Hyperspectral Image Classification Applications: A Case Study

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Abstract- In the present scenario, endangered food security, precision farming are the triggering factors, which demands the maximum yield with the minimum resources. Therefore the economical management of food production processes needs meticulous information regarding the agricultural customs. The remote sensing applications may provide accurate information about crop condition with respect to space and time. The Hyperspectral Image (HSI) possesses rich spectral features information which aids in distinct classification of objects whereas rock and minerals can be distinguished easily compared to multispectral images. Detection of minerals through airborne or satellite based HSI is an advantageous in remote steep terrains with different scales on the earth or different planets such as moon, mars etc.

Keywords- Hyperspectral Image, Land cover classification, mineral extraction, mineral mapping, precision farming.

I. INTRODUCTION

Modern Space technology plays an important role in accurate and fast decisions by policymakers for the development of the country. These decisions may involve the state or national level domains such as forestry, farming, geological and environmental applications [15].

The information obtained from Hyperspectral image through its enormous number of spectral channels aids in understanding of content and state of the earth resources. An application might require particular spectral signature available in specific spectral bands. The objects, elements, constituents and concentration of the matter are evidently recorded as spectral signature. The spectral reflectance and absorption characteristics of each end member must be known *a priori* for knowledge discovery through Hyperspectral image analysis. In this paper, couple of case studies are considered in agriculture and mineral mapping applications to understand the process of applying HSI in these domains. The weed identification among the vegetable crops has been identified as case study in precision farming application. This framework has the components of data acquisition, pre-processing and classification models. The results of supervised classification models such as LDA and SVM for this corn crop has been analyzed for the performance evaluation. The experimental set up and shortcomings of this work are also discussed.

A case study of mineral ore identification has been illustrated to appreciate the HSI classification in mineral mapping applications. The mineral ore end members detection such as Chlorite, Calcite, high and medium Al muscovite by applying Mean Square Cross Prediction Error-Based Blind Source Extraction (MSCPE-BSE) model has been discussed. The evaluated results obtained through various traditional mineral recognition methods along with a blind signal extraction method are tabulated[6].

This paper summarizes the related work in the application of HSI in precision farming and mineral mapping domains, discusses basics of spectral signature in both the fields, HSI processing models, results and performance evaluation of the models in order.

II. LITERATURE SURVEY

A novel statistical tool for vegetation biochemistry has been developed which uses Hyperspectral images [23]. The anomaly target detection using Weight Sparse Auto-Encode (SAE) algorithm has been proposed in HSI by combining adjacent pixels with distance [14]. The accuracy of chlorophyll content of potato plant was improved by fusing both multispectral and HSI in precision farming application [3]. The crop type identification is also experimented for red and green crops [28]. The classification of seven rice species crops by constructing and optimizing feature band set (FBS) with object-oriented classification (OOC) approach has resulted in 98.65% accuracy with the good quality of segmentation [26].The crop yield capability is improved by optimal water absorption by root and soil. Therefore measurement of water distribution using HSI has been experimented within a Rhizobox [22]. Ji'an Xia. et al, presented HSI classification for Oilseed Rape water logging stress levels using Artificial Neural Network(ANN) and Support Vector Machine(SVM) in parallel mode[10]. The performance of SVM was found stable for large datasets. There are few experiments were carried out for pesticide residue determination applying HSI [Shih-Yu Chen et. al. 2015], plant disease detection using SVM with Radial Basis Function(RBF) [19] and self supervised weed detection in between vegetable crops with the help of ground vehicle [1] which is considered as case study for detailed discussion.

Various experiments were conducted in mineral mapping application using HSI classification models. The mineral identification was carried out in metal-rich deposits, in steep terrain across microns to kilometer scale using both multispectral and HSI using Material Identification Characterization Algorithm (MICA) [20]. The mineral absorption features in the vegetation are also discovered using HSI by Reference Spectral Background Removal (RSBR) method [8]. To improve mineralogical information for mineral mapping application, the mining of structural and mineralogical from Hyperspectral drill core scans are developed using parallel framework [11]. The identification of Fumarole Sulfates, Salton sea are introduced using Hyperspectral Long Wave Infra Red (LWIR) mapping algorithm [18], Mafic minerals on Mars by nonlinear Hyperspectral Unmixing method [2] and footprints of gold minerals [4] were carried out by processing Hyperspectral image. The minerals like Calcite, Chlorite and Muscovite were determined by suppressing the background by using the knowledge target signal distribution[27] which is selected for a case study in mineral mapping application.

III. BACKGROUND

A. Agriculture application

The presence of vegetation in the image scene is determined by its spectral signature which is characterizes as shown in Figure 1. The leaf pigments, cell structure and water content records its signature in visible, Near Infra Red (NIR) and Short Wave Infra Red (SWIR) respectively. The study of green peak, chlorophyll absorption well, red edge, NIR plateau and water absorption features reveals constituent of the leaf and deductions are tabulated in Table I. The causes of the change in spectral signature informs the status of the vegetation. The measurement of reflectance level at the spectral bands of 480nm, 620nm and 840nm discloses the effective nitrogen content [7]. Correspondingly, quantity of the chlorophyll content may be estimated around 475nm and 550nm. For the analysis of different circumstances of the vegetation, the characteristics of the reflection curves are shown as in Figure 2. The healthiness of the vegetation records in visible and Infra Red (IR) band in reflection curve. Typically the values at both the IR and visible are more for healthy and less for stressed vegetation. But SWIR region records vise versa as represented in Figure 2.

The site specific plant conditioning may be assessed by discriminating pure vegetation spectrum from mixture of soil and tree characteristics [12,5]. In this method, different magnitude of components exists and absorption characteristics are evaluated for the given sample and result is used to estimate the sub-pixel cover fraction in a mixed HSI pixel.

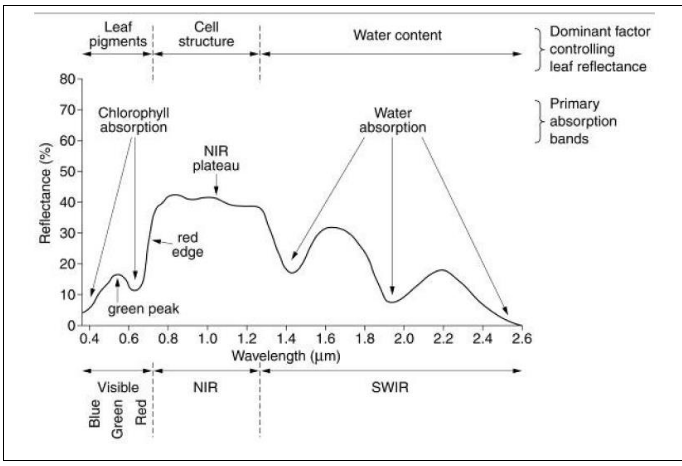
The appropriate crop selection for the available land decides the quantity and quality of the crop yield. Therefore land suitability mapping is significantly assists in better crop yield. The blend of Geographical Information System (GIS), satellite image analysis contributes majorly in the preparation of soil suitability map. The agriculturists may use these maps to select appropriate crop for the given soil in a certain season for enhanced yield. The research has revealed the correlation between soil compaction and a pixel [9, 17].

The important parameters like quantity of water, soil moisture and nutrition, nitrogen concentration, weather and so on decides the crop yield at the given time. Out of these key parameters, few uncertain parameters such as diseases, insect pests also decides food production. The yield predictions models are built to calculate total yield using the above mentioned key parameters with crop properties. Taking the help of GIS, Global Positioning System(GPS), plant distribution data, the rate of change of crop growth to accurately predict the crop yield. The model with real time data may help farmers to determine the appropriate farming method to improve the crop yield. [16, 13, 29].

Compared to multispectral data, HSI produces better classification accuracy. The regular data collection between seeding to harvesting helps in change detection. The data collection prior to seeding gives information about soil suitability which includes constituents of soil, texture, fertility so on. Mid season data collection informs about weed species, insect infestation and effect of diseases on the plant. The results obtained may help the agriculturists to select the suitable herbicide or pesticide application

B. Geological Applications

A individual matter shows evidence of a distinct spectral signature as a result of its distinctness in absorption and reflection of electromagnetic radiation in various spectral bands of HSI. Many characteristic parameters of minerals such as vibration process, transfer of charge properties, conduction bands, electronic processes etc. govern the absorption and reflection signature. Typical spectral signature of few minerals are shown in Figure 3, in which characteristics of chlorite, calcite, Talc, Amphibole etc. has been shown as in Figure 3. The Quartz signature shows its signature in thermal IR spectrum region because of vibration process as tabulated in Table II. As well, Amphiboles exhibits its unique signature in Very Near Infra Red(VNIR) region due to charge transfer effect. The existence of Manganese in rhodocrosite influences the carbonates signature in SWIR and Thermal IR region [24]. The evaluation of target spectral characteristics is made with reference spectra using spectral matching techniques. The HSI classification method labels the mineral present in the image landscape [25].



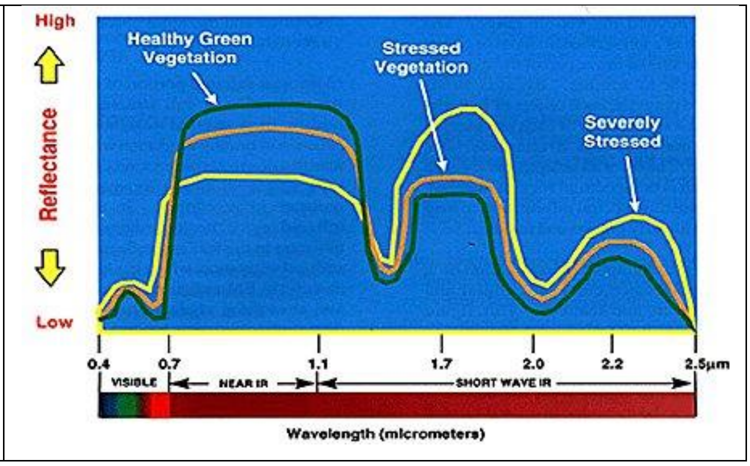


Fig.1: Typical Reflection curve for vegetation

Fig.2: Typical Reflection curve at different conditions of vegetation

Table I. Absorption features in vegetation reflectance

Wavelengths	Constituents	Inference
430-450nm- Blue 640-660nm - Red	Chlorophyll-a, chlorophyll-b absorbs blue and red color.	Causes the green peak around 500nm-600nm
430-450nm- Blue	Xanthophylls and carotenoids	Determines the color of fruit and flowers and yellow color in autumn.
430-450nm- Blue 640-660nm - Red	Polyphenols (brown pigments)	Absorb with decreasing intensity from the blue to red when the leaf is dead.
700-1300nm (Near Infra Red)	Leaf pigment and cellulose	Absorption is very low and the reflectance or transmittance reaches maximum values. NIR plateau increases with increasing no. of cell layers, cell size and intercellular spaces.
1300nm-2500nm (Mid Infra Red)	Water and foliar constituents such as protein, cellulose, lignin and starch.	Water absorption influences overall reflectance in the MIR range.

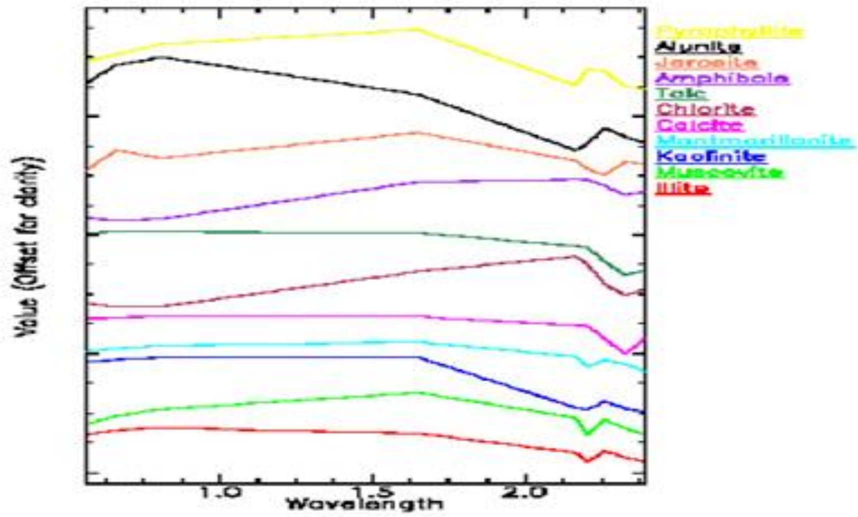


Fig.3: Spectral Signatures of minerals

IV. Applications of HSI in agriculture, land cover and mineral mapping: Case Study

The couple of applications with diverse features are considered as case studies. The architectural block for agriculture, land cover and mineral detection are presented as in Figure 5(a), Figure 5(b) and Figure 5(c) respectively.
The scheme shown in Figure 4(a) depicts a corn crop field which is selected to acquire HSI data to classify the crop and weed. The autonomous vehicle mounted with Hyperspectral camera was traversed across the field to collect HSI [1].

The block diagram given in Figure 4(b) is modeled to assess the performance of the land cover classifier. To calculate classification accuracy of the model distinct dataset with diverse environmental characteristics are chosen. In this experiment, Indianpines HSI having the spectral range of 400nm-2500nm comprising of 220 bands covering the area of 4miles^2. Around 1/3rd of the Indianpines image scene contains buildings, highways, railway track and rest of scene contains the forest vegetation and agriculture land. The ground truth classes containing road, wheat fields, soya bean, oats, railway track and so on, which are totally 16 classes available.

As a case study for mineral mapping application, AVIRIS sensor was used to collect copper ore at Nevada, USA as shown in Figure 4(c). The spatial resolution of the image scene was 20m^2/pixel and captured over 3km^2 area. The number of spectral bands were 188 with the resolution of 10nm in the spectral range of 0.2 to 2.4µm. In conjunction with ground truth, USGS spectral library was also used to improve the classification accuracy of the model.

Alexander Wendel et al. presented a technique to distinguish between the crop and the weed applying self-supervised classification architecture as depicted in Figure 5(a). As a first step, computing Normalized Difference Vegetation Index (NDVI) for non-vegetation pixels to suppress the background. Then, manually, testing samples were selected as weed or crop for successive steps. However, through NDVI computations training samples are generated. Then, All the samples are preprocessed and transformed to Principle Component Analysis (PCA) domain. The classification model was trained and tested with the corresponding samples to predict the pixel as crop or weed.

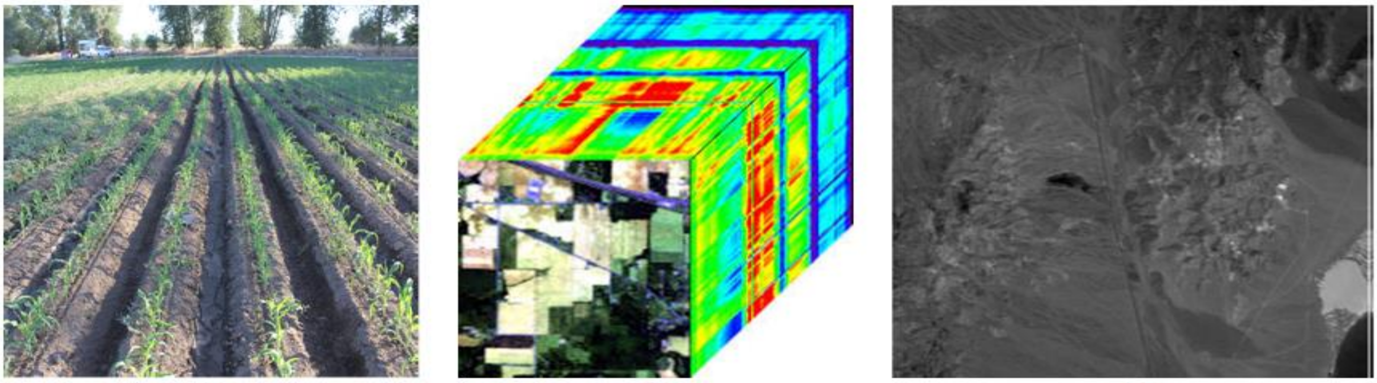
The autonomous vehicle was traversed in the field in both inward and outward directions and the HSI camera acquired the image two rows per scan with 5130 lines of pixels. The crops were scanned two times to obtain four labeled sets in both the directions. To obtain bias free data, semi-randomly, the data was selected. About six different weeds were predicted using the proposed method, such as Baryardgrass, red dock and so on.

Table II Spectral Signature of Minerals

Mineral Name	Signature Detail	Cause of Signature
Limonite (Iron Oxide)	UV-Blue Region	Fe-O charge transfer effect
Quartz	Thermal IR	Vibrational Process
All Carbonates	SWIR and Thermal IR region	Manganese in rhodocrosite.
Clay	Thermal IR region	Al-OH feature appears at 11µm

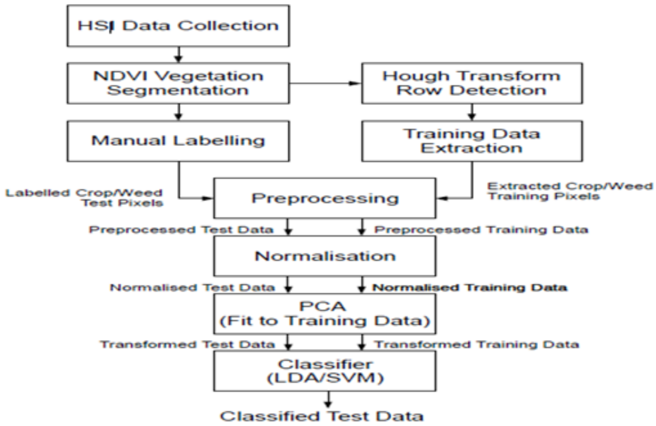
Shivakumar B.R. et al., proposed neural network based deep learning techniques for HSI classification[21]. The model is presented as in Figure 5(b) with denoising, dimensionality reduction as preprocessing modules and Convolution Neural Network module as classifier module. The denoising step employs auto encoder method to reduce the noise as well as to improve the perception quality of the spectral bands which are contaminated by the additive noise with different noise densities and also the water absorption bands. In combination with auto encoder and PCA resulted in Auto Encoder and Principle Component Analysis(AEPCA) technique in which dimensionality reduction operation is carried out to reduce the spectral channels from 220 to 30. Hence reducing the processing load on classification model. The experiment was conducted with diverse dataset having different land cover, image characteristics with distinct sensors, resolution. The classifier model is built based on deep learning CNN model, which is invariant to location and distortion produces better classification accuracy for multi class labeling. Therefore the performance of the proposed model is capable of high dimensional HSI classification with few available training samples.

Yani Hou et al., discussed a model for the separation of target mineral signature out of multiple mineral mixture signatures in HSI applying Mean Square Cross Prediction Error-Based Blind Source Extraction (MSCPE-BSE) technique as shown in Figure 5(c). In the beginning, for the experimentation, particular minerals spectral signatures were mixed applying linear mixture model. Using autoregressive model reference target mineral signatures are produced as a prior knowledge. Then, created as the reference prior knowledge. Further, the Correlation Coefficient (CC) for target and assumed signal which exists in mixture using MSCPE-BSE algorithm. In this research work, Cuprite data set was used to identify four different minerals such as Calcite, Chlorite, high-Al muscovite and med-Al muscovite by computing CC value of extracted and mineral spectra. The proposed technique effectively reduce the background and found the approximate the target distribution in the HSI.



(a) (b) (c)

Fig 4. Input HSI for agriculture, land cover and mineral mapping applications (a) Rows of corn for weed detection [1] (b) Input Hyper Spectral Image for land cover (Shiva Kumar B R et. al.2018) (c) Hyperspectral image for mineral mapping [27]



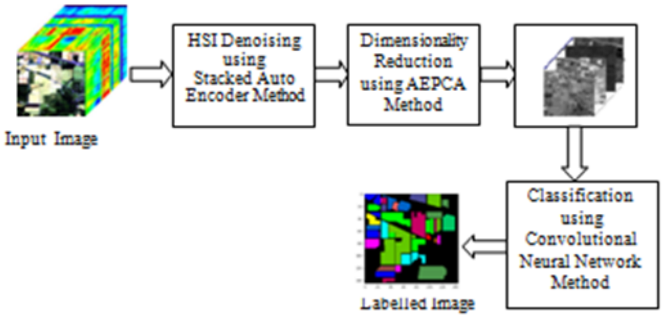


Figure 5(a). Self Supervised processing pipeline for the weed detection [1]   Figure 5(b). HSI processing for land cover classification [21]

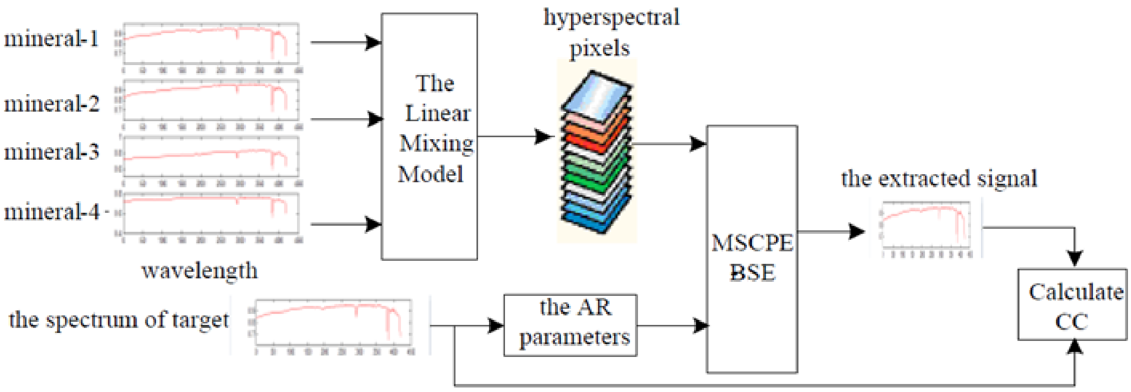


Figure 5(c). Mineral signal Extraction Framework [27]

V. EXPERIMENTAL RESULTS OF AGRICULTURE, LAND COVER AND MINERAL MAPPING APPLICATIONS

The experimented conducted for weed and crop classification using SVM and LDA binary classifiers produced the results as shown in Table III. The training of the model is done by feeding four datasets with tenfold cross validation on individual dataset. One set of data is used to train and other three sets are used for testing the model resulting mean and median values as in Table III. By investigating the results, SVM performed better over LDA method. The result analysis revealed that, the weed pixels are misclassified as crop pixels.

Table III Performance evaluation of weed and crop detection algorithm using LDA and SVM

Classifier-Data	Median	Mean
LDA-Crop	0.92	0.90
LDA-Weed	0.92	0.92
SVM-Crop	0.92	0.92
SVM-Weed	0.94	0.94

The deep learning based dimensionality reduction and classification model is evaluated using Indianpines image and obtained classification accuracies are given in Table IV. The experiment has been conducted for different number of dimension reduced components such as 10 to 150 by applying AE,PCA and AEPCA techniques. From the table it can be observed, more number of components are yielding greater accuracy, but after 50 components the classification accuracy significantly not moving up. Among all these methods AEPCA model used for dimensionality reduction significantly producing 97% classification accuracy for just 30 components which represents all 220 bands. This shows 14% of total number of spectral bands producing 97% accuracy.

Table IV. Comparison of classification accuracy obtained after dimensionality reduction using PCA,AE and AEPCA for classification of Indianpines images.

Number of Components	PCA	AE	AE-PCA
10	0.8881	0.8069	0.9012
20	0.9363	0.8225	0.9431
30	0.9469	0.8300	0.9669
50	0.9587	0.8912	0.9735
100	0.9606	0.8875	0.9681
150	0.9712	0.9225	0.9790

In the mineral mapping application, the target signal is extracted from mixture of multiple spectral signatures. The resultant values obtained are given as in Table V. From the experimental results, the pixel value with larger value deduce the probability of target pixel occurrence in the signal may be high. On the other hand, lower CC value represents the dark pixel with lesser intensity. It can be interpreted from the Table V, the CC values are above 95% when the parameters are optimal.

Table V: Probability for mineral identification when CC of the signals are highest

Minerals	P level	Q value	CC value
High-Almuscovite	78	25	0.9999
Med-Almuscovite	27	1	0.9527
Calcite	44	17	0.9998

VI. CONCLUSION

To appraise the application of HSI classification, a case study is carried out, which is limited to agriculture, mineral mapping and land cover applications. Through this study, the basics of characteristics of Hyperspectral image spectral signature, target member characteristic interpretation in agriculture and mineralogy domains are appreciated. The workflow for specific crop determination, crop status identification, land cover classification and also for target mineral detection are discussed with one example for each case. The experimental set up for weed detection, land cover classification and mineral identification are discussed along with the corresponding results. This paper show glimpses of the application of HSI in precision farming, mineral identification, land cover application which is the highly demanding in the modern era.

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