Research article

Mobility Assessment for Sustainable Rural Development: Conversion of Conventional Mobility Data and Historical Analysis

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Abstract Dawei Special Economic Zone (DSEZ) Project is one of the largest petrochemical industrial estates in South East Asia which aims to transform the country into a pivotal hub for regional connectivity and logistics. Socio-economic factors determine local lifestyles, including mobility pattern, and directly impact on rural sustainability. Changes in mobility may represent not only generating alternative opportunities associated with socio-economic development, but also the vulnerability of rural people which can be a significant challenge for social sustainability in a rural area. Consequently, mobility can be one of the powerful indexes to assess impacts resulted in socio-economic changes in a long-term. The objectives of this paper are to: convert conventional mobility data to spatiotemporal data and visualize them; and to assess the change of mobility in 2005, 2010 and 2015 with respect to social parameters such as sex and age. A total of 345 individual respondents were stratified-randomly selected for assessing one-day mobility. Conversion of conventional mobility data was conducted using online maps. Historical analysis of mobility data was conducted after performing mobility data validation. The result shows that different mobility was observed by sex and age group. Average increases of males' mobile distance between 2005/2010 and 2010/2015 show 2.6 and 1.7 times increase, while that of females shows 1.6 and 2.6 times, respectively. Especially, working age females show a high increase in 2010/2015. The study concluded that mobility data obtained in different formats in different time periods can be integrated and visualized for long-term mobility assessment. This contributes to better understand how local people is responding to such socio-economic development. Mobility can be an important parameter and further provides significant perspectives to policy development for sustainable rural development.

Keywords mobility, GPS-Logger, Myanmar, rural development, socio-economic changes

INTRODUCTION

The economic transition from an isolated country to opening up to the global economy is creating opportunities to develop a high potential for economic growth for Myanmar. Dawei Special Economic Zone (DSEZ) is one of the newly emerging largest petrochemical industrial estates in South East Asia. This aims to transform the country into a pivotal hub for regional connectivity and logistics. This project includes the development of the Dawei deep seaport, an industrial estate and highway road and rail links to Thailand with a total investment of 8.6 billion US$ (Mahesuan Kruewan, 2014).

In developing countries, socio-economic factors determine local life styles, including mobility pattern, and directly impact on rural sustainability. Changes in mobility may represent not only generation of alternative opportunities associated with socio-economic development, but also the vulnerability of rural people. This vulnerability is a significant challenge for social sustainability in a rural area. As sociological diversity such as age, sex, and economic status generates different mobility pattern, it is needed to understand heterogeneous diverse local impacts from socio-economic development for aiming sustainable rural development.

The increased flow of foreign investment in the telecommunication sector in Myanmar has facilitated to the mobile phone penetration (World Bank, 2015); therefore, ways of obtaining mobility data have been largely shifted from conventional methods such as questionnaire survey and diaries to Global Positioning System (GPS) survey by loggers and mobile phones. However, conventional mobility data can be mainly displayed as static (Sheller and Urry, 2006), and is visualized only at the individual level (Yu and Shaw, 2004). On the other hand, comparison of two different mobility data set obtained in different format was mainly studied only in the developed countries including Australia, Canada, Sweden, Switzerland, the UK, and the USA where geographic information has been well developed (Kelly, Krenn, Titze, Stopher, and Foster, 2013; Stopher, FitzGerald, and Xu, 2007). Furthermore, disaggregated mobility analysis by sociological components has not been focused. In this regard, integrating two different mobility data obtained in different formats in different time periods is needed for a long-term mobility assessment.

Therefore, the objectives of this study are to: (1) convert conventional mobility data to spatiotemporal data and visualize mobility data, and (2) assess mobility changes in 2005, 2010 and 2015 with respect to social parameters such as sex and age. This research is expected to contribute to integrate different mobility data set and assess a long-term mobility for rural sustainability associated with the socio-economic development.

METHODOLOGY

Study Area and Data Set

The study area is located in Dawei, Tanuntharyi Region, Myanmar, 132 km from the border of Thailand. The DSEZ consists of five zones such as heavy, medium, light industry and a combination of these, with a total area of 250 km^2 (Min & Kudo, 2012). Villages in the DSEZ mainly depend on agricultural activities such as plantation and paddy cultivation; however, the project development has led to the reconstruction of villagers' mobility patterns due to the creation of employment opportunities and development of roads. The study purposively selected rural villages dependent on rural agricultural activities (Fig. 1).

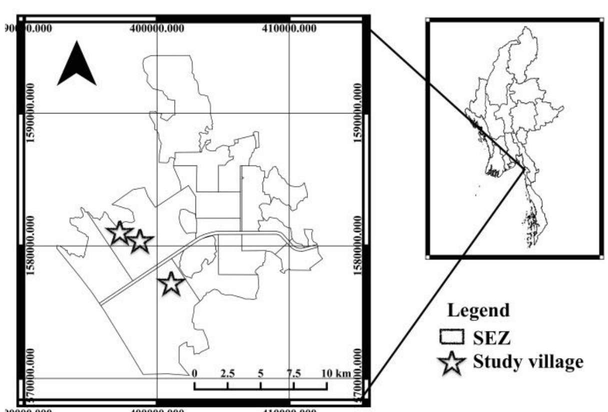

Fig. 1 SEZ in Dawei

A field survey was conducted in 2015 to collect mobility data and personal profiles. Stratified random sampling by sex and age was employed to understand characteristics of mobility. Non-spatial personal attributes such as age, sex, marital status, education level, household status, occupation, monthly household income and mobile mode were collected through a pre-tested questionnaire conducted earlier in 2014. Spatial information such as origin, destination, direction, distance, and duration in 2005, 2010 and 2015 was also collected. The study also employed formal and informal interviews with key informants such as village heads, using checklists.

Wearable GPS components such as " i-gotU USB Travel & Sports Logger – GT-600" were used to log mobility and validate the questionnaire mobility data. This device recorded 24-hour mobility with a 5-second interval using the motion detection mode. A maximum of 38 devices was distributed at one time to a total of 345 respondents aged over 16 years old. Both questionnaire and GPS log data are available from the 345 samples.

Research Flow

The following Fig. 2 is the overall methodology consists of four major steps. First, mobility data from the questionnaires was indexed and converted to spatiotemporal information such as time, speed/hr., direction, and geographical coordinate by utilizing online mapping service. Those converted mobility data was visualized in an animation format. All indexed spatiotemporal data are listed in a timeline and saved in a comma-separated values (csv) format. Simultaneously, non-spatial attributes such as age, sex, marital status, education level, household status, occupation and household income, were also integrated with the file. Visualization of the mobility was done using the visualization tool such as Mobmap (Center for Spatial Information Science, n.d.). Details of the moving segment such as the total number of mobility, mobile distance, and mobile duration were manually calculated from the questionnaires and listed. In this study, a single mobility is defined from a staring from a location to a destination, such as from home to a workplace.

Second, stay point and moving point extraction from GPS log data was performed. The spatiotemporal data such as time, latitude and longitude were extracted from the devices. The split of segments was conducted to extract stay points with outlier detection and removal technique utilized by Witayangkurn et al., (2013) Eq. (1):

$$Distance\ (p_{start}, p_{end}) < D_{threh}\ and\ TimeDiff\ (p_{start}, p_{end}) > T_{threh} \tag{1}$$

Where the parameters D_{threh}, considerable maximum distance as a stay point, and T_{threh}, minimum time spending at the same place, are adjustable. In this study, a stay point is detected if $T_{threh} > 20$ minutes and $D_{threh} <= 300$ meters. Extracted stay points are listed by start-time, end-time, duration, distance in meters, average speed in km/hr and the total number of stay points. Additionally, outlier detection and noise removal technique were applied by using standard deviation (σ).

Third, validation of two data sets was performed with respect to the selected parameters. The following Eq. (2) was used to calculate differences in the number of one-day mobility, mobile distance, and mobile duration.

$$Relative\ Change\ (x, y) = Absolute\ difference /\ Max\ (x, y)*100 = |\triangle| /\ Max\ (x, y)*100 \tag{2}$$

Where x is the data from the questionnaire and y is the data from the GPS loggers.

Fourth, changes in these parameters in 2005, 2010 and 2015 were further analyzed based on social parameters such as sex and age. In this process, mobility made out of villages such as in Yangon and Thailand, and unfixed mobility such as daily employment at various places within or outside the villages, were excluded.

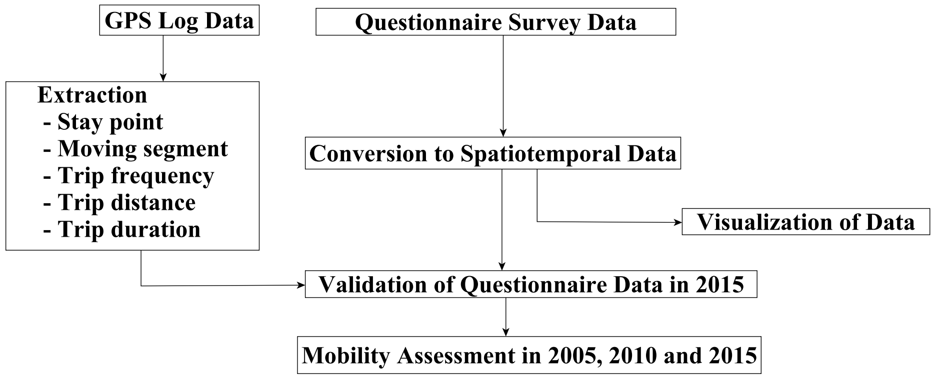

Fig. 2 Overall methodology

RESULTS AND DISCUSSION

Conversion of Questionnaire Mobility Data to Spatiotemporal Data and its Visualization

Mobility data obtained from the questionnaire survey was indexed and converted to the spatiotemporal data (Fig. 3). All mobility data is simultaneously visualized and shown in an animation format (Fig. 4). Those mobility data can be also displayed according to the attributes obtained from questionnaires. As traditional mobility data such as questionnaires and diary can be only displayed at the individual level (Yu and Shaw, 2004), visualization of a large volume of mobility data is difficult to display simultaneously and compare historical mobility. However, the study result makes mobility data visualize simultaneously, as a result, more useful mobile characteristics in different time periods can be extracted. Illustrative visualization is easy to understand and more information can be obtained for a better understanding of the underlying tendency behind the data (Andrienko, Andrienko, & Augustin, 2007).

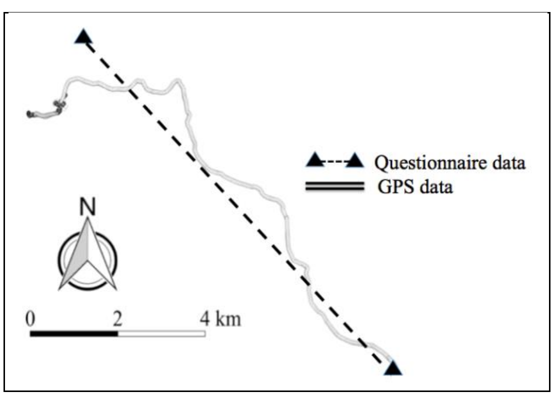

Fig. 3 Conversion of questionnaires data

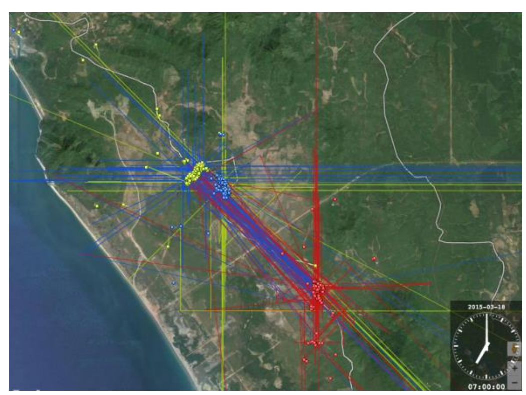

Fig. 4 Visualization of questionnaire mobility data

Comparison of Two Data Sets

To validate the questionnaire survey data, the average differences between two data sets were calculated. This reveals a total of 543 mobility, with a total 1,936.3 km of mobile distance and 7,457.0 minutes of mobile duration from the questionnaires while data from the GPS log shows a total of 403 mobility, 2,302.0 km of mobile distance and 7,403.6 minutes of mobile duration. The result shows the average differences between the two data sets as 25.1%, 34.9% and 38.0% in the number of mobility, mobile distance and mobile duration, respectively (Table 1). Those differences between the two data sets can be generated from different setting during data processing or understanding of individual mobility among local people. Several studies conducted in the developed countries such as Australia, United State of America and the United Kingdom show much larger differences in mobile duration between GPS and self-reported data, 75.4%, 62.4%, 46.7%, respectively (Kelly et al., 2013). In this line, the level of error allows us to utilize the mobility data in 2015, 2010 and 2005 obtained from the questionnaire survey.

Table 1 Average difference of two data sets

	Average differences (%)
Number of Mobility	25.1
Mobile Distance	34.9
Mobile Duration	38.0

Change in Mobility

Mobile distance in 2005, 2010 and 2015 was compared and the results of yearly change are described in Table 2. The results show that the number of mobility does not show much difference over a period of 10 years. Mobile distance increases yearly and the changes are 1.9 (2005-2010), 2.1 (2010-2015) and 4.1 (2005-2015) times. Mobile duration also increased in 2010; however, in 2015, it again decreased to a duration similar to 2005. Based on these trends, it can be said that the main change in mobile behavior is the increase of the mobile distance and this can result from the change in modes such as walking, traveling by motorbike, car or other modes. It can be confirmed that as the mobile distance increases, the mode also changes. Indeed, the motorbike mode increased 5.9 times from 2005 (9.2%) to 2015 (54.0%). Furthermore, project-induced employment opportunities as local project staff, surveyors, and road construction workers have largely contributed to this mobility increase.

Table 2 Average number of mobility, mobile distance and mobile duration by year

	2005	2010	2015
Number of Mobility	2.3	2.1	3.0
Mobile Distance (km)	2.3	4.1	9.2
Mobile Duration (min)	40.6	58.4	46.0

Change in Mobile Behavior by Sex and Age

Sex and age are among the important parameters for assessing mobility change. The mobile distances in 2005, 2010 and 2015 were compared with respect to sex and age (Table 3 & 4). The average increase rate of mobile distance during 2005-2010 and 2010-2015 is 2.6 and 1.7, and 1.6 and 2.6 for males and females, respectively.

The notable increase in the female age group 16-20 years during 2010-2015 (2.9 times) is due to occupational changes from being a student to working in agriculture, non-agriculture and other activities. Furthermore, some females travel to a city university, so making the search for higher education is one of the main driving factors for this age group. The higher increase rate for the female age group 21-30, and 31-40 years during 2010-2015 (4.9 and 3.7 times, respectively) is also found resulted in their engagement in project-related employment, including as office staff and as laboratory workers at the project camp, and business work in the city. This large increase was generated with the combination of a significant increase in the use of motorbike mode of travel to work. On the other hand, for the male age group 31-40, and 41-50 years, the rate during 2010-2015 decreases by 1.3 and 1.2 times, respectively. This is probably due to non-significant changes in occupation for males. Furthermore, for the male age group 51-60 years, the rate during 2010-2015 increases by 3.0 times. This notable increase is the result of increased engagement in non-agricultural activities, such as driving car taxis.

Based on the findings of this study, it can be said that surrounding socio-economic development largely affects local activities. Furthermore, occupation and mobility modes are significant factors influencing the mobility of the villages.

Table 3 Average mobile distances by sex and age group

Age	2005		2010		2015	
	M	F	M	F	M	F
(A) 16-20	1.2	1.2	4.3	4.0	7.3	11.6
(B) 21-30	4.8	1.1	5.9	1.7	11.1	8.3
(C) 31-40	3.0	2.2	8.9	1.1	11.9	4.1
(D) 41-50	3.4	2.2	11.1	2.7	13.4	7.5
(E) 51-60	4.0	3.1	6.1	4.1	18.3	1.7
(F) 61<	1.4	0.9	4.2	1.5	5.7	1.6
Average	2.8	1.8	6.5	2.8	11.6	6.8

Note: M stands for male and F stands for female
Unit is km

Table 4 Increase rate of mobile distance

Age	2005-2010		2010-2015	
	M	F	M	F
(A) 16-20	3.6	3.3	1.7	2.9
(B) 21-30	1.2	1.5	1.9	4.9
(C) 31-40	3.0	0.5	1.3	3.7
(D) 41-50	3.3	1.2	1.2	2.8
(E) 51-60	1.5	1.3	3.0	0.4
(F) 61<	3.0	1.7	1.4	1.1
Average	2.6	1.6	1.7	2.6

Note: M stands for male and F stands for female

CONCLUSION

Socio-economic developments reconstruct local livelihood. Mobility largely represents changes of activities associated with the development. Thus, this study conducted mobility assessment in a long-term by integrating two different data sets in different formats in different time period, and visualized them. Mobility data from questionnaire survey was converted to spatiotemporal data and visualized together with GPS data in an animation format. Those mobility data from questionnaires was further validated by GPS log data for assessing historical mobility pattern. Mobility trend during 2005-2015 with respect to social parameters was further analyzed. Large increases in motorbike-based mobile distance for working age females employed either with the project or in non-agricultural activities were found. This mobility assessment and its visualization contribute to better understand activity changes and it diversity associated with project development. Mobility can be a powerful parameter to assess both opportunity and vulnerability along with the huge and accelerated project development. This further provides significant perspectives to policy development for sustainable rural development.

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