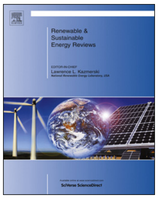
Renewable and Sustainable Energy Reviews 48 (2015) 27–34

Contents lists available at ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser



Developing a fuzzy clustering model for better energy use in farm management systems

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ARTICLE INFO

Article history:
Received 26 August 2014
Received in revised form
6 February 2015
Accepted 8 March 2015

Keywords:
Energy use management
Farm management
Environmental impacts
Artificial intelligence
c-Means fuzzy clustering

ABSTRACT

Wheat is considered as one of the most important strategic crops in Iran, and Iran agricultural ministry has some special plans to encourage farmers to cultivate this crop, so that farmers are willing to cultivate this crop through the country. The previous studies carried out by researchers in Iran showed that the energy consumption in cultivation of this crop is not efficient and there is a high degree of inefficiency in wheat cultivation in Iran. Also, wheat cultivation in Iran is responsible for a high amount of greenhouse gas (GHG) emissions. In order to differentiate between efficient and inefficient farms, a *c*-means fuzzy clustering model has been developed and the surveyed wheat farms have been clustered based on three features, i.e. GHG emission, energy ratio and benefit cost ratio. The results showed that the farms which were selected as cluster 2 had the best performance where the total input energy and total GHG were calculated as 38,826.9 MJ per ha and 3185 kg$CO_{2,eq}$ per tonne of crop. In other words, the farms in cluster 2 outperformed cluster 1 and 3 where they performed 34 and 19% better than the two other clusters in terms of energy input and 9 and 27% in CO_2 emission per tonne of produced crop. The higher output energy and lower input energy in farms of cluster 2 have caused a better economic performance where the benefit cost ratio was calculated as 1.9. The results of this study demonstrate the successful application of fuzzy clustering approach for better use of energy in cropping systems which can lead to a better environmental and economic performance.

Contents

1. Introduction

The importance of agriculture is undeniable. Food security depends on agricultural production. Agriculture uses a substantial amount of

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http://dx.doi.org/10.1016/j.rser.2015.03.029
1364-0321/

energy from different renewable and non-renewable sources [66]. Additionally, agriculture supplies energy in the form of bio-energy [1–3]. Energy management, and thus the flow of energy in agricultural production, is critical to reduce the negative effects of energy consumption on the environment and to ensure food security [4–6,67].

Different methodologies have been developed and combined to investigate energy flow and environmental issues related to agriculture. In the beginning, researchers studied energy inputs and outputs to show what kinds of energies and energy sources were used in agriculture [7–11]. These studies were followed by those that used non-parametric methods such as data envelopment analysis (DEA) to differentiate between efficient and inefficient agricultural producers [1,12,13]. Another methodology, which was the focus of several studies, was life cycle assessment (LCA). This approach has been used to show the hot spots or environment friendly alternatives in a production chain [14–17]. Artificial intelligence has also been widely used in these studies to predict the level of production or output energy on the basis of the energy input [18,19]. In addition, some researchers have combined above methodologies to reach better conclusion [20–23]. For example, in some studies DEA was combined with LCA to determine how environment friendly efficient and inefficient units are or in some other studies LCA methodology was combined with artificial intelligence to predict and optimized environmental indices [23,24,68].

The methods discussed above evaluate farms as production units and make recommendations for improving these units based on the results obtained, while it is not taken into account each production unit has its own unique management styles, level of technology, policies, and practices. Therefore, it is not logic to consider all farms similar and consequently the recommendations which are made to improve the efficiency of some farms may be inappropriate for some others. To deal with this problem, clustering is a valuable approach. Clustering is one branch of unsupervised learning and is an automated process that groups similar samples into categories called clusters. In other words, this method takes a heterogeneous population and divides it into a number of sub-categories or clusters which are homogeneous. What distinguishes between classification and clustering is that clustering does not rely on pre-defined categories. The application of clustering models is well established in literature and its successful application is reported by researchers [25–29].

Clustering techniques can provide an appropriate insight into a better management in energy systems. In a study conducted by Ogston and Zeman [30] this approach was utilized to distribute energy resources for large-scale demand management. In another study, the energy performance of school buildings was classified based on clustering techniques and the potential for energy and environmental improvements has been reported [31]. Dai and Kuosmanen [32] used clustering methods for energy regulation. They reported that cluster-specific efficiency rankings provide more meaningful benchmarks than the conventional approach of using the intensity weights obtained as a side-product of efficiency analysis.

Despite all valuable application of clustering methods in energy management systems, it has not yet employed in agricultural systems with the aim of improving energy efficiency. Therefore, the main objective of this study was to develop a clustering model and investigate how clustering can help agricultural decision makers and farm managers to improve the management of their farms.

2. Materials and methods

2.1. Case study selection and data processing

This study evaluated the application of clustering in agricultural systems. The first step in this process was to select one the most prevalent crop system for the region under study. The Esfahan province of Iran is located between the latitudes of 30–42° and 34–30° north and the longitudes of 49–36° and 55–32° east. Two hundred and sixty-five wheat farmers in Fereydonshar, Esfahan participated in a face-to-face questionnaire.

A few features were chosen to act as criteria for separating the farms into clusters. The features used to cluster farms into three groups were greenhouse gas (GHG) emissions, energy ratio, and benefit cost ratio.

The most important agricultural inputs in wheat cultivation in selected region were manure, N, P and K-based fertilizers, diesel fuel, seeds, pesticides and human labor. Table 1 presents the energy coefficients for these agricultural inputs.

The GHG emission coefficients for the agricultural inputs were exercised and the total GHG emissions were estimated to evaluate the effect of optimizing agricultural inputs on GHG emissions. The three greenhouse gases considered in this study were carbon dioxide (CO_2), nitrous oxide (N_2O), and methane (CH_4). The values of direct and indirect emissions related to inputs used were estimated using the results found in the literature and IPCC guidelines [33,34]. The following relationships were used to convert the three GHGs to $CO_{2,eq}$:

$$1 \quad \text{kg } CO_2 = 1 \quad \text{kg } CO_{2,eq} \tag{1}$$

$$1 \quad \text{kg } CH_4 = 23 \quad \text{kg } CO_{2,eq} \tag{2}$$

$$1 \quad \text{kg } N_2O = 296 \quad \text{kg } CO_{2,eq} \tag{3}$$

The amount of produced CO_2 equivalent was calculated by multiplying the input application rate by its corresponding emission coefficient as shown in Table 2.

Two different kinds of emissions can be distinguished in agricultural practices. The first one is those emissions occur while the inputs are produced (including extraction of raw materials,

Table 1
The energy coefficients of different inputs and outputs for wheat production (adapted from Khoshnevisan et al. [15]).

Inputs	Unit	Energy equivalent (MJ/unit)
A. Inputs		
1. Human labor	h	1.96
2. Diesel fuel	L	47.8
3. Pesticides	kg	120
4. Chemical fertilizers		
Nitrogen (N)	kg	78.1
Phosphate (P_2O_5)	kg	17.4
Potassium (K_2O)	kg	13.7
5. Manure	kg	0.3
6. Seed	kg	13
B. Output		
1. Wheat	kg	13
2. Wheat straw	kg	17.25

Table 2
Greenhouse gas (GHG) emission coefficients of agricultural inputs (adapted from Anonymous [33]).

Inputs	Unit	$kgCO_2$/Unit	$kgCH_{4,eq}$/ Unit	$kgN_2O_{,eq}$/ Unit	$kgCO_{2,eq}$/ Unit
Diesel	MJ	87.64E−3	–	–	87.64E−3
Nitrogen (N)	kg	2827E−3	8.68E−3	9.64E−3	5,880.6E−3
Phosphate (P_2O_5)	kg	964.9E−3	1.33E−3	0.051E−3	1,010.7E−3
Potassium (K_2O)	kg	536.3E−3	1.57E−3	0.012E−3	576.1E−3
Seed	kg	151.1E−1	0.28E−3	0.4E−3	275.9E−3
Pesticide	kg	9886.5E−3	25.53E−3	1.68E−3	10,971.3E−3
Electricity	MJ	114.48E−3	0.367E−3	0.005E−3	124.42E−3
Manure	kg	5E−3	–	–	5E−3