An Assessment of Artificial Intelligence and Machine Learning Applications in Remote Sensing for Crop Classification.

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Abstract*—: Since its inception, remote sensing has proved to be extremely useful in a wide variety of fields such as climate sciences, land use mapping, bio-ecology, etc. One of the fields in which it has had an impact is crop mapping. With the rise of the world's population along with the commoditization and globalization of foodstuff markets across the planet, this revolutionizing of crop mapping was fortuitously timed, as the demand for accurate data about the world food supply increased dramatically. In the present day where climate change-induced systemic shocks and world political instability combined with environmental degradation caused by conventional agriculture threaten global food security, water and soil resources will have to be shepherded with extreme care. Therefore timely, large-scale, accurate, and granular data about crop types and their distribution is of vital importance, and remote sensing-based crop classification using cutting-edge machine learning and artificial intelligence methods will provide great help in gathering such data. In this paper, we will conduct a review of the literature in the field of crop classification, paying special attention to the latest developments in the field. We will also expand upon the importance of the field in an ecological and food security-based context, after reviewing the literature we will enlist the most relevant and fundamental research gaps with the current and future progress of the field in mind. After enlisting the research gaps, we will then suggest possible future directions of research in the field, with the latest trends in agricultural practices and remote sensing in mind.

Keywords*— Artificial Intelligence, Crop Classification, Deep Learning, Literature Review, Machine Learning, Remote Sensing, Vegetation Index.

I. INTRODUCTION

A. Importance of Crop Classification

The world is currently experiencing a polycrisis, in which multiple climate and economic stresses intersect and severely disrupt the stability of our global system leading to an extreme or potentially catastrophic degradation of humanity's future well-being [1]. A key part of this polycrisis is the food crisis, which has contributed to social unrest and the migration crisis [2]. The current food crisis has been triggered by the Russo-Ukrainian War and has negatively impacted consumer prices, food quality, and other sectors of the food industry [3]. It also has the potential to further disrupt the political stability of the world order, because countries in the Middle East, North Africa, and the Sahel region are completely dependent on Ukraine and Russia for foodstuff supply, especially wheat [4]. Food supply in these regions of the world has been critical to prevent social and political upheaval, one of the most important factors contributing to the Arab Spring was the 2008-2009 food crisis [5,6].

There has been an increase in overall world hunger and threats to food security with 828 million people being affected by hunger in 2021, an amount 150 million greater than were affected in 2019, this regression will also affect the UN Sustainable Development goal of eliminating world hunger by 2030 [7]. Many have reacted by calling for the promotion of a new more resilient and diverse system, grounded in the principles of agroecology and other alternative methods of agriculture along with the principles of food independence and the localization of food supply as a panacea to our current ills [8,9]. While others in the face of the disruption to the global food supply system during the pandemic, see very little need to make qualitative changes in the global food system [10] with many insisting that the very model of rapid adoption of innovation, crop monoculture, and high-volume international trade will help us to ride out the current crisis [11].

Whatever the path that is taken we face the double challenge of Increasing food yields along with minimizing our overall negative environmental impact, of which agriculture is a key contributor. The magnitude of the increase in food supply required will be between 60% to 35% [13] which will necessitate an increase in agricultural production. This results in the difficulty that, the majority of virgin agricultural land available for expansion is located in forests in the tropics, the vast majority of the current expansion of cropland occurs in tropical forests [14], and the destruction of these forests has extremely adverse effects on the environment, the cutting of forests is the cause of a substantial portion of the world's Carbon emissions [15] with swathes of former tropical forestland emitting far more Carbon per hectare than grasslands or pastures [16] this expansion will under a scenario where drastic action is not taken lead to extremely widespread and potentially destabilizing biodiversity declines [17].Despite this grim prognosis, there are possibilities of substantially increasing crop yield (by 100% to 180%) without causing further biodiversity losses, soil pollution, and increased greenhouse gas emissions [18] but it requires careful management of available land and soil resources, which can only be achieved with extensive knowledge of crop spatial distribution.

