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# Integration of Bayesian Networks with GIS for Dynamic Avalanche Hazard Assessment: NSDI Perspective

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## *Abstract*

*Natural hazard assessments are core to risk definition and early warning systems and play a fundamental role in the prevention of major damages. Traditional hazard identification methods are static. For this reason, new information and conditions cannot be easily included in the pre-defined hazard assessments. The Bayesian Networks can be used effectively for dynamic hazard identification. In this study, a methodology based on the Bayesian Networks model is presented for dynamic avalanche hazard assessment, in which changed and renewed data can be included in the system. In the proposed methodology, the integration of the Bayesian Networks and Geographical Information Systems (GIS) is modeled in the National Spatial Data Infrastructure (NSDI) perspective. In this structure, it is possible to combine and analyze the data obtained from different sources and factors for avalanche hazard can be dynamically updated with real-time updated data and temporal hazard mapping can be produced. The proposed methodology provides a generic structure and has an attribute making it applicable for dynamic mapping studies for other disasters.*

Keywords
Dynamic Hazard Assessment, Avalanche, Bayesian Networks, GIS, NSDI

# Dinamik Çığ Tehlike Değerlendirmesi İçin Bayes Ağlarının CBS'ye Entegrasyonu: UKVA Perspektifi

## *Özet*

*Doğal afetlerle ilgili çalışmalarda tehlike değerlendirmesi, risk tanımlama ve erken uyarı sistemlerinin temelidir ve büyük kayıpların engellenmesinde önemli bir rol oynamaktadır. Klasik tehlike tanımlama yöntemleri statiktir. Bu nedenle, yeni bilgi ve koşullar önceden tanımlanmış tehlike değerlendirmelerine kolayca dahil edilemez. Bayes Ağları, dinamik tehlike tanımlaması için etkin bir şekilde kullanılabilir. Bu çalışmada, değişen ve yenilenen verilerin sisteme dahil edilebildiği dinamik çığ tehlike değerlendirmesi için Bayes Ağlarına dayanan bir yaklaşım sunulmuştur. Önerilen metodolojide, Bayes Ağlarının ve Coğrafi Bilgi Sistemlerinin (CBS) entegrasyonu, Ulusal Konumsal Veri Altyapısı (UKVA) perspektifinde modellenmiştir. Bu yapıda, farklı kaynaklardan elde edilen verilerin birleştirilmesi ve analiz edilmesi mümkün olup, çığ tehlikesi için etken faktörler gerçek zamanlı güncel verilerle dinamik olarak güncellenerek zamansal tehlike haritaları üretilebilir. Önerilen metodoloji genel bir yapı sunmaktadır ve diğer afetlere yönelik dinamik harita üretimi çalışmaları için uyarlanabilir niteliktedir.*

Anahtar Sözcükler
Dinamik Tehlike Değerlendirmesi, Çığ, Bayes Ağları, CBS, UKVA

## 1. Introduction

Hazard assessment plays a fundamental role in the prevention/reduction of the losses of life and property and this assessment is a first step in the realization of risk analysis of natural disasters (Anderson-Berry and King 2005; Pine 2008; Jonkman et al. 2012; Villa et al. 2015; Xin et al. 2017). Many of the hazard assessment approaches used today are static (Xin et al. 2017) and do not have a dynamic dimension that can integrate the changing conditions and new warnings into the system (Villa et al. 2015). Until now, dynamic systems have generally been regarded as only part of early warning systems, and time-dependency has not been an important factor in the hazard and risk assessment (Narasimhan 2003; Villa et al. 2015; Xin et al. 2017). In the static approach, the updating of the hazard maps is often carried out after many years due to the difficulty of the revision of hazard maps with information updates. Therefore, these maps are often misleading. This problem becomes even more critical when the process and operational parameters continue to change. For this reason, a dynamic and flexible approach is needed in order to adapt to ever-changing data and information (Xin et al. 2017).

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The accuracy of hazard maps is a very critical issue. Because all the information declared for disasters has a direct effect on issues such as creating panic on citizens and decreases in the real estate values. For this reason, it is necessary to be very careful in the production of hazard maps. The issue becomes particularly critical when maps are produced within the framework of specific legislation governing the matter and are therefore accepted as legally approved documents (Annoni et al. 2010). Because early warning systems require higher hardware, higher resolution data, and advanced modeling techniques, they are very costly. Therefore, early warning systems are implemented only in the hazardous and risky areas, rather than in every area (Pulwarty and Sivakumar 2014). For this reason, new hazardous areas emerging under changing conditions must be identified. Therefore, the creation of dynamic hazard maps is a prerequisite for the forecasting/early warning systems to function properly.

Major disasters have caused the need to overcome the limitations of conventional static methods for hazard and risk assessment, and researches have begun on dynamic systems with emerging information and communication technologies (Villa et al. 2015). Over time, the process parameters change, so the hazards and hazard formation routes also change (Xin et al. 2017). Dynamic approaches for hazard and risk enable the identification and evaluation of risks that change over time or that arise and increase during the process. Dynamic methods aim to deal with uncertainties, system complexity, real-time changing conditions and real-time information from different resources and provide a more flexible structure than conventional static approaches. With this dynamic mapping, dynamic changes of the internal and external conditions of the system are achieved and the hazard or risk situation is updated (Villa et al. 2015). However, in order to achieve dynamic character, computer-assisted estimation techniques must be used as a part of the process. Avalanche event, which is caused by numerous factors, is also a dynamic process due to rapidly changing conditions over time (McClung and Schaerer 2006). Avalanche formation is mainly related to the conditions of the land, snow cover and weather (Kadıoğlu 2008), and the causative factors can be handled as meteorological (precipitation, wind intensity and direction, air temperature, humidity, etc.), and land and topographical (vegetation cover, slope, aspect, and other topographic formations) (Turkish General Directorate of Disaster Affairs 1999). Meteorological factors can cause an avalanche under suitable topographic and terrain conditions. In general, the effects of precipitation (snow, rain, precipitation intensity), wind (speed, direction, high altitude winds, local wind conditions), temperature (current and previous temperature conditions), and relative humidity are important meteorological factors (Taştekin 2003).

The snow conditions vary according to the land and time. Because meteorological factors show dynamic characteristics and change at a considerable level in a short time (Taştekin 2003). In addition, vegetation cover shows semi-dynamic characteristics and doesn’t change frequently (Rawat and Kumar 2015). Topographical factors are static and do not change significantly for many years unless human intervention or extreme nature events occur (Hodges 2003). It is possible to determine the avalanche hazard by acting on the factors affecting the formation of an avalanche (Kadıoğlu 2008). Rapid changes in the instability of snow accumulation give a dynamic character to the avalanche prediction. For this reason, an avalanche prediction in any avalanche path can ideally be carried out by starting with the first snowfall in winter and then revising this prediction with new information (McClung and Schaerer 2006). However, new information or changing conditions cannot be easily included in existing hazard maps (Xin et al. 2017).

The dynamic process in which the results are updated with the integration of new information is similar to the Bayesian revision with the use of updated information as time progresses (McClung and Schaerer 2006). In this context; the Bayesian Networks can be used to add dynamics to the hazard assessment process by adding new information (Grêt-Regamey and Straub 2006; Straub and Grêt-Regamey 2006; Eckert et al. 2010; Landuyt et al. 2015; Villa et al. 2015; Xin et al. 2017).

In this study, we focus on the assessment of avalanche hazard by dynamic mapping approach. In this context, a methodology based on the Bayesian Networks has been proposed in the integration of data from different sources and/or sensors and dynamic avalanche hazard mapping. The proposed approach is based on the integration of Geographical Information Systems (GIS) and Bayesian Networks in the National Spatial Data Infrastructure (NSDI) perspective.

