State Of The Art On Current Trends On Neural Networks And Normalized Difference Vegetation Index

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Abstract— The Normalized Difference Vegetation Index (NDVI) quantifies vegetation by measuring the difference between near-infrared (which vegetation strongly reflects) and red light (which vegetation absorbs) [1]. The near-infrared (NIR) and red spectral bands used in deriving NDVI are traditionally, but not always, sourced from space-based sensing platforms. Machine learning techniques including k-nearest neighbors (KNN), random forest (RF), and support vector machines (SVM) have been widely used in recognizing patterns from NDVI analysis, and applied in domains including prediction of vegetation growth, classification of crops and monitoring of ecosystems. However, in recent years, various types of artificial neural network (ANN) have become more popular algorithms of choice due to their higher performance in these non-linear problem domains. This report reviews recent application of ANNs for crop prediction and classification using NDVI, with all reviewed papers published during or after 2015. Given the latest research is actively developing more sophisticated data pre-processing and ANN implementations to maximize the predictive value of NDVI suggests the state of art with ANNs and NDVI is strong.

Index Terms— Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Spiking Neural Networks (SNN), Biomass Evaluation, Normalized Difference Vegetation Index (NDVI), State of the Art

I. Introduction

The last 50 years has seen the world population rise to six million from three, creating a high demand for food [2]. The F.A.O. (Food and Agriculture Organization of the United Nations) predicts continued population growth of 30% up to 2050, with food production needing to increase by 70% to support the population [2]. China's population alone stands at 1.4 billion as of 2019 [3], and as they discovered for themselves, adverse crop yield variability can seriously impact the economy, when in 2011 a drought in Yunnan Province cost an estimated 340 million U.S. dollar loss and significant price increases [4]. Incidentally it's worth noting 25% of the reviewed journals herein are published by Chinese authors, suggesting environmental and crop evaluation holds high interest and importance.

At the same time further pressure is placed on ecosystems by climate change, with rising average temperatures, water pollution, chemical usage, and increasing urbanisation and industrialisation of the landscape. A specific example reported by [5] shares a concern that despite Lake Tai being the 3rd largest freshwater lake in China and contributing significantly to the local economy, it's ecosystem has been in decline since the 1980's, attributed to rapid industrial development in the area. With many environmental stressors constraining the productivity and wellbeing of ecosystems, food security, defined as the state of physical and economic access to adequate amounts of nutritious, safe and culturally appropriate food, is at risk. Furthermore, countries are responsible for protecting and sustaining their own ecosystems. This includes pledging intended nationally determined contributions (INDC) to the U.N. via the Paris accord. For example, Cambodia pledges to increase forest cover to 60% of national land area by 2030, Suriname, a small, heavily rain forested South American country, pledging to fully protect all mangroves, and Bolivia ending illegal deforestation by 2020 [6].

Understanding these multiple pressure points stressing our agricultural and ecosystem landscape we can therefore appreciate the value of end-to-end systems enabling smart understanding, management and decision making at the field, region and country level. As the authors of [7] state, "*ecosystems need to be better understood by monitoring, measuring and analyzing continuously various physical aspects and phenomena*". This paper will look at the applied use of 3 components in such systems: biomass sensing platforms for data collection, NDVI as a data source for biomass analysis, and machine learning algorithms that make sense of the collected data for the purpose of biomass prediction and classification, with an emphasis on a variety of neural network-based models.

We will see how these components support at individual farmer scale, helping them predict optimal crop harvest times and [8] proposing to "*guide field management decisions, potentially leading to significant environmental and economical benefits. For example, the early detection of weed infestations in aerial imagery enables developing site-specific weed management (SSWM) strategies, which can lead to significant herbicide savings, reduced environmental impact, and increased crop yield*". At country level scale we'll see how rice paddy fields can be managed and are reminded that "*Rice is one of the world's major staple foods, especially in China. Highly accurate monitoring on rice-producing land is, therefore, crucial for assessing food supplies and productivity*" [9]. Delivering into the hands of service owners and policy makers the best possible understanding of the composition, health and wellbeing of ecosystems including forest, grasslands and other above ground biomass (AGB) with application of our 3 components will be illustrated. As [10] states, a better understanding "*helps to estimate net primary productivity, carbon stock and other biophysical parameters*" and can help determine and support sustainability and protection obligations.

This paper is organized as follows. Section II provides an overview of biomass data collection. In Section III the NDVI index commonly used for biomass analysis is further detailed. Section IV explains what an ANN is. Section V presents highlights in state-of-art application of various types of ANN in biomass evaluation. Section VI closes with final thoughts.

II. Biomass Data Collection

A. Direct Ground Based Measurement

One method to collect data for evaluation of AGB is conventional, direct "in the field" sampling, that often includes harvesting, oven drying and weighing of crops and trees. This is the most accurate method and hence often provides a ground truth against which the performance of remote evaluation methods can be measured and validated, however it is labour intensive, expensive and destructive. Where time-series analysis is required for biomass evaluation over seasons, or area of study is large, manual direct sampling is not practical.

Given the high cost and impracticality of manual monitoring efforts, better alternative direct measurement solutions may be achieved with networked Internet of Things (IoT) sensors measuring water levels, soil pH, sunlight exposure, and carbon dioxide, transporting data via 4G/5G telecommunications into cloud computing for store, discovery and analysis. Although an extremely interesting proposition, further review here is beyond the scope of this paper.

B. Remote Space Based Satellite Sensing Platforms

Remote sensing of Earth surface from space-borne platforms is well-proven. "*The remotely sensed normalized difference vegetation index (NDVI) has been used to study the health and biomass of natural grasslands since the 1970s*" [11]. The ability to collect biomass data on greater spatial and more frequent time-series temporal scales is invaluable in supporting agro-ecosystem and environment management that would otherwise be too expensive and laborious with manual methods.

Satellites used for biomass monitoring, and specifically the collection of data that can derive biomass indices such as NDVI, include Landsat (U.S.), MODIS (U.S.) and HJ-1A (Chinese), are typically equipped with a charge-coupled device (CCD) scanner for digital imaging. The HJ-1A satellite, launched in 2008 [12], can cover a ground width of 700km, with its onboard CCD resolving to a ground pixel resolution of 30m with 4 spectrum bands in the wavelength range 0.43–0.52 (B1), 0.52–0.60 (B2), 0.63–0.69 (B3), and 0.76–0.90µm (B4). Band B3 senses the red wavelength, and B4 near-infrared (NIR).

