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Abstract

The increasing frequency and intensity of heavy snowfall events due to climate change pose significant risks to agricultural facilities, particularly lightweight structures such as greenhouses. This study develops a probabilistic risk management framework using a Markov chain approach to analyse snow load dynamics under varying climatic conditions, incorporating the effects of snow density changes due to temperature fluctuations. Time-series meteorological data from 99 weather stations across South Korea over the past 20 years were utilised to calculate hourly snow loads. Cluster analysis was employed to classify snow load states, and transition probabilities between states were derived to construct Markov transition matrices. The framework evaluates failure probabilities of various greenhouse specifications, highlighting the influence of structural thresholds and regional snowfall patterns. Areas prone to heavy snowfall exhibited significantly higher failure probabilities compared to regions with milder conditions. National-scale failure probability maps were developed to provide actionable insights for disaster mitigation, emphasising the importance of region-specific risk management strategies. Results demonstrate the critical role of snow density in snow load evolution and its implications for structural safety. This study underscores the necessity of integrating probabilistic models with structural safety assessments to enhance the resilience of agricultural facilities against extreme snowfall events, offering a robust tool for sustainable agricultural practices.

Key words: Heavy snowfall; agricultural facility; Markov chain; risk management; failure probability.

Introduction

The increasing frequency and intensity of extreme weather events due to climate change pose significant challenges to infrastructure and agriculture worldwide (Ferdowsi *et al.*, 2024; Rincon *et al.*, 2024; Yang *et al.*, 2024). Amongst these events, heavy snowfall has emerged as a critical hazard, particularly in regions with significant horticultural activity (Kwon and Chung, 2017; Lee *et al.*, 2020a; Seo *et al.*, 2025). In South Korea, greenhouses are widely used and constitute a major component of the agricultural sector. As of 2022, greenhouses covered an area of 52,808 hectares, of which 99.2% are plastic greenhouses (MAFRA, 2023). Agricultural facilities such as plastic greenhouses are inherently lightweight structures, making them especially vulnerable to snow load-induced structural failure (Lee *et al.*, 2008; 2020b; 2022).

Consequently, these structures suffer ongoing damage and numerous economic losses, as they are designed with relatively low strength due to the low expected loss of human life (Lee *et al.*, 2025; Peña *et al.*, 2020). Over the past 20 years, damage to plastic greenhouses in South Korea has amounted to USD 648 million, affecting an area of 261,023 hectares, with annual damages reaching as high as USD 231 million (MOIS, 2024). The damages caused by heavy snowfall, in particular, have underscored the urgent need for effective risk management strategies. Thus, there is a pressing need to shift from the existing paradigm of post-disaster recovery to a proactive system focused on damage prevention.

Previous studies have explored various approaches to mitigate the impacts of heavy snowfall on agricultural facilities. Unlike other weather-related disasters that occur abruptly over short periods, the damage caused by heavy snowfall can often be effectively prevented with appropriate measures (Lee *et al.*, 2020a). Specialised reinforcement posts have been developed and recommended for installation inside greenhouses, and the use of heating systems to prevent snow accumulation on greenhouse roofs has also been advised (Lee *et al.*, 2021). However, determining the timing of warnings and ensuring sufficient time for effective responses remain significant challenges (Kim *et al.*, 2021).

Numerous specialised structural analysis models have been developed to reflect the structural characteristics of greenhouses (Briassoulis *et al.*, 2016; Kendirli, 2006; Lee *et al.*, 2020b; Ryu *et al.*, 2014; Yu *et al.*, 2013). Furthermore, the government has implemented disaster-resistant facility standards and safety design criteria to mitigate the impacts of weather-related disasters, enforcing compliance with these standards through legal regulations (MAFRA, 2014; 2022). Yu *et al.* (2017) evaluated and refined the existing greenhouse design standards based on snow depth to reflect nationwide snowfall characteristics, aiming to propose improvements to the current design criteria. However, many of these studies have focused on establishing design standards based on average snow unit weights and snow depths. These approaches often fail to account for critical factors such as variations in snow density under different wet or dry snow conditions and the dynamic evolution of snow loads over time.