## 2. Bayesian Networks

Bayes’ theorem was developed by Thomas Bayes (1702-1761). Essentially, the Bayes' theorem is an extended form of the concept of conditional probability (Bajpai 2009). Bayes’ theorem is a probability model that allows the prediction of the posterior probabilities of an event by changing and updating the prior probabilistic expectations of that event as a result of newly added information (Bajpai 2009; Doğan et al. 2012; d'Acremont et al. 2013; Akıncı et al. 2014). In this context, if more data/information can be provided about the probability of a random variable being calculated, it can be updated and corrected with the Bayes' rule. In other words, the probabilities predicted based on previous observations can be corrected according to the results of new information and observations (Jebb 2017; URL-1 2017). Bayes' theorem modifies a prior probability, yielding a posterior probability, via the Equation 1 (Kelly and Smith 2011).

$$P(H|D)P(D) = P(D|H)P(H) \tag{1}$$

As can be seen from Equation 1, there are 4 components of the Bayes' theorem. These components are explained in Table 1 (Kelly and Smith 2011).

*Table 1: Components of Bayes' theorem*

| Term | Definition |
|---|---|
| $P(H \mid D)$ | Posterior distribution, which is conditional upon data D that is known related to the hypothesis H |
| $P(H)$ | Prior distribution, from knowledge of the hypothesis H that is independent of data D |
| $P(D \mid H)$ | Likelihood, or aleatory model, representing the process or mechanism that provides data D |
| $P(D)$ | Marginal distribution, which serves as normalization constant |

A Bayesian Network is based on the Bayes' theorem (Stassopoulou et al. 1998) and is a graphical-mathematical construct (Ames and Anselmo 2008) as a directed acyclic graph and covers nodes, edges and Conditional Probability Tables (CPT). Nodes are variables, directed edges between nodes represent dependencies and causal relationships between variables, and CPT is the conditional probabilities of linked variables (Stassopoulou et al. 1998; Qiu et al. 2015; Jebb 2017). Bayesian Networks are used to probabilistically model the processes and to graphically configure the information (Stassopoulou et al. 1998; Ames and Anselmo 2008; Çinicioğlu 2015). Bayesian Networks provide a flexible structure because they provide a causal relationship (Stassopoulou et al. 1998).

Bayesian Networks allow explicit modeling of related parameters, causal relationships, and associated uncertainties. Probabilities can be obtained from observations, expert knowledge, and literature (Papakosta and Straub 2015).

A Dynamic Bayesian Network is an extended form of the standard Bayesian Network (static). The general structure of a Dynamic Bayesian Network (Hwang et al. 2011) is presented in Figure 1. If there is a link going from node A to node C, then A is said to be a 'parent node' of C, and C is said to be a 'child node' of A (Kragt 2009).

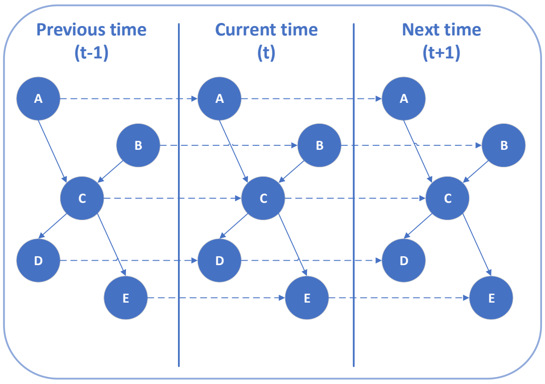


*Figure 1: A structure of Dynamic Bayesian Network*

## 3. A Framework for Dynamic Avalanche Assessment

The classical methods used in the production of hazard maps are inadequate because of the need for higher dynamism in the maps for disaster management. In order to be able to get effective results, these maps should be based on update and real-time data as much as possible (Annoni et al. 2010). With the integration of GIS and Bayesian Networks, dynamic hazard maps can be created by updating the hazard map with changing parameters.

### 3.1. Determination and definition of variables

In this study, a comprehensive literature review was carried out to determine the variables. Some practical studies utilized in this study are given in Table 2. In this study a number of variables not included in Table 2 were added based on theoretical literature studies (Osterhuber 1999; McClung and Schaerer 2006). Depending on these studies, the variables for dynamic avalanche assessment were determined as land cover, elevation, slope, aspect, plan curvature, profile curvature, terrain roughness, air temperature, rainfall, relative humidity, wind speed, wind direction, radiation, sunshine duration, and snowpack depth.

Following the identification of the variables, the definitions/intervals of the variables were specified to calculate conditional probabilities for the Bayesian Network. The definitions/intervals of the variables are provided in Table 3. As in the specification of the variables, the definitions/intervals of the variables required for conditional probabilities were determined based on the literature survey.

*Table 2: Variables used for avalanche hazard assessment in some practical studies*

| | Elevation | Slope | Aspect | Plan | Profile | Tangential | Terrain | Vegetation | Land Cover | Air Temperature | Wind Speed | Wind Direction | Cloudiness | Radiation | Sunshine Duration | Snow Temperature | Snowpack Depth |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Naresh and Pant 1999 | | | | | | | | | | x | x | x | | | | x | x |
| Srinivasan et al. 1999 | | | | | | | | | | x | x | | x | | x | x | x |
| Maggioni and Gruber 2003 | | x | x | x | | | | | | | | | | | | | |
| Cookler and Orton 2004 | | x | x | | | | | | | | x | | | | | | x |
| McCollister and Birkeland 2006 | x | x | x | | | | | x | | | | | | | | | |
| Cordy et al. 2009 | | | | | | | | | | x | x | | | | | | x |
| Barbolini et al. 2011 | | x | | x | | | | x | | | | | | | | | |
| Covăsnianu et al. 2011 | x | x | x | | x | | x | | x | | | | | | | | |
| Suk and Klimánek 2011 | | x | x | | x | x | | x | | | | | | | | | |
| Tarragüel et. al. 2012 | | x | x | | x | | | | x | | | | | | | | |
| Bühler et al. 2013 | x | x | | x | | | x | x | | | | | | | | | |
| Jaedicke et al. 2014 | | x | x | | | | | | | | | x | | | | | |
| Helbig et al. 2015 | | x | | | | | | | | x | | | | x | | | |
| Yilmaz 2016 | x | x | x | x | x | | | x | | | | | | | | | |
| Aydın and Eker 2017 | x | x | | | x | | x | | | | | | | | | | |
| Kim and Park 2017 | x | x | | x | x | | | | | | | | | x | | | |
| Kumar et al. 2017 | x | x | x | | x | | x | | x | | | | | | | | |

*Table 3: States of the variables for calculation conditional probabilities*

| Variable | Number of states | States | | References |
|---|---|---|---|---|
| ***Land cover*** | 14 | Artificial surfaces | | Turkish General Directorate of Geographic Information Systems 2012; Teich 2013 |
| | | Agricultural areas | | |
| | | Broad-leaved Forests | High density | |
| | | | Mid density | |
| | | | Low density | |
| | | Coniferous Forests | High density | |
| | | | Mid density | |
| | | | Low density | |
| | | Mixed Forests | High density | |
| | | | Mid density | |
| | | | Low density | |
| | | Scrub and/or herbaceous vegetation associations | | |
| | | Open spaces with little or no vegetation | | |
| | | Other areas | | |
| ***Elevation*** (categorization based on equal interval classification taking into account the maximum and minimum elevation values of Turkey) | 6 | <1000 m | | Elibüyük and Yılmaz, 2010; Selçuk 2013 |
| | | 1000-1500 m | | |
| | | 1500-2000 m | | |
| | | 2000-2500 m | | |
| | | 2500-3000 m | | |
| | | >3000 m | | |
| ***Slope*** | 5 | < 10° | | Kriz 2001; McClung and Schaerer 2006; Brugnot 2008 |
| | | 10-28° | | |
| | | 28-35° | | |
| | | 35-45° | | |
| | | 45-55° | | |
| | | >55° | | |
| ***Aspect*** (can be separately assessed for winter and spring) | 9 | N | | Kumar et al. 2017 |
| | | S | | |
| | | E | | |
| | | W | | |
| | | NE | | |
| | | NW | | |
| | | SE | | |
| | | SW | | |
| | | Flat | | |
| ***Plan curvature*** | 3 | Concave: curvature < -0.2 | | Maggioni and Gruber 2003 |
| | | Convex: curvature > +0.2 | | |
| | | Flat: -0.2 < curvature < +0.2 | | |
| ***Profile curvature*** | 3 | Concave: curvature < -0.2 | | Maggioni and Gruber 2003 |
| | | Convex: curvature > +0.2 | | |
| | | Flat: -0.2 < curvature < +0.2 | | |

*Table 3: States of the variables for calculation conditional probabilities (continued)*

| | | | |
|---|---|---|---|
| ***Terrain roughness*** | 6 | <0.001 | Kumar et al. 2017 |
| | | 0.001-0.005 | |
| | | 0.005-0.01 | |
| | | 0.01-0.05 | |
| | | 0.05-0.1 | |
| | | >0.1 | |
| ***Air temperature*** (long-term average can be assessed for winter/spring) | 3 | Min temperature longer than 24 hours < -10 C° or maximum temperature difference between day and night >8 C° | Woodmencey and Nalli 2010; Turkish Disaster and Emergency Management Presidency 2015 |
| | | -10 C° < Min temperature longer than 24 hours < -4 C° | |
| | | Other conditions | |
| ***Rainfall*** (long-term average of maximum daily total rainfall can be assessed for winter/spring) | 6 | 1-5 mm | Turkish General Directorate of Meteorology 2017 |
| | | 5-20 mm | |
| | | 20-50 mm | |
| | | 50-75 mm | |
| | | 75-100 mm | |
| | | >100 mm | |
| ***Relative humidity*** (long-term average of maximum daily relative humidity can be assessed for winter/spring) | 4 | 95-100 % | McClung and Schaerer 2006 |
| | | 90-95 % | |
| | | 85-90% | |
| | | <85 % | |
| ***Wind speed*** (long-term average of maximum daily wind speed can be assessed for winter/spring) | 5 | <8 m/sec | Germain 2016 |
| | | 8-15 m/sec | |
| | | 15-20 m/sec | |
| | | 20-25 m/sec | |
| | | >25 m/sec | |
| ***Wind direction*** (Depending on the seasonal (winter/spring) dominant wind direction) | 2 | Leeward side | Nefeslioglu et al. 2013; Rudolf-Miklau et al. 2015 |
| | | Other | |
| ***Radiation*** (long-term average of maximum daily radiation can be assessed for winter/spring) | 6 | <1 kWh/$m^2$-day | Şahan et al. 2015; Yiğit 2015; U.S. Geological Survey 2016; Kıncay 2017 |
| | | 1-2 kWh/$m^2$-day | |
| | | 2-3 kWh/$m^2$-day | |
| | | 3-4 kWh/$m^2$-day | |
| | | 4-5 kWh/$m^2$-day | |
| | | >5 kWh/$m^2$-day | |
| ***Sunshine duration*** (long-term average of maximum daily sunshine duration can be assessed for winter/spring) | 6 | <1 hr | Turkish General Directorate of Meteorology 2017 |
| | | 1-2 hr | |
| | | 2-3 hr | |
| | | 3-4 hr | |
| | | 4-5 hr | |
| | | >5 hr | |
| ***Snowpack depth*** (long-term average of maximum snowpack depth can be assessed for winter/spring) | 8 | <15 cm | Liu et al. 2009; Germain 2016 |
| | | 15-50 cm | |
| | | 50-100 cm | |
| | | 100-150 cm | |
| | | 150-200 cm | |
| | | 200-250 cm | |
| | | 250-300 cm | |
| | | >300 cm | |

## 3.2. Dynamic Bayesian Network model development

Following the determination and definition of the variables, a Dynamic Bayesian Network was created. Figure 2 shows the Bayesian Network for the dynamic avalanche hazard assessment. The Bayesian Network includes the variables that correspond to avalanche hazard. Connecting lines show the causal relationships among the variables. This Bayesian Network models the joint probability distribution of a set of variables for avalanche hazard.

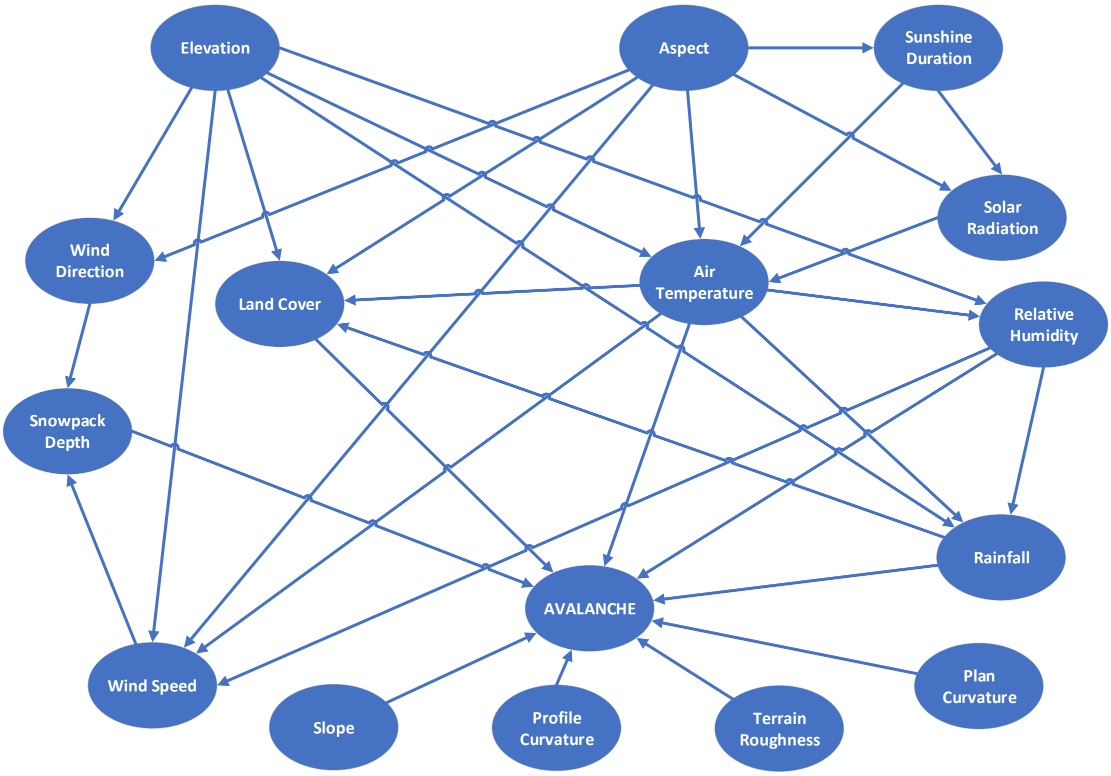


*Figure 2: Dynamic Bayesian Network for the avalanche hazard assessment*

Dynamic Bayesian Network was proposed for continually integrating data and consequently for updating the avalanche hazard. This will be possible by continuously generating and updating spatial data in the GIS environment. Different versions of the Bayesian Network may be needed because of the different conditions in different areas (e.g. some data cannot be obtained from each area). For this reason, the model should be extensible, in other words it should be updated to produce new versions. In addition, in this model, the arcs reflect the direction of causation. But many algorithms have been developed for learning causal of Bayesian Networks from data (Spirtes et al. 2000; Neapolitan 2004; Korb et al. 2009). For this reason, it should also possible to use the models based on various algorithms in line with the requirements and preferences of users.

### 3.3. NSDI perspective

In this study, an approach based on the integration of GIS and Bayesian Networks within the NSDI framework is presented for an avalanche hazard assessment (Figure 3). The proposed approach is dynamic and it is based on the principle of the transferring field observations on the system in real time and identifying changing hazards with inputs updated at specified or desired periods. Thus, for example, an avalanche hazard map can be updated annually for "winter" and "spring" season. In this way, the parameters that change in winter and spring can be evaluated more accurately. In addition to the annual seasonal maps, it can be possible to get the updated maps at any time. In this approach, it should be ensured that the dynamic hazard assessment is carried out entirely by the system but is flexible enough to allow for user intervention when necessary. This flexibility will provide convenience in situations such as adding new factors to the network and network updating in the light of the developments on data access and new scientific facts. For the approach of the dynamic avalanche hazard assessment considered in this study, it is necessary to have an infrastructure in which atmospheric data such as snow cover, direction and intensity of wind, air temperature can be accessed in real time. Thus, parameters to be used in avalanche hazard evaluation can be automatically updated with the data to be added in real time. In addition to this, current data access and system integration for vegetation cover and other dynamics should be provided. In this way, the renewed hazard situation under changing conditions will be able to be up-to-date. But at this point, it is necessary to seek an answer to the question of how to access real-time.

As known, many initiatives in the world, especially INSPIRE (Infrastructure for Spatial Information in Europe) aimed to improve the availability and accessibility of data by developing national spatial data infrastructures since the beginning of the 1990's. These typically involve the provision of core data sets within the framework of general user requirements, documentation of existing spatial data sets and services through metadata and catalogs, and access through distributed internet-based services within agreed rules and protocols (Cömert and Akıncı 2005; Bostancı et al. 2007; Annoni et al. 2010; Bossomaier and Hope 2015).

Today, as a result of changing conditions and technological developments, expectations from NSDI's are increasing. In this context; with the online transmission of data from geo-sensors and other data integration, it is possible to implement advanced applications in the framework of the NSDI (URL-2 2017). Geo-sensors can be described as geographically referenced devices that take environmental stimuli (physical, chemical, or biological) and convert them into an electrical signal (Bröring et al. 2011). For this reason, satellite-based sensors providing a wide variety of information about the earth (image, land cover, vegetation cover indexes, etc.), aerial sensors for detailed images, laser scanners, fixed or moving sensors located near, above or below the ground surface that measure physical characteristics such as pressure, temperature, humidity, and events such as wind, rain, earthquake, and allows the tracking and monitoring of vehicles and living, are covered in this context (Annoni et al. 2010). A sensor is a basic unit, a sensor system is a group of different sensors that serve a common purpose connected to a single platform and sensor networks are based on a large number of interconnected sensors that are distributed over geographical areas and automatically generate useful information by combining different sensing capabilities (Bröring et al. 2011).

Sensor technology continues to evolve with smaller, cheaper, smarter and more energy efficient devices and is being used in more and more applications, especially in disaster management, environmental monitoring, precision agriculture, early warning systems (Bröring et al. 2011). As a result of technological advances, various international organizations and governments have recognized the need for sensor networks, standardized protocols, sensor communication methodologies and procedures that enable sensors to communicate over the web (URL-2 2017). This issue has been the driving force for the Open Geospatial Consortium (OGC) to launch the SWE (Sensor Web Enablement) Initiative in 2003. The SWE Workgroup has developed a standard package that can be used as the building blocks of the Sensor Web. SWE defines the Sensor Web as web-accessible sensor networks and sensor data accessible with defined and standardized protocols and Application Programming Interfaces (APIs) (Bröring et al. 2011). In 2016, INSPIRE has released standards for sensor web access under the heading "Guidelines for the use of Observations & Measurements and Sensor Web Enablement-related standards in INSPIRE Annex II and III data specification development" (URL-3 2017). In fact, large-scale sensor networks have already been used in science and technology since the 1990s. The new situation is that these sensors and sensor networks are activated by the web. Individual sensors can then be discovered, assigned and accessed via web standards, and networks can transfer information through interoperability regulations (Annoni et al. 2010), integration of sensor data with other spatial data can be achieved (URL-2 2017).

In our country, there is a necessity to carry out the studies of NSDI, which is in the effort to be established for many years and called as the Turkish National Geographic Information System (TNGIS), in line with these technological developments and the increasing expectations as a result of changing circumstances. Therefore, sensor networks need to be constituted by establishing an infrastructure that will adapt to new technologies and the goals and priorities of TNGIS need to be renewed to provide access to real-time data.

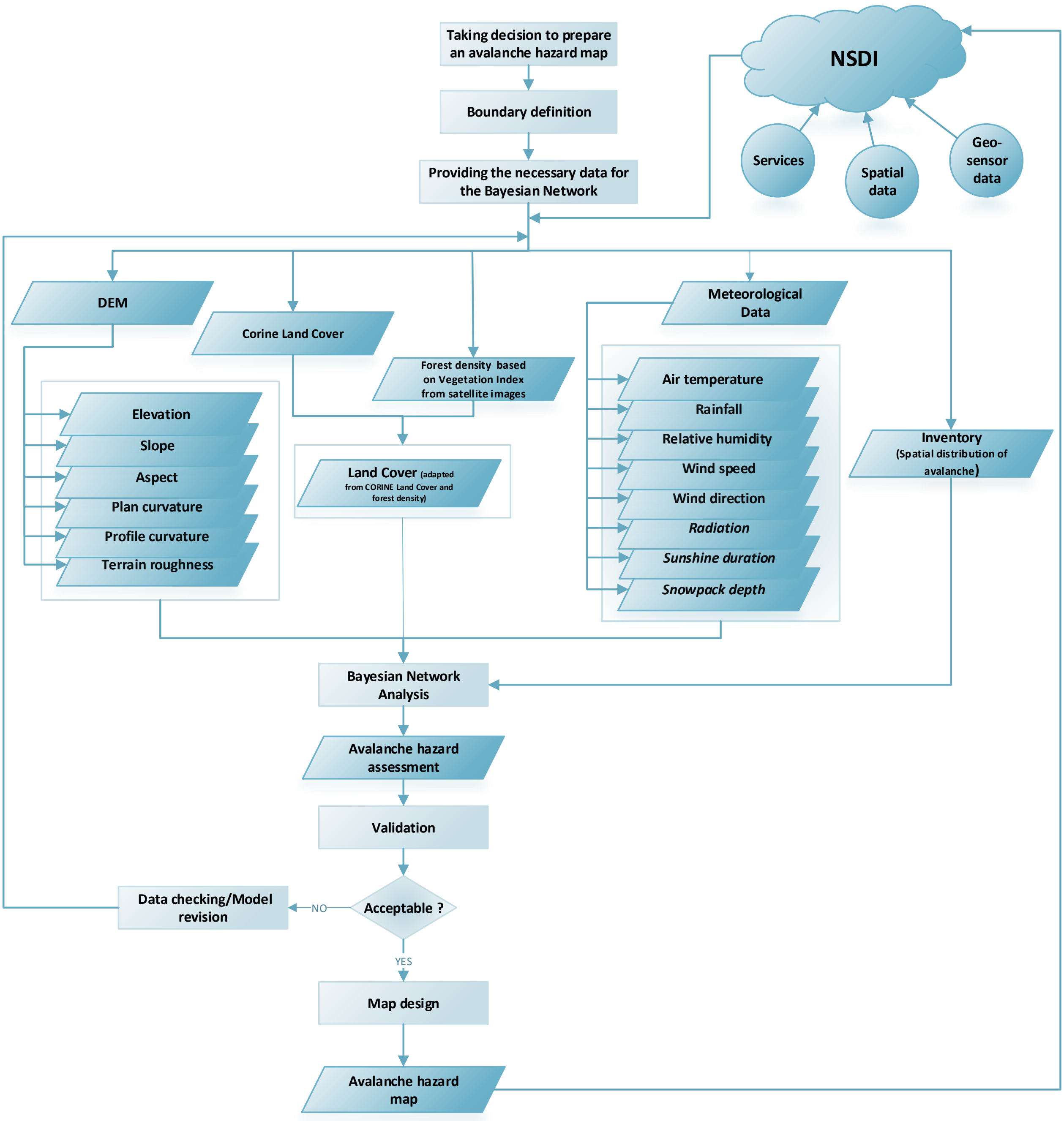


*Figure 3: Integration of GIS and Bayesian Networks within the NSDI framework*

## 4. Conclusion

Risk assessments and forecasting/early warning systems should be realized through as realistic maps as possible. For this reason, this study deals with how to define probable avalanche hazard in response to update and real-time inputs by means of Bayesian Networks-based methodology. While the scope of the study is limited to dynamic avalanche hazard mapping, the same method can be applied to other fields by creating a similar Bayesian Network model.

Ensuring timely access to accurate information is crucial in planning and decision-making process. However, the accuracy and up-to-date of the data is much more critical in the management of emergencies such as disaster and accident. Therefore, real-time data obtained from the geo-sensors needs to be accessible within the scope of NSDI for natural disaster risk management and other environmental studies, including hazard identification.

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