation of schools, playgrounds, vegetation patches, built-up surfaces and paved areas.

In next step deep neural network model was applied to learn hierarchical features and to discover informative features automatically through training in data unlike traditional classifiers because it relays on manually derived indices. In that convolutional layers captured fine spectral variations subsequently spatial structures, shapes and textures characteristic of school campuses. Once training was done the entire Hyperion scene produce a classified raster representing school rooftops, playgrounds, paved area, vegetation and other surrounding asserts. At first, spectral signatures of major land cover classes extracted from Hyperion hyperspectral dataset of Tirupati District. The spectral signatures for our main study are visualised in figure 4.

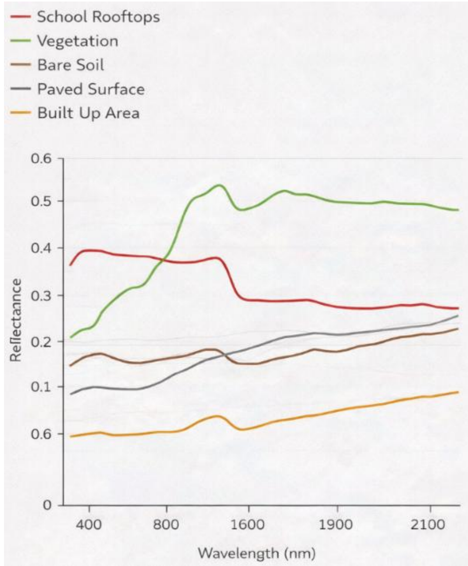

Figure 4. Spectral Signatures from Hyperion Dataset of Major Classes

The figure 4 shows clear reflectance differences between vegetation, rooftops, bare soil, paved surfaces and built-up areas across the 400–2100 nm wavelength range derived from the Hyperion study area dataset with wavelength on x-axis and reflectance on y-axis. Next, the classification output generated from the deep neural remote sensing model applied to the Hyperion hyperspectral image is visualised in figure 5.

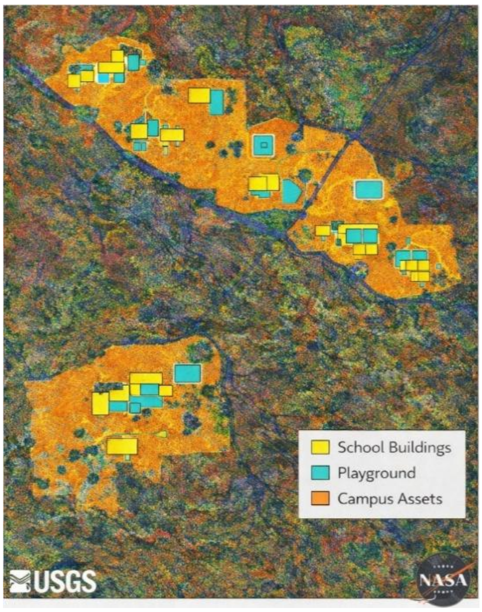

Figure 5. Classification of School Buildings, Playgrounds, and Surrounding Campus Assets

The figure 5, clearly visualises school buildings, playgrounds, and surrounding campus assets as separate thematic classes. School buildings appear as compact rectangular patches, while playgrounds form larger open areas adjacent to the buildings, and other campus assets occupy the remaining built-up portions of the campus. The clear separation between classes indicates that the model successfully captured both the spectral characteristics and spatial context of each feature. The results demonstrate particularly strong performance in distinguishing vegetation and surrounding built-up land from school infrastructure, which is traditionally challenging when using conventional pixel-based classifiers. It states post- classification filtering and vector cleaning effectively reduced noise and fragmentation as categorized polygons maintain spatial continuity. There are areas with dense concentrations of schools seen in number of places and areas with sparse schooling encircled by rural terrain in other places.

In order to determine how trustworthy, the categorization results were an accuracy evaluation was carried out afterwards. To make sure the main land cover groups were well represented were used a stratified technique to obtain independent validation samples. The confusion matrix was generated to compare predicted classes is visualised in figure 6.

