FOOD VULNERABILITY ANALYSIS IN THE CENTRAL DRY ZONE OF MYANMAR

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Abstract

The central dry zone of Myanmar is the most water stressed and also one of the most food insecure regions in the country. In the Dry Zone, the total population is 10.1 million people in 54 townships, in which approximately 43 % of people live below the poverty line and 40 – 50 % of the rural population is landless. Agriculture is the most important economic sector in Myanmar as it is essential for the national food security and a major source of livelihood of the people. In this region the adverse effects of climate change such as a late or early onset of the monsoon season, longer dry spells, erratic rainfall, increasing temperatures, heavy rains, stronger typhoons, extreme spatial-temporal variability of rainfall, high intensities, limited rainfall events in the growing season, heat stress, drought, flooding, sea water intrusion, land degradation, desertification, deforestation, and other natural disasters are believed to be major constraints to food security. Theses extreme climatic events are likely to increase in frequency and magnitude, leading to serious drought periods and extreme floods. Food insecurity is an important thing that must be reviewed because it affects the lives of many people. For food vulnerability, we use the following indicators: slope, precipitation, vegetation, soil, erosion, land degradation and harvest failure in ArcGIS software. The erosion is influenced by rainfall and slope, while land degradation is directly related to vegetation, drainage and soil. In the meantime, the harvest failure can be generated by rainfall and flood potential zones. The results show that around 45 % of the area studied comes under a very high erosion danger level, 70 % are in the average harvest failure zone, 59 % are in the intermediate land degradation area, and overall around 45 % of the studied area comes under the insecure food vulnerability zone. Our analysis shows that an increase in the alluvial farming by 1745.33 km^2 since 1988 has helped reduce the insecure food vulnerability. The food vulnerability map is also relevant to increased population and low income areas. This paper is helpful for identifying the areas of food needs in central dry zone of Myanmar.

Keywords: food vulnerability, alluvial farming, remote sensing, GIS.

Introduction

The world's population is expected to grow almost 10 billion by 2050, boosting agricultural demand – in a scenario of modest economic growth – by some 50 percent compared to 2013. Income growth in low- and middle-income countries would hasten a dietary transition towards higher consumption of meat, fruits and vegetables, relative to that of cereals, requiring commensurate shifts in output and adding pressure on natural resources. In World Food Conference the term "food security" was defined as "exists when all people, at all times, have physical and economic access to sufficient, safe and nutritious food to meet their dietary needs and food preferences for an active and healthy life". Food security incorporates a measure of resilience to future disruption or unavailability of critical food supply due to various risk factors including droughts, shipping disruptions, fuel shortages, economic instability and wars. In the years 2011-2013, an estimated 842 million people were suffering from chronic hunger. The [1] (Food and Agriculture Organization), identified the four pillars of food security as availability, access, utilization, and stability. The United Nations [2] recognized the Right to Food in the Declaration of Human Rights in 1948 and has since noted that it is vital for the enjoyment of all other rights.

Over the past century, enormous progress has been achieved worldwide in improving human welfare. Societies have changed radically thanks to quantum leaps in technology, rapid urbanization and innovations in production systems. Similarly, much remains to be done to fulfill the vision of the Food and Agriculture Organization of the United Nations [1]: to create 'a world free of hunger and malnutrition and one in which food and agriculture contribute to improving the living standards of all, especially the poorest, in an economically, socially and environmentally sustainable manner'. Projected growth in the world's population is expected to be concentrated in Africa and South Asia and in the world's cities. By mid-century, two-thirds of the global population will live in urban areas. Low-income countries will see large increments in the 15 – 24 years age group. The population will

continue to grow in South Asia until mid-century and in sub-Saharan Africa until at least the end of the century. By the year 2100, Asia and Africa are expected be home to a combined population of 9 billion, out of the projected 11 billion people who will inhabit Earth

In Myanmar, 44 percent of households had problems meeting food needs [3] despite being part of a major agricultural region [4]. According to [4], 58 % of those living in the region are farmers and 25 % are farm laborers. Similarly, other studies [5] also indicate that farming and casual labor in the agriculture sector are the two key livelihood activities in the Dry Zone [6]. The vulnerabilities of many farming communities are increasingly complex as Myanmar undergoes unprecedented political, social and environmental changes, making the design of impactful development interventions challenging. Food insecurity and flood risk are very common in the Dry Zone (Fig. 1). A survey conducted by [7] found that 18 % of households had inadequate food for consumption and more than a quarter of children under the age of five were underweight. Households with poor access to land and markets and those relying on casual labor are the most likely to have insufficient food. Farming households are more likely to be food-secure, but food security is precarious even for these families. In 2010, the food security of 41 % of farming households was adversely affected by dry spells [8].
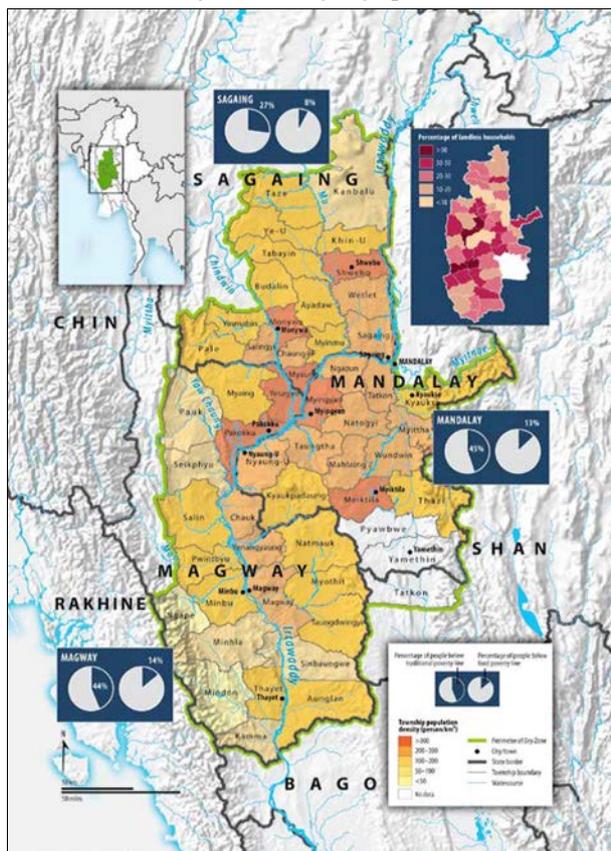

Fig. 1. The demographics of Myanmar's Dry Zone, showing the population density of townships and distribution of landless households. (Source: Boundary/townships as defined by the Myanmar Information Management Unit [MIMU] [Map Id.: MIMU983V01], March 2013 [www.themimu.info/]; Statistics on population density, poverty and landless households from JICA 2010)

Remote sensing and GIS technology can help to access food insecurity through satellite data and socio-economic data such as soil condition/thickness, rate of erosion and harvest/crop failure. The erosion is directly related to rainfall and slope, which we can get from rainfall stations and elevation map/DEM. Land degradation level is based on vegetation condition, drainage and soil solum thickness. While harvest failure can be generate by rainfall and flood potential zones. With remote sensing technology, the analyst will know the locations that are vulnerable for experiencing food insecurity and it will help the local government to distribute the food needs for the community based on the analysis. Spatial modeling for food insecurity was usually performed using quantitative modeling methods of tiered-overlay where each parameter has a weight for each factor. So that, the greater the value of the factor, the greater the influence to the result. Besides of physical parameter, we also used the social and economic parameters, which are the society's income information on the population in the study area that is vulnerable to the poverty line [9]. So that the mapping of food insecurity is very helpful for managing equitable distribution of food to the local community needs. The main objective of this research work is (1) build a model for food security through remote sensing and GIS, (2) identify the different levels of food insecurity, (3) identify the different parameters, which used to identify food insecurity, (4) identify most influential factors of food insecurity and (5) identify location distribution of food insecurity in the study area.

Materials and methods

To know the food vulnerability in the study area, we used primary (satellite data) and secondary data such as slope, precipitation, vegetation, soil, erosion, land degradation and harvest failure, ground truth data for land use/cover classes and topographic sheets. The ground truth data were collected using Global Positioning System (GPS) for the year of 2016 in the month of June to August for image analysis and classification accuracy. The specific satellite images used were Landsat 8 OLI (Operational Land Imager) for 2016 [7]. All image processing work were done in ArcGIS software and generate thematic layer (Fig. 2). The whole spatial modeling for food vulnerability was complete in following steps:

Slope map: To generate slope map, we used Digital Elevation Model (DEM), which we get from USGA website (https://www.usgs.gov/). Then the slope was classified according to Table 1 and then gives different weightage according to their sensitivity [8, 9].

Table 1. Classification of slope perameter

Class	Slope (%)	Weightage
Flat	< 4	1
Slope slightly	$4 - 12$	2
Rather steep	$12 - 24$	3
Steep	$24 - 40$	4
Very steep	$40 <$	5

Vegetation map: was generated by landsat 8 OLI imagery. First we make Normalized Difference Vegetation Index (NDVI) then classcify image based on color tone. Dark red color show thick vegetation and light

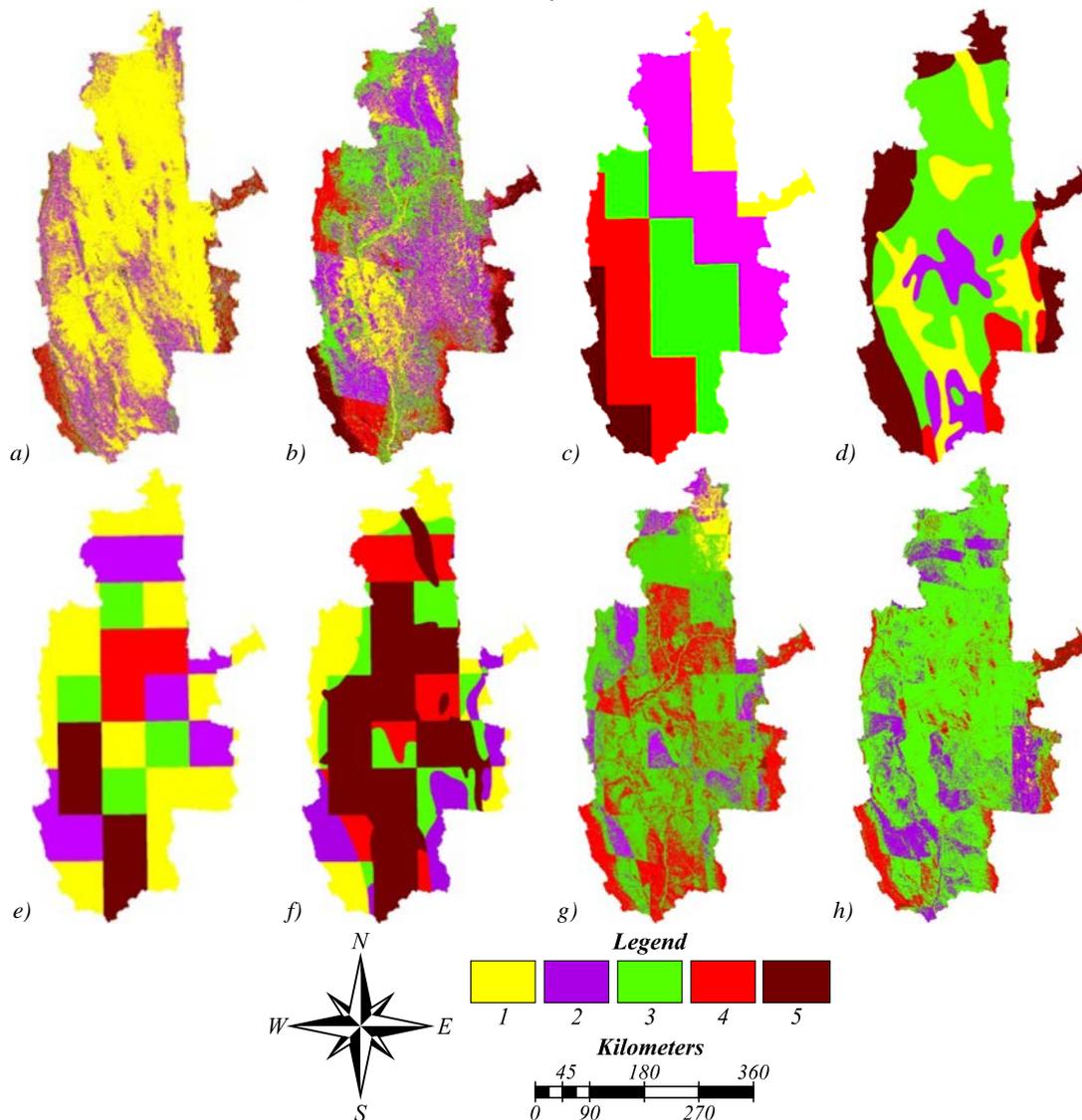tone thin vegetation [8, 9]. The vegetation classification   show in following Table 2 and Fig. 2.

Fig. 2. Thematic layers which used to generate food vulnerability map:
a) slope; b) vegetation cover; c) precipitation; d) soil; e) erosion; f) erosion danger level; g) land degradation; h) harvest failure

Table 2. Classification of vegetation cover

Class	Slope (%)	Weightage
Very bad / thin	< 20	1
Bad / thin	20 – 40	2
Average	40 – 60	3
Good / thicker	60 – 80	4
Very good / thick	80 <	5

Precipetation map: We get precipetation map from GWSP (Digital Water Atlas http://atlas.gwsp.org/index.php) with 0.5 degree. For analysis work, first shapefile was convert into raster file with 30×30 m cell size by mean value (Fig. 2). Then mean annual precipetation value were assigned weightage according to Table 3 [8, 9].

Table 3. Classification of annual precipetation

Mean annual precipitation	> 15	15 – 25	25 – 35	35 – 50	50 <
Weightage		1	2	3	4	5

Soil map: We get soil map from GWSP (Digital Water Atlas http://atlas.gwsp.org/index.php) with 0.5 degree. For analysis work, first shapefile was convert

into raster file with 30×30 m cell size by mean value (Fig. 2). Then soil value were assigned weightage according to Table 4 [8, 9].

Erosion map: We get erosion map from GWSP (Digital Water Atlas http://atlas.gwsp.org/index.php) with 0.5 degree. For analysis work, first shapefile was convert into raster file with 30×30 m cell size by mean value (Fig. 2). Then erosion value were assigned weightage according to Table 5.

Erosion danger level modeling: We use soil and erosion map (Table 6) for erosion danger level and generate erosion danger level map (Fig. 2) based on Table 7. Around 45 % study area comes under very high erosion danger level (Fig. 3) due to lose soil, sparse vegetation and uncertain rain intensity.

Land degradation modeling: This modeling is based on erosion danger level, vegetation cover and slope. All these parameters have weighted, according to their effectiveness/sensitivity. Now in land degradation modeling,

vegetation cover parameter weight is 45, erosion danger level is 35 and slope parameter weight is 20.

Table 4. Classification of Soil characteristics

Soil thickness	Soil characteristics	Weightage
Very thin	Yellowish brown regosol and grey grumosol complex, grey regosol, greyish brown regosol, association of litosol and brown mediteran complex	1
Thin	Dark grey grumosol, dark grey andosol, association of yellowish brown andosol and litosol complex	2
Average	Kambisol, litosol, and renzin, brown mediteran, reddish brown mediteran, and reddish brown mediteran, complex latosol and renzina	3
Deep	Brown latosol, reddish latosol, complex reddish brown latosol, and litosol	4
Very deep	Greyish brown alluvial	5

Table 5. Classification of erosion parameter

Class	Erosion (ton/ha/year)	Weightage
Very low	< 20	1
Low	$20 - 80$	2
Average	$80 - 200$	3
High	$200 - 450$	4
Very high	$450 <$	5

Table 6. Calculation of erosion danger level based on soil thickness and erosion

Soil thickness	Erosion class				
	1	2	3	4	5
5	I	II	III	IV	V
4	II	III	IV	V	V
3	III	IV	V	V	V
2	IV	V	V	V	V
1	V	V	V	V	V

Table 7. Classification of erosion danger level

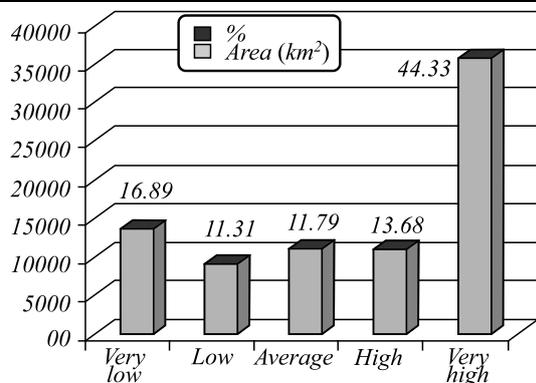| Class	Erosion danger level	Weightage	Area Km^2	%
Very low	I	1	13670.66	16.89
Low	II	2	9153.65	11.31
Average	III	3	11162.35	13.79
High	IV	4	11072.88	13.68
Very high	V	5	35878.93	44.33

Fig. 3. Graphical representation of erosion danger level

Then the result was classified as Table 8. Analysis shows that around 59 % area under medial type of land degradation (Fig. 4). The influence parameters for land degradation are low vegetation cover, high slope and high erosion rate, which is also increase food vulnerability.

Table 8. Classification of land degardation

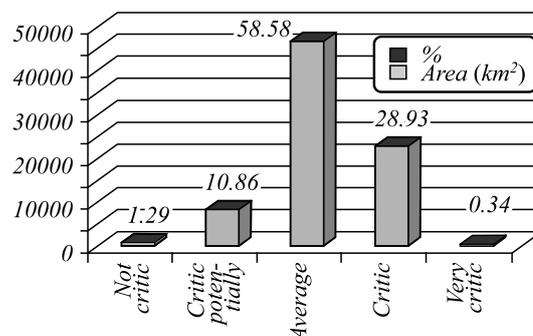| Class	score	Weightage	Area Km^2	%
Not critic	< 100	1	1025.73	1.29
Critic potentially	$100 - 200$	2	8615.88	10.86
Average	$200 - 300$	3	46472.51	58.58
Critic	$300 - 400$	4	22954.27	28.93
Very critic	$400 <$	5	270.02	0.34

Fig. 4. Graphical representation of land degardation

Harvest failure modeling: This modeling was generated by 3 parameters: 1) Terrain unit, 2) flood risk and 3) vegetation cover. Then it was classified based on its score as follow in Table 9. We find that almost 70 % central dry zone area comes under middle type of harvest failure (Fig. 5); this is also increase high food insecurity.

Table 9. Classification of harvest failure

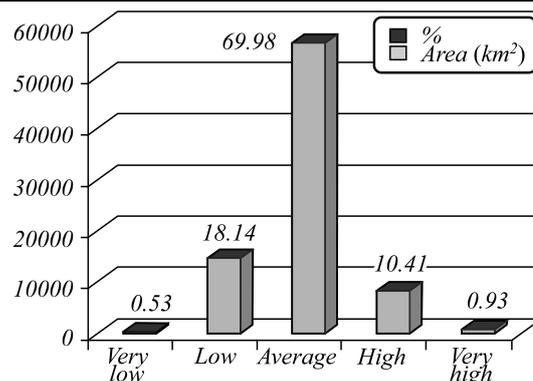| Class	% harvest failer	Weightage	Area Km^2	%
Very low	< 2	1	433.46	0.53
Low	$2 - 5$	2	14722.05	18.14
Average	$5 - 10$	3	56787.62	69.98
High	$10 - 15$	4	8450.45	10.41
Very high	$15 <$	5	756.84	0.93

Fig. 5. Graphical representation of harvest failure

Food vulnerability modeling: This is the final modeling. It's generated by following parameters: vegetation cover, precipitation, land degradation and harvest failure parameter.

Vegetation cover factor $(V) =$
$$= 0.007A^2 - 1.7109^A + 101.53;$$
Annual precipitation factor $(ACH) =$
$$= -0.0078B^2 - 2.0304^B - 11.424;$$
Land degradation factor $(LD) =$
$$= -0.0242C^2 + 3.5117^C - 1.4752;$$

Harvest failure factor (HF) =
  = −0.0472D² + 4.7183^D − 6.080.

While *A* is vegetation cover score, *B* annual precipitation score, *C* land degradation score and *D* harvest failure score. Then, food endurance level will be calculated by following formula [9]:

Food vulnerability (Y) =
= (0.1255×V) + (0.1671×ACH) + (0.2808×LD) +
+ (0.4273×HF).

Analysis shows that 52.60 % central dry zone area under enough of food class but around 45 % study area is under insecure food class area (Table 10 and Fig. 6*b*).

Table 10. Classification of food vulnerability

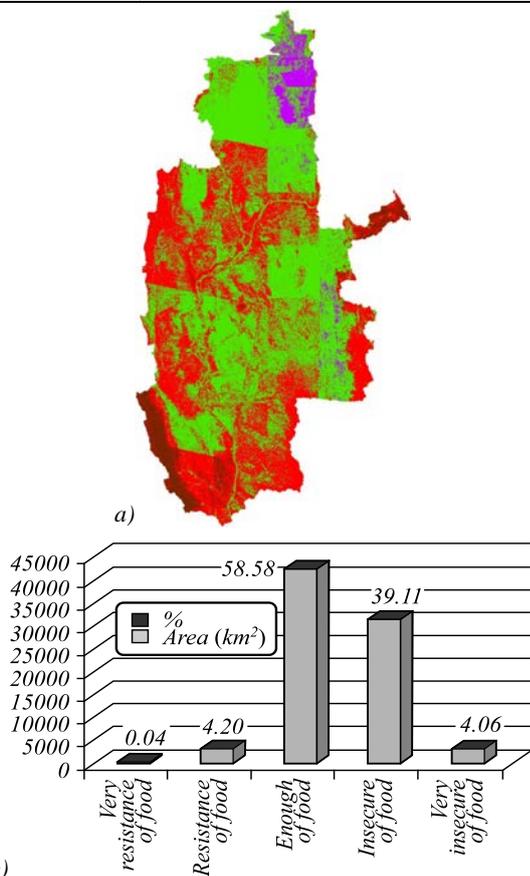| Y	Explanation	Area Km²	%
< 20	Very resistance of food	30.47	0.04
20 – 40	Resistance of food	3409.64	4.20
40 – 60	Enough of food	42689.48	52.60
60 – 80	Insecure of food	31743.87	39.11
80 <	Very insecure of food	3291.29	4.06

a)

b)

Fig. 6. a) Food vulnerability map; b) graphical representation of food vulnerability map

Results and discussion

The Central Dry Zone is mostly that, with the Irrawaddy River (joined by the Chindwin River), owing through it from north to south (Fig. 1). The Bago Hills range runs parallel to the Irrawaddy River in the southern part of the Dry Zone, gaining altitude towards the north and ending in southeast Mandalay. Fertile alluvial soil is found along the banks of the major rivers, but the Bago

Hills are sandstone and have less fertile sandy soil. As its name suggests, the Dry Zone is the driest region of the country, with annual rainfall between 500 and 1,000 mm.

In this research work food vulnerability determined by vegetation cover, land degradation, precipitation and harvest failure risk. Precipitation reflects the abnormal rainfall in the area that`s why many time, its cause of droughts and floods. This abnormal rainfall can influence harvest result because every plant has each standard of water amount to grow. If rainfall intensity is too high, then the plant growth will be disturbed or may be died. That rainfall anomaly also can cause harvest failure. If annual precipitation is high, then harvest failure will also high. Based on the precipitation data center to northeast part has the highest annual precipitation amount [10].

Vegetation covers also influence food vulnerability because the appearance of vegetation cover means that the soil can be planted. Vegetation also decrease flood risk by absorbing water for photosynthesis and tight caught the soil. So vegetation cover also reduces the amount of erosion. Results show that around 45 % central dry zone area, comes under very high erosion danger level. Erosion danger level is influenced by erosivity, erodibility, length and slope index, plant management and soil conservation. Erosivity indicates the power of rainfall intensity that can cause soil to erosion. High intensity of rainfall is increase the possibility of high erosion. Soil erodibility is the sensitivity of a particular type of soil to erosion where it is influenced by soil characteristics, soil thickness and vegetation covers [11].

Land degradation means soil is too bad for plantation. Land degradation can be caused by erosion and vegetation cover. Degraded land is determined if there is no vegetation cover or only sparse vegetation covers. Around 60 % study area affected by middle type of degraded land. Based on the map of degradation Land some parts in the center, border of the area and south part is highly degraded in central dry zone of Myanmar due to highly dry area and hilly sandstone and sandy soil or very less fertile soil.

Food vulnerability map (Fig. 6a) show very less area with very resistance food class, only some patches in the study area. A small part of study area is in class of resistance of food vulnerability in the northeast part due to dry area. Around 50 % area, maximum in central and north part is come in enough of food vulnerability class; it's due to alluvial farming and monsoon rain. Approximately 45 % central dry zone area of Myanmar comes under high insecure food vulnerability class. Maximum south part, some patches of center, maximum North West and border part comes in insecure food vulnerability class due to harsh climatic condition and unplanned management and polices. A small part of south west comes in very insecure food vulnerability class. The main cause of this class is high erosion rate, less fertile soil, slope and hill terrine [12].

Myanmar has various ecological zones with rice as the main crop. While rice and other crops are the backbone of agricultural production, livestock and fisheries

provide protein foods and contribute partially, if not fully, to livelihoods of the rural populations. In the past, hydro-meteorological hazards have affected rice production in many regions in Myanmar and are probably the main triggers of food insecurity. In the most food insecure zones, drought is the major agricultural challenge as indicated in the World Food Programme's Food Security Assessment in Dry Zone in 2011.

Alluvial farming: Alluvial farming can be seen as a good example for food security in flood risk area in the central dry zone of Myanmar (Fig. 7). Lower rainfall amounts or dry periods result in lower river discharge and foster the accumulation of sandbars in the river bed. Moreover, land use changes and forest logging have an additional influence on sedimentation loads in the river and create new fertile floodplains. Most likely, these processes have a visible impact on alluvial farming in the dry zone because more fertile arable land with good access to irrigation water is available. This is of even higher importance in the light of an increase in dry spells and changed timing of the monsoon rain in the dry zone. Our land use/cover analysis shows an increase in alluvial farming by 1745.33 km^2 since 1988. Most of the alluvial farmers grow crops like onions because of market prices, suitability to alluvial land and short-term benefits (personal communication with citizens of the dry zone). Concurrently, small-scale alluvial farming implies a potentially higher flood risk and related crop failure and loss of yields for the farmers and livelihoods of their families and communities.

Conclusions

This research work show that food vulnerability modeling is possible by remote sensing and GIS techniques with the help of food vulnerability related parameters. Overall 45 % study area comes under very high erosion danger level, 70 % under average harvest failure, and 59 % intermediate land degradation area, so overall 45 % study area comes under insecure food vulnerability zone. Food vulnerability is influenced by the precipitation anomaly, vegetation cover, degradation land, and harvest failure risk.

Fig. 7. Study area photographs during ground truth an field verification in central dry zone area of Myanmar

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