The HJ-1A revisit period for observation of the same earth point is 2 days, illustrating the availability of image data for crop phenology study over cycles and seasons. The authors of [9] state that phenology derived from satellite time series "*plays an important role in vegetation monitoring and land-cover classification because it can capture vegetation information of different growth stages. Its classification accuracy is higher than using monotemporal images over a region with different landscapes*". This is due to crops having different temporal profiles [13], and therefore multiple images of a given crop over time can more easily classify it than a single image. Leveraging satellite data for analysis has become more common since archives Landsat became freely available in 2008 [2].

C. Unmanned Aerial Vehicles (UAV) Sensing Platforms

At field scale, UAVs are increasingly used as flexible, inexpensive sensing platforms collecting high resolution imaging for precision agriculture applications. They "*can be equipped with commercially available, high-resolution multispectral sensors to collect valuable information for vegetation monitoring*" [8].

III. The NDVI Index

A. What Is NDVI?

A vegetation index (VI) is a calculated value from the combination or transformation of multispectral data to assess the condition and development of biomass. Many different vegetation indexes have been developed, including RVI (Ratio Vegetation Index) and TVI (Triangular Vegetation Index). NDVI, proposed by Rouse et all in 1974 [14] is the most commonly used for remote sensing of biomass. Healthy biomass reflects more near-infrared (NIR) and absorbs more red light, thus NDVI can be calculated using the sensed values of these two spectral wavelengths.

B. Calculation of NDVI

NDVI is calculated as follows:

$$NDVI = \frac{(NIR - R)}{(NIR + R)}$$

where NIR and R represent the reflective value of biomass in infrared and red band respectively [1]. Fig. 1 illustrates the formula for calculating the NDVI index for the same sample area in two different temporal periods.

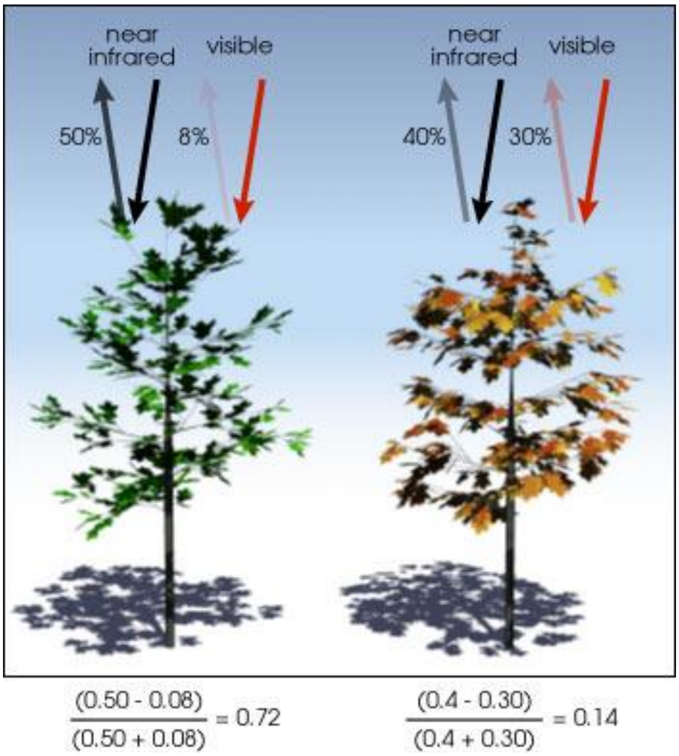

Fig. 1. Illustrated NDVI calculation [1]

The greener leaves on the left tree contain higher levels of chlorophyll (green pigments), reflecting more NIR and absorbing more red light. With NDVI values ranging from -1 to 1, a higher NDVI index is calculated for the greener tree, indicating healthier, denser vegetation. Negative values highly likely represent water, with values close to +1 indicating high possibility of dense green leaves. A value of 0 indicates the absence of green vegetation and could indicate an urban area [1]. The NDVI index increases with crop growth, maximising at peak productive stage, and hence can be used for time series evaluation. Once the NDVI values are derived they can be used as features in machine learning algorithms for applications including yield prediction, biomass health and classification.

C. Further Considerations Using NDVI

One shortcoming of NDVI measurements sourced from satellites is noise introduced by cloud cover. Quite often this renders the data unusable, increasing the challenge of evaluating biomass in monsoonal regions such as South East China. One solution introduced by [15] for time series uses smoothing "*per-pixel by applying Swets-method. This procedure identifies cloud-impacted measurements and replaces them with interpolated values*".

Depending on the complexity of both the problem to be solved and the algorithm types learning the domain, a significant amount of training data may be required. However, as an example, MODIS satellite only became operational in 2000, meaning available data is relatively small [4]. With regard to data pre-processing, the majority of papers researched indicate some form, including atmospheric correction [16] [5], orthorectification (alignment correction) [8] and clustering [17] before input into machine learning models as features. Others highlighted the augmentation of NDVI, either with fusion of multiple NDVI sources (Landsat with MODIS [9]), blending data from different instruments (satellite NDVI with ground base soil moisture measurements [16]) or using multiple VI (NDVI with SAVI – soil-adjusted VI, [5]), again for provision of additional features.

IV. Artifical Neural Networks

"*Machine learning can be defined simply as the ability of a machine to learn and perform without being explicitly programmed*" [18]. Many different algorithms have been used to model problems in machine learning, including decision trees, random forest and gradient boosting. However, recent progress in ANNs has enabled the surpassing of other machine learning algorithm benchmarks in a wide variety of applications, including image and speech recognition, natural language understanding and bioinformatics [19].

An ANN is a model inspired by the human brain with neurons that combine multiple input signals and produce output signals. The model has 3 layer types: input, hidden and output. The input layer acts just like the senses of a human, like eyes and ears, taking in information. Hidden layer(s) consist of a number of neurons that accept values from the previous layer and apply a function before passing the calculated value onto the next layer. The final layer type is output which generates values, typically continuous for a regression problem and binary for classification.

