ADVANCES IN AGRICULTURAL AND FOOD RESEARCH JOURNAL

Review Article

Predictive Modelling for Rice Weeds in Climate Change: A Review

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Abstract: Rice (*Oryza sativa* L.) is an essential staple food not only for Asians but also for people worldwide. However, weeds in rice fields can cause yield reduction due to their tendency to compete for resources. These significant biological obstacles can potentially cause complete yield loss if inappropriately managed. In addition, future climate change can cause rice weeds to become more competitive against cultivated rice plants by providing new favourable conditions for the unwanted species to expand aggressively. As the effect of climate change on rice weeds has been studied, the abiotic parameters, including carbon dioxide concentration, atmospheric temperature, drought, and soil salinity, can be used to construct predictive modelling to forecast rice weed infestation. Suppose the weed invasion in rice fields can be predicted accurately based on the weather information. In that case, the farmers can prepare the countermeasure early to avoid high yield loss. However, some challenges must be faced by the researchers as the weed invasion depends not only on the climate alone. This review summarises the effect of climatic variation on weed infestation in rice fields. It also discusses how predictive modelling had been developed based on the information on the environmental conditions.

Keywords: rice; weed; climate change; predictive modelling

Received: 3rd March 2022

Received in revised form: 5th August 2022

Available Online: 25th September 2022

Published:

Citation: Abd Manaf, M. N. H., Juraimi, A. S., W. A., F., Che'ya, N. N. Predictive Modelling for Rice Weeds in Climate Change: A Review. *Adv Agri Food Res J* 2023; 4(1): a0000317. https://doi.org/10.36877/aafrj.a0000317

1. Introduction

Rice is Malaysia's third most significant crop and one of the world's most important food sources (Hakim *et al.*, 2010). However, weed is wreaking havoc on rice production worldwide (Hakim *et al.*, 2013). In addition to increased weed development and altered weed flora, climate change's direct effects on rice plants may harm rice growth and production (Prasad *et al.*, 2017). Climate change, including rainfall, daylight hours, temperature, relative humidity, and drought season length (Alam *et al.*, 2014), can affect weed invasion and crop-weed competition, favouring weeds due to their better tolerance (Iqbal *et al.*, 2020). Climate change is a severe issue that can potentially alter the natural phenological features of plants and weeds, as evidenced by the discovery of new species as alien species (Roslim *et al.*, 2021). Farmers fail to be aware of and take safeguards in case of weed invasion prediction due to a lack of understanding of weather conditions (Rahman *et al.*, 2020). Furthermore, the dynamic shift in quantity and dominance of weeds makes invasion prediction for the coming season more difficult (Juraimi *et al.*, 2013).

Several researchers have successfully developed predictive models for rice yield forecasting based on weather variables. Artificial neural network-based localised models were built to estimate rice production in a study conducted in South Korea. The study's key characteristic was integrating the spatial interpolation technique with the statistical crop model (Park *et al.*, 2018). Meanwhile, a study conducted in West Bengal, India, discovered that the detrended production index could estimate wet-season rice yield using multiple regression analysis based on maximum temperature, rainfall, and relative humidity (Biswas *et al.*, 2017). Another study also proved that the random forest method had greater accuracy than supporting vector regression for yield prediction for three types of rice cultivars for different districts in Bangladesh based on six years of weather parameters and rice production (Rahman *et al.*, 2020).

Thus, a similar method also may be implemented to develop a predictive model for forecasting weed population in rice fields based on weather parameters. With the help of remote sensing technologies, more data can be collected and analysed quickly by using current powerful modern computers. Forecasting weed infestations based on climate change can provide farmers with an early and real-time warning system, allowing them to take appropriate action. The impact of climate variation on weed infestation in rice fields is summarised in this review. It also addresses how environmental data can be used to construct predictive modelling and the obstacles that this entails.

2. Rice, Weed and Climate Change

2.1 Rice Farming

Rice is a staple food in most countries and serves as a source of sustenance for the inhabitants (Rahim *et al.*, 2017). Rice has long been a staple of daily life in Southeast Asian countries, including Malaysia (Rahim *et al.*, 2017). Farmers in Malaysia's northern and eastern regions, particularly Kedah and Kelantan, plant rice in large quantities due to the abundance of flat, lying, flat ground (Norasma *et al.*, 2020). Wetland rice farming requires a constant, plentiful freshwater supply and low and flat ground (Norasma *et al.*, 2020; Simma *et al.*, 2017).

A study divided Rice land habitats into four categories: irrigated, rainfed lowland, upland, and deep-water (Khush, 1997). Irrigated rice is the principal technique farmers use since it covers a larger area and produces more rice than other rice areas (Juraimi *et al.*, 2013). Around 57 % of Peninsular Malaysia's rice output comes from 10 granary areas with sophisticated irrigation and drainage systems (Dilipkumar *et al.*, 2017). However, changes in rainfall patterns worldwide due to climate change have threatened water supplies and rice productivity (Simma *et al.*, 2017).

