Business Intelligence Model for Disaster Management: A Case Study in Phuket, Thailand.

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ABSTRACT

This research presents the conceptual Business Intelligence (BI) model for disaster management. BI can provide agility capacity for decision making in dynamic environment among different agencies. This project designs and develop a data warehouse using multi-dimensional model for severity analysis of flood and landslide in risk area using case study from Department of disaster prevention and mitigation (DDMP), Phuket, Thailand. The concept of BI can be applied for extremely heterogeneous data structures and data platform environment to improve data quality and expose to better decision-making for disaster management. In the next stage of this project, we will integrate more data sources from other agencies for example GIS data from Phuket land-use planning and flooding prediction model database. The result of this study will help organization deploy BI more effectively.

Keywords

Business Intelligence; data warehousing; decision support system; conceptual model; disaster management.

INTRODUCTION

Disaster management is commonly described in four phases including preparedness, response, recovery, and mitigation (Public Safety Canada, 2011; Summary, 2013). Each phase has the different activities which require the data to support as the following:

Preparedness phase is aimed at preventing a disaster at first phase. In the event a disaster occurring, then it will try to control its effect through suitable response and recovery strategies (National Preparedness Guidelines, 2009). The activity of preparedness includes planning, organizing, training, equipping, evaluation and improvement activities (Kadam, 2012) which requires the related information (plans, resources, and organizations) (Flachberger and Gringinger, 2016).

Response phase occurs after the crisis event has occurred, the aim is to minimize losses, saving lives, damages, and alleviating suffering (Summary, 2013). The Information which is required for the response may contain resources, needs, damages, threats and collaborations (Flachberger and Gringinger, 2016). The related activities include search, rescue, and emergency relief.

Recovery phase wants to return the community's systems and the activities back to normal in long-term. This phase is not similar to the response phase in its concentrations; recovery efforts are concerned with issues and decisions (Public Safety Canada, 2011). The activities of recovery phase such as claims, grants, and repair of importance infrastructure. Besides, the information is required for reducing damage (Flachberger and Gringinger, 2016).

The mitigation phase: effort to manage and reduce the risk to life and property. The information is required for decision support such as hazard, risk, forecasting, and impact of disaster (Flachberger and Gringinger, 2016; Eckle et al., 2016)

For examples in figure 1, each phase of the disaster management has the distinctive principles and information for employments (Flachberger and Gringinger, 2016; Summary, 2013). This information has in the both related public and private agencies, which are responsible for disaster management such as Federal Emergency Management Agency (FEMA) and Non-Governmental Organization (NGO) (Summary, 2013). In addition, there are also relevant agencies in Thailand such as Meteorological Department of Thailand, Department of Water Resources, and Department of Disaster Prevention and Mitigation in Thailand. Including data from social network such as Facebook, Twitter, and Crowdsourcing (Alexander, 2013; Calderon et al., 2014).

Data is distributed in dissimilar data sources which are multiple formations and extremely heterogeneous data. Those data sets make a large volume and a variety of data that can be classified into three types: structured data, semi-structured data, and unstructured data (Goes, 2014). The problem of research is the combining information from various sources into the data warehouse for decision-making processes. Therefore, the challenge of research is the data integration from heterogeneous data sources and constructed data warehouse for the agility and collaboration of disaster management. The concept of data agility can also apply to data warehouse architecture in real time to quickly adjust disaster management.

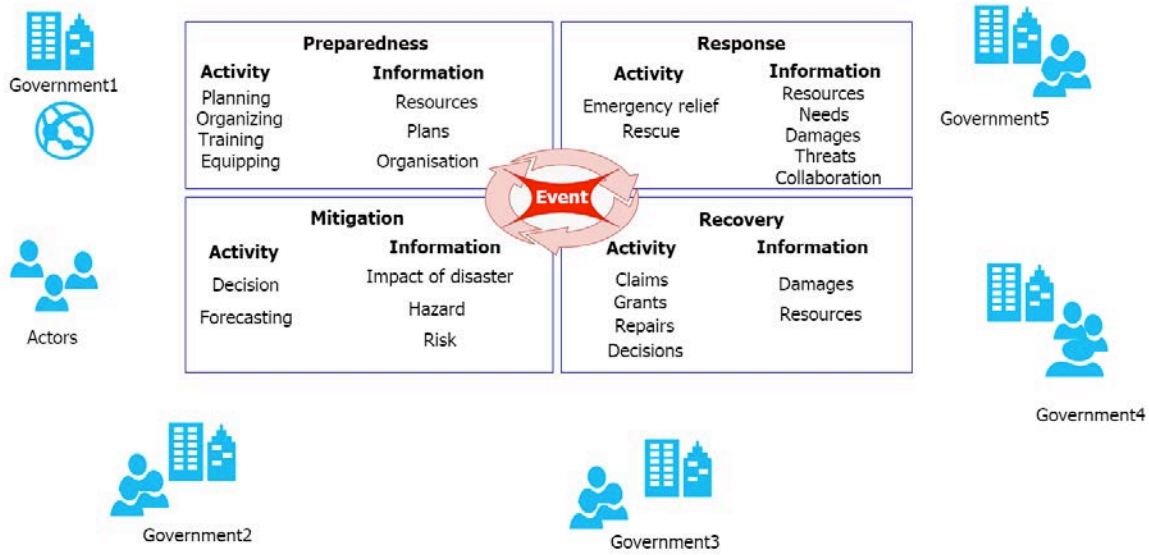

Figure 1. Information requirement for disaster management phases.

Nowadays, Information technology is commonly used to manage the problems of information (complexity, incompleteness, and variety). Examples of Information technology includes Management Information System (MIS), Customer relationship management (CRM), Enterprise Resource Planning (ERP), Big Data, Data mining and BI (Asghar et al., 2009). In addition to technologies are applied for knowledge: predictive modeling, association analysis, data segmentation and clustering, classification and regression analysis, and anomaly detection, in various applications (Chen and Storey, 2012). However most of the data processing, data warehouse, and data analytics are necessary workflows on BI platform which includes Microsoft, IBM, Oracle, and SAP (Sallam et al., 2011). BI can be integrated and improve data from many data sources for the complete process of decision making (Asghar et al., 2009; Chen and Storey, 2012). On the one hand, the risk is reduced and managed by Information technology (Iwasaki, 2013). The benefit of data warehouse is classified to four characteristics: subject-oriented, integrated, time-variant and nonvolatile. Subject-oriented, a data warehouse is used to analyze a specific subject area. For example, "Location" can be a specific subject. Integrated, a data warehouse can be integrated data from multiple data sources to a single database. Time-variant, Historical data is kept in the data warehouse which store many month or years of data for historical analysis. Non-volatile, historical data in a data warehouse is not modified (Chaudhuri, S. and Dayal, U., 1997).

This research presents the Business Intelligence model for disaster management. Next is methodology: data collection, data pre-processing, multi-dimensional model (fact tables and dimension table), BI analytics and data visualization. The final part is involved in the discussion, conclusion and work in the future. Researchers require to convert heterogeneous data into a single unified structure and stored for decision-making so researcher defined research questions. How to apply BI concept in disaster information management for decision making?

From questions, researchers studied and applied literature; disaster management, information technology management, and data integration, then we design the conceptual BI model for disaster management. Moreover, we selected Phuket province, Thailand in this case study because this province is the top business tourism and was involved in a natural disaster in 2005 (Henderson, 2007). Then research focused analysis as the following; 1)

the severity of risk areas by floods and landslides. 2) The population and number of households were affected by the drought. The result can help employees for decision support in the case study.

RELATED WORK

Business Intelligence (BI) refers to the set of techniques and tools that help to transform a large amount of data from disparate sources into meaningful information to support decision-making and improve organizational performance. The most organizations use BI for analyzing data. BI has emerged as a major driving force for organizational performance (Ramakrishnan et al., 2012). Technically, the processes of BI include; Extract, Transformation, and Load (ETL) process, data warehouse, online analytical processing (OLAP), data mining, decision models and visualizations (Li Zeng et al.,2006; Olszak et al., 2003; Zhong et al., 2006). Most BI applications are used in Business and marketing while BI application of disaster management is scanty. The data warehouse is the core of business intelligence system which stores aggregated and historical data (Ballou and Pazer, 1985). It is loaded from many operational data sources i.e. MIS, CRM, ERP and other legacy systems (Ballou and Pazer, 1985; Li Zeng et al., 2006; Olszak et al., 2003). The transformed data into a data store that is subject-oriented, integrated, time-variant, and non-volatiles which are based on available information and enable people to decision making and trends in the future. A popular conceptual model that influences the front-end tools, database design, and the query engines for OLAP is the multidimensional view of data in the warehouse. The attributes of a dimension may be related to a hierarchy of relationships. The types of design data warehouse are star schema, snowflake schema, fact constellation schema. Star Schema structure is easier to query. These are the classic characteristics of the data warehouse (Bill Inmon, 1991). The data warehouse of the disaster was produced to response and recovery strategies (National Preparedness Guidelines, 2009).

Chen and Storey classified Business Intelligence & Analytics (BI&A) and provide a framework that identifies the evolution, applications, and emerging research fields of Business Intelligence & Analytics (BI&A). They represented the trend and growing of BI (Chen and Storey, 2012).

Gao et al. produce platform using crowdsourcing with crisis mapping that is called Ushahidi. In order to be more proficient and most effective in settling the emergency, the individuals from the reaction aggregate must subscribe to the brought together regulatory control of a data administration framework to guarantee information uprightness (Gao et al., 2011).

Nascimento et al. presented the conceptual architecture to handle the influx of information in Emergency Situations. Their Models were used to data implementation (from raw data sources to visual representations). Moreover, the solution help to identify interesting information on the dashboard (Nascimento et al., 2016).

Aulov et al. described AsonMaps which is the platform for collection, aggregation, visualization, and analysis. AsonMaps can geolocated information that be extracted from Instagram and Twitter. They focus a use-case scenario on Hurricane Sandy that devastated the East Coast of the United States in fall of 2012. They used NOAA's SLOSH model and P-Surge (probabilistic surge model) to produce a forecast for Hurricane Sandy (Aulov et al., 2014).

Sung et al. classified applications for the communication of disaster in Taiwan. It can be divided into 5 types include Educational apps, Follow-up apps, Disaster message boards, Alert notification, Location, sensor, and hazard maps. The mobile application has more important in disaster management so it occurs increasing data sources (Sung et al., 2011).

Calderon et al. studied to analyzing the sort of communications that happen through social media during a crisis, specifically a case study selected Hurricane Sandy. They claimed two areas of work; namely collective intelligence and group decision-making software. They need to increase effectiveness between people during the crisis, through technology and information. The collective intelligence of users, allowing them to make better individual and group decisions, so to help those afflicted by a disaster or those attempting to provide relief to help themselves. They were not so concerned information flows. They are interested in information as a necessity for collective decision-making (Calderon et al., 2014).

Olszak and Ziemba introduced the methodology of BI system, creation, and implementation. This research focus two major stages, 1) BI creation stage involves tools and technologies, which include ETL, data warehouse, OLAP, data mining and presentation tools. 2) BI consumption involves the fundamental changes in the enterprise. The researchers focused on the issue that organizations require some cultural background to go along with information system and information technology when building and implementing a BI system. This suggested a methodology of building and implementing BI system also need sound business practices set by the enterprise (Olszak and Ziemba, 2007).

Asghar et al. developed BI model that link dimensions of BI and processes, which is essential during the lifecycle of BI system development, for disaster management organization in Pakistan as a case study. The model is implemented and validated using Oracle BI tools and techniques. The data source has structured data from a part organization. They provide exploratory abilities on the data, and linkages among BI processes from the conceptual BI dimensions (Asghar et al., 2009).

CONCEPTUAL BI MODEL

Previous data in the BI system were stored as the database with relational structure (Asghar et al., 2009). However, at present, there are copious data: structure, semi-structured and unstructured, as identified in the definition of Big Data (Goes, 2014). Big Data is essential to disaster analysis and hence, the conceptual of BI and Big data is integrated and created as the model on disaster management. In this research, there will be defining conceptual of BI model for disaster management and figure 2 illustrates work process which can be divided into 9 phases including event, disaster phases, response, actor/center, data services, data storage, evaluation, BI analytics and BI virtualization as follows.

First phase: disaster can be categorized as 2 types including natural disasters such as drought, flood, wildfire, earthquake, landslide, and Tsunami or man-made disasters including transport accident, industrial accident, attack, or other accidents (Chandran, 2013; Kadam, 2012). It is necessary to manage disaster to handle with possible occurrences. However type of disaster is the first requirement, is applied with the second phase for defined and designed the data warehouse.

Second phase: Disaster phase uses the term "Disaster management" that has four phases including mitigation, preparation, response and recovery which are substantially different in terms of functions and processes. For example, mitigation is exercised for the longer term than another 3 phases. Preparation is to create the strategy to prevent disasters and to control functions of response and recovery. Response requires emergency service and local experts while recovery, the final phase, is targeted to recover the affected area. The information of disaster management flows from authorities and agencies to the public, from the public to authorities and from peer-to-peer (Goggins et al, 2010; Kadam, 2012; Public Safety Canada, 2011; Summary, 2013).

The third phase is about disaster actors and agencies such as U.S Federal Emergency Management Agency (FEMA), governments, hospitals, NGOs which are connected with the devices or system resulting in various and bountiful disaster data beneficial to analysis (Kim et al., 2014; Public Safety Canada, 2011).

Fourth phase: communication devices when disaster occur such as cloud, GPS, website, CCTV, sensor, satellite, employee and facsimile (Fax) which can transmit data externally and internally (Flachberger & Gringinger, 2016). Some data are managed as the database but some are dissipated without proper organization. Thus, it is necessary to create the data bank for different data storage (Kadam, 2012; Public Safety Canada., 2011).

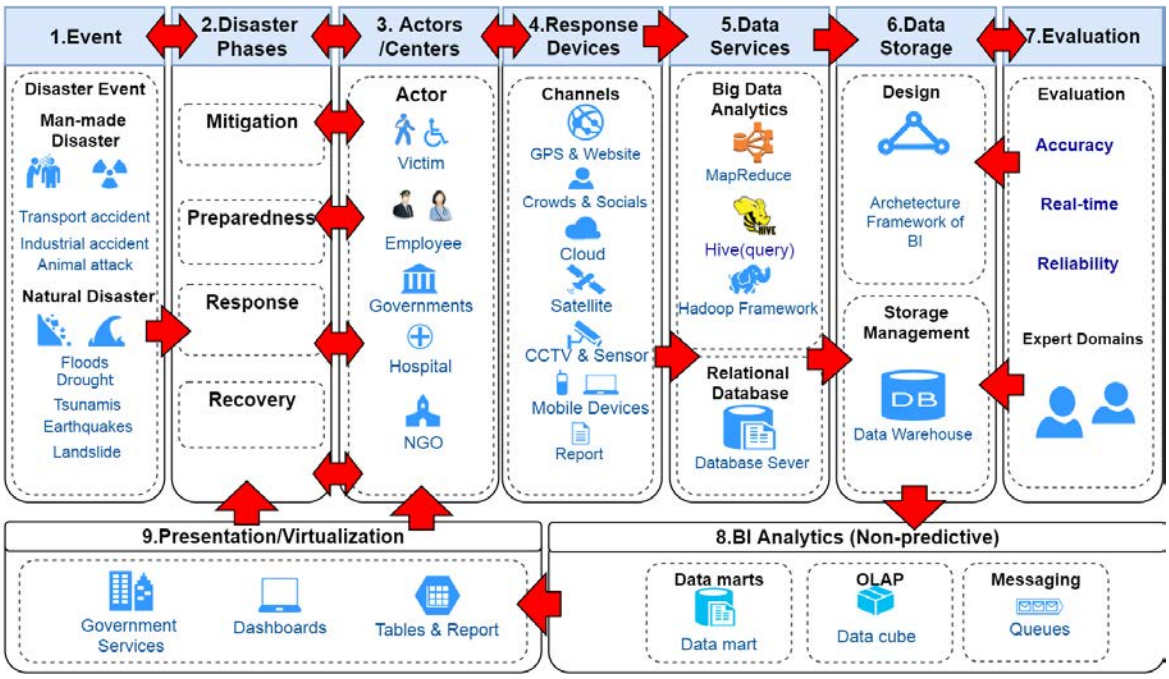

Figure 2. Conceptual Model of BI on disaster management

The fifth phase is the data collection from data services. They are divided two services follow as; 1) Big Data environment is defined by 4V'd: volume, velocity, variety, and veracity. Volume is big data's primary attribute, as terabytes or petabytes of it are generated by organization. Velocity is the speed data is generated and processed. Variety is the data come in all form: structured (traditional databases like SQL), semi-structured (with tags and markers), and unstructured (NO SQL). Kim et al., 2014) Big data is integrated by data-management systems for example, Hadoop which is open-source platform is the most widely applied technology for managing storage and access, overhead associated with large heterogeneous datasets, and high-speed parallel processing. That is called the distributed file system (HDFS) (Zikopoulos et al., 2012). HBase is used to store data and Hive is used for data summarization and ad hoc querying (Thusoo et al., 2010). 2) the relational database of the related agencies which is various structured data. Nevertheless, those data must be extracted and transformed by ETL process that is called data pre-processing, can be exercised to reduce irrelevant data and to improve data (Kim et al., 2014; Olszak et al., 2007; Shivtare and Shelar, 2015; Zhong et al., 2008).

Sixth phase: data warehouse is defined by a multidimensional conceptual model, store data from data pre-processing. Data warehouse is mostly implemented on standard or extended relational DBMSs, ROLAP and MOLAP servers. However, the data warehouse contains fact tables, dimension tables, and hierarchies into a multidimensional model in the form of star or snowflake schema (Asghar et al., 2009). Moreover, each fact table is defined measure and gain value. The designing data warehouse is significant and time-consuming; it is necessary to use the principles of the Business requirement to design the structure customized by the users and to improve data quality for effective analysis (Nascimento and Vivacqua, 2016; Olszak et al., 2007; Zhong et al., 2008).

Seventh phase: data warehouse evaluation is necessary for analysis. The factors of data warehouse evaluation can be divided 3 parts as the following: 1) structure of fact tables and dimension tables include accuracy, reliability and real-time. 2) The data quality of data sources. 3) Based on actual usage (Asher et al., 2009; Kim, 2014).

The eighth phase is BI analytics such as data marts, OLAP, and data searching which are the result effective and quick analysis required by the users with a multi-dimensional overview (Asghar et al., 2009). Data required for specific analysis will be stored as data marts that data dimension can be easily presented.

Ninth phase is the presentation from BI analytics so that the users can understand it quickly and easily. For data representation in cubes as a user interface. The data display can hierarchical operations; roll up and drill down at multiple levels of aggregations. Furthermore, the data visualization contains traditional graphics (point, bars, circular and histograms), table, report, tendency, complex forms (with the use of colors and geometric symbols), real images or mappings to the more representations by use of diagrams (trees, graphs and networks) (Nascimento et al., 2016). It is crucial to recognize the instruments of the users and presentation format. Examples of data visualization tools as Ushahidi (Ushahidi, 2013), VisTrails, the matplotlib library, Power BI, and Oracle dashboard. (Asghar et al., 2009; Chaudhuri and Dayal, 1997; Oliveira et al., 2014).

CASE STUDY

BI model in figure 2 is applied to a study area, Phuket province in Thailand. Phuket was selected as study area according to information about occurred natural disasters (floods, landslides, and droughts), provided by local authorities and previous interviews within the local expert domains. The scopes of research analyze as follows; 1) the severity in risk areas of floods and landslides. 2) The quantity of population and households were affected by the drought. Moreover, figure 3 represents research methodology. Researchers organized the research method as follows: data collection, data pre-processing, designed data warehouse (multidimensional model), BI analytics, and results.

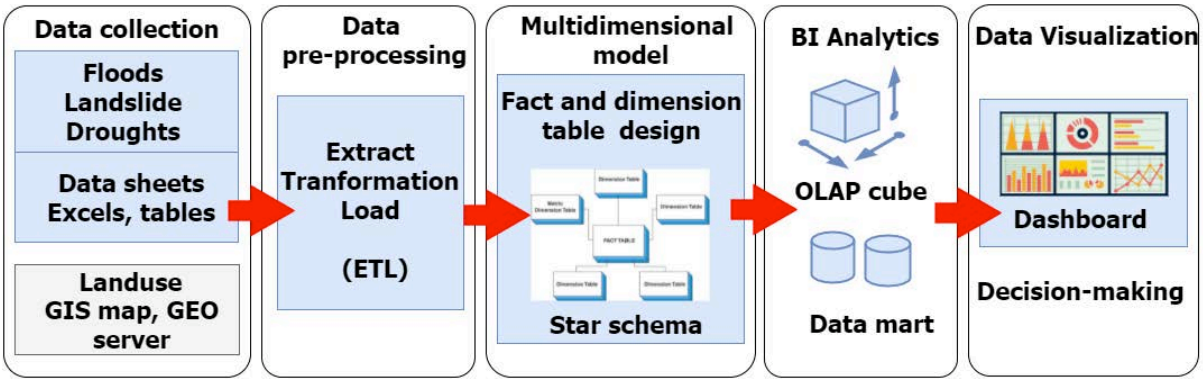

Figure 3. Research methodology

Data collection

In the case study, researchers collected secondary data from the Department of Disaster Prevention and Mitigation in Phuket center. The secondary data are extremely heterogeneous, both semantically and structurally, which contain information on several object types such as villages, sub districts, districts, population, households, time, geographical features, warning system, training, flood and landslide reports, and drought reports. These data were stored documents and table reports using the Thai language. Besides, we find and collect latitude and longitude of location points using Google Maps. Then, the data integration is created for disaster information management.

Data preprocessing

The researcher applied ETL process using SQL Server Integration Services (SSIS) on Microsoft Visual Studio 2015 and Windows SQL server 2014. SSIS is used to reduce noise data, convert data, set attributes and updates to multidimensional model (Shivtare and Shelar, 2015). For example, researchers need to convert the disaster subtype data from flat file to foreign key in dimension table (DIM_FLOODTYPE) using Dataflow which has many functions such as Lookup and Merge Join for data transformation. Then, converted data are loaded into the data warehouse.

Data warehouse

Data warehouse is the core of BI, must apply the information requirement for defined grain, measurement, user, dimension tables, fact tables, and BI analytics. Data warehouse or multidimensional data contains seven dimension tables (geographical features, Phuket location, time, flood types, water for agriculture, water for use, and water reserves). Each dimension table has two languages; Thai and English. Moreover, Data warehouse has two fact tables (flood and landslide table and drought table) and they were stored in data marts as the follow:

- Phuket location table (DIM_PHUKETLOCATION) has 10 attributes; 1) dimension key (KEY_LOCATION) 2) safety location (SURVIVAL_LOCATION) 3) district (AMPHOE) 4) sub district (TAMBON) 5) village number (MOO) 6) village (BAAN) 7) latitude 8) longitude 9) population (POPULATION) 10) number of households (HOUSEHOLD). For example of hierarchy such as district (Thalang) => sub district (Pa Khlok) => village number (no.2) => village (Baan Pa Khlok).
- Time table (DIM_YEAR) has three attributes; dimension key (KEY_YEAR) and year B.E. (YEAR_TH) 3) year A.D. (YEAR_EN).
- Type of floods table (DIM_FLOODTYPE) contains dimension key (KEY_FLOODTYPE) and type of floods (FLOOD_TYPENAME). For example of hierarchy such as Flood => Drainage Flood => No.1
- Geographical features table (DIM_TYPELOCATION) contains 2 parts: 1) dimension key (KEY_TYPELOCATION) and 2) geographical features.
- Water for consumption table (DIM_WATER_USE) contains dimension key (KEY_WATER_USE) and the sufficient quantity of water at the village level.
- Water for agriculture table (DIM_WATER_ AGRICULTURE) contains dimension key (KEY_WATER_ AGRICULTURE) and the sufficient quantity of water at the village level.

- FACT_DROUGHT is the fact table to compute the quantity of population and households which are affected by the drought. FACT_DROUGHT is designed and related 5 dimension tables; DIM_WATER_USE, DIM_WATER_AGRICULTURE, DIM_YEAR, and DIM_PHUKETLOCATION. The measure of this fact is the quantity of population and households in village level.
- FACT_FLOOD_LANDSLIDE is the fact table which is divided three parts, primary key, foreign key and the measure. The measure of this fact table is computed from the score severity in risk areas. The score of severity was classified according to table 1. Furthermore, the Department of Disaster Prevention and Mitigation also acknowledged and suggest the factors of calculated the score of severity in table 2.

FACT_FLOOD_LANDSLIDE is related to four dimension tables; DIM_PHUKETLOCATION, DIM_YEAR, DIM_TYPELOCATION, and DIM_FLOODTYPE. We map them on the logical multidimensional star schema that is called data warehouse shown in figure 4. Then, the data warehouse can be pre-computed to Online Analytical Processing (OLAP).

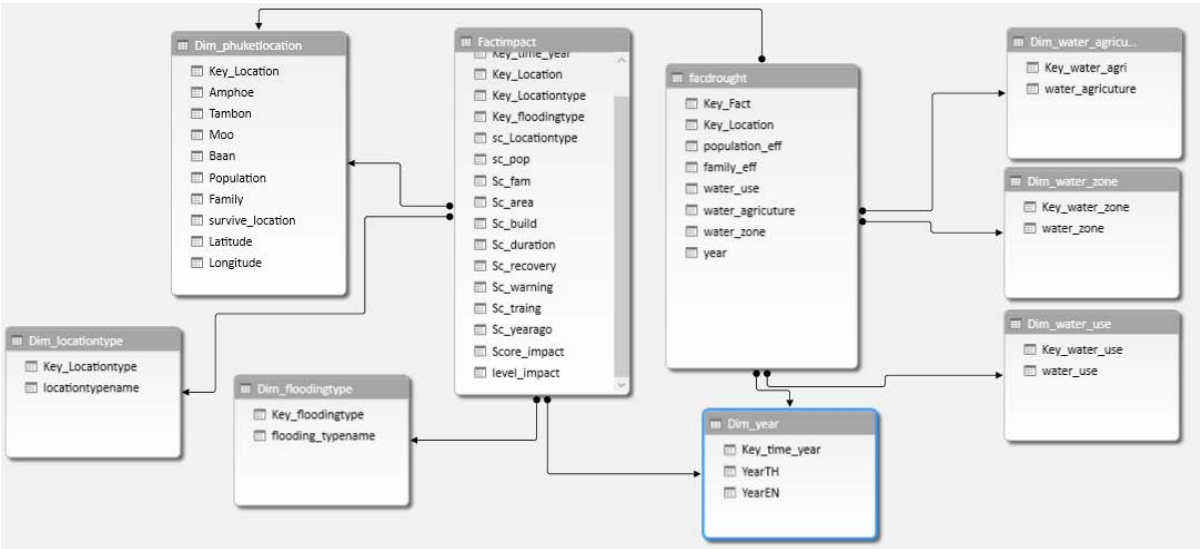

Figure 4. Multidimensional model

Table 1. Score of the severity in risk areas

Score range	Severity level
$0 \leq \text{Score} < 30$	1 (Low)
$30 \leq \text{Score} < 60$	2 (Medium)
$\text{Score} \geq 60$	3 (High)

Table 2. The factor of severity in risk areas

No.	Factor
1	Geographical features
2	The damage that occurs as population, households, buildings and agricultural areas.
3	Duration the occurrence of the disaster.
4	Rescue tools
5	Warning system
6	Training staff
7	The number of occurrences in the past.

BI analytics and data visualization

Researchers analyze the data warehouse using OLAP engine. Researchers use Microsoft Power BI Desktop (Power BI) which is BI tool for BI analytics and BI visualization. We implement the multidimensional schema in logical level, import to Power BI. Moreover, we select the visual presentations (graph, table, and map) from user requirement. There are two factors for presentations; measure and filter. The measure of visual presentation is based on the value in the fact table. Moreover, the dimension tables can be used to filter or axis. The users can select common operations to include drill down, roll up, and pivot on the dashboard. In the case of study, we have classified two reports on dashboard; 1) the severity in risk areas of floods and landslides. 2) The quantity of population and households was affected by the drought.

For examples, figure 5 presents the first dashboard that shows an overview of severity in risk areas of floods and landslides in Phuket province. We analyze from the measure in fact table (FACT_FLOOD_LANDSLIDE), the score of severity and the severity level in each tuple of the multidimensional model. The information can be presented from shallow level to deep level, which depends on defined grain and hierarchy. Figure 6 shows the location of Thalang districts in Phuket, has five sub districts and twenty-seven risk villages. Furthermore, the results of two risk villages (Baan Ta Reua and Baan Nua Toon) are presented two big red points on Bing map. The score of Baan Ta Reua is 61 and Baan Nua Toon is 63. They have the high level of severity in risk areas of floods and landslides in 2015. The right table of the dashboard shows the severity score, the severity level, and the quantity of population and households in each risk villages. Besides, line chart shows the percentage of the geographical features and pie chart shows the percentage of flood types.

The second dashboard in figure 7, the quantity of population and households were affected by drought in Phuket. This dashboard contains the slicer, map, table, and bar graphs. The left map shows an impact of drought which consist of the total number of people and families in each village. They are taken as a measure in the fact table (FACT_DROUGHT). Then, the dashboard has 2 bar graphs, the sufficient quantity of water for agriculture and consumption. The results of bar graphs as follow: 1) the number people of sufficient water is more than the number people of non-sufficient water for agriculture 2) the number people of sufficient water is less than the number people of non-sufficient water for agriculture consumption. Moreover, the data display of dashboard can hierarchical operations; roll up and drill down at multiple levels of aggregations. Figure 8 shows Krasatti sub district of Thalang district, Phuket province has sixteen affected villages in 2015. Two villages (Baan Daan and Ban Phru Somphan) represent the big blue points on the map, are high impact by drought. These dashboards are easy to understand and they operate data display at agility. They can be applied to planning and preparation in the future.

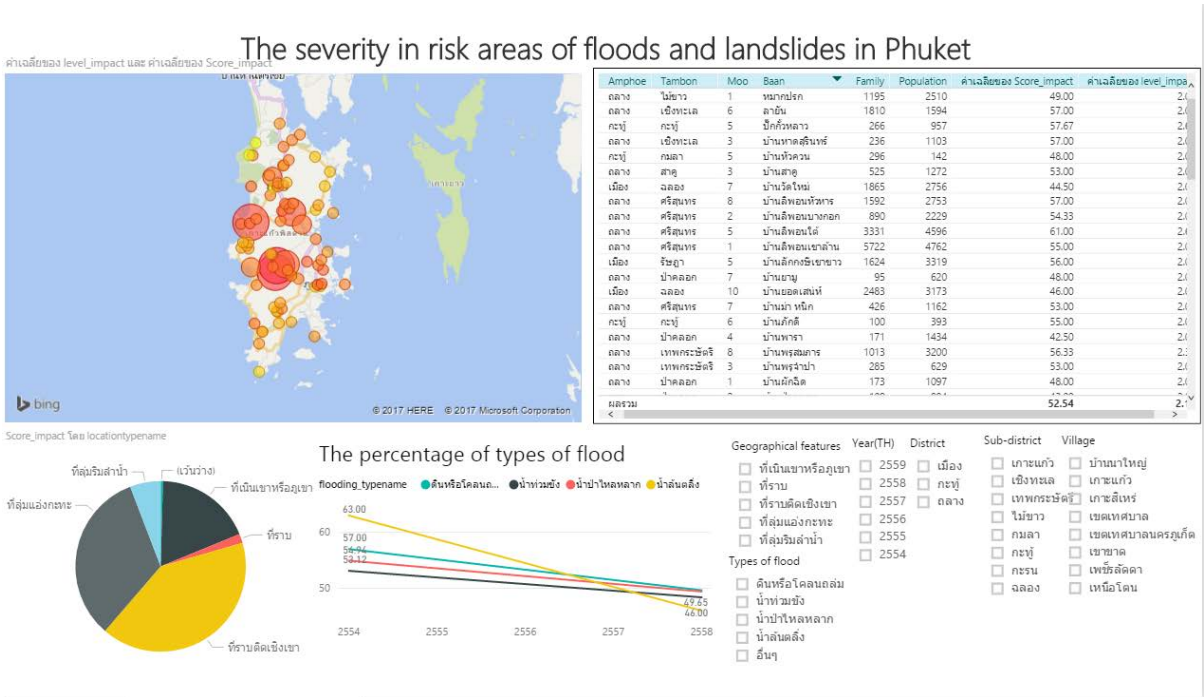

Figure 5. The overview dashboard of the severity in risk areas of floods and landslides in Phuket province.

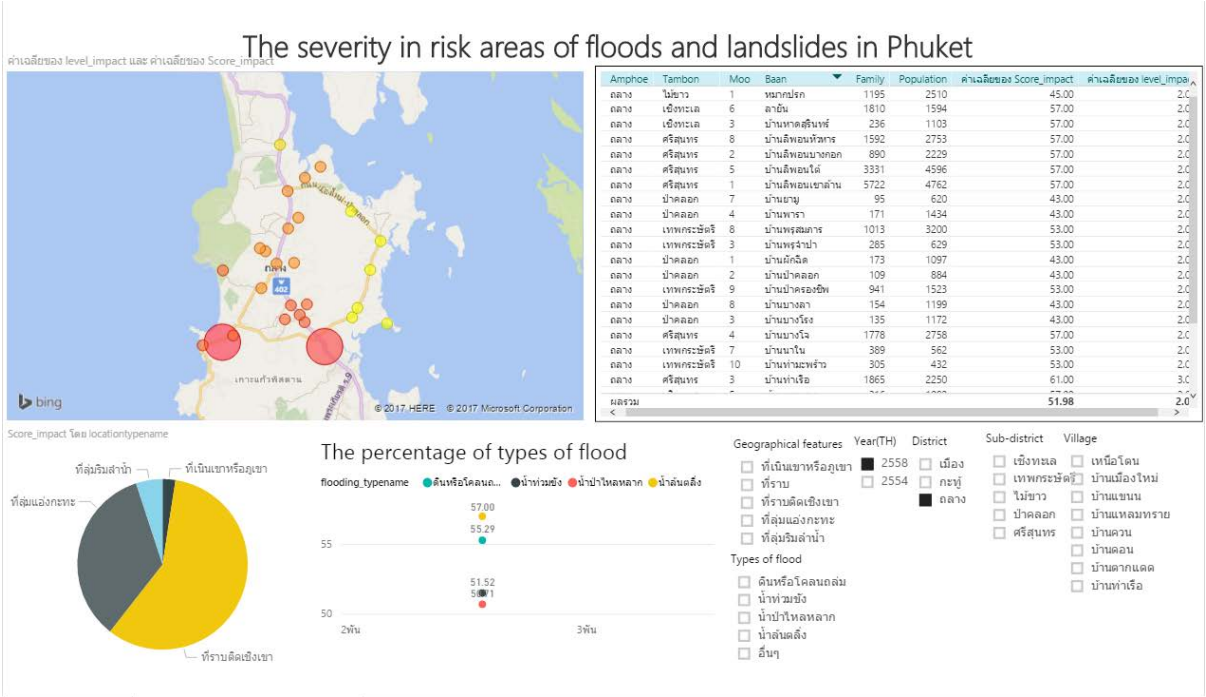

Figure 6. The dashboard of the severity in risk areas of floods and landslides in Thalang, Phuket province (in 2015).

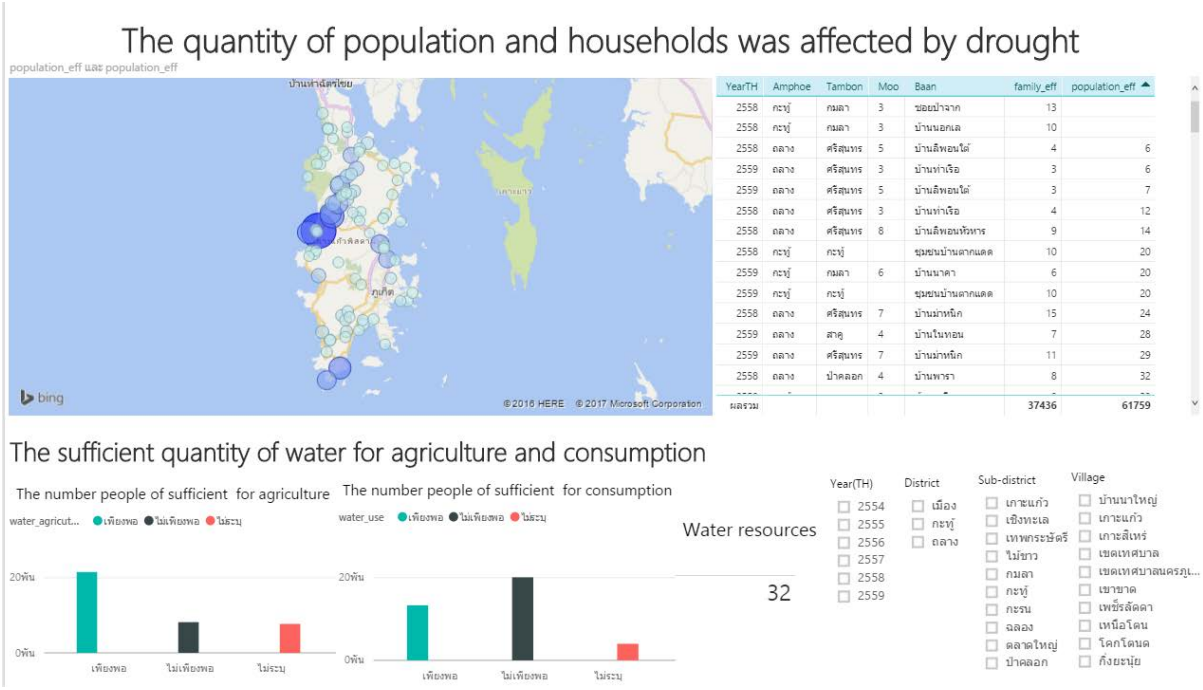

Figure7. The overview dashboard of the quantity of population and households was affected by the drought in Phuket.

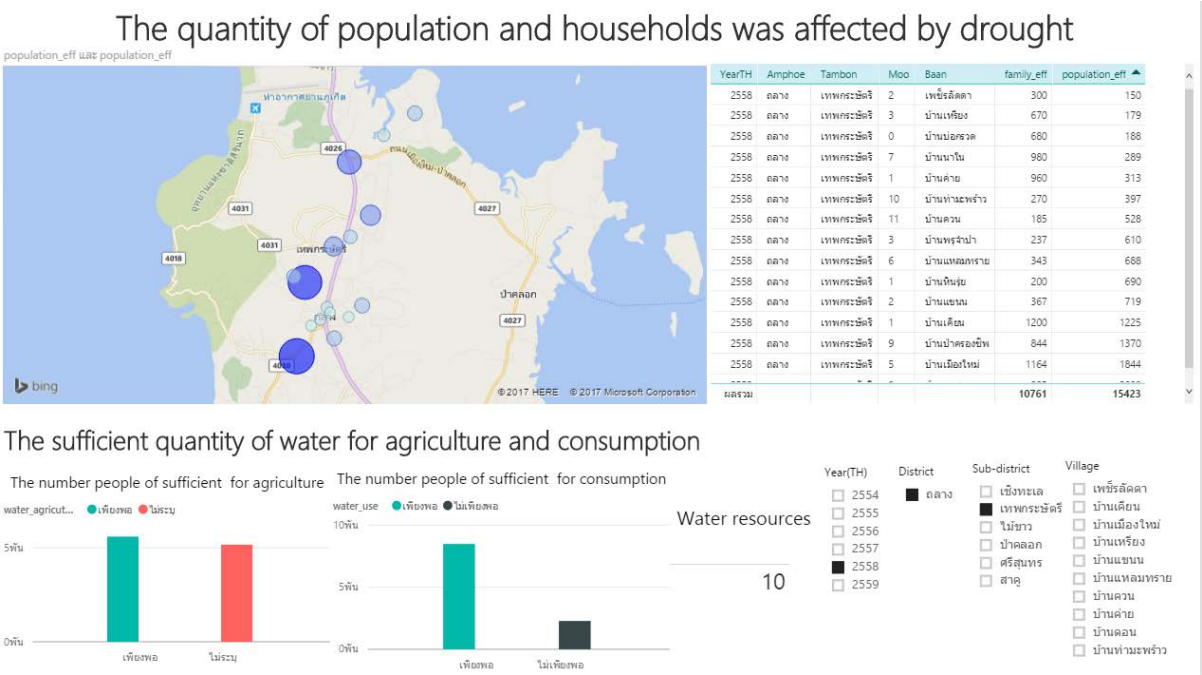

Figure8. The dashboard of the quantity of population and households was affected by the drought in Thep Krasatti, Thalang, and Phuket province (in 2015).

DISCUSSION

There are many BI contributions in decision-making for disaster management area:

Sharing information among disaster management agencies is the key success for decision making in each phase of disaster management life cycle. Using data integration techniques in BI can extract data from the variety of data resources such as databases, documents, media files, web services, satellites, scientific instruments, and web pages. Loading in Data warehouse, is used to store disaster information in specific subject area. User can select the specific subject, is based on multidimensional model. It contains the measurement in fact tables which improve effective analysis (the severity in risk areas). Moreover, data warehouse can analyze the historical disaster data to help the scenario forecast. Then, the raw data is not transformed in old databases. These are the features that are different from general database (Online transaction processing: OLTP). Data analysis using BI analytic (OLAP) can be represented in the multiple dimension of data. BI analytic can execute the multidimensional model from hierarchical operations; roll up and drill down at multiple levels. Filtering out irrelevant information and summarize information which are syntheses of all the relevant data can help for more situation understanding and decision making. Using interactive dashboard with the ability to filter, sort, group, drill down and visualize data also allow to easily delivering information and analytics understanding.

From the prior results, we collect some feedback from domain experts in DDMP Phuket. There are some issues in data quality and usability. Data quality; 1) data dimension design and the measurements in this system can be affectively used for strategic plan improvement in flood, landslide, and drought prevention. 2) The capability of roll up and drill drown in area dimension can help user deeply understand in the specific area. However, there is some suggestion in time dimension which can be improved to be more level of the hierarchy. Usability; because the project is in the first stage of development. Therefore, there are some limitations in data source acquisition and data integration. However, this pilot project will be extended to the next stage which can promise for disaster risk assessment and planning in the future.

CONCLUSION

Data Integration for disaster management is challenging because of the complexity in disaster management life cycle which involve with different data sources from different agencies. This research applies Business Intelligence (BI) model for disaster management area using the case study from Department of disaster prevention and mitigation (DDMP), Phuket, Thailand. Focusing on 1) the severity in risk areas of floods and landslides. 2) The quantity of population and households affected by the drought.

In summary, using BI technology in disaster management data integration can provide agility capacity for decision making in the dynamic environment among different agencies. In next phase of this research, GIS data

from Phuket land-use planning and flooding prediction model database will be used for more insight integration analysis. The result of this study will help organization deploy BI more effectively to support their decision making during the disaster management operations.

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