ANNs are proven to be particularly good at solving complex, non-linear problems, and hence suited to biomass evaluation. As [10] comments, "*linear relations are rather rare entities in ecological modelling*" and "*ANN has been developed to handle practical problems and accordingly applied extensively in the fields of forestry, landscape ecology, hydrological modelling, terrain characterization*". Their suitability is in part due to their ability to iteratively reweight values as they are passed into neurons before summing for output to next layers with techniques such as back propagation. As the authors of [20] describe it, "*the procedure repeatedly adjusts the weights of the connections in the network so as to minimize a measure of the difference between the actual output vector of the net and the desired output vector*". Cost functions such as quadratic (mean squared error) or cross entropy compare the calculated value or prediction against ground truth values from training observations. Optimisation of cost calculation, traditionally with stochastic gradient descent, is used to minimise the cost, and the updated weight back propagated for recalculation, giving neurons and the network as a whole the ability to learn from mistakes. Increasing the number of hidden layers and neurons within them can support modelling greater problem complexity.

The hierarchical architecture of a simple multilayer perceptron neural network with back propagation is presented in Fig. 2, consisting of connected neurons in an input layer, 1 hidden layer and an output layer.

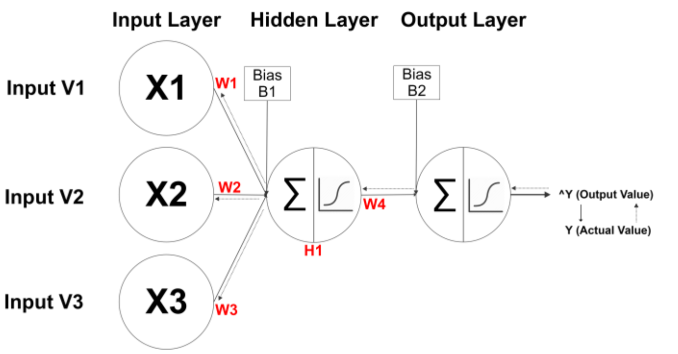

Fig. 2. Multilayer perceptron neural network with back propagation

The input layer has units for each of the input variables (for e.g. NDVI index value, soil pH, slope aspect), which are then passed forward with estimated weights to the hidden layer containing 1 neuron. ∑ represents a combination function in the hidden layer neuron unit that sums the input features multiplied by associated weight with added estimated bias, all in a linear summation as follows:

Bias B1 + (V1 * W1) + (V2 * W2) + (V3 * W3)

The hidden layer neuron unit also contains an activation function, represented in Fig. 2 by the sigmoid S curve, which receives the result of the combination function as a real number and transforms it with a non-linear function. Example functions include tanh, which centres around 0, with range -1 to 1 and a steeper gradient in comparison to the function log (0 to 1, used for binary target classification for e.g.). The function used is selected according to the problem domain and target value, essentially to determine when the neuron should light up or activate. It is these functions that give neural networks their powerful non-linear behaviour. The output layer also has an activation function with weighted combination, bias and transfer. The dashed lines represent the back-propagation learning concept, with comparison between calculated output value and training actual value determining the error cost. An epoch is one complete pass over the training dataset by the network. At the end of 1 epoch the summed error difference between all calculated and actual values is fed back through the network to update the weights. The network is cycled through for many epochs (10, 100 etc) until the cost is minimised. Of course, far greater mathematical and architectural complexity is introduced with network types that feature more sophisticated optimisation, convolution, recursion and temporal persistence.

V. ARTIFICAL NEURAL NETWORKS IN BIOMASS EVALUATION

Dr Frank Rosenblatt, a psychologist of Cornell University, is credited with defining the perceptron in 1957, demonstrating via mathematics and computer simulation that neural networks with variable weight connections could be trained to classify spatial patterns into prespecified categories [21]. NDVI was introduced by Rouse et al. in 1974 with the paper "*Monitoring Vegetation Systems In The Great Plains With ERTS*" [14] which then detailed "*a method developed for quantitative measurement of vegetation conditions over broad regions using ERTS-1 MSS data"* with *"radiance values recorded in ERTS-1 spectral bands 5 and 7*". Band 5 is red and 7 NIR, with ERTS-1 (Earth Resources Technology Satellite) renamed to Landsat-1 by NASA. Given the reviewed papers were published from 2015 suggests the state of research and application of NDVI data feeding ANNs for biomass evaluation is still very healthy. It implies there is a perfect storm of big data availability with the computing resources and algorithmic complexity to make sense of it for higher performing solutions.

A. Utility

The analysis of NDVI with NNs is being applied to the management of some of today's most pressing challenges, which include classification of land use (forest, grass, farm, impervious) [13] [9] , quantification of supply in field and forestry [4] [10] [5] [17] [16] [15] [11] , and anomaly detection (weeds, landslides, deforestation) [22] [8]. From China to Canada these 2 components are supporting efforts to improve the forecasting of crop yield, "*applied to estimate the winter wheat in Shandong province, one of the main winter-wheat-growing regions of China*" [4] and "*help policy makers and grain marketing agencies in planning for exports and imports*" [17]. Given ANNs are being used as algorithm of choice for such important, nation-scale food security management supports the argument that the state of NDVI with ANNs is strong. An awareness that ecosystems have an intricate relationship with climate and are under stress from human development highlights the fact we are working with such complicated systems influenced by many interacting, varied factors. The authors of [11] support the use of ANNs with "*non-linear models are better than the corresponding linear models*", expanded upon by [16] with "*usage of NN provides better solutions when they are applied to complex system that may be poorly understood*". This is further evidence the state of NDVI with ANNs is strong today.

Advantages ANNs have over other machine learning models is both their superior flexibility in adapting their architecture to accommodate the complexity of the problem by changing the number of neurons and layers used [10], and the array of ANN model types available. In the study of crop phenology over growing cycles and seasons, neural networks come into their own as a more powerful tool over traditional machine learning algorithms like RF and SVM, which are not able to correlate several time series images, as "*they manage features independently of each other, ignoring any temporal dependences which data may exhibit*" [13]. This is the benefit of models like recurrent neural networks (RNN) and "*the long short-term memory (LSTM) model, to perform land cover classification considering multitemporal spatial data derived from a time series of satellite images*" [13].