Rice production must be sustained because it is the primary food source for most of the world's population (Rahim *et al.*, 2017). Rice production also helps farmers' social and economic well-being by giving them employment and opportunity (Rahim *et al.*, 2017). Research anticipated that rice demand would grow faster than output (Paiman *et al.*, 2020). The Malaysian government purchased rice from several nations to compensate for a shortfall in home production (Dilipkumar *et al.*, 2017). Furthermore, poor weed control can diminish rice output (Norasma *et al.*, 2020).

2.2 Weeds in Rice Farming

Weeds have always been an issue in ancient times (Paiman *et al.*, 2020). Weeds are unwelcome plants that grow alongside crops (Galal & Shehata, 2015; Paiman *et al.*, 2020). Weed infestations have a devastating impact on crop productivity and yields (Pantazi *et al.*, 2016). During the crop-growing season, they interfere with the field activities of rice production systems (Talla & Jena, 2018). In most cases, weeds take advantage of disturbed environments that allow them to utilise available resources and flourish abundantly (Paiman *et al.*, 2020). They compete with crops for all resources, such as nutrients, light, space, and water, which harms agricultural output (Galal & Shehata, 2015; Talla & Jena, 2018). Weeds can also have allelopathic effects on rice plants, decreasing plant height and dry weight parameters and inhibiting crop growth and development (Ismail & Siddique, 2012).

Furthermore, the current practice employs homogenous herbicide application, resulting in severe environmental damage and low crop field productivity (Pantazi *et al.*, 2016). A uniform rate of herbicide spraying across the entire field can potentially lead to excessive herbicide usage as only specific area of the rice farm is invaded by weeds (Rosle *et al.*, 2021). In addition, most farmers today use more herbicides than the manufacturer recommends to achieve unfailing results for controlling weed growth (Mohammadzamani *et al.*, 2009).

The excessive usage of herbicides can affect soil fertility and water quality. Soil toxicity caused by herbicides can reduce the development of micro- and microorganisms in the soil, including earthworms and beneficial microbes that change the soil's nutrient status, soil properties, plant health, and agricultural productivity (Hasanuzzaman *et al.*, 2020). These herbicide residues can pose substantial risks even at low concentrations in the aquifer and water bodies. This severely threatens water quality parameters and results in the drastic extinction of aquatic life, including fish, frog, oyster, algae, and plankton (Hasanuzzaman *et al.*, 2020).

Thus, site-specific weed management minimises herbicide usage and reduces input costs. According to a study, employing a digital management map (DMM) for variable rate application (VRA) can result in up to a 13% reduction in herbicide application costs when compared to a homogenous herbicide application rate for the entire selected field (Mohammadzamani *et al.*, 2009).

In Malaysia, depending on the planting method, season, location, rice cultivars, growth rate, predominant weed flora, weed density, management practices, and infestation duration, the rice yield losses caused by weeds have ranged between five and 85% (Dilipkumar *et al.*, 2020). The yield loss caused by grasses, broadleaved weeds, and sedges was estimated to be 41, 28, and 10%, respectively (Juraimi *et al.*, 2013; Karim *et al.*, 2004). Climate, weed species and density, rice varieties, growth rate, management strategies, and the rice ecosystem all play a role in yield losses (Juraimi *et al.*, 2013). Weed control is also more critical in direct-seeded systems than transplanted systems because weeds can develop simultaneously or before rice plants in direct-seeded systems, causing severe competition (Galal & Shehata, 2015).

Different types of grasses, sedges, and broadleaf weeds make up the weed flora population in the rice field (Paiman *et al.*, 2020). Sedges are the second most abundant principal rice weeds behind grasses (Yaduraju & Mishra, 2008). Sedges were the most frequent weeds throughout the primary season, followed by broadleaved weeds and grasses (Juraimi *et al.*, 2010). Grasses are usually the most prevalent early in the season, whereas sedges and broadleaf weeds take over (Yaduraju & Mishra, 2008). Some examples of common rice weeds in Malaysia are presented in Table 1, with five weed species for each type.

Table 1. Some common weed species in rice fields in Malaysia (Hakim *et al.*, 2013; Mansor *et al.*, 2012).

Weed group	Scientific name	Common name	Life cycle
Grasses	*Leptochloa chinensis*	Feather grass	Annual
	Echinochloa crusgalli	Barnyard grass	Annual
	Echinochloa colona	Jungle rice	Annual
	Oryza sativa complex	Weedy rice	Annual
	Ischaemum rugosum	Wrinkled grass	Perennial
Sedges	*Fimbristylis miliacea*	Lesser fimbry	Annual
	Scirpus grossus	Creater club-rush	Perennial
	Cyperus iria	Grasshopper’s cyperus	Annual
	Cyperus difformis	Small-flowered umbrella plan	Annual

Weed group	Scientific name	Common name	Life cycle
	Scirpus juncoides	Bulrush	Annual
	Ludwigia hyssopifolia	Seedbox	Annual
	Sphenoclea zeylanica	Gooseweed	Annual
Broad-leaved	*Monochoria vaginalis*	Pickerel weed	Annual
	Sagittaria guyanensis	Lesser arrow-head	Perennial
	Limnocharis flava	Yellow bur-head	Perennial

2.3. Climate Change Effects on Rice Weeds

Agriculture is highly climate-dependent (Alam *et al.*, 2014). Besides agronomics and genetic factors, climate change has a long-term impact on crop output and productivity (Stuecker *et al.*, 2018). Moreover, it has been demonstrated that exogenous forcing reduces the effects of genetics (Bell *et al.*, 1995). The impact of climate change may directly or indirectly influence the physiology of plants (Bir *et al.*, 2018). According to Alam *et al.* (2014), the effects might vary depending on the place, period, and crop. A study has stated that climate influence on rice production differs significantly by location and is strongly seasonally modulated (Stuecker *et al.*, 2018). Malaysia is also no exception. Modern climate change caused by human activities, like emissions of greenhouse gases, aerosols, and land use changes, substantially impacted Malaysia's agriculture (Alam *et al.*, 2014; Bir *et al.*, 2018).

Several factors, including the changes in atmospheric CO_2 levels, rainfall amount, daylight hours, temperature, relative humidity, and the length of the drought season, are some of the abiotic conditions that can affect plant physiology (Alam *et al.*, 2014; Bir *et al.*, 2018). Soil salinisation in rice fields, especially near the coastal areas, is also an abiotic factor affecting plant growth (Dasgupta *et al.*, 2018). These factors highly influence the dynamics of weed species, distribution, and competitiveness within weed populations and crops (Bir *et al.*, 2018).

The degrees of weed invasion and crop-weed competition is anticipated to shift as the environment changes (Jinger *et al.*, 2017). Because many weeds resist climate change and have superior adaption, this change will likely benefit them (Iqbal *et al.*, 2020). Under water stress, high temperatures, and light-intensity circumstances, C_4 weed species are expected to adapt better than C_3 rice plants (Karki *et al.*, 2013; Rodenburg *et al.*, 2011). The expense of weed control could also increase due to the changes in weed growth patterns caused by climate change (Kwon *et al.*, 2013).

2.3.1 Water Regime

In the area where fresh water is available, farmers use the traditional irrigated method to flood the rice field (Chan *et al.*, 2012). Moreover, for places with less water, farmers can implement the rain-fed rice approach or use aerobic rice culture on their farms (Akinbile *et al.*, 2011; Girmay Reda & Tripathi, 2016). However, with the uncertainty of climate change, water availability might be interrupted, which can cause drought, and some places may receive higher rainfall amounts than expected, leading to flooding. The usual agriculture practices of a local rice farm may need to be altered to adapt to the changing environment, including weed management. Water regime treatments significantly impacted the types of weeds (Abou El-Darag *et al.*, 2017).

An experiment conducted with soil moisture stress conditions found that weed density increases under moisture-stressed conditions (Ghimire *et al.*, 2022). Annual weeds with broadleaf species were the most observed under soil moisture stress. *Ageratum conyzoides*, *Drymaria cordata*, *Digitaria* spp, *Lindernia nummularia*, and *Bidens Pilosa* are weed species that have increased with the deficiency of soil moisture (Ghimire *et al.*, 2022). Another related study in field conditions also found that the dry weight of *Echinochloa crus-galli* was significantly promoted under water shortage (aerobic conditions) (Abou El-Darag *et al.*, 2017). At the same time, *Cyperus difformis* increased dramatically under saturated and flooded conditions. Juraimi *et al.* (2011) also stated that weed population and biomass under continuous field capacity conditions were higher than in continuously flooded conditions. Even though the value of summed dominance ratio (SDR) for broadleaf weeds (e.g., *Monochoria vaginalis* and *Limnocharis flava*) was reduced by around 13.0 – 25.8% under field capacity conditions, the SDR value increment for grass weeds (e.g., *Echinochloa crus-galli*, *Echinochloa colona*, and *Leptochloa chinensis*) was tremendously promoted up to 120.6 – 142.1% (Juraimi *et al.*, 2011).

A greenhouse study was conducted to determine the effect of aerobic and saturated conditions on the growth and reproduction of *Leptochloa chinensis* (Awan *et al.*, 2015). The growth parameters were higher in aerobic than saturated conditions when *Leptochloa chinensis* was cultivated without rice. Under water-limited environments, *Leptochloa chinensis* can grow taller and generate more biomass of plants (107%) and inflorescence (183%) under aerobic conditions as opposed to saturated ones (Awan *et al.*, 2015).

However, a study done on *Echinochloa crus-galli* found that the growth and seed production of *Echinochloa crus-galli* were higher in flooded conditions than in aerobic conditions when grown alone without rice plant interference (Chauhan & Abugho, 2013). The aboveground shoot biomass and seed number production of *Echinochloa crus-galli* plants were significantly higher in flooded conditions than in aerobic conditions at 46-47% and 26-44%, respectively. Both studies by Awan *et al.* (2015) and Chauhan & Abugho (2013) showed no significant difference between water treatments when grown with rice interference.