The snow density or the unit weight of snow is a crucial factor in assessing snow loads on structures, affecting the design and safety standards of agricultural facilities and other infrastructure. Numerous studies have highlighted its variability under different conditions, focusing on key meteorological factors such as temperature and precipitation (Lee *et al.*, 2015; Valt *et al.*, 2018). One of the most significant findings is the strong correlation between snow density and temperature (Anderson, 1976; Hedstrom and Pomeroy, 1998; Lee *et al.*, 2024; Wetzel *et al.*, 2004). As temperatures rise, snow transitions from dry to wet, leading to an increase in density, while colder conditions maintain lower densities. This distinction between wet and dry snow has become essential for calculating snow loads and developing safety standards, as wet snow poses higher structural risks due to its greater density.

In addition to temperature, the relationship between snow density and snow depth has been widely studied. Snow density increases with depth due to compaction, particularly in wet snow conditions, necessitating the development of predictive models that incorporate both factors (Pomeroy *et al.*, 1998; Yu *et al.*, 2017). These models, often including variables such as air temperature, wind speed, humidity, and solar radiation, provide a framework for estimating snow density more accurately (Boone and Etchevers, 2001; Lee *et al.*, 2024; Lehning *et al.*, 2002). However, refining these models to address regional climatic differences and expanding their applicability to diverse structural scenarios remain ongoing challenges.

Meanwhile, many studies have explored various methodologies, including stochastic models, to predict snowfall and mitigate disaster-related damage. Roebber *et al.* (2003) investigated key factors affecting snow ratio analysis, a metric used to estimate snow depth based on forecasted precipitation. Byun *et al.* (2008) utilised the Weather Research and Forecasting (WRF) model to predict snowfall and derived a logistic regression equation for estimating the snow ratio. Kim *et al.* (2014) assessed probable snowfall for various return periods, factoring in climate change impacts using daily snowfall data. Oh and Chung (2017) aimed to estimate the financial damage caused by heavy snowfall in various facilities using historical disaster data, and established snow depth thresholds for categorising heavy snowfall damages. These studies commonly relied on daily meteorological data and a range of weather factors to estimate snow depth from forecasted precipitation. However, the focus of these studies was on estimating long-term maximum snowfall values, leaving short-term snowfall prediction for warning systems unexplored (Lee *et al.*, 2020a). Moreover, the simplified analyses conducted in these studies often did not account for the structural implications of snow loads.

Currently, the operational heavy snow warning system relies on snow depth measurements at a specific moment, functioning as a straightforward alert system (Oh *et al.*, 2017). This approach has limitations in predicting future risks and preparing effective preventive measures. Kwon and Chung (2017) attempted to predict heavy snowfall damage costs by developing a multiple regression model based on disaster statistics and snow depth data. However, their study only considered representative structures and failed to consider various facility types. Moreover, regional climate variations and the differing vulnerability of various facilities highlight the need for a probabilistic risk management. To address these gaps, probabilistic risk assessment models have been developed, incorporating stochastic approaches such as the Markov chain to predict meteorological phenomena (Gui and Shao, 2017; Ochola and Kerkides, 2003; Zhou *et al.*, 2017). Lee *et al.* (2020a) applied the Markov chain to estimate the probability of structural failure for agricultural facilities over specific time intervals. However, these models could not account for the critical influence of snow density variations due to environmental fluctuations or the actual loads acting on structures.

Therefore, this study aims to present a Markov chain-derived risk management strategy for agricultural greenhouse facilities reflecting the environmental conditions and the resulting loads. To this end, we collected time-series meteorological data on snow depth and temperature, and analysed the temporal evolution of snow loads and failure probabilities of agricultural structures using the Markov chain approach. The novelty of this study lies in its comprehensive consideration of snow density variations and its application to a probabilistic risk management framework tailored to agricultural facilities.

Materials and Methods

Meteorological data and snow density

Time-series snow depth and temperature

Meteorological time-series data on hourly snow depth over the past 20 years (from 2004 to 2023) were collected from 99 weather stations across South Korea, provided by the Korea Meteorological

Administration. The data include only measurements recorded during periods of snowfall, implying that no records exist for times without snowfall. However, snow depth can still be measured as long as snow remains on the ground, even in the absence of new snowfall, and such measurements are also included in the dataset. Alongside the snow depth data, temperature data were also collected to investigate the relationship between snow type (dry or wet) and snow density. These temperature measurements are critical for understanding variations in snow characteristics and their impact on snow load estimations. Temperature data were collected only at the time points when snow depth data were measured.