In China, "*the landslides of Shenzhen dated on 20 December 2015 led to the loss of 69 lives and dozens of buildings in ruins*" [23]. The authors proposed a system for the survey of landslide-prone areas to identify landslide potential, a key feature being the ability to assess land cover change over time. They delivered a solution using a Deep Convolution Neural Network (DCNN) model that had a reported high capacity in landslide detection and providing a solution for disaster emergency services that has real, tangible benefit in saving lives and preventing economic loss. In further landslide risk assessment research, the authors of [22] report their neural network model surpassing the overall classification accuracy of other algorithms including KNN and SVM when NDVI data is fused with SWIR (Short Wave Infrared), and comment that in addition to landslide detection "*an added benefit would be the timely detection of undesirable practices such as deforestation*", which this author believes really adds value and delivers a readily available solution for monitoring policy commitments according to the Paris accord as an example. Consider that more than 50,000 people have been reported killed by 4800 landslides between 2004 and 2016, with 700 of those landslides attributed to human activity including illegal mining and hill cutting [24]. This evidence alone supports the use of models like CNNs in monitoring landscape use with the referenced research proving their effectiveness when combined with NDVI in the domain of image change detection.

At field level for smart farming, [8] proposes "*a novel crop/weed segmentation and mapping framework that processes multispectral images obtained from an unmanned aerial vehicle (UAV) using a deep neural network (DNN)*". The fact that NDVI and ANNs are being integrated into solutions alongside newer, affordable technologies like commercial drones and sensors available off-the-shelf that can empower independent farmers with real-time precision crop management lends further weight to the argument the state of NDVI with ANNs is strong. With the authors providing their solution as a benchmark tool for others to evaluate crop/weed classifiers and thus continue research forward further supports this claim.

B. Data Preprocessing

In order to prepare for ANN modelling and extract the greatest possible predictive performance, all the reviewed research included some form of data pre-processing. At a basic level, and standard practice for machine learning, "*all the input data were normalized within the boundary (0–1) for modeling in ANN*" [11]. Other studies fused NDVI data from multiple satellite sources (MODIS & Landsat) [9], blending NDVI with additional vegetation indexes (NDVI, EVI, MSAVI, TVDI etc) [16] [5] [17], soil moisture data collected from sample sites [16] and land surface temperature (LST) from Landsat 8 satellite images [9]. Clustering data from smaller sites into larger regions by soil type was done in [17]. Studies [8] and [10] geo-referenced and orthorectified images, which corrects alignment and ensures uniform scale, and as stated by [8], "*enables representing crop or field properties of a large farm in a quantitative manner (e.g., a metric scale) by making use of georeferenced images*" and "*allows for feeding stacked images to a DNN for subsequent classification*".

In the estimation of soil moisture, [16] utilizes discrete wavelet transform (DWT) as a data pre-processing technique "*that provides a time-frequency representation of an analyzed signal*" which can "*produce a good local representation of the signal in both time and frequency domains and provides considerable information about the structure of a physical process to be modelled*". In essence, the NDVI values are decomposed into wavelet sub-time series as an output of a 2 by 2 matrix of coefficients where amplitude is a function of scale and translation, with translation representing time and scale indicating frequency.

Having reviewed the range of pre-processing techniques used in the literature it can be claimed that NDVI remains very much the most widely used of available vegetation indices with very active research in transforming or augmenting it to extract the best possible predictive value when used to feed ANNs.

C. Topologies

All the reviewed papers implement networks in which layers containing neurons are connected. However, they differ in how features are pre-processed for the input layer, how the network is trained, the number of neurons within a given layer, the number of hidden layers, how they trigger neuron activation, how cost is evaluated and how they optimise. Approaches taken by the reviewed literature will be illustrated to provide supporting evidence the state of art in NDVI with ANNs is strong.

Some of the architectures used for solving the biomass evaluation problem use supervised learning where ANNs are trained by data annotated with ground truth which, for example, explicitly indicates the correct crop classification for a given observation. When mapping paddy rice fields for classification, the authors collected the crop type ground truth at 580 points [9] distributed over the sample area. In a solution to classify crop/weed at field level, the authors collected ground truth at the pixel level [8] and labelled training data accordingly. However, clean and correctly labelled training data in sufficient quantity is not always available due to a number of reasons including cost, manual effort, available expertise and geographic location. As [23] remarks in relation to landslide risk assessment, "*samples should be extracted by experts and it is difficult to acquire appropriate landslide samples in many areas where there is no landslides that have recorded in the past*". Implementing an unsupervised learning method where the system did not need to know about previous landslides calculates the Manhattan distance to measure degree of change between two images. For these rice crop and landslide assessment solutions a convolutional neural network (CNN) was used. CNNs are an application of deep learning that leverages more complex, deeper networks with more layers. They are models well established for the extraction of features in image analysis and object recognition, with an "*outstanding capacity for image classification*" [23]. Given the interest in them versus ANNs, as illustrated by the Google Trends search term comparison in Fig. 3, research and application of CNNs in the last 3 years is very active.

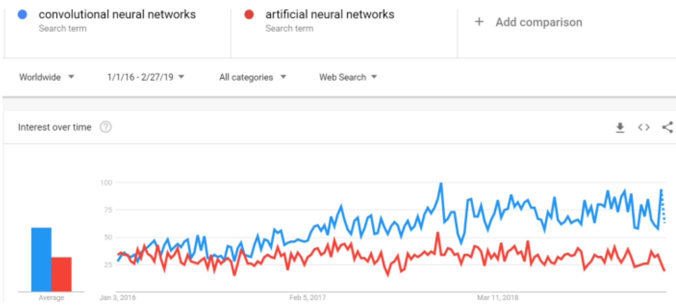

Fig. 3. Google trend comparison CNN vs ANN

A convolution is the combined integration of 2 functions, and in the context of a CNN is the convolved layers generated after several feature detectors have been applied to an input image. Feature detectors, sometimes referred to as kernels, represent how impervious rock, rice crops or trees may look like through digital representation, and are used to extract main features whilst throwing away unnecessary pixel information and reducing image size for easier network computation. As the authors of [7] describe it, they "*encode multiple lower-level features into more discriminative features, in a way that is spatially context-aware. They may be understood as banks of filters that transform an input image into another, highlighting specific patterns*". We know images of biomass and landscape contain many non-linear elements such as varying colour shades and crop shapes. As stated for typical ANNs, they are powerful models in addressing complex, non-linear problems, and the same applies to CNNs, with the convolved layers passed through rectifier functions to enhance the non-linearity of the convolution function. After pooling to preserve image features whilst further reducing image size, a vertical transformation of the pooled features in matrix form is done so a column of features can be injected into the network input layer. The architecture of the CNN model used for landslide detection [23] is shown in Fig. 4, with 2 convolutional layers, 2 pooling layers and a flattened, fully connected layer. This is a very elegant unsupervised approach that reduces time series images to their main feature set for change detection and avoids the need for manual feature engineering and labelling. This example demonstrates state of art with NDVI with ANN for tangible, real-world use case.