B. An overview of the field of Crop Classification

Crop classification on a large scale, before satellite images or ariel photography, was carried out physically via surveys which consumed far more resources along with time. Later Ariel radar and photos along with LANDSAT (It is interesting to note that the launching of LANDSAT has been commonly thought to inaugurate the scientific revolution of remote sensing [19]) data were used for large-scale crop classification, various equations were used to transform the data, and the classification of the data was carried out using probability-based models [20,21] accuracies were low with the highest reaching ~77% [22], with only a limited amount of crop types being used and frequent confusion between related crop classes.

During and before the turn of the millennium hyperspectral data was beginning to be used, and the usage of radar images obtained from ariel surveys greatly dropped in terms of frequency. Probability-based methods were still in use but had fallen in terms of prominence relative to other classification methods because, they gave less accurate results as compared to other methods like Support Vector machines and if they were used it was either in conjunction with or as a hybrid with other methods [23] A rise in the popularity of Support Vector Machines occurred [24,25] probably because hyperspectral remote sensing data was relatively scarce and traditional classification methods fared poorly with regards to the scanty data as compared to Support Vector machines because; in the Support Vector machine method, the training samples located on interclass borders are given a higher weightage[26]. Due to the availability of hyperspectral data, crop Indices like NDVI and NIR were beginning to be used which in a multi-temporal dataset helps to differentiate the crops based on their phenology (growing cycle), however, feature engineering was usually performed on the time series data such as fitting a sigmoid function to such data [27] Neural networks were beginning to be used, with some success since they did not rely on probabilistic assumptions and neither needed particular requirements about normality in datasets, they produced accuracies of up to ~94% on the field level [28].

Currently, Random Forest classifiers are being used for classification tasks very often, especially with time series and multispectral data. This is because the random forest method is more resistant to the ill effects of overfitting and error-induced noise in the data, along with the fact that it makes no assumptions concerning the data's properties and that it is computationally less expensive than most classification methods [29,30]. The random forest method has been used on a very wide variety of data along with diverse terrain types since it shows a high degree of accuracy even in fragmented landscapes [31,32,33]. It was also used to both select the features and conduct the classification for time series NDVI and NDWI data with success [34]. The use of Support Vector machines has also remained popular due to their power to extract useful features even with a relatively small dataset, it is also an appealing method to deal with data sets with a high amount of dimensionality. When NDVI time-series data was used to classify crops via the Support Vector Machine method, with the training data samples being purposely restricted to 44 parcels the method provided an overall accuracy of 90% [35]. When compared with other classifiers like Random Forest in using time-series data for classification tasks, it performs almost as well or better at the tasks [36,37] A classification method that has seen a dramatic uptick in usage has been neural networks,_especially deep neural networks. With the increase in both data volume and quality along with data sets becoming open source on an operational basis, neural networks are positioned to take advantage of this. Neural networks also carry the advantage of not needing feature engineering since the networks extract the representations themselves [38] It has also shown good performance concerning other classification methods for example neural networks have outperformed Support Vector Machines by 8-6% [39,40].

II. Literature Review

To identify possible future research fields, along with currently extant research gaps, we have selected six recent papers in the field of Crop Classification to carry out a Literature review. By carrying out the review we seek to throw light on the current state of the field along with avenues for improvement. The papers were selected according to various metrics including whether original or unusual methods were used in classification, paper quality etc. to ensure that an accurate picture was being conveyed.

A. A Dual Attention Convolutional Neural Network for Crop Classification Using Time-Series Sentinel-2 Imagery

[41] The study was executed to ascertain the usefulness of a novel Deep Learning architecture to classify crops and land use types as compared to other more conventional classifiers. The study area that was chosen was located in Aq Qala county of Golestan Province in Iran, the climate of this area is mixed, with a humid southern and semi-arid northern portion. This combined with the fact the area chosen is vital to the annual crop production in Golestan province makes having accurate and timely crop monitoring systems in the area important. Reference samples were collected manually in situ using a handheld GPS. NDVI (Normalized Difference Vegetation Index) was used due to the simplicity in deriving it and its proven discriminatory ability with regards to crop phenological cycles, the spatial information would be an 11 by 11-pixel input patch and both pieces of information would be obtained for 13 different moments in the year from the Sentinel-2 satellites.