In this study, data collection and analysis were conducted for 99 weather stations across the country. However, as it is impractical to include the results for all 99 locations, six representative weather stations were selected based on climatic zones, and the detailed process for these stations are presented in the manuscript. The first weather station selected is Seoul, located in the central inland climatic zone and representing the capital city of South Korea. The second station is Gunsan, situated in the western coastal climatic zone, which is characterised by relatively mild winters. The third station is Yeosu, representing the southern coastal climatic zone, known for its warm and humid winter climate. The fourth station is Pohang, located in the southern part of the eastern coastal climatic zone, which experiences relatively mild conditions during winter. The fifth station is Sokcho, in the northern part of the eastern coastal climatic zone, where heavy snowfall and frequent snowstorms occur during winter. The last station is Daegwallyeong, located in the northern mountainous climatic zone, characterised by high altitudes, cold conditions, and significant snowfall. These six regions were selected as representative weather stations for this study because they exhibit distinct climatic characteristics, particularly with regard to snowfall, enabling a diverse interpretation of meteorological phenomena. The descriptive statistics of snow depth and temperature data from these stations over the past 20 years are summarised in Table 1.

Snow density and reference snow load

The snow load acting on an actual structure when snow accumulates is significantly influenced not only by the depth of the accumulated snow but also by its density or unit weight. Snow density varies with weather conditions, particularly temperature (Lee *et al.*, 2024). However, the current structural design code calculates the design snow load by estimating the maximum snow depth corresponding to a specific return period and multiplying it by the mean unit weight of snow presented in Table 2 (Lee *et al.*, 2015; Rural Development Administration, 2015). This mean unit weight is typically derived based on snow conditions observed during low temperatures when maximum snow accumulation occurs. It is determined solely by snow depth and applies uniform values depending on the range, which presents a limitation. Accordingly, various studies have been conducted to evaluate and predict snow density and unit weight. However, these previous studies did not identify a clear relationship between snow depth and snow unit weight, nor did they account for the underestimation of the water equivalent of snow in precipitation gauge data.

As temperature rises, snow tends to take the form of wet snow, resulting in increased density, while a decrease in temperature leads to dry snow, which has a lower density. A mathematical modelling approach for snow density as a function of temperature have been proposed by Anderson (1976), based on data collected from the Alta region in Utah, United States, as follows in equation 1:

$$\rho_s = \begin{cases} 50 + 1.7(T_a + 15)^{1.5} \text{ for } -15℃ \le T_a \le 2℃ \\ 50 \text{ for } T_a < -15℃ \end{cases} \quad \text{(Eq. 1)}$$

where ρ_s is the snow density, and T_a is the air temperature. In addition, Wetzel *et al.* (2004) proposed a simple linear relationship between temperature and snow density, as shown in the following equation 2.

$$\rho_s = 160 + 8T_a \text{ for } -18℃ \le T_a \le -3℃ \quad \text{(Eq. 2)}$$

However, these relationships are often overly simplified and valid only within limited temperature ranges. A formula considered suitable for estimating snow density in South Korea, as suggested by Jo *et al.* (2020), is based on measurements by the US Army Corps of Engineers (1956) and Schmidt and Gluns (1991). Hedstrom and Pomeroy (1998) developed the following exponential function to calculate the snow density as a function of temperature as shown in equation 3:

$$\rho_s = 67.92 + 51.25\, e^{T_a/2.59} \quad \text{(Eq. 3)}$$

This formula effectively captures the phenomenon where rising temperatures lead to the formation of wet snow and an increase in snow density. Although it was originally developed for the Canadian Prairies, it remains one of the most widely used and validated parameterisations across diverse climatic regions (Cebulski and Pomeroy, 2025a; Cebulski and Pomeroy, 2025b; Harvey *et al.*, 2025). Several studies, including those conducted in the East Asian region, have successfully applied this formulation without substantial bias, demonstrating its robustness and suitability for our application (Katsushima *et al.*, 2023; Lundquist *et al.*, 2021). Therefore, this study utilised the formula to calculate snow density and snow load. The upper limit for snow density was set at 300 kg/m^3 based on literature, as this represents the typical density of wet snow. Using time-series meteorological data, the snow load was calculated on an hourly basis by combining temperature-dependent snow density and snow depth. The resulting snow load data represent the load from snow accumulation on flat surfaces, independent of roof slopes, and serve as a reference value for assessing structural snow loads.

Effective duration of snow load

Unlike natural disasters such as strong winds or earthquakes, which occur abruptly within a short period of time, snowfall develops over a relatively long duration (Lee *et al.*, 2020a). Agricultural facilities, in particular, are lightