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Agricultural Land Conversion in Northwest Iran

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ABSTRACT: Agricultural Land Conversion (ALC) has been introduced as one of the most important factors affecting ecosystem. This type of conversion has led to several challenges in agricultural development and human life. Monitoring ALC plays a crucial role when dealing with such challenges. The main objective of this study was to monitor the trend of ALC in the Qazvin province located in Northwest Iran from 1990 to 2010 using remote sensing data. The results showed that 44,845 ha of agricultural lands (3.03% of the total agricultural lands of the province) were converted to non-agricultural lands, of which, 32,033 and 10,243 ha (2.16% and 0.69% of total agricultural lands of the province), were respectively transformed to saline lands and urban areas and infrastructures. Our projection for 2030 shows that among other uses, the conversion of agricultural lands to the saline lands and urban areas and infrastructures will stay most likely. However, the conversion probability for irrigated and orchard lands to urban areas and infrastructures will be more than the saline lands while the conversion probability for dry and rangelands to the saline lands will be more than urban areas and infrastructures.

Key words: Agriculture, Land conversion, Land use change, Climate change, Iran

INTRODUCTION

Agricultural land conversion (ALC), as a types of land use/cover change (LUCC), is understood as one of the most important factors that can affect and be affected by climate change (Biro *et al.*, 2013; Debolini *et al.*, 2013; Lambin *et al.*, 2000; Liu *et al.*, 2012; Miyake *et al.*, 2012; Mondal and Southworth, 2010; Salvati and Carlucci, 2010; Turner II, 2002, 2009; Vitousek, 1994). Climate change has recently been one of the most complex challenges that has affected all the countries in the world (World Bank, 2010). Among others factors, such as emissions of CO_2 (Muñoz-Rojas *et al.*, 2012) and alterations in the global nitrogen cycle (Wu *et al.*, 2013; Yu *et al.*, 2012), LUCC is understood as one of the most important. LUCC and specially ALC are recognized as an unavoidable phenomenon during economic development and population growth (Tan *et al.*, 2009; J. J. Zhang *et al.*, 2013b). ALC, among various types of LUCC, is the most important one in many countries in which agriculture is the major source of income. Since the world population expected to rise to about 9 billion by 2050 (FAO, 2011), demand for food and infrastructures will further increase (Dyson, 1999; Ewert *et al.*, 2005; Johnson, 1999; Rosegrant *et al.*, 2001) and the ALC trend will be further intensified. For example, in Mato Grosso area in Brazil the net cropped area expanded by 43% during the 2001 to 2007(Arvor *et al.*, 2012). But in China, since 1980, the conversion of agricultural land to non-agriculture has been widespread and intense (Ho and Lin, 2004; Su *et al.*, 2011) and cultivated land was significantly reduced (J. Wang *et al.*, 2012). In some European regions, urban sprawl has also affected vast agricultural areas in the past few years (European Environment Agency, 2006; Mazzocchi *et al.*, 2013). On the other, over half of the population in the developing world, that includes 3.1 billion people (45% of all humanity), live in rural areas. Roughly, 2.5 billion of them make their livelihoods from agriculture (Hossein Azadi and Barati, 2013). For these people land is a means to secure their food, livelihood and social status (Caldeira, 2008). That is why for many economies, especially developing countries such as Iran, monitoring ALC is of primary importance (Hossein Azadi and Barati, 2013). In Iran, agricultural lands have more rapidly changed over the past 50 years than any time before and are expected to accelerate in the future (Bahrami *et al.*, 2010). According to Iran‘s Statistical Center, agriculture is one of the most important sectors of the country's economy that currently contributes to 10% of the country's GDP and 18.2% of the total employment

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and agricultural products form about 30% of the country's non-oil exports (Hossein Azadi and Barati, 2013). Nevertheless, the pace of ALC has been intensified in Iran. Recently, the lands are more fragmented and this process has aggravated the ALC (H. Azadi *et al.*, 2011). For example, in Norway smaller farmers has encouraged many to leave agriculture (Forbord *et al.*, 2014). According to the FAO Statistical Yearbook (FAO, 2012), Iran has one of the highest rates of the ALC. The arable land per capita during 1970-2009 has decreased 2.1% in the country compared to -1.46% as for the global rate. Iran's Agricultural Land Organization has reported that between 2005 and 2010, more than 74,755 ha of agricultural lands have changed to non-agriculture. Although other sources (such as the Agriculture Bank of Iran) have reported these changes up to 200,000 ha. Accordingly, despite the important role of the agricultural sector in the country's economy, this sector has considerably been threatened by ALC. Therefore, having a clear understanding of ALC and its drivers is vital for Iran's economy and sustainable agricultural land use management. Since monitoring ALC remains imperative and is considered as an essential first step to identify the main driving forces of ALC (Burgi *et al.*, 2004). Using remote sensing (RS) and Geographic Information Systems (GIS) data, this paper aims to study the trend of ALC from 1990 to 2010 in Northwest Iran.

MATERIAL&METHODS

The study was conducted in the Qazvin province located in Northwest Iran between the north latitude of 35°232 - 36°492 and east longitude of 48°442 – 50°532 that covers 15,636 km^2 (Fig. 1). The province is divided to five counties, 19 localities (Bakhsh) and 46 rural districts. In 2012, the province held a population of 1.2 million, of which 72% lived in urban and 27% in rural areas. Although this province covers only about 1% of the total area of Iran, its contribution to the country's economy reaches up to 5% and more than 3% of Iran's agricultural products (from 2% to 20% of main products) are produced in this province that shows the importance of the province economy in the country. Landuse patterns for July 1990 and 2010 were mapped by Landsat TM images. At first, each Landsat image was georeferenced to the local coordinate system based on 1:50,000 scale topographic maps. Then the geometric, radiometric and atmospheric corrections were used. Finally, each image classified using MAXLIKE module, which is one of the supervised classification methods used to generate a map in which each pixel assigned to a class based on its multispectral composition. The classes are determined based on the spectral composition of training areas defined by the user. All these processes were carried out in the five steps as follows. Through a fieldwork nine different types of landuses were determined. Then, the areas which were later used as training sites for each landuse or cover class were defined. After digitizing the training sites (training samples), the statistical characterization of each informational class was created (signatures) (Eastman, 2003). Then, by comparing different signatures, the best bands combination to separate different landuses and covers was defined. For this case, the best composites of the bands were 3, 5, and 7. In the third step, the images were classified by the MAXLIKE procedure. The total area was divided into nine classes, including rangeland (RL), dry land (DL),

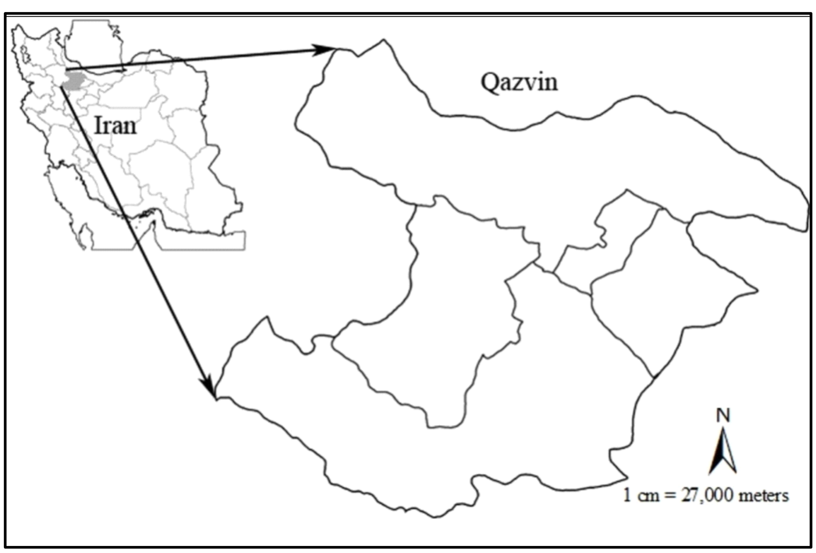

Fig. 1. Location of the Qazvin province (the study area) in Iran

irrigated land (IL), orchard land (OL), saline land (SL), forest (F), water body (WB), urban areas and infrastructures (UI) and other land covers (OC).

After classification, there may be many cases of isolated pixels that belong to a class which differs from the majority that surrounded them. This may be an accurate description of reality, but for mapping purposes, a very common post-processing operation is to generalize the image and remove these isolated pixels. In this study, the generalization is done by passing a median filter over the result (using the FILTER module in IDRISI). The median filter replaces each isolated pixel with the most frequent occurring class within a 3x3 window around each pixel. This effectively removes class patches of one or a few pixels and replaces them by the most common neighboring class. The final stage of the classification process usually involves an accuracy assessment that gives insight into 'how good the classified image' is. In fact, any map should be accompanied by an indication of the accuracy. Accuracy assessments determine the quality of the information derived from remotely sensed data. One of the main important indexes in this field is the Kappa index. For this study, the indexes, which derived from 70 actual field control points, were 0.752 for year 1990 and 0.793 for 2010. All the above procedures were performed by the IDRISI Kilimanjaro (Eastman, 2003) and ERDAS (ERDAS, 2010). Fig. 2 shows the landuse maps of the study area for the years 1990 (A) and 2010 (B).

The monitoring was performed by computing the transition areas (Tables 1 and 2) and probability matrix (Table 3) using the Markov and CrossTab modules in the IDRISI Kilimanjaro software. A Markovian process is the one in which the state of a system at the time 2 (2010) can be predicted by the state of the system at the time 1 (1990). The transition matrix records the probability that each land use category or class would change to every other category, while the transition areas matrix records the number of pixels or the areas that are expected to change from each land use type to others over the specified number of time intervals. Each row of the matrix represents the probabilities for the various kinds of landuse classes. P_i for each row at the time 1 was estimated by Eq. 1:

$$p_i = \frac{x_i}{\sum x_i} \quad (\text{Eq. } 1)$$

Where:
P_i *is* the probability of each kind of landuse class, and
x_i is the number of pixels in cell for each row.

Furthermore, this matrix can be used for determining the probability of each land use changes over a specified time period in the future. In general, for

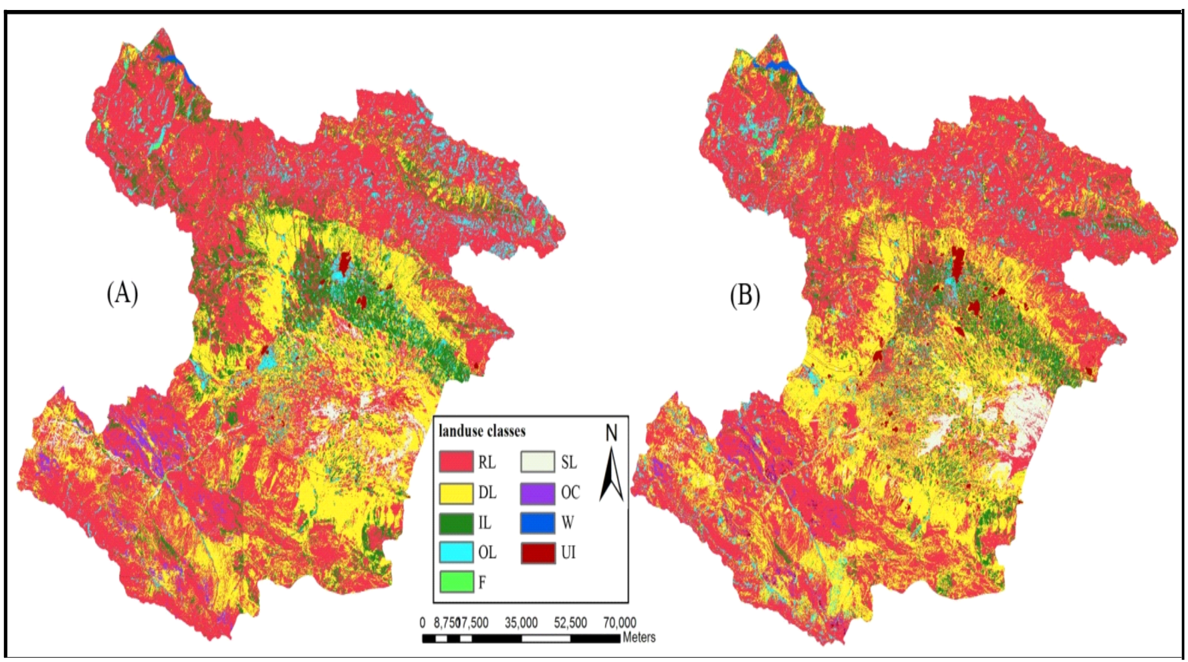

Fig. 2.The land use maps of study area: (A) 1990 and (B) 2010
RL (Range Land), DL (Dry Land), IL (Irrigated Land), OL (Orchard Land), SL (Saline Land), F (Forest), WB (Water Body), UI (Urban and Other Infrastructures) and OC (Other Land Covers)

example, the probability of changing the RL in 1990 (i) to the DL in 2030 (j), which is denoted by $p^{(2)}_{12}$, can be computed by (Eq. 2) as follows:

$$p_{12}^{(2)} = \sum p_{11}p_{12} + p_{12}p_{22} + p_{13}p_{32} + p_{14}p_{42} + p_{15}p_{52} + p_{16}p_{62} + p_{17}p_{72} + p_{18}p_{82} + p_{19}p_{92} \quad \text{(Eq. 2)}$$

Generally, if a Markovchain has r states, then:

$$p_{ij}^{(n)} = \sum_{k=1}^{r} p_{ik}p_{kj} \qquad \text{(Eq. 3)}$$

In Eq. 3, p is the value of each cell within the transition matrix of a Markov chain. The $p^{(n)}_{ij}$ gives the probability that the Markov chain, starting in the state i, will be in the state j in n steps (Ross, 1997).

RESULTS & DISCUSSION

Fig. 2 and Tables 1 and 2 show that in 1990, RL, DL, IL, and OL were dominant in the study area. They were respectively covering 55.22, 25.31, 10.71, and 4.59% of the total area of the study site that altogether correspond to 95.8% (about 1,498,000 ha) of the area which has been covered by agricultural lands. In 2010, the agriculture areas decreased to 94.7%, which indicates that during this period, 44,845 ha (3%) of these lands have changed to non-agricultural lands. Also, in 2010, the shares of different agricultural landuse classes have been as follows: RL (55.04%); DL (28.6%); IL (7.33%) and OL (3.74%). As shown in the tables, the percent of RL, IL and OL areas have decreased -0.18, -3.37, and -0.84%, respectively. Conversely, the share of the DL areas increased by 3.28%, from 1990 to 2010. However, among the RL, IL and OL areas, the share of the IL areas decreased more intensely (-3.37%) than the others.

According to the tables, by 2010, up to 3% (44,845 ha) of agricultural lands (including 2.3% of RL, 5.8% of DL, 0.8% of IL and 0.5% of OL) were converted to non-agricultural lands. Most of these lands (71%) changed to SL and somewhat (22.8%) to UI. It means that during this period, 32,033 ha of agricultural lands (14,075 of RL, 17,783 of DL, 149 of IL and 26 ha of OL) were converted to SL whereas 10,243 ha (4,321 of RL, 4,503 of DL, 1,050 of IL and 369 ha of OL) were changed to UI. As shown in the tables, the RL and DL have mainly converted to SL. In contrast, most of the IL and OL were converted to UI. Furthermore, for the period of 1990 to 2010, the saline areas expanded from 1.84 to 2.86%. It means that 15,846 ha of the lands were converted to saline lands.

Table 1. The surface of different land use classes and its changes between 1990 and 2010 (transition areas matrix)
a. RL (Range Lands), DL (Dry Lands), IL (Irrigated Lands), OL (Orchard Lands), SL (Salin Lands), F (Forest), WB (Water Bodies), UI (Urban and Other Infrastructures) and OC (Other Land Covers)

		Landuse 2010 (hectare)[a]									Total
		RL	DL	IL	OL	F	SL	OC	WB	UI	
Landuse 1990 (hectare)[a]	RL	635205	146871	36587	24543	56	14075	1694	57	4321	863408
	DL	99968	243730	24540	4621	49	17783	619	4	4503	395817
	IL	76009	40832	42019	6959	196	149	181	9	1050	167404
	OL	32604	7305	10540	20369	474	26	5	1	369	71693
	F	757	90	182	1730	675	1	0	0	5	3440
	SL	7827	7411	719	163	1	11885	227	0	611	28844
	OC	8102	601	39	88	0	130	9040	0	2132	20130
	WB	22	11	11	43	0	0	0	2743	0	2831
	UI	141	276	54	23	0	642	12	0	8902	10052
Total		860636	447128	114690	58539	1451	44691	11778	2814	21894	1563620

Table 2. Share of different land use classes and its changes between 1990 and 2010 (transition areas matrix).
a. RL (Range Lands), DL (Dry Lands), IL (Irrigated Lands), OL (Orchard Lands), SL (Saline Lands), F (Forest), WB (Water Bodies), UI (Urban and Other Infrastructures) and OC (Other Land Covers)

		Landuse 2010 (%)[a]									Total
		RL	DL	IL	OL	F	SL	OC	WB	UI	
Landuse 1990 (%)[a]	RL	73.57	17.01	4.24	2.84	0.01	1.63	0.20	0.01	0.50	55.22
	DL	25.26	61.58	6.20	1.17	0.01	4.49	0.16	0.00	1.14	25.31
	IL	45.40	24.39	25.10	4.16	0.12	0.09	0.11	0.01	0.63	10.71
	OL	45.48	10.19	14.70	28.41	0.66	0.04	0.01	0.00	0.51	4.59
	F	21.99	2.63	5.30	50.30	19.62	0.02	0.01	0.00	0.14	0.22
	SL	27.14	25.69	2.49	0.56	0.00	41.20	0.79	0.00	2.12	1.84
	OC	40.25	2.98	0.19	0.44	0.00	0.65	44.91	0.00	10.59	1.29
	WB	0.79	0.39	0.39	1.52	0.00	0.00	0.00	96.91	0.00	0.18
	UI	1.41	2.75	0.54	0.23	0.00	6.38	0.12	0.00	88.56	0.64
Total		55.04	28.60	7.33	3.74	0.09	2.86	0.75	0.18	1.40	100

Table 3. The transition probability matrix of different land use classes to the other classes between 2010 and 2030
a. RL (Range Lands), DL (Dry Lands), IL (Irrigated Lands), OL (Orchard Lands), SL (Saline Lands), F (Forest), WB (Water Bodies), UI (Urban and Other Infrastructures) and OC (Other Land Covers)

		Landuse 2030 (Probability)[a]									Total
		RL	DL	IL	OL	F	SL	OC	WB	UI	
Landuse 2010 (Probability)[a]	RL	0.601	0.228	0.078	0.056	0.000	0.027	0.004	0.001	0.004	1
	DL	0.332	0.490	0.083	0.022	0.000	0.059	0.003	0.000	0.012	1
	IL	0.507	0.226	0.201	0.053	0.002	0.001	0.001	0.002	0.006	1
	OL	0.500	0.112	0.147	0.226	0.009	0.001	0.000	0.001	0.005	1
	F	0.229	0.027	0.072	0.495	0.175	0.000	0.000	0.000	0.001	1
	SL	0.334	0.261	0.029	0.010	0.000	0.345	0.015	0.000	0.007	1
	OC	0.486	0.041	0.002	0.006	0.000	0.010	0.457	0.000	0.000	1
	WB	0.000	0.013	0.088	0.050	0.000	0.000	0.000	0.849	0.000	1
	UI	0.073	0.105	0.012	0.003	0.000	0.002	0.000	0.000	0.805	1

Table 3 indicates the probability of future changes for RL and DL to UI. As shown in the table and Fig. 3, the probability of the conversion to UI is higher than to SL while this probability for changing from IL and OL to SL is more than converting to UI.

Table 2 indicates that 73.6% of rangelands have remained unchanged during 1990-2010. About 24% of the converted RL have changed to the other agricultural landuse classes (more to DL, and less to IL and OL). This finding is consistent with studies in the Lahn-Dill Highlands (Germany) and in the Mashonaland central province (Zimbabwe) where Hietel et al. (2007) and Kamusoko et al. (2009) respectively found that land-cover changes occurred mainly between arable and grassland. The rest of the RL were mainly converted to saline lands (1.63%) or other land uses (0.2%). F. Zhang et al. (2013a) also reported the same changes in China. They showed that salinisation of grasslands has been much faster than cultivated land and more than 75% of all newly salinised lands are grasslands.

According to Table 3 and Fig. 3(a), the probability of future RL change (for 2030) to DL is more than to the other landuses and covers (0.228) and the probability of changing the OL and IL to RL is more than the others (respectively, 0.5 and 0.507). Among

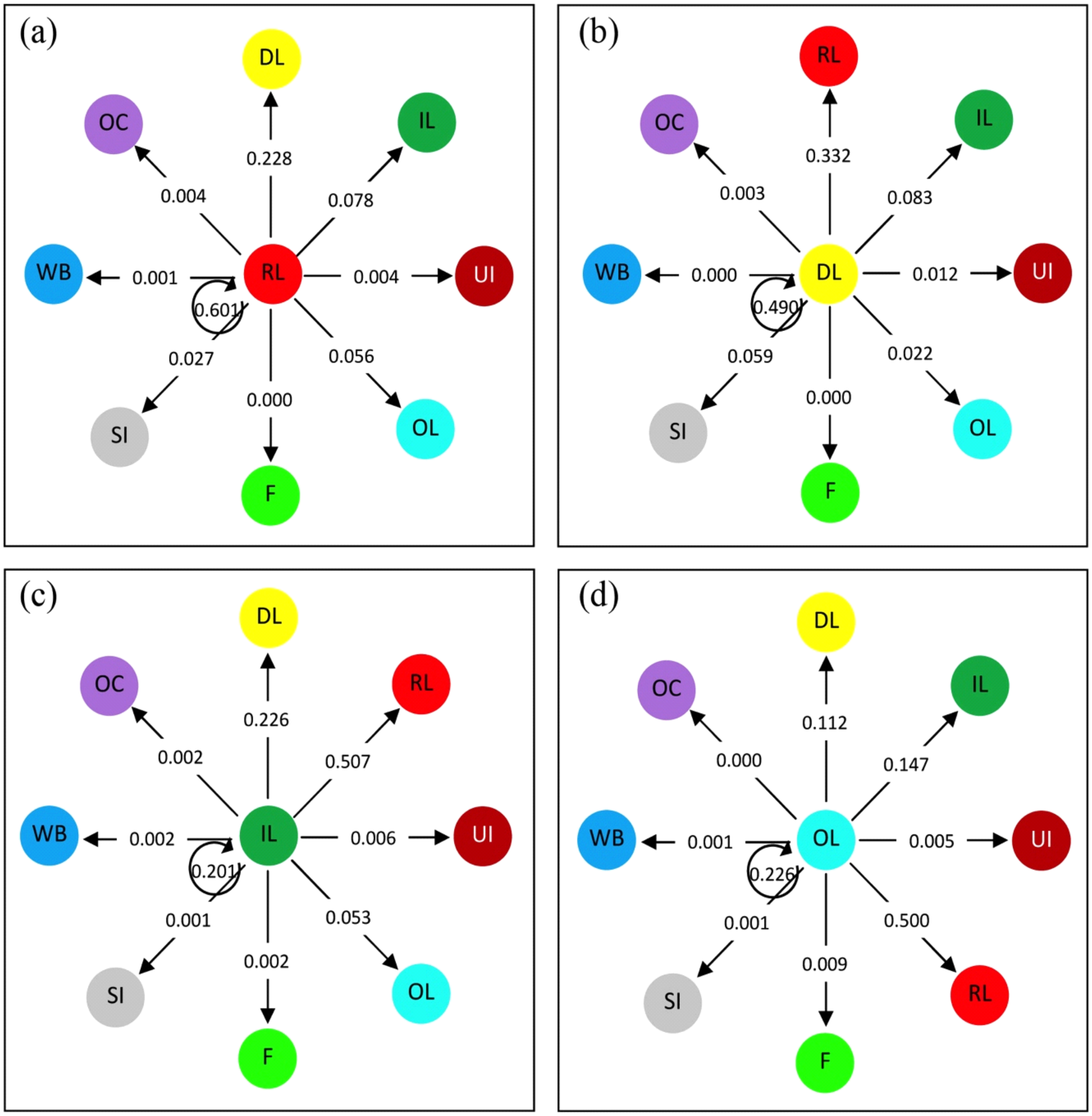

Fig. 3. Diagram of the future changing probability of agricultural lands between 2010-2030.RL (Range Lands), DL (Dry Lands), IL (Irrigated Lands), OL (Orchard Lands), SL (Saline Lands), F (Forest), WB (Water Bodies), UI (Urban and Other Infrastructures) and OC (Other Land Covers)

non-agricultural landuses, the probability of changing the RL to SL remains the most (0.027). On the other hand, the probability of changing these land uses to SL will increase from 0.016 (for 1990-2010) to 0.027 (for 1990-2030).

As shown in Table 2, until 2010, 38.4% of the DL have changed to other landuses and covers, in which 32.6% of these lands are converted to the other agricultural lands (25.3% to RL, 6.2% to IL and 1.2% to OL), and 6.2% of them have changed to non-agricultural lands, especially to SL (4.5%). During the same period, approximately 1% (1,584 ha) of the IL and 1.2% (875 ha) of the OL are converted to non-agricultural lands. The same changes among arable land, grassland and fallow land are reported by Hietel et al. (2007) and Kamusoko et al. (2009). Furthermore, Table 3 and Fig. 3(b) show that, by 2030, the probability of changing DL to SL is more than other non-agricultural landuses and covers (0.059). Among the agricultural lands, the probability of changing SL to DL is more than the others (0.228). Instead, among the non-agricultural lands, the probability of future changes of SL to DL remains the most (0.261).

According to Table 2, by 2010, about 75% of the IL is converted to the other landuses. The majority (74%) of these lands have changed to the other agricultural lands (45.4% to RL, 24.4% to DL and 4.2% to OL), and about 1% of them changed to non-agricultural lands, mostly to UIs (0.63%). Instead, from 1990 to 2010, around 4.2% of the RL and 6.2% of the DL and 14.7% of the OL were converted to the IL. This is in line with findings of Ho and Lin (2004) and Wang et al. (2012) who found that agricultural land during the past few decades has been converted to non-agriculture, respectively in China and Indonesia.

Table 3 and Fig. 3(c) also show that in the future (by 2030), among the agricultural lands, the probability of the IL conversion to RLs is more than to the DL or OL (0.453). But for the non-agricultural lands, this probability, especially to UI, is more than the others (0.006). Also, like DL, the expansion probability of the SL within IL will increase by 2030 compared to 1990-2010. Although Ho and Lin (2004) indicated that the conversion of agricultural land to non-agricultural land has been widespread and intense in China, they did not specify the conversion types of agricultural to non-agricultural lands.

Between 1990 to 2010, 71.5% of OL have changed (Table 2), of which, 70.4% occurred among the agricultural lands (45.5% to RL, 10.2% to DL and 14.7% to IL).The rest (1.1%) changed to non-agricultural lands; mainly to the UI. In contrast, by 2010, 2.8% of RL and 1.2% of DL and 4.2% of IL have changed to OL.

The probability of future OL changes to non-agricultural lands is 0.007 (Fig. 3(d) and Table3). Within the agricultural lands group, this probability for RL is higher than the others (0.5). This means that the chance of conversion for OL to RL is more than to DL or IL. However, among the non-agricultural lands, this chance for UI is more (0.005) than the other non-agricultural lands (i.e., SL, OC and WB). According to Azadi et al. (2011), Fukamachi et al. (2001) in Japan, Hitel et al. (2007) in Germany and Lichtenberg and Ding (Lichtenberg and Ding, 2008) in China, the development of infrastructures (such as road construction), also contributes significantly to ALC.

Tables 1 and 2 indicate that during the 20 years (1990-2010), UI areas increased from 0.64% (10,052 ha) to 1.4% (21,894 ha) in the study site. This means that UI areas increased to 11,842 ha, of which, 10,243 ha were the result of ALC. These lands include 2.78% of total agricultural lands, of which, 1.77% (5,553 ha) were farm lands (IL and DL). As other researchers (H. Azadi *et al.*, 2011; Fukamachi *et al.*, 2001; Ho and Lin, 2004; Lichtenberg and Ding, 2008; Schulz *et al.*, 2010; Tan *et al.*, 2009) have reported, it seems that UI has expanded within the agricultural lands significantly. And as mentioned by Shrestha et al. (2012) in Southwest America, Su et al. (2011) in Hang-Jia-Hu region of China and EEA (2006) in Europe, rapid urbanization leads to agricultural land fragmentation. Furthermore, based on our study and the probability of the future UI conversion (Table 3 and Fig. 2), the urbanization trend will further be intensified by 2030 (from 0.098 to 0.127).

CONCLUSION

This paper monitored the agricultural land conversion during the past two decades (from 1990 to 2010) using RS data and their probability of future change (by 2030). As showed by Mazzocchi et al. (2013), FAO (2012), Behnassi and Yaya (2011), IFAD (2010) and Azadi et al. (2011), our study also revealed that the surface of agricultural lands has decreased significantly. More specifically, the share of the IL areas decreased more intensely (-3.37%) than the other agricultural land uses, and this decrease will be more intensified by 2030. However, based on our study, the future probability of conversion for IL and OL is more than RL and DL. Since agriculture has an important role in food security and development (Vermeulen *et al.*, 2012; World Bank, 2008) and access to adequate food is one of the most important aspects of food security, this decrease in IL and OL can be a serious threat to food security. In line with Leh et al. (2013), Azadi et al. (2011; 2013), Shresthaet al. (2012) and EEA (2006), this study also showed that urban sprawl is one of the main threatening drivers of the ALC. However, the threat of UI for IL and OL has been realized much more. Since the role of the IL and OL in rural and agricultural economy is vital, and because about one third of the population of the study area live in rural areas, conversion and degradation of these lands can be a serious threat for rural development (Kamusoko *et al.*, 2009).

As discussed by Zhang et al. (2013a; 2007) and Xiujun (2000) in China, our study also showed that the saline land expansion (salinization) has been the main threat for DLs and RLs, and this expansion will be continuing by 2030. Given that the salinization is a major process of land degradation and it is also considered to be one of the main drivers of the loss of agricultural land and crop yield (Thomas and Middleton, 1993), the saline expansion should be cautioned as a main threat for food security in agri-rural development. In addition, increasing the dust emission from the saline land (Chen *et al.*, 2009) could worsen this situation.

Given the fact that most of the ALC has occurred within different types of agricultural lands, as a conclusion, we recommend monitoring not only the conversion of agricultural land to non-agricultural land, but also monitoring the conversion of different types of agricultural lands from one to another. The study of Williams and Schirmer (2012) in south-eastern Australia also showed that the most widespread of the land use changes was growth in farm lands.

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