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

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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>
<thead>
<tr>
<th>Weed group</th>
<th>Scientific name</th>
<th>Common name</th>
<th>Life cycle</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grasses</td>
<td><em>Leptochloa chinensis</em></td>
<td>Feather grass</td>
<td>Annual</td>
</tr>
<tr>
<td></td>
<td><em>Echinochloa crusgalli</em></td>
<td>Barnyard grass</td>
<td>Annual</td>
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<td></td>
<td><em>Echinochloa colona</em></td>
<td>Jungle rice</td>
<td>Annual</td>
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<td></td>
<td><em>Oryza sativa complex</em></td>
<td>Weedy rice</td>
<td>Annual</td>
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<td></td>
<td><em>Ischaemum rugosum</em></td>
<td>Wrinkled grass</td>
<td>Perennial</td>
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<td></td>
<td><em>Fimbristylis miliacea</em></td>
<td>Lesser fimbry</td>
<td>Annual</td>
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<tr>
<td>Sedges</td>
<td><em>Scirpus grossus</em></td>
<td>Greater club-rush</td>
<td>Perennial</td>
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<td></td>
<td><em>Cyperus iria</em></td>
<td>Grasshopper’s cyperus</td>
<td>Annual</td>
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<td><em>Cyperus difformis</em></td>
<td>Small-flowered umbrella plan</td>
<td>Annual</td>
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<td>Weed group</td>
<td>Scientific name</td>
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<tr>
<td>Broad-leaved</td>
<td><em>Scirpus juncoides</em></td>
<td>Bulrush</td>
<td>Annual</td>
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<td></td>
<td><em>Ludwigia hyssopifolia</em></td>
<td>Seedbox</td>
<td>Annual</td>
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<td></td>
<td><em>Sphenoclea zeylanica</em></td>
<td>Gooseweed</td>
<td>Annual</td>
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<td></td>
<td><em>Monochoria vaginalis</em></td>
<td>Pickerel weed</td>
<td>Annual</td>
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<td></td>
<td><em>Sagittaria guyanensis</em></td>
<td>Lesser arrow-head</td>
<td>Perennial</td>
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<tr>
<td></td>
<td><em>Limnocharis flava</em></td>
<td>Yellow bur-head</td>
<td>Perennial</td>
</tr>
</tbody>
</table>

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 CO₂ 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, C₄ weed species are expected to adapt better than C₃ 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°C and 3°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*, *Dopatium junceum*, and *Lindernia* spp., demonstrate an increase in weed density at temperatures up to 2°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 (CO2)

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 CO2 and
other climate change elements will have diverse effects on weeds, crops, and their interactions (Korres et al., 2017).

Increased CO₂ levels are likely to be most beneficial for C₃ plants, whereas C₄ plants will not likely be impacted because they already have metabolic processes to concentrate CO₂ 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 C₄ 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, CO₂ concentration +200 μmol mol⁻¹) and also found elevated CO₂ 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 C₃ plant like cultivated rice, but weedy rice responds more toward the elevation of CO₂. According to a study, increasing CO₂ (700 ± 50 μmol mol⁻¹) extended seed bank viability, increased weedy rice biomass, and seed shattering (Balbinot et al., 2022). Under a CO₂ 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 CO₂ levels also result in higher rates of photosynthesis, seed production, and spikelet sterility in weeds when treated with CO₂ levels of 400 and 700 μmol mol⁻¹ (Piveta et al., 2020). Rising CO₂ 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 C₄ photosynthetic pathway respond to atmospheric CO₂ less than C₃ crops, a mix of C₃ and C₄ weeds is present in most agronomic conditions (Korres et al., 2016). Higher CO₂ levels stimulate biomass production of both C₃ and C₄ species (Korres et al., 2017). Nevertheless, findings from numerous research show significant and vast variability in how the weed community reacts to high CO₂ 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 CO₂, but Cyperus rotundus and Eleusine indica did not (Mahajan et al., 2012).

It has also been demonstrated that elevated CO₂ levels increase weeds' tolerance to herbicides (Mahajan et al., 2012). Elevated CO₂ makes Echinochloa colona more resistant to the ACCase-inhibitor cyhalofop-butyl (Refatti et al., 2019). Raised CO₂ levels might affect herbicide efficacy, depending on weed species. Opposing Echinochloa colona, weedy rice's tolerance to imazethapyr was unaffected by increasing CO₂ (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](image-url). 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](https://example.com/figure2.png)

**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 maize (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 competitiveness, 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 equation, 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.


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**References**


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