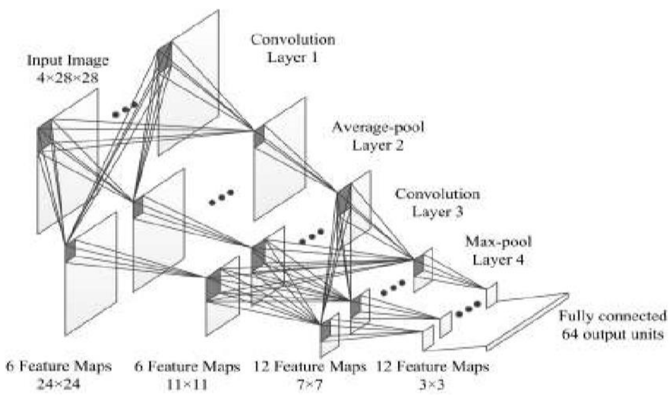

Fig. 4. Structure of CNN for landslide detection [23]

In crop yield forecasting on the Canadian prairies [17] the research applied a Bayesian Neural Network (BNN) architecture to resolve overfitting. Overfitting is where the network performs well with test data but less well with unseen data as it is too tightly conformed to training data noise and thus unable to generalize. As the authors describe it, "*using Bayesian probability theory, the probability distribution of the network weights given the training data is calculated. For a data set, rather than selecting the single optimal weight vector, the probability distribution of the weights from the given data set is determined*" [17]. They claim that in comparison to standard ANNs, their BNN model delivers higher performance, further evidence of continued research into alternative optimization approaches for extracting maximum value from NDVI data.

One solution for estimating vegetation biomass uses a neural network based on particle swarm optimization (PSO), which attempts to mimic the behaviour of flocks of birds or a school of fish. The authors argue that "*Traditional neural networks use gradient descent for performance optimization. However, the gradient descent method has limited ability to deal with complex high-dimensional spaces and is often trapped by local optima*" [5]. They further explain that "*Particle swarm optimization is a metaheuristic, as it makes few or no assumptions about the problem being optimized and can search very large spaces for candidate solutions*" [5]. They use PSO to optimize by iteratively attempting to improve candidate particle solutions, according to a measure of quality, that are moving around a search space. Improvement is guided by both each particle's own best-known position and that of the other particles in the swarm. Generally, the swarm is expected to converge on the best-known global solution.

This solution specifically applies segmented PSO (SPSO), first proposed in 2017, to "*avoid being trapped by local optimal solutions, maintaining the diversity of the particle swarm is critical*" [5]. During neural network optimisation using a function like gradient descent, parameters can get stuck in local optima rather than finding the global optimum. In SPSO one particle is designated the global leader, while the remainder of the population is segmented into 3 groups. During each iteration of the optimisation, the global leader is static to anchor the global optimum, while local leaders maintain proximity to the global and their own optimal solution. Each follower particle looks to improve, moving in the search space whilst tracking both its own local and global leader. This author proposes that the behaviour of particles tracking their local leaders to maintain diversity helps prevent overfitting and therefore of particular interest. Fig. 5 illustrates the segmented particle swarm movement.

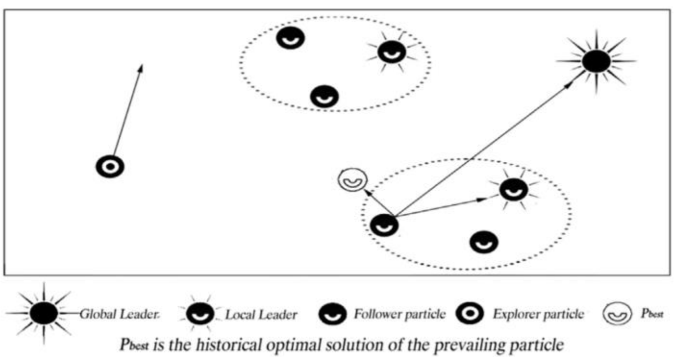

Fig. 5. Division and movement of particle swarm [5]

[13] proposes a solution for land cover classification using satellite NDVI time-series data using recurrent neural networks (RNN), explicitly the long short-term model (LSTM). Being able to correlate and analyse multiple images of a given point can facilitate higher classification accuracy as the crop phenology can help distinguish crop type. RNNs are especially appropriate for processing a dynamic series of images across time, essentially capturing temporal correlations by recursion [13]. They "*explicitly manage temporal data dependences, since the output of the neuron at time t−1 is used, together with the next input, to feed the neuron itself at time t.*" [13]. In other words, the network contains loops in which a controlled amount of previous and current information can be persisted into the next step of the network, giving it a form of memory for enhanced learning by previous experience.

The approach to classification evaluation was intriguing, as the authors not only tested classification accuracy of direct output from the RNN (LSTM) itself, but also assessed a stacked classifier architecture using the LSTM to process time-series data then feed more traditional RF and SVM classifiers with a new, temporal-free data representation. Table I provides landcover classification results using the Reunion Island time series dataset. Note the LSTM itself not only delivered best accuracy in single classifier architecture but also improved the performance of RF and SVM when stacked, with SVM(LSTM) the best overall combination. This clearly illustrates how "classical" RF and SVM models benefited from the LSTM being able to process temporal data and output new features, and how such research using NDVI with a combination model stack can be argued state of art.

TABLE I
COMPARISON OF MODEL ACCURACY ON REUNION ISLAND [13]

Method	Accuracy	F-Measure	Kappa
RF	81.19% ± 0.72%	79.40% ± 0.75	0.77 ± 0
SVM	81.59% ± 0.47%	80.01% ± 0.43%	0.77 ± 0
LSTM	86.23% ± 0.62%	86.11% ± 0.58%	0.83 ± 0
RF(LSTM)	86.15% ± 0.50%	85.97% ± 0.48%	0.83 ± 0
SVM(LSTM)	**86.41**% ± 0.60%	**86.23**% ± 0.56%	**0.83** ± 0

Another reviewed example using NDVI time-series presents the first application of spiking neural networks (SNNs) to the estimation crop yield, specifically winter wheat in Shandong province, China [4]. This in itself can be argued as novel and therefore state of art. SNNs are considered to be the 3rd generation of neural networks, mimicking the biophysical nature of the neuron. A high-level architecture overview of the SNN is shown in Fig. 6.

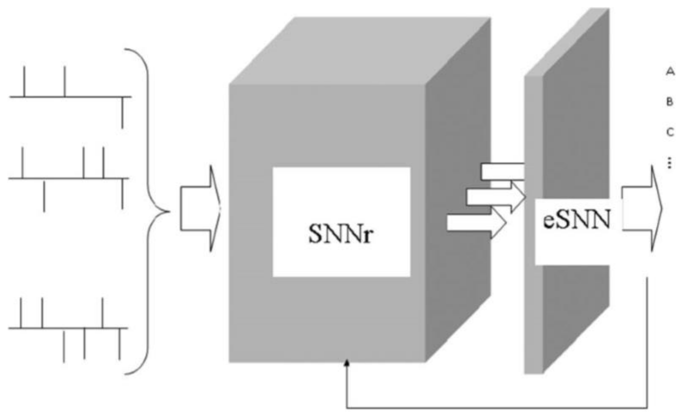

Fig. 6. General architecture of the NeuCube SNN [4]

The authors adapted a NeuCube SNN architecture, originally used to process streams of spatiotemporal brain data at the millisecond timescale. The justification for use of an SNN is based on the claim "*traditional ANNs, have a limited capacity to achieve the integration of complex and long temporal spatial/spectral components because they usually either ignore the temporal dimension or oversimplify its representation*" [4]. The SNN encodes the activity of continuous NDVI data across time. When enough NDVI input is collected and exceeds neuron membrane thresholds, a positive spike is emitted for positive changes and negative spikes emitted for negative changes. After spike emission, neuron state is reset with no further spiking for a period of time known as the absolute refractory period. Encoding of the NDVI input into a spike train feeds the SNNr (SNN reservoir) which accumulates the temporal information for crop yield prediction by the eSNN output regressor.

With evidence showing research to improve the predictive capacity of NDVI in resolving complex, non-linear problems with sophisticated model architectures further supports state of art with NDVI and ANN is actively healthy.

D. Performance

This review has illustrated the state of the art is strong in using derived NDVI for pattern detection applying ANNs to such problems as crop yield prediction, crop classification and landscape anomaly detection. One common theme observed over all reviewed articles is the reported high performance of ANNs, including their superiority over more traditional machine learning algorithms, especially in the context of complex, non-linear, multi-temporal or class imbalance problem domains. In modelling grassland biomass, [11] confirms "*that the ANN model developed in this study performs better than do the multi-factor regression models*". This claim is further supported by [10] with "*results confirmed the superiority of ANN over other models in terms of several statistical significance and reliability assessment measures*" and "t*he SNN performed much better than the other traditional approaches*" [4]. The authors of [13] lend further weight to the claim with "*All these results indicate that the LSTM model is well suited to extract long short temporal dependences as opposed to common classification approaches that do not explicitly leverage temporal correlations. This is particularly evident on low represented and highly mixed classes: tree crops, summer crops*". Using RNNs to classify land cover using time-series, they additionally commented "*regarding well represented classes, it obtains similar or slightly better results with respect to RF and SVM*" [13]. What was particularly interesting here was the dual-stack approach use of RNNs in modelling spatial-temporal data to generate new features for input into RFs and SVMs, improving the accuracy performance of those traditional classifiers by ~5%.

This theme of ANN models delivering impressive results continues. With SNNs, the authors were able to predict wheat crop yield 6 weeks in advance with a measured accuracy of 95.64%, with a correlation coefficient of 0.81 compared with 0.67, 0.56 and 0.67 for the popular linear regression, KNN and SVR (support vector regression) approaches respectively [4]. Similarly high results were attained in the use of a CNN-based architecture for paddy-rice crop classification with "*overall accuracy of 97.06% and a Kappa coefficient of 0.91, which are 6.43% and 0.07 higher than that of the support vector machine method, and 7.68% and 0.09 higher than that of the random forest method, respectively*" [9]. However, in evaluations comparing different machine learning algorithms, ANNs did not deliver winning solutions in every single test. In crop yield forecasting in the Canadian prairies, the BNN outperformed other models in estimation of barley, but multiple linear regression was best in predicting canola yield. The authors attributed this to the non-linear models only consuming MODIS NDVI data. They suggested the "*relationship between crop yield and MODIS-NDVI is essentially linear*" [17]. By fusing NDVI with EVI (Enhanced Vegetation Index) for input into their linear models the blended dataset provided additional predictive features that improved accuracy.

An important point is raised by [11], that despite their ANN performance unparalleled in comparison with other modelling approaches in the domain of image and signal processing as evidenced here, the computational workings of ANNs are not easy to explain. Depending on use case and what is considered "*good enough*" performance, other, more easily explained classifiers such as decision trees, RF and SVM may be acceptable alternatives.

VI. CONCLUSION

It is reasonable to summarize, given the literature reviewed as published since 2015, that ANNs consuming derived NDVI image data to evaluate biomass typically offer levels of performance beyond what's possible to extract from other machine learning algorithms. In very active research we've seen ever more sophisticated ANN variations including RNNs and SNNs being applied that can better model crop phenology using time-series images. By its continued prevalence in recent research, NDVI is still regarded as the single most important vegetation index, although several approaches have blended with other data sources to maximise non-linear target attributes.

With the environment under increasing pressure from climate change and human development, there appears to be real opportunities to benefit from an increase in smarter farming ecosystem management given today's perfect technology storm of available time-series satellite data, accessible machine learning software, elastic and affordable cloud computing, connected IoT and more capable UAV platforms. Knowing exactly when to harvest for maximum crop yield and planning for it throughout the complete supply chain brings significant benefit, as does knowing when to selectively apply herbicides or take action on newly identified deforestation or areas at risk of landslide. This can only encourage continued academic research. However, this author fears these capabilities will benefit only the largest corporations and wealthiest nations. With a digital divide denying developing countries access to the necessary data, technologies, communications infrastructure and expertise [2], there is a risk smart biomass evaluation solutions will not be available to areas such as poorer African countries where such systems can have the most impact. There are also legitimate concerns around data privacy, with farmers concerned their land use and crop development information may be misused by competitors or stock market speculators [2].

The author hopes that in an increasingly connected world of big data, with freely available time series satellite datasets and a growing library of open-source software development and machine learning toolkits, full end-to-end packaged products to support biomass monitoring and evaluation can be placed in the hands of many, regardless of location and wealth, for improved farming and ecosystem care.

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Appendix A – Literature Table

Literature	Ref	Year	Category	Reason Used / Notes
What Is NDVI (Normalized Difference Vegetation Index)?	[1]	2018	DEF	Definition of NDVI, example NDVI calculation
A review on the practice of big data analysis in agriculture	[2]	2017	CTX, SAT, PRI	Setting context food security and access to technologies, Landsat public domain data, NDVI data privacy and misuse
Demographics of China	[3]	2019	CTX	China population
Spiking Neural Networks for Crop Yield Estimation Based on Spatiotemporal Analysis of Image Time Series	[4]	2016	PRE, SAT, CTX, CHN, SNN	Setting context with food security and volume of MODIS data. Crop yield estimation, SNN with NeuCube architecture
Adaptive neural network based on segmented particle swarm optimization for remote-sensing estimations of vegetation biomass	[5]	2018	PRE, SAT, ENV, CHN, DAF	Setting context with environmental stress, pre-processing with atmospheric correction, data fusion, use of particle swarm optimisation with representation
Paris 2015: Tracking country climate pledges	[6]	2015	ENV	Paris accord policy pledges
Deep learning in agriculture: A survey	[7]	2018	CTX, CNN	Setting context with ecosystem management, description on convolution in CNN
WeedMap: A Large-Scale Semantic Weed Mapping Framework Using Aerial Multispectral Imaging and Deep Neural Network for Precision Farming	[8]	2018	CLA, UAV, CTX, CNN, ORT	Setting context with farm management, field-level classification using commercially available UAV platforms, orthorectification of images
Mapping Paddy Rice Using a Convolutional Neural Network (CNN) with Landsat 8 Datasets in the Dongting Lake Area, China	[9]	2018	CLA, SAT, CTX, CNN, TIM, DAF	Setting context with food security. Time series with CNN, data fusion
An alternative approach for estimating above ground biomass using Resourcesat-2 satellite data and artificial neural network in Bundelkhand region of India	[10]	2017	PRE, SAT, CTX, ORT, IND	Setting context with ecosystem management, non-linearity, orthorectification
Modeling grassland above-ground biomass based on artificial neural network and remote sensing in the Three-River Headwaters Region	[11]	2018	PRE, SAT, CTX, CHN	Setting context with history of NDVI, non-linearity and ANNs being black boxes
Satellite HJ-1A/B/C	[12]	2015	DEF	CCD/spectral bands/revisit details on HJ-1A satellite
Land Cover Classification via Multitemporal Spatial Data by Deep Recurrent Neural Networks	[13]	2017	CLA, SAT, RNN, TIM	Details on time-series image processing with temporal dependencies, RNN with accuracy comparison with other classifiers
Monitoring Vegetation Systems in the Great Plains with ERTS	[14]	1974	DEF	Intuition behind NDVI from inventor Rouse et al
A comparison of machine learning algorithms for regional wheat yield prediction using NDVI time series of SPOT-VGT	[15]	2016	PRE, SAT, TIM, DAF	Time series with interpolation to handle cloud-cover, data fusion
Spatio-temporal Soil Moisture Estimation Using Neural Network with Wavelet Preprocessing	[16]	2017	PRE, SAT, DAF, TIM	Atmospheric correction, NDVI data fusion, non-linearity, time series data pre-processing with wavelet transformation
Crop yield forecasting on the Canadian Prairies by remotely sensed vegetation indices and machine learning methods	[17]	2016	PRE, SAT, CTX, BNN, DAF, CLU, CAN	Setting context with food security, clustering of data into regions, data fusion with additional VI to enhance NDVI, BNN
Land Cover Prediction from Satellite Imagery Using Machine Learning Techniques	[18]	2018	DEF	Defining machine learning
Deep Learning	[19]	2015	CTX	Setting context with ANN use cases
Learning representations by back-propagating errors	[20]	1986	DEF	Definition of back propagation
Neural Networks - Then and Now	[21]	1991	CTX	Setting context with background of ANNs
Feasibility Study of Land Cover Classification Based on Normalized Difference Vegetation Index for Landslide Risk Assessment	[22]	2016	CLA, SAT, CHN	Performance of ANN compared with other classifiers
Automated Landslides Detection for Mountain Cities Using Multi-Temporal Remote Sensing Imagery	[23]	2018	CLA, SAT, CNN, CTX, TIM, CHN	Setting context with use case and challenges in labelling data. CNN with time series, CNN architecture
Global fatal landslide occurrence from 2004 to 2016	[24]	2018	CTX	Setting context for use case

Category Key

BNN Bayesian Neural Network
CAN Canada
CHN China
CLA Classification
CLU Clustering
CNN Convolutional Neural Network
CTX Context
DAF Data fusion
DEF Definition
ENV Environment
IND India
ORT Orthorectification
PRE Prediction
PRI Privacy
RNN Recurrent Neural Network
SAT Satellite sourced NDVI
SNN Spiking Neural Network
TIM Time series
UAV UAV sourced NDVI

Land Cover Classification via Multitemporal Spatial Data by Deep Recurrent Neural Networks

Dino Ienco, Raffaele Gaetano, Claire Dupaquier, and Pierre Maurel

***Abstract*—Nowadays, modern earth observation programs produce huge volumes of satellite images time series that can be useful to monitor geographical areas through time. How to efficiently analyze such a kind of information is still an open question in the remote sensing field. Recently, deep learning methods proved suitable to deal with remote sensing data mainly for scene classification(i.e., convolutional neural networks on single images) while only very few studies exist involving temporal deep learning approaches [i.e., recurrent neural networks (RNNs)] to deal with remote sensing time series. In this letter, we evaluate the ability of RNNs, in particular, the long short-term memory (LSTM) model, to perform land cover classification considering multitemporal spatial data derived from a time series of satellite images. We carried out experiments on two different data sets considering both pixel-based and object-based classifications. The obtained results show that RNNs are competitive compared with the state-of-the-art classifiers, and may outperform classical approaches in the presence of low represented and/or highly mixed classes. We also show that the alternative feature representation generated by LSTM can improve the performances of standard classifiers.**

***Index Terms*—Deep learning, land cover classification, recurrent neural networks (RNNs), satellite image time series.**

I. Introduction

MODERN earth observation programs produce huge volumes of remotely sensed data every day. Such information can be organized in time series of satellite images that can be useful to monitor geographical zones through time. How efficiently manage and analyze remote sensing time series is still an open challenge in the remote sensing field [12].

In the context of land cover classification, exploiting time series of satellite images, instead that one single image, can be fruitful to distinguish among classes based on the fact they have different temporal profiles [1]. Despite the usefulness of temporal trends that can be derived from remote sensing time series, most of the proposed strategies [7], [11] directly apply standard machine learning approaches [i.e., random forest (RF) and support vector machine (SVM)] on the stacked images. Since these approaches did not model temporal correlations, they manage features independently of each other, ignoring any temporal dependences which data may exhibit. Recently, the deep learning revolution [18] has shown that neural network models are well adapted tools to manage and automatically classify remote sensing data, while standard convolutional neural networks' (CNNs) techniques are well suited to deal with spatial autocorrelation, the same approaches are not adapted to correctly manage long and complex temporal dependences [3]. A family of deep learning methods especially tailored to cope with temporal correlations are recurrent neural networks (RNNs) [3] and, in particular, long short-term memory (LSTM) networks [9]. Such models explicitly capture temporal correlations by recursion and they have already proved to be effective in different domains, such as speech recognition [8], natural language processing [13], and image completion [17]. Only recently, in the remote sensing field, the work proposed in [14] performs preliminary experiments with LSTM model on a (small) time series composed of only two dates to perform supervised change detection. The task was modeled as a binary classification problem (change versus no-change). To the best of our knowledge, RNNs (i.e., LSTM) have not yet been considered to deal with land cover classification of deeper time series. Like any other deep learning model [3], LSTM can be used as a classifier itself or employed to extract new discriminative features (or representation). In the latter case, the extracted features are successively used to feed a standard learning algorithm that does not consider temporal dependences (i.e., RF, Naive Bayes, KNN, and SVMs).

In this letter, we evaluate the quality of RNN models—LSTM—to deal with land cover classification via multitemporal spatial data that are derived from satellite images time series (SITS). We perform experiments on two study areas: 1) the *Thau* basin, a site located in the south of France, from which, we obtain a time series of three dates and 2) the *Reunion Island*, a region of France located in the Indian Ocean (east of Madagascar) from which, we derive a 23 observation time series; While on the first area, we conduct an object-oriented classification, and on the second site, we have performed a pixel-based prediction showing the general applicability of RNNs models to both object and pixel-level analyses. We also assess the RNN model (i.e., LSTM) as feature extractor evaluating the quality of the new generated features to feed the same baseline classifiers that we have used as reference methods.

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Spiking Neural Networks for Crop Yield Estimation Based on Spatiotemporal Analysis of Image Time Series

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***Abstract*—This paper presents spiking neural networks (SNNs) for remote sensing spatiotemporal analysis of image time series, which make use of the highly parallel and low-power-consuming neuromorphic hardware platforms possible. This paper illustrates this concept with the introduction of the first SNN computational model for crop yield estimation from normalized difference vegetation index image time series. It presents the development and testing of a methodological framework which utilizes the spatial accumulation of time series of Moderate Resolution Imaging Spectroradiometer 250-m resolution data and historical crop yield data to train an SNN to make timely prediction of crop yield. The research work also includes an analysis on the optimum number of features needed to optimize the results from our experimental data set. The proposed approach was applied to estimate the winter wheat (*Triticum aestivum L.*) yield in Shandong province, one of the main winter-wheat-growing regions of China. Our method was able to predict the yield around six weeks before harvest with a very high accuracy. Our methodology provided an average accuracy of 95.64%, with an average error of prediction of 0.236 t/ha and correlation coefficient of 0.801 based on a nine-feature model.**

***Index Terms*—Crop yield forecasting, estimation, machine learning, Moderate Resolution Imaging Spectroradiometer (MODIS), normalized difference vegetation index (NDVI), remote sensing, spiking neural networks (SNNs).**

I. Introduction

Crop production plays a vital role in food security and economic development of a country. In the past years, the fluctuation of crop yield in China attracted a great concern in economy and even led to food crisis of the whole country. For example, a continuous drought in Yunnan Province in 2011 caused approximately 340 million U.S. dollar loss because of the substantial crop yield reduction and further resulted in significant price increases [1].

Application of remote sensing data to agriculture and crop production has been popular, especially based on the predictive empirical models, because it is possible to efficiently and quantitatively estimate crop yield by such data [2]–[5]. The normalized difference vegetation index (NDVI), a product derived from satellite multispectral data, can be used to estimate the vegetation health and monitor changes in vegetation [4], [5]. It is calculated from the normalized total reflectance of the red and near infrared (NIR) bands, ranging from -1.0 to $+1.0$ [6]. A higher NDVI indicates more green coverage, whereas a lower NDVI signifies the loss of growth and vigor of the crop. Therefore, the NDVI temporal profile rises with the growth of crops and typically reaches the peak level during the productive stage, and declines around the harvest [7]. NDVI data derived from the National Oceanic and Atmospheric Administration (NOAA) Advanced Very High Resolution Radiometer (AVHRR) have been used to forecast crop yield in many countries since the 1980s. For instance, monthly global area coverage NDVI data were used to estimate cop yield in Mediterranean African countries [8]. Decadal average NDVI data were adopted to forecast corn yield in Swaziland [9]. Similar studies have been conducted for various crop types in many other regions, e.g., wheat in Morocco [10] and Italy [11], millet in Senegal [12], and corn in Kenya [13].

NDVI data from the Moderate Resolution Imaging Spectroradiometer (MODIS) available from 2000 to the present have made significant improvements addressing the shortcomings from AVHRR [14], [15]. In past years, studies have been conducted to set up the relationship between crop yield and NDVI data from MODIS. The spatial accumulative and smoothed MODIS-NDVI data were used to estimate winter wheat production in Shandong province, China [16]. MODIS data were used to establish an empirical approach to winter wheat estimation in Kansas and Ukraine [17]. Weighted NDVI temporal series from MODIS were applied to forecast sugarcane yield in Kenya [18] and using MODIS-NDVI data with an analysis of cropland mask choice and ancillary data for annual crop yield forecasting in Midwestern U.S. [19].

The NDVI information is data intensive and correlates nonlinearly with spatial-based crop yield. Therefore, a proper model building technique for crop yield prediction is essential. A general method previously used by researchers was based on statistical model building [20]–[22]. Black [23] suggested that

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