2.3.2 Air temperature

As a result of climate change, global warming impacts rice-paddy ecosystems, mainly through changes in plant growth rates, affecting both rice crop output and biodiversity (Kwon *et al.*, 2013). Elevated temperatures give weeds a significant advantage, adversely affecting rice production (Bir *et al.*, 2018). Weeds may grow exponentially due to temperature changes, with some species spreading to higher latitudes and altitudes (Mahajan *et al.*, 2012). Although there is minor temperature variability, scientists also estimated that if warming remains unabated under business-as-usual emissions (RCP8.5), temperatures may rise by four degrees Celsius by the end of the century, limiting rice production (Stuecker *et al.*, 2018).

Rising temperatures enhance weed growth in paddy fields. An experiment was conducted in a temperature control chamber to investigate the impact of temperature on rice weed (Ghimire *et al.*, 2022). The findings demonstrated that weed density rises at 2^{o}C and 3^{o}C compared to ambient temperature. Annual weeds of broadleaf species were the most frequently observed in the rice field under high-temperature conditions. Rice weed species, including *Digitaria* spp, *Monochoria vaginalis*, *Polygonum hydropiper*, *Bidens pilosa*, *Dopatrium junceum*, and *Lindernia* spp., demonstrate an increase in weed density at temperatures up to 2^{o}C higher (Ghimire *et al.*, 2022).

A study was done in Daejeon, Korea, to investigate the growth behaviour of rice weeds in phytotron under field conditions and also found that the rice weeds grew faster with the temperature rise (Bir *et al.*, 2018). At an ambient temperature of +3.4°C, *Ludwigia prostrata* showed a significant dry weight and leaf area increase, 211.8% and 214.3%, respectively. *Sagittaria sagittifolia*, a perennial weed, grew at a 124.8% higher dry weight at +3.4°C than ambient temperature (Bir *et al.*, 2018).

To assess the impact of increased temperature on rice-weed competition, three years of pot experiments under phytotrons were carried out in Suwon, Korea (Song *et al.*, 2021). Elevated temperatures promoted the competitiveness of water chestnut (*Eleocharis kuroguwai*) and late watergrass (*Echinochloa oryzicola*). Rice yield reduction of both weeds under high temperatures was mainly due to decreased rice panicle and increased weed competitiveness.

Earlier germination and promoting germination range are some weed enhancement competitiveness under high-temperature conditions (Kwon *et al.*, 2013). In comparison to species related to high germination temperatures (e.g., *Cyperus rotundus* at 46°C germination temperature), those with relatively lower germination temperatures (e.g., *Bidens tripartita* at 24°C germination temperature) tended to have smaller leaves, shorter stems, and earlier flowering and germination periods (Kwon *et al.*, 2013).

2.3.3 Atmospheric carbon dioxide (CO_2)

Long-term human activity increased atmospheric carbon dioxide (CO2) from 371.82 to 407.05 ppm between 2000 and 2018 (Anjali *et al.*, 2021). By 2050, the CO2 level is predicted to rise by up to 5%, possibly even more, to 600–800 ppm (Korres *et al.*, 2016). Fossil fuel combustion, deforestation, and strong demand for food have all been identified as the primary causes of the elevated CO2 level (Fogliatto *et al.*, 2020). Increasing CO_2 and other climate change elements will have diverse effects on weeds, crops, and their interactions (Korres *et al.*, 2017).

Increased CO_2 levels are likely to be most beneficial for C_3 plants, whereas C_4 plants will not likely be impacted because they already have metabolic processes to concentrate CO_2 at the carboxylation site (Korres *et al.*, 2016). A microcosm experiment found that increased CO2 encouraged the development of C3 upland rice under monoculture, not C_4 *Echinochloa crus-galli* (Tang *et al.*, 2009). Another study was done with a 1:1 mixture in a paddy field supplemented with free air carbon dioxide enrichment (FACE, CO_2 concentration +200 μmol mol^{-1}) and also found elevated CO_2 significantly increased rice's biomass, tillers, leaf area index (LAI), and net assimilation rate (NAR) while lowering those of *Echinochloa crus-galli* (Zeng *et al.*, 2011).

Weedy rice is also a C_3 plant like cultivated rice, but weedy rice responds more toward the elevation of CO_2. According to a study, increasing CO_2 (700 ± 50 µmol mol^{-1}) extended seed bank viability, increased weedy rice biomass, and seed shattering (Balbinot *et al.*, 2022). Under a CO_2 concentration of 500 ppm, biomass production of weedy rice increased with increasing tillering (53.0-92.6% increment), affecting inter-specific competition in the rice field (Anjali *et al.*, 2021). Increased CO_2 levels also result in higher rates of photosynthesis, seed production, and spikelet sterility in weeds when treated with CO_2 levels of 400 and 700 µmol mol^{-1} (Piveta *et al.*, 2020). Rising CO_2 levels in regions where weedy rice is prevalent may enhance its seed bank persistence and potential competition, adversely affecting rice production (Balbinot *et al.*, 2022).

Even though many weed species with a C_4 photosynthetic pathway respond to atmospheric CO_2 less than C_3 crops, a mix of C_3 and C_4 weeds is present in most agronomic conditions (Korres *et al.*, 2016). Higher CO_2 levels stimulate biomass production of both C_3 and C_4 species (Korres *et al.*, 2017). Nevertheless, findings from numerous research show significant and vast variability in how the weed community reacts to high CO_2 due to interactions with temperature, light, water, and nutrition (Korres *et al.*, 2016). According to research conducted in Jabalpur, India, a few weed species, including *Dactyloctenium aegyptium* and *Echinochloa colona*, responded to high CO_2, but *Cyperus rotundus* and *Eleusine indica* did not (Mahajan *et al.*, 2012).

It has also been demonstrated that elevated CO_2 levels increase weeds' tolerance to herbicides (Mahajan *et al.*, 2012). Elevated CO_2 makes *Echinochloa colona* more resistant to the ACCase-inhibitor cyhalofop-butyl (Refatti *et al.*, 2019). Raised CO_2 levels might affect herbicide efficacy, depending on weed species. Opposing *Echinochloa colona*, weedy rice's tolerance to imazethapyr was unaffected by increasing CO_2 (Piveta *et al.*, 2020).

3. Machine Learning

Predictive modelling is a part of machine learning methodologies that involve a learning process by which to learn from training data to perform a task (Liakos *et al.*, 2018). The data used in machine learning consist of a set of features that can be nominal, binary, ordinal or numeric (Liakos *et al.*, 2018). The selection and transformation of features can be made automatically using machine learning techniques (Vali *et al.*, 2020).

According to Liakos *et al.* (2018), The performance of the machine learning model in a specific job is measured using a performance metric that improves over time as the model gains more experience. Various statistical and mathematical models are used to calculate the performance of machine learning models and algorithms. The trained model can be used to classify, predict, or cluster new samples (testing data) when the learning process is completed using the expertise gained throughout the training phase.

Machine learning tasks are often divided into broad categories based on the type of learning (supervised/unsupervised), learning models (classification, regression, clustering, and dimensionality reduction), or the learning models used to complete the task (Liakos *et al.*, 2018; Mohidem *et al.*, 2021). A typical machine learning is visualised in **Figure 1**.

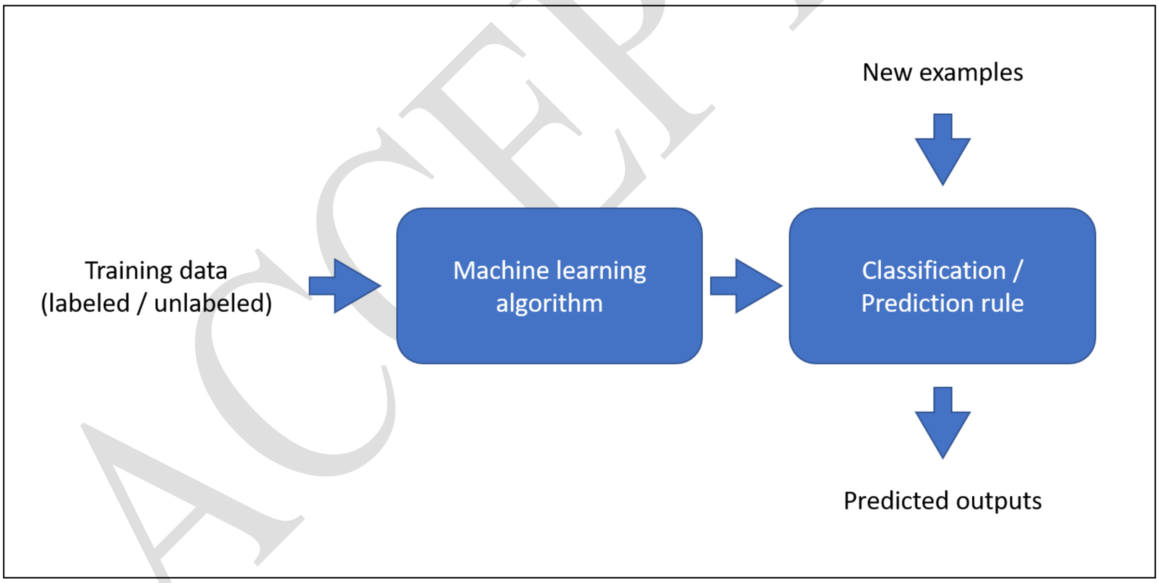

Figure 1. A typical machine learning approach. Retrieved from Liakos *et al.* (2018).

The researchers used supervised, unsupervised, and semi-supervised learning methodologies for machine learning (Hasan *et al.*, 2021). In supervised learning, data is given with examples of inputs and outputs to develop a general rule that maps inputs to outputs (Liakos *et al.*, 2018). To predict the missing outputs (labels) for the test data, the acquired expertise (trained model) is applied in supervised learning. On the other hand, unsupervised learning does not differentiate between training and test sets since the data is unlabeled (Liakos *et al.*, 2018). The learner analyses input data to uncover hidden patterns.

3.1 Soft Computing Technique

Soft computing is a set of highly consistent methods at the target level and distinctive at the method level (Gupta *et al.*, 2018). Unlike traditional computing (complex computing), soft computing techniques tolerate ambiguity, imprecision, and partial truth and do not require rigorous mathematical definitions. (Royo-Esnal *et al.*, 2020). Weed modellers are particularly interested in algorithmic modelling because it breaks from an 'ideal system' characterised by complete and accurate information. Instead, it focuses on a natural, unpredictable, and complex system (Li *et al.*, 2019). Soft computing-based models can deal with such systems in this regard (Royo-Esnal *et al.*, 2020).

Soft computing techniques-based approaches have lately been offered as alternate models to address some issues (Royo-Esnal *et al.*, 2020). Weed emergence modelling has recently benefited from new soft computing techniques such as artificial neural networks (Movassagh *et al.*, 2021). Soft computing techniques are well renowned for their flexibility and uncertainty tolerance. However, they have some drawbacks, such as a low extrapolation capability (Royo-Esnal *et al.*, 2020). Hence, a diverse set of observed circumstances is required to capture data variability. Artificial neural networks as a modelling framework and genetic algorithms as optimisation engines have been proposed as soft computing tools for weed emergence modelling (Royo-Esnal *et al.*, 2020).

3.2. Artificial Neural Network

Artificial neural network (ANN) models are based on the behaviour of biological networks in human and animal brains. They can simulate complex processes like pattern production, cognition, learning, and decision-making (Liakos *et al.*, 2018; Royo-Esnal *et al.*, 2020). An artificial neural network (ANN) is a simplified model of a biological neural network structure made up of interconnected processing units arranged in a specified topology (Liakos *et al.*, 2018).

ANNs have been widely employed in various knowledge-based applications, and they do not require any user-specific problem-solving algorithms instead of learning from examples (Movassagh *et al.*, 2021). ANNs are typically depicted as interconnected processing units that communicate by exchanging signals (Royo-Esnal *et al.*, 2020). The connections have numeric values modified using a predefined algorithm during the training phase. An ANN model's architecture, learning process, and activation functions are all factors to consider (Royo-Esnal *et al.*, 2020).

ANNs have supervised models commonly used to solve problems like regression and classification (Liakos *et al.*, 2018). Radial basis function networks, perceptron algorithms, back-propagation, and robust back-propagation issues are some learning techniques typically employed in ANNs (Liakos *et al.*, 2018). Yilmaz *et al.* (2022) implemented a feed-forward ANN with three layers: an input layer, a hidden layer, and an output layer. The feed-forward network's structure, which consists of neurons connected via connections, is illustrated (**Figure 2**). Hidden neurons serve as the connection between the first and last layers.

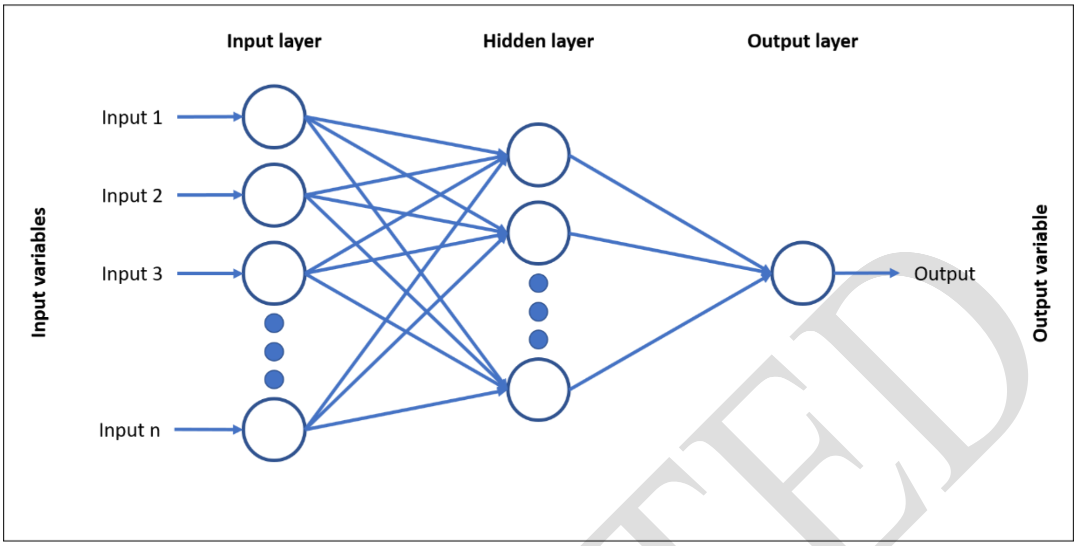

Figure 2. The basic design of a standard three-layered feed-forward neural network. Extracted from Yilmaz *et al.* (2022).

Deep ANNs, like regular ANNs, comprise numerous processing layers that are used to learn complicated data representations at multiple levels of abstraction (Liakos *et al.*, 2018). Deep ANNs are also known as deep learning (DL) and deep neural networks (DNNs) (LeCun *et al.*, 2015). They are a relatively recent area of machine learning research that allows for building computational models (Kamilaris & Prenafeta-Boldú, 2018; Liakos *et al.*, 2018). DNNs are just ANN with additional hidden layers between the input and output layers, and they can be supervised, partially supervised, or even unsupervised (Liakos *et al.*, 2018). One of the critical advantages of DL is that the feature extraction process is sometimes conducted by the model itself (Liakos *et al.*, 2018). The convolutional neural network (CNN) is a typical DL model in which feature maps are retrieved by conducting convolutions in the picture domain (Liakos *et al.*, 2018). Other common DL architectures include deep Boltzmann machines, deep belief networks, and auto-encoders (Liakos *et al.*, 2018).

3.3 Predictive Modelling

Various modelling methodologies and tools for predicting and mapping the projected ranges of habitat appropriateness of various invasive weeds have been created (Clements *et al.*, 2014). These models have assisted in determining the future regional distributions of these species in response to various conditions, including climate change (Lundy *et al.*, 2014). Niche-based species distribution models allow researchers to project modelled niches into new regions under future climate change scenarios and eventually estimate the geographical distribution of appropriate environments (Clements *et al.*, 2014).

Predictive models are essential in changing climate for studying weed responses in rice fields. Since climate change modelling is constantly fine-tuned, predictive models for weed responses must be updated simultaneously (Clements *et al.*, 2014). Predictive modelling and a better understanding of weed biology and ecology should help early warning systems track changes in weed distributions and their effects due to climate change (Clements *et al.*, 2014; Shanmugapriya *et al.*, 2019). However, the ability to predict future changes in weed distribution must be complemented by sufficient resources to develop, implement, and monitor these technologies to prevent new weed invasions (Clements *et al.*, 2014).

4. Modeling in Rice Weeds

4.1. Weed Emergence and Dynamic Model

Weed emergence models are valuable tools for analysing emergence dynamics in the field (Royo-Esnal *et al.*, 2020). A weed emergence model was developed using a mathematical model that describes field emergence data as a function of field environmental variables, notably temperature and precipitation (Ramesh *et al.*, 2017; Royo-Esnal *et al.*, 2020). Photoperiod and soil management practices can also influence field emergence dynamics, which can be a valuable component in improving model accuracy (Royo-Esnal *et al.*, 2020).

Nonlinear regression (NLR) techniques were used to develop numerous emergence models (Pedroso *et al.*, 2019; Song *et al.*, 2021). According to Royo-Esnal *et al.* (2020), Weibull and its variants have been widely utilised for parameterisation in nonlinear regression models, while others, such as Gompertz and Logistic, have also proved successful. Probit regression, Boltzmann, Chapman and Hill functions, Gaussian, Linear, General-Logistic, and Wang and Engel functions have been the least used models.

Because they are simple to create and apply, NLR sigmoidal-type models based on cumulative thermal or hydrothermal time have become the most prevalent strategy (Royo-Esnal *et al.*, 2020). Empirical NLR models use environmental variables, including temperature, soil moisture, and, most recently, light, to forecast both the timing and quantity of cumulative proportion (Royo-Esnal *et al.*, 2015). They are based on the thermal or hydrothermal-time principle, which states that seeds must accrue some growing degree days (°Cd) before germination and emergence can be completed (Royo-Esnal *et al.*, 2020).

4.2. Rice Weed Competition

A helpful resource for making integrated weed management decisions is an empirical model of the effects of weed interference on crop yield. Various mathematical weed-crop interference models have been created to measure competitive interactions and estimate production loss, including a rectangular hyperbolic equation. The weed density-based rectangular hyperbola model has been widely used to predict crop yield losses, including rice, wheat, soybean, and maise (Mamun, 2014; Moon *et al.*, 2014). The interference evaluation between weed species and crops was done either by a single or several weed species. Even more, a study has been done by using single weed species. However, several weed species' effect on crop yield is more likely to represent the natural field situation (Mamun, 2014).

A field experiment by Mamun (2014) in direct-seeded rice field cultivation found that a rectangular hyperbolic equation fitted well to predict rice yield as a function of weed densities. The economic thresholds (ET) were also successfully estimated by considering the weed control cost and rice yield price. He found that the ET values of weeds were 4.72–9.17 plants m^{-2} in a direct-seeded rice field by considering the weed competitivity, weed control costs, and price of grain.

Like Mamun (2014), a study by Song *et al.* (2021) also used the rectangular hyperbolic model but under elevated temperature. Song *et al.* (2021) found that water chestnut (*Eleocharis kuroguwai*) and late watergrass (*Echinochloa oryzicola*) both exhibited an increase in competitiveness as a result of the elevated temperature. The relationship was well demonstrated by rectangular hyperbolic equitation, which can be used to predict the level of weed interference on rice grain yield under various elevated temperatures.

Besides climatic variation, another combined model using herbicide dose on rice-weed competition has also been developed. A rectangular hyperbolic model can estimate an optimum herbicide dose for rice farming weed density. The model was used with parameter estimates to forecast rice yield and determine the quantities of flucetosulfuron and azimsulfuron needed to reduce rice yield loss brought on by *Echinochloa crus-galli* and *Echinochloa kuroguwai*, respectively, to an acceptable level (Moon *et al.*, 2014).

Weed-crop interference models, especially the rectangular hyperbolic model, help investigate competition relationships between weeds and rice, which can be utilised to support decision-making. The models can also predict crop yield and determine the economic threshold levels, especially for weed management in direct-seeded rice cultivation. Besides, the combined model developed different climatic conditions (e.g., under elevated temperature) can also provide predictive information for rice grain yield caused by environmental stress and weed interference under future climate conditions to prevent high yield loss.

4.3. Image Modelling

Weed emergence models can potentially be valuable tools for automating weed control procedures. However, gathering the necessary data (such as through seedling counts) is labour-intensive and time-consuming. Suppose equivalent weed emergence models could be produced using image-derived data rather than physical counts. In that case, the data generated may be increased to provide more reliable models (Piskackova *et al.*, 2020). Remote sensing technologies come in handy.

A robust approach for image classification has been developed using DL, which is employed in many disciplines of agriculture (Kamilaris & Prenafeta-Boldú, 2018). Semantic segmentation aims to classify pixel-by-pixel (Kamath *et al.*, 2022). A class is chosen for each pixel from a predefined list of classes. Semantic segmentation employs fully convolutional networks (FCNs) (Kamath *et al.*, 2022). These FCNs are algorithms that automatically learn features and construct forward and reverse processes from beginning to end.

With promising results that have an accuracy of over 90%, Kamath *et al.* (2022) successfully classified images of two types of weeds (sedge and broad-leaved weed) under natural conditions by utilising DL-based semantic segmentation. Semantic segmentation models used in the study were PSPNet, UNet, and SegNet, where PSPNet had the best performance. This finding promotes the invention of in-field weeding robots or machines and in-field herbicide sprayers for rice fields that utilise optimal herbicide usage, helping promote sustainable agriculture and site-specific weed control.

Using conventional RGB cameras, Piskackova *et al.* (2020) demonstrated that weed emergence forecasting models can be created using a simple image analysis method based on time-dependent changes in weed cover comparable to models developed using seedling counts. The relative emergence of actual seedling counts was used to confirm the models created using cumulative pixel data. The crop and weeds were segmented using three semantic segmentation models: SegNet, Pyramid Scene Parsing Network (PSPNet), and UNet. This method will benefit researchers working on weed emergence models, offering a potentially low-cost and user-friendly data collection tool.

Besides RGB imaging, one of the potential methods for automatically differentiating between crops and weeds is hyperspectral imaging. Vegetation may now be categorised and mapped at various taxonomic scales, frequently down to the species level, thanks to hyperspectral sensing, which analyses reflectance from RGB (visible spectrums) to shortwave infrared wavelengths (non-visible spectrums) (Sulaiman *et al.*, 2022). A study found that six wavelengths (415 nm, 561 nm, 687 nm, 705 nm, 735 nm, and 1007 nm) from hyperspectral images of barnyard grass, weedy rice, and cultivated rice plant can achieve 100%, 100%, and 92% of recognition rates, respectively (Zhang *et al.*, 2019). Random forests and support vector machine models were used in the study as the classification models to discriminate rice and weeds based on spectral features.

With the help of remote sensing and machine learning technologies, researchers and farmers can utilise site-specific weed management (SSWM), especially using the right amount of herbicide in the rice field. It will be of great help to the farmers in the future if there is a mobile interface in a smartphone app capable of real-time monitoring and warning of weeds in the rice field.

5. Conclusions

Climate change alters weed distribution in rice fields, affecting weed management as it depends on weed species' appearance and distribution. Predictive modelling can help farmers make an early countermeasure in weed management, including herbicide preparation based on weed type. Models based on local metrological data and weed emergence or distribution can be constructed through machine learning. In the future, it is hoped that a holistic predictive model with high accuracy can be established in Malaysia. Still, it requires a considerable amount of historical information on weed surveys and metrological data on several areas with varying seasons, soil conditions, agriculture practices, and water management for scientists to develop a complete model that farmers can use around Malaysia. Using remote sensing technology for weed surveys and mapping in predictive modelling development can reduce the time and labour cost required instead of conventional weed counting surveys.

Author Contributions: Conceptualization, M.N.H.A.M., A.S.J. and M.H.M.R; methodology, N.N.C. and A.S.M.S.; validation, M.N.H.A.M.; investigation, A.S.J. and N.N.C.; resources, A.S.J., N.N.C. and M.H.M.R; writing—original draft preparation, M.N.H.A.M.; writing—review and editing, A.S.J.; supervision, A.S.J., N.N.C., A.S.M.S., A.A and N.M.N.; project administration, A.S.J.; funding acquisition, A.S.J.

Funding: This research was funded by Research Project entitled "Pest and Disease Monitoring Using Artificial Intelligent for Risk Management of Rice Under Climate Change" under Long-term Research Grant Scheme (LRGS), Ministry of Higher Education, Malaysia (LRGS/1/2019/UPM01/2/5; vote number: 5545002).

Acknowledgments: The authors are grateful to the Research Project entitled "Pest and Disease Monitoring Using Artificial Intelligent for Risk Management of Rice Under Climate Change" under Long-term Research Grant Scheme (LRGS), Ministry of Higher Education, Malaysia (LRGS/1/2019/UPM01/2/5; vote number: 5545002) also sincerely acknowledges the University Putra Malaysia for providing facilities.

Conflicts of Interest: The authors declare no conflict of interest.

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