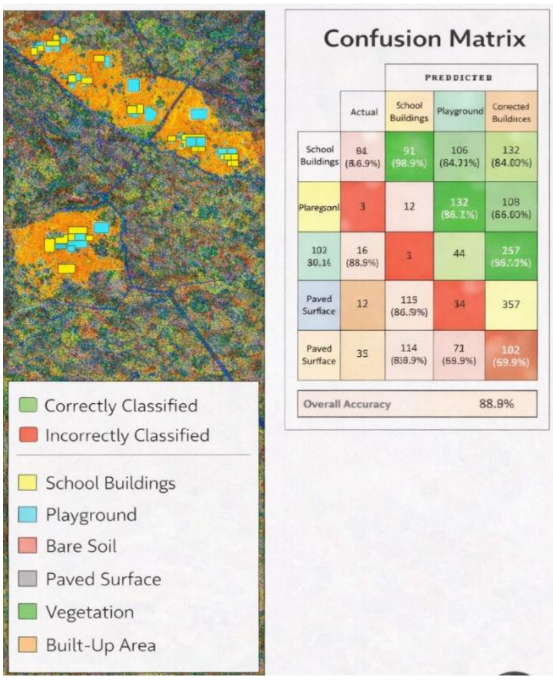

Figure 6. Map and Confusion Matrix Spatial Distribution with Accuracy

The Figure 6 shows spatial distribution of correctly and incorrectly classified pixels together with confusion matrix generated from validation samples. Correctly classified features are shown as green overlays, while misclassified pixels appear in red. The spatial visualization indicates most errors occur along class boundaries and in mixed pixels, particularly where playground surfaces transition into bare soil or paved areas. Within interior of each campus, the classification remains spatially consistent, confirming that deep neural model effectively captured the core spectral–spatial characteristics of school infrastructure.

The corresponding confusion matrix provides quantitative evidence of classification reliability. Overall accuracy reached approximately 88.9%, indicating good agreement between predicted classes and reference samples. School buildings and playgrounds achieved comparatively high user's and producer's accuracies, demonstrating that these features were well discriminated from surrounding land-cover types. Misclassification was primarily observed between bare soil, paved surfaces and certain portions of built-up areas, which share similar spectral responses, particularly in the short-wave infrared region.

In next step, the classified raster layers were subsequently transferred into QGIS for further analysis. School buildings and campus assets were vectorized to create polygon features that could be integrated with demographic and administrative datasets. Topological corrections were carried out to remove slivers, merge fragmented polygons and ensure spatial accuracy. The school catchment zone of tirupati is shown in figure 7.

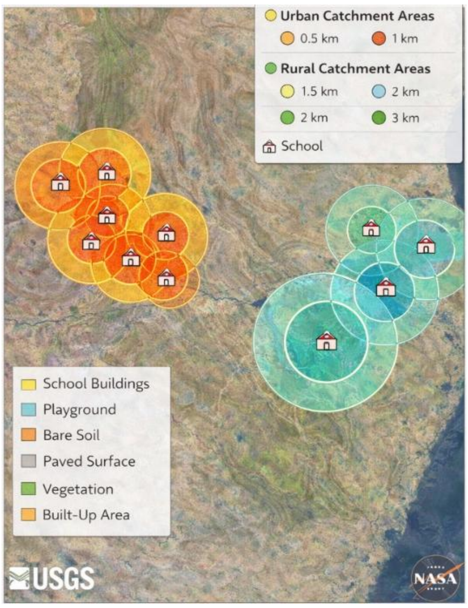

Figure 7. School Catchment Zones of Tirupati District

The Figure 7, illustrates the school catchment zones generated using GIS-based distance buffers for both urban and rural environments in Tirupati District. Rural schools were given wider radius (1.5-3Km) to reflect dispersed settlements and limited institutional availability, whereas urban schools were given smaller radii (0.5-1km) to reflect shorter walking distances and higher school density. There is noticeable difference in accessibility between areas as seen on map. Multiple schools may serve same population due to near proximity of urban clusters which are characterized by overlapping catchments. Students in rural locations may have lengthier commutes due to greater spatial isolation of their catchments as some places go beyond boundaries of nearby schools. The significance of location based design in ensuring appropriate educational coverage across district is underscored by these patterns which clearly demonstrate spatial imbalance in school accessibility.

After then, distance based buffers were used to create school catchment zones for later accessibility. The realistic walking distances in urban and rural areas were represented by different buffer thresholds. The number of residents servied within each school's service area was calculated by intersecting these catchment boundaries with population information. Figure 8 shows the local population density and research area catchment zones.

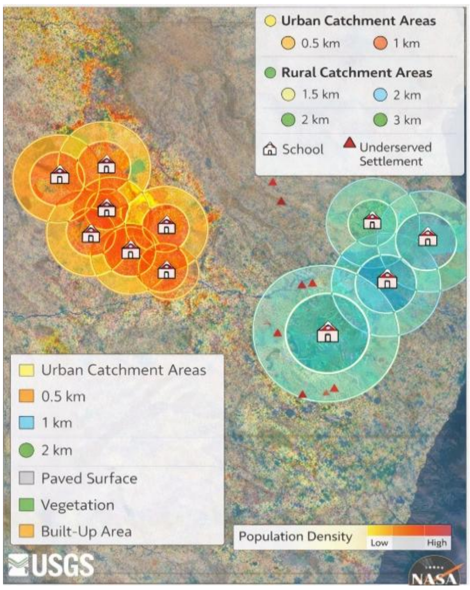

Figure 8. Population Density and Catchment Zones of Tirupati District

Figure 8 displays school catchment zones of Tirupati District overlaid on top of population density. Wherever there is a high concentration of people and school accessibility is low, the map makes it obvious. Overcrowding at current schools may be an issue in urban areas where catchments overlap densely. However, population density layer shows some of these zones can support extremely large populations. Although being bigger in area rural catchments contain inhabitants are spread out. It is clear that communities are placed outside the recommended walking distance when there are several red triangles outside buffer limits, symbolizing underserved settlements. Children in these areas particularly those still in elementary school may face longer commutes and lower enrolment rates. Both high-density metropolitan areas and isolated rural settlements require focused planning interventions as combined image shows accessibility difficulties are affected by both distance and population distribution.

Next, a multi criteria suitability analysis was conducted for infrastructure planning. Then normalized and weighted spatial parameters including population density, distance from schools, closeness to road networks and limited land use zones. Based on results of weighted overlay analysis he district was divided into three zones: very suitable, somewhat suitable and unsuitable for future school building. The figure 9 shows the sustainability mapping.

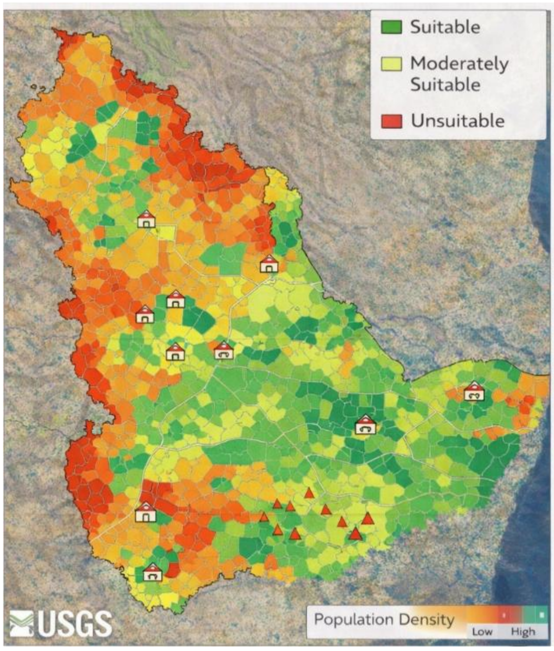

Figure 9. Suitability Map for Establishing Future Schools in Tirupati District.

Figure 9 displays multi-criteria geographical study that took into account factors such population density, land use restrictions, road proximity and accessibility. The three levels of suitability classes for district: suitable, somewhat suitable and unsuitable. In areas with favourable land availability, accessibility and demand like peri-urban belts and transit corridors, large contiguous regions are deemed “suitable”. Zones that are somewhat suitable are generally found in transitional rural areas are places where schools could be possible ut they could need some extra infrastructure. Most unsuitable locations are thinly inhabited or ecologically sensitive places where buildings additional school would be impossible. Several schools are suited in somewhat appropriate zones, according to distribution of existing schools around suitability surface whereas underprivileged communities prefer to congregate near places are currently undeveloped but acceptable. These results indicate optimize accessibility and coverage future school development should give preference to high appropriate locations are next underserved areas.

Finally, visualised integrated decision support map to show school locations, extracted campus assets, catchment buffers and suitability zones across the Tirupati District can see in figure 10.

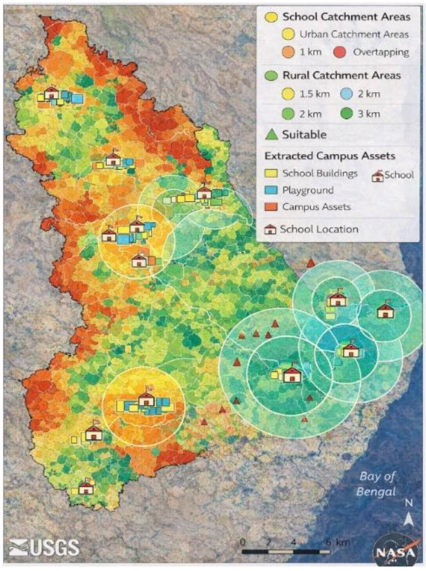

Figure 10. Visualises location of School, Catchment Area, Extracted Assets and Suitability Zones in Map

Figure 10 displays complete spatial synthesis which permits simultaneous viewing of planning priority areas, infrastructure distribution and accessibility. Redundancy in some areas is shown overlapping urban catchments viewed in conjunction with suitability surface patterns make it clear numerous unserved communities are located next to udeal areas for strategically constructing new schools. In addition, planners are able to compare current state of facilities with demand because the presence of extracted school assets such as playgrounds, rooftops and campus structures. In sum, map shows how authorities may spot service delivery shortages, optimize resource allocation and build new educational infrastructure more effectively by integrating deep neural classification with GIS which enables evidence based decision making.

The study results show Tirupati District’s school infrastructure might be better assessed and planned by combining deep neural remote sensing with GIS based spatial analysis. Accurate extraction of school buildings, playgrounds and other campus assets was made possible using hyperion hyperspectral image that underwent atmospheric correction, dimensionality reduction and deep neural spectral spatial classification. The classification was very accurate proves that hyperspectral deep learning methods can map educational infrastructures very precisely.

Overall, the research process data-driven strategy for bettering educational infrastructure design is available through integration of deep neural hyperspectral classification with GIS based modelling of other districts are still facing same problem of unequal school access, they can use this model because it is transferable, scalable and appropriate. Future education planning can be wiser more inclusive and sustainable with this frameworks continuing development incorporation of higher resolution imagery and more specific socio-economic information.

5. CONCLUSION

Schools are key part of social infrastructure for developing human capital and making sure all students have equal access to educational facilities is a big planning problem indistricts that are growing quickly. This study showed unplanned population groth in Tirupat District has led to uneven access to schools especially between urban and rural areas.

By proposed socio-technical approach, integrating Deep Neural Remote Sensing with GIS based spatial analysis a comprehensive and data-driven framework for school infrastructure assessment was developed. Hyperspectral deep learning enables accurate extraction of school buildings, playgrounds and campus assets from Hyperion imagery. While GIS based catchment and accessibility analysis related overlapping service areas in urban regions and underserved settlements in peripheral and rural areas. The appropriateness research also found the best places for future schools based on how easy it is to get them, how many people live nearby and how the property is used. In general, proposed framework facilitates fair school design by making decisions based on facts and geography. It also offers a scalable strategy that may be used in other areas with comparable problems with educational infrastructure.

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REFERENCES

Yuan, Q., Shen, H., Li, T., Li, Z., Li, S., Jiang, Y., Xu, H., Tan, W., Yang, Q., Wang, J., Gao, J., Zhang, L., (2020) Deep learning in environmental remote sensing: achievements and challenges. Remote Sens. Environ. 241, 111716. https://doi.org/ 10.1016/j.rse.2020.111716.

Zhong, L., Hu, L., Zhou, H., (2019) Deep learning based multi-temporal crop classification. Remote Sens. Environ. 221, 430–443. https://doi.org/10.1016/j.rse.2018.11.032.

Liu, S., Shi, Q., (2020) Local climate zone mapping as remote sensing scene classification using deep learning: a case study of metropolitan China. ISPRS J. Photogramm. Remote Sens. 164, 229–242. https://doi.org/10.1016/j.isprsjprs.2020.04.008.

Dou, P., Shen, H., Li, Z., Guan, X., Huang, W., (2021) Remote sensing image classification using deep-shallow learning. IEEE J. Sel. Top. Appl. Earth Observations Remote Sensing 14, 3070–3083. https://doi.org/10.1109/JSTARS.460944310.1109/ JSTARS.2021.3062635.

Wang, H., Zhao, X., Zhang, X., Wu, D., Du, X., (2019) Long time series land cover classification in China from 1982 to 2015 based on Bi-LSTM deep learning. Remote Sensing 11, 1639. https://doi.org/10.3390/rs11141639.

Cheng, G., Yang, C., Yao, X., Guo, L., Han, J., (2018) When deep learning meets metric learning: remote sensing image scene classification via learning discriminative CNNs. IEEE Trans. Geosci. Remote Sensing 56 (5), 2811–2821. https://doi.org/ 10.1109/TGRS.2017.2783902.

I. Bachri, M. Hakdaoui, M. Raji, A. C. Teodoro, A. Benbouziane, (2019) Machine learning algorithms for automatic lithological mapping using remote sensing data: A case study from souk arbaa sahel, sidi ifni inlier, western anti-atlas, morocco, ISPRS International Journal of Geo-Information 8 (6) 248.

Z. Wang, R. Zuo, H. Liu, (2021) Lithological mapping based on fully convolutional network and multi-source geological data, Remote Sensing 13 (23) 4860.

H. Shirmard, E. Farahbakhsh, R. D. Müller, R. Chandra, (2022) A review of machine learning in processing remote sensing data for mineral exploration, Remote Sensing of Environment 268 112750.

L. Yu, A. Porwal, E.-J. Holden, M. C. Dentith, (2012) Towards automatic lithological classification from remote sensing data using support vector machines, Computers & Geosciences 45 229–239.

R. N. Clark, G. A. Swayze, K. E. Livo, R. F. Kokaly, S. J. Sutley, J. B. Dalton, R. R. McDougal, C. A. Gent, Imaging spectroscopy: Earth and planetary remote sensing with the usgs tetracorder and expert systems, Journal of Geophysical Research: Planets 108 (E12).

X. Chen, T. A. Warner, D. J. (2010) Campagna, Integrating visible, near-infrared and short-wave infrared hyperspectral and multispectral thermal imagery for geological mapping at cuprite, nevada: a rule-based system, International Journal of Remote Sensing 31 (7) 1733–1752.

Y. Weilin, M. Yan, L. Shengwei, (2016) Application of radar and optical remote sensing data in lithologic classification and identification, in: IEEE International Geoscience and Remote Sensing Symposium, pp. 6370–6373.

Y. Lu, C. Yang, Z. Meng, (2021) Lithology discrimination using sentinel-1 dual-pol data and srtm data, Remote Sensing 13 (7) 1280.

A. B. Pour, Y. Park, T.-Y. S. Park, et al., (2018) Regional geology mapping using satellite-based remote sensing approach in northern victoria land, antarctica, Polar Science 16 23–46.

C. E. dos Anjos, M. R. Avila, A. G. Vasconcelos, et al., (2021) Deep learning for lithological classification of carbonate rock micro-ct images, Computational Geosciences 25 (3) 971–983.

M. Pal, T. Rasmussen, A. Porwal, (2020) Optimized lithological mapping from multispectral and hyperspectral remote sensing images using fused multi-classifiers, Remote Sensing 12 (1) 177.

A. B. Pour, M. Hashim, Y. Park, J. K. Hong, (2018) Mapping alteration mineral zones and lithological units in antarctic regions using spectral bands of aster remote sensing data, Geocarto International 33 (12) 1281–1306.

R. R. Girija, S. Mayappan, (2019) Mapping of mineral resources and lithological units: a review of remote sensing techniques, International Journal of Image and Data Fusion 10 (2) 79–106.

H. Shirmard, E. Farahbakhsh, E. Heidari, A. Beiranvand Pour, B. Pradhan, R. D. Müller, R. Chandra, A comparative study of convolutional neural networks and conventional machine learning models for lithological mapping using remote sensing data, Remote Sensing 14 (4).

M. Sgavetti, L. Pompilio, S. Meli, (2006) Reflectance spectroscopy (0.3–2.5 μm) at various scales for bulk-rock identification, Geosphere 2 (3) 142–160.

L. Bruzzone, B. Demir, (2014) A Review of Modern Approaches to Classification of Remote Sensing Data, Springer Netherlands, pp. 127–143.

W. Sun, Q. Du, (2019) Hyperspectral band selection: A review, IEEE Geoscience and Remote Sensing Magazine 7 (2) 118–139.

Yao C, Luo X, Zhao Y, Zeng W, Chen X (2017) A review on image classification of remote sensing using deep learning. In: 2017 3rd IEEE international conference on computer and communications (ICCC), https://doi.org/10.1109/CompComm.2017.8322878, pp 1947–1955

Li Y, Zhang H, Xue X, Jiang Y, Shen Q (2018) Deep learning for remote sensing image classification: a survey. Wiley Interdiscip Rev Data Min Knowl Discov 8(6):1264.

Li S, Song W, Fang L, Chen Y, Ghamisi P, Benediktsson JA (2019) Deep learning for hyperspectral image classification: an overview. IEEE Trans Geosci Remote Sens 57(9):6690–6709.

Paoletti M, Haut J, Plaza J, Plaza A (2019) Deep learning classifiers for hyperspectral imaging: a review. ISPRS J Photogramm Remote Sens 158:279–317.

Song J, Gao S, Zhu Y, Ma C (2019) A survey of remote sensing image classification based on CNNs. Big Earth Data 3(3):232–254.

Cheng G, Xie X, Han J, Guo L, Xia G-S (2020) Remote sensing image scene classification meets deep learning: challenges, methods, benchmarks, and opportunities. IEEE J Sel Top Appl Earth Observ Remote Sens 13:3735–3756.

Alem A, Kumar S (2020) Deep learning methods for land cover and land use classification in remote sensing: a review. In: 2020 8th international conference on reliability, infocom technologies and optimization (Trends and Future Directions) (ICRITO), IEEE, pp 903–908.

Vali A, Comai S, Matteucci M (2020) Deep learning for land use and land cover classification based on hyperspectral and multispectral earth observation data: a review. Remote Sens 12(15):2495.

Kuras A, Brell M, Rizzi J, Burud I (2021) Hyperspectral and lidar data applied to the urban land cover machine learning and neural-network-based classification: A review. Remote Sens 13(17):3393.

Zang N, Cao Y, Wang Y, Huang B, Zhang L, Mathiopoulos PT (2021) Land-use mapping for high-spatial resolution remote sensing image via deep learning: a review. IEEE J Sel Top Appl Earth Observ Remote Sens 14:5372–5391

Mehmood M, Shahzad A, Zafar B, Shabbir A, Ali N (2022) Remote sensing image classification: a comprehensive review and applications. Math Probl Eng 2022:1–24.

Przemysław Aszkowski, Bartosz Ptak, Marek Kraft, et al., (2023) Deepness: Deep neural remote sensing plugin for QGIS, SoftwareX, Volume 23, 101495, ISSN 2352-7110, https://doi.org/10.1016/j.softx.2023.101495.