The Novel Neural-Network Architecture tested in this study has two streams, the first stream will be used to extract the spatial features of the data via convolutions. The process begins by extracting shallow deep features through the application of a multi-scale convolution block, followed by a spectral attention block which examines the inter-channel relationships within the feature maps. To reduce the dimensionality and increase their efficiency, a max-pooling layer is applied. The deepening of feature representation is further facilitated through the use of multi-scale residual blocks, which aim to capture more meaningful and abstract features. The second stream concentrates on the extraction of deep spatial features, primarily through the use of spatial attention blocks, it employs a similar structure as the first stream. To make a prediction, the deep features from both streams are passed through a flattening layer and then a dense layer, the final decision-making step is carried out using a soft-max layer. This two-stream attention block-based network was compared with R-CNN (recurrent-convolutional neural network), 2D-CNN, 3D-CNN, and CBAM (convolutional block attention module) Neural networks along with the XGBOOST and Random Forest classifiers.

By taking advantage of Spatial, Spectral, and temporal features of the data in their Architecture the Authors have produced a model that has performed the best among a selection of state-of-the-art classifiers, the low accuracy of Random Forest compared to other classifiers in the dataset is noted, and this somewhat anomalous result is most probably due to the way the data was split into 3% training 0.1% validation and 96.9% test sets. The authors tested for the Impact of change in time-series NDVI on the classification results and found that increasing the time series from two to seven months increased classification accuracy by 2.31%.

B. Deep learning-based multi-temporal crop classification

[42] The primary objective of this study was to test the usage of Deep Learning based classifiers in extracting features from temporal information and classifying data using those features in an end-to-end manner thus eliminating the process of manually designing features (feature engineering) which is brittle and time-consuming. The temporal data that was used was EVI (Enhanced Vegetation Index time series), which was chosen because it is also used by human experts to classify crops by eye so discrepancies and inaccuracies in the Deep neural networks could be identified. The study also seeks to break ground on the use of 1-dimensional convolution neural networks for temporal feature representation as Recurrent neural networks have mainly been used on temporal data even though 1D-CNNs are theoretically well suited for the task; along with trying to make the inner working of these deep neural networks clearer through the use of pathbreaking visualization methods. The area of the study is located in Yolo County which is situated in the Northern portion of the California. The EVI was calculated from LANDSAT images raging from the fifth day to the three hundred and sixty fifth day of the year, both the LANDSAT 7&8 satellites were used, missing values were linearly interpolated. The land parcels defined by the CDWR were used as a unit while partitioning the dataset, they were split in a 60:20:20 ratio of training, validation, and test sets. Six classifiers were used in total 1D-CNN, RNN, Multi-Layer-Perceptron (MLP), Support Vector Machine (SVM), Random Forest (RF), and XGBOOST, for the non-deep learning classifiers hyper-parameters were chosen using random search, while for the MLP grid searching was used to choose the hyperparameters.

The 1D-CNN shows the most accuracy while classifying the dataset thus validating its use for multi-temporal data, the RNN achieved an accuracy of 82.41%, this was even lower than any of the non-neural network-based models, despite being designed for use on temporal datasets. The derived time series data from HANTS and TIMESAT seems to have little effect on the accuracy of classification most probably because there are enough data points for every class so that even by transforming the datapoints in certain ways no further patterns or insights can be extracted from it.

C. Crop classification using spectral indices derived from Sentinel-2A imagery

[43] The study area was located within the Hokkaido province of Japan. Data was obtained from the Sentinel-2A satellite which collects the reflectance for 13 bands, the 3 atmospheric bands were discarded because they mainly collect data about the atmospheric variables, and the other band's resolution was converted to 10 m. Seven observations of the study site were available however due to poor quality only one observation during the growing period was used. The unit used in the study was polygon-shaped crop fields first, the average spectral reflectance in each band for every polygon was calculated and then using those values ninety-one different published spectral indices were obtained for all the field polygons. Three datasets were used, 1) Spectral bands 2) Vegetation Indices, and 3) Spectral bands + Vegetation indices, each dataset was partitioned in the ratio of 50:25:25 training validation and testing sets. The only classifier that was used in this study was Random Forest (RF), instead of optimizing just two of its hyperparameters the authors made use of an extra three hyperparameters to increase accuracy.

The authors chose to use Bayesian optimization which is better at choosing the hyperparameters for new datasets. It was assumed that including both spectral bands and indices would result in improved classification accuracy, however, we see a degradation in accuracy probably because the random forest method assumes that there is no correlation between the input variables. On applying data-based sensitivity analysis 4 bands and 8 spectral indices were found to be the most important input variables to the classifier which had the best information density, these were bands 2, 4, 11, and 12 along with indices PVR, VARIgreen, SIPI, GARI, mNDVI, REIP, EPIChlb, and NDII. When this combination was utilized the highest Overall Accuracy (OA) of 93.1% was obtained.

D. Crop classification in a heterogeneous agricultural environment using ensemble classifiers and single-date Sentinel-2A imagery

[44] The study was conducted near Roorkee in the Sate of Uttarakhand in India; the topography and land use of the study area are highly heterogenous. The values of 10 multi-spectral bands were obtained from the Sentinel-2A satellite constellation, the bands which had a spatial resolution of 20m were magnified to a resolution of 10m using the nearest neighbour (NN) method. The ground truthing was carried out manually using field surveys and GPS. Four ensemble classifiers were used; Random Forest (RF), XGBOOST, Adaboost.M1, and Schotastic Gradient Boosting (SGB) along with a Support Vector Machine (SVM) classifier. The dataset was divided into ten different groups, which were then used to set the fine-tuning of the models, the hyperparameters of the various models were set by iterating and using grid search. Out of the classifiers applied XGBOOST and Random Forest method have resulted in the most accuracy with Support Vector Machine performing the worst, out of the ensemble classifiers used Adaboost.M1 method has the least accuracy.

E. *Crop Classification Using Multi-Temporal Sentinel-2 Data in the Shiyang River Basin of China*

[45] The study area that was chosen was located in the Shiyang River basin area of China, which is the most populated inland river basin of China. The data used was collected from the Sentinel-2 satellite constellation, over a large time period, and from all the observation bands, eight different crop types were chosen to be Classified. The ground truthing of the data was carried out manually using a hand-held GPS. The Random Forest method was used to classify the images. A total of 11 images obtained from the Sentinel-2 constellation spread throughout the growing season were used, and an increase in accuracy was noted when multitemporal images were utilized instead of just single-date imagery. A maximum accuracy of 0.94 was obtained when full use of the multi-temporal data was made, the most optimal combination of image dates was found to be the 213th and 243rd days of the year indicating that the end of the growing season when phenological cycles are most pronounced might be more useful for obtaining data to increase classification accuracy as compared to the start of the growing season since the very earliest date (113) appeared last in the optimal date combinations.

F. *Crop Classification for Agricultural Applications in Hyperspectral Remote Sensing Images*

[46] The paper's main goal was to demonstrate the effectiveness of a novel method for band selection of hyperspectral data for use in the fields of crop classification. The datasets used were obtained from the Airborne visible/infrared imaging spectrometer (AVIRIS) sensor. The novel method used to select the bands from the AVIRIS sensor was based on partitioning the data into three partitions and then selecting the relevant bands based on metrics that correlated closely with the physical realities of the crops to be classified. The partitions corresponded to the visible spectrum, Near-Infrared spectrum, and Short-wave Infrared spectrum, first the most useful band was extracted from the visible spectrum by selecting the ones with the most information entropy (amount of information) then for the Near Infrared partition, the band was selected based on NDVI and finally for the short-wave infrared range band were selected based on the Modified Normalized Difference Water Index (MNDWI). The model that was used on this data was a conventional CNN. The datasets used were the Indian Pines and the Salinas datasets, both being obtained using the AVIRIS sensor.

For the Indian Pines dataset, the most accurate crop classified was minimum-tilled corn and minimum-tilled soybean, and for the Salinas dataset, they are the fallow land which is ploughed roughly, and the lettuce with a six-week growing period. The range of accuracy for the Indian Pines dataset (95.97–99.35%) was inferior to that obtained by the Salinas dataset (94.53–100%.) most probably due to the lower resolution of the Indian Pines dataset.

III. Research Gaps

A. *Use of models specifically designed to take advantage of the data.*

In classification methods like Random Forest and Support Vector Machines, one has to engineer input features for use in training and prediction. Take as an example, extracting spatial features from remotely sensed images, which commonly requires predefined spatial filter parameters like Gray-level cooccurrence matrix, extended morphological features, wavelet texture, etc that have to be set by hand using experience and domain knowledge. However, because of their specificity and the variety that spatial properties show at low levels, it makes it difficult to completely describe the data using these methods [49,50]. Deep Learning methods can extract the features from the data itself thus preventing any loss of information in the pre-processing stage and simplifying the data pipeline to potentially such an extent that Francois Chollet the creator of the Keras Deep-learning library even said that "deep learning removes the need for feature engineering" [51,52].

As an example, CNN was used to extract spatial-spectral features, through 1-dimensional convolution across the spectral dimension [53], 2-dimensional convolution across the spatial dimensions [54] and 3-dimensional convolution across the spectral and the spatial dimensions simultaneously [55] for remote sensing applications. Classification tasks using data collected in the field of remote sensing and its sub-fields has seen a rise in the use of Deep learning classifiers, with one of the reasons being the ease of feature extraction and the end-to-end nature of such classifiers. Deep learning-based classifiers especially Long short-term memory (LSTM) architecture based RNN's have been used to engineer features for large-scale temporal data-sets which fare much better than normal Convolutional Neural Networks (CNN) [56,57]. Despite this newfound popularity, there are very few instances of deep learning models being designed in such a way as to take advantage of every aspect of the data collected and capture a holistic spatial-temporal-spectral view of the data.

In our review of the literature, we have only found two studies that have designed such deep learning models to specifically utilize the richness of data collected for remote sensing purposes. Both novel architectures mentioned performed remarkably well, with the dual stream attention-module-based architecture achieving an overall accuracy (OA) of 98.54% far outperforming previous benchmark studies involving conventional deep learning models. Adding to the previous results, the model used in the other study achieved an excellent accuracy of 96.5% far above the accuracy provided by conventional classification methods and more accurate than most deep-learning-based methods. These results along with the paucity of studies using specifically hand-crafted deep-learning models indicate the need for vastly more studies involving novel deep neural networks designed to synergistically utilize the whole spectrum of data available via remote sensing to classify crops.

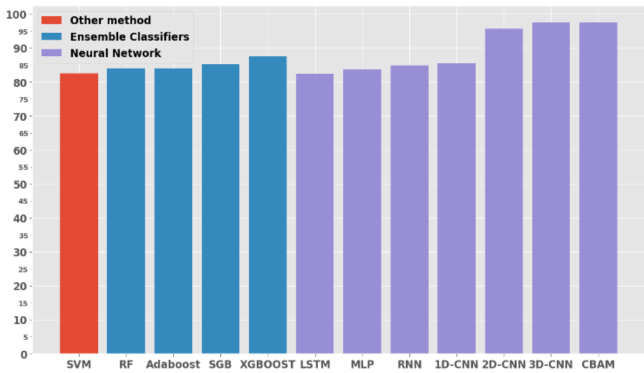

Fig. 1. The Overall Accuracy (OA) of each classification method used in the reviewed studies.

B. Usage of Synthetic Aperture data (SAR)

With continued Carbon emissions into our atmosphere, we will see a worsening of the effects caused by anthropogenic climate change, with one of the most devastating among the myriad effects being an increase in the occurrence of devastating weather events like Hurricanes, Extreme precipitation events, Heatwaves, etc [60]. There has also been an increase in the global cloud due to the same reasons with the amount of cloud cover being found to be correlated with the global mean temperature [61,62]. These factors combined will result in a degradation of the quality and availability of optical and hyperspectral remotely sensed data due to atmospheric interference from the greatly increased frequency of extreme weather events. Synthetic Aperture Radar (SAR) does not suffer from the same drawbacks as conventional remote sensing methods, the presence of cloud cover does not cause a degradation of its accuracy, and it can be used to mitigate the issues caused by cloud cover and atmospheric interference in the conventional methods [63]. The backscatter from the emitted SAR is more informative as compared to the reflectance values of bands, because the SAR backscatter is influenced by physical factors such as the moisture content of the soil, the roughness, and the features of the landscape itself, this is important since the type of farming practiced which is determined by the landscape is influential on the crop type grown. SAR backscatter also provides information on the plant stem thickness along with the physical state of the crop elements which are determined by the crop growth stage [64]. Thus, SAR can also be used to distinguish crops based on stages in the phenological cycle.

Polarized SAR can further increase the information used for classification, this is because the different type of scatterings corresponds to different densities, textures and arrangements of the plant elements. The interaction between the plant canopy, stem and the soil itself gives rise to different scattering types, as an example volume (VH and HV) scattering will be more present in plants with larger canopies like orchards and minimum in ones with small canopies like wheat [65] The use of SAR was at first almost predominantly used for crop classification in the early 1980s period as discussed above however, it has somewhat fallen out of prominence. For classification purposes, a combination of polarimetric SAR and optical images works best. In one study it was found that using dual polarization (VV + VH) SAR images along with derived features like the Grey Level cooccurrence matrix (GLCM) and the coherency combined with optical images reached accuracies of 99.35% and 99.81% when using Random Forest (RF) and Support Vector Machine (SVM) classifiers respectively [66]. Another study used band reflectance data from bands 2-7 Of Landsat along with multispectral SAR data and concluded that the accuracy (~92%) of the classification was improved by using both data sets [67]. In comparison Techniques using only derived features such as GLCM and curve similarity metrics performed slightly or significantly worse as compared to integrated methods [68]. The use of Synthetic aperture data, especially polarimetric SAR needs to be further investigated, along with its use to complement the conventional spectral and hyperspectral data used for crop classification.

C. Incomplete Utilization of spectral Indices

Spectral indices, which are varied transformations of bands obtained by satellites, are one of the most used tools in the field of remote sensing in general and crop classification in particular. This is for two reasons, the first is that they help to encapsulate the data from multiple bands into one data point, and the secondly is that they reveal several pieces of information about the biophysical state of the plant that cannot be obtained from the band data in of itself [69]. There are at least ninety-one different published vegetation indices including the Green Difference Vegetation Index (GDVI), Normalized Difference Infrared Index (NDII), etc but the vast majority of them have not been considered for crop classification. Many families of indices have good potential at predicting crop types correctly due to their correspondence with physical variables, a good example of this would be the Short Wavelength InfraRed (SWIR) family of indices which has a close correspondence to the various chemical constituents of a leaf such as the pigments and leaf water, it is for this reason that it is also used to determine the water content of foliage [70,71].

On the other hand, the Normalized Difference Vegetation Index is probably the most utilized index [72]; if we compare the frequencies of mentions of this index in papers using the Google Scholar search tool against SWIR indices like Normalized Difference Moisture Index or the Normalized Burn Ratio the ratio between each index is 1:35 and 1:17 respectively. Even In the literature survey conducted for this paper most of the papers mentioned used the NDVI index or its derivatives and the Environmental Vegetation Index (EVI). This underutilization is even though SWIR band-based indexes have been successfully used to classify a wide variety of crop types in areas with varied climatological situations.

As an example, the authors of a study of the management of pasturelands in the Brazilian Amazon used various SWIR-based indices such as NDMI, NBR, and NBR-2, to specifically classify the burned state of the land, with the SWIR-based indices being most important to indicate the secondary growth forest and secondary burn pastureland [73]. In another study, the authors used the SWIR based indices to investigate the effect of conversion into crop and pasturelands on the soils of the Cerrado region of Brazil [74]. Red Edge-derived Vegetation indices have also been shown to correlate with biophysical indicators like the area of the leaf, the energy production of the plant and the energy absorbed by the plant as a fraction of the total light energy [75,76]. This indicates the need to diversify the spectral indices used for crop classification and experiment with the effects of various alternate indices, especially those that closely correlate with biophysical variables related to plant structure and function.

D. Excessive focus on conventional modes of agriculture

Nearly every paper that explores the field of crop classification focuses on the classification of crops grown in a ‘modern’ conventional setting using large-scale Industrial agriculture. It conveys a skewed perspective by ignoring and marginalizing ‘alternative’ methods of agriculture which practice sustainable methods while maximizing agricultural output in a holistic manner like agriculture based on organic and agroecological principles [77] It also conveys an inaccurate impression with regards to scale of farms, by wholesale ignoring small-holder farms which play an important and oversized role in securing constant and adequate food supply in the global south [78] .

A good example that is taken from one of the literature survey studies [79], is the Central Valley of California which is one of the most intensely farmed regions in the United States [80]. It contains the county with some of the worst air quality in the United States: San Joaquin County. This Air pollution is in large part caused by the rampant application of Nitrogen-based fertilizers to croplands resulting in the fact that the state croplands contribute to 32 % of its Nitrate air pollutants [81]. Pollution of the Central Valley Groundwater has also occurred due to nitrate runoffs from croplands, with the Tulare Basin and San Joaquin Basin being intensely affected [82] In this context, agroecological methods seem much more appealing [83].

In the practical field, agroecology shows both resilience and potential for profit, with farms that practice such methods faring against extreme events much better and having been shown to have the potential to produce higher levels of profit as compared to industrial farms [84]. Thus, more attention should be paid to crop classification studies in areas and places where a form of agriculture practiced that differs from Industrial agriculture takes place,

Fig 2. The locations where the reviewed studies were carried out.

IV. Proposed Methodology

To overcome the identified research gaps in the field of remote sensing-based crop classification, a comprehensive methodology can be devised. This methodology should encompass the following steps and considerations:

A. *Development of Deep Learning Models for Holistic Data Utilization:*

- Data Collection: Gather a diverse dataset of remote sensing imagery, including optical, hyperspectral, and SAR data, covering different crop types and agricultural practices.
- Data Preprocessing: Standardize and preprocess the data, ensuring compatibility and quality across various sources. Take into account information about the chosen agricultural area when conducting preprocessing and feature engineering.

B. *Integration of Synthetic Aperture Radar (SAR) Data*

- Data Collection: Acquire SAR data alongside optical and hyperspectral data for the study area, covering various time intervals and crop types.
- Polarimetric Analysis: Use Polarimetric SAR since it captures more information about crops, such as leaf density and stem thickness along with information about the area such as surface roughness and soil tillage.

C. *Diversification of Spectral Indices*

- Spectral Index Selection: Identify a broad spectrum of spectral indices, including SWIR and Red Edge-derived indices, which have the potential to reveal crucial information about crop types and biophysical conditions.
- Data Enhancement: Calculate and incorporate the selected spectral indices into the dataset, considering their correlation with biophysical variables related to plant structure and function.

D. *Inclusion of Sustainable Agriculture Practices*

- Identify Study Areas: Select study areas where sustainable agriculture practices, such as organic and agroecological farming, are prevalent., and a diverse variety of crops are grown.
- Comparison with Conventional Agriculture: Compare the performance of the models in sustainable agriculture settings with that in conventional agriculture settings, searching for identifiable patterns or differences in the data.

E. *Performance Evaluation*

- Quantitative Evaluation: Assess the classification accuracy of the developed models using standard metrics such as overall accuracy, F1-score, and confusion matrices.
- Qualitative Evaluation: If a non-mapped or semi-mapped region is chosen then conduct field visits to evaluate the ground accuracy of the classification. Talk to local experts if present.

F. *Data Accessibility and Knowledge Sharing*

- Data Sharing: Share the collected datasets, preprocessing codes, and trained models with the research community to encourage further exploration in the field.
- Disseminate knowledge and encourage collaboration, by choosing an open-source license which allows further modifications to be made to the source code, and which allows for redistribution.

V. Conclusion

Here, we have analyzed the need for crop classification along with an overview of recent developments in this field, especially in the application of Artificial Intelligence and Machine learning methods to the task of crop classification. With the Information gathered, we have identified certain research gaps and probable future paths in research for deepening our understanding and competence in this field. In this spirit, we have elaborated on a possible future classification task that would in our opinion help to address the research gaps listen here and increase our domain knowledge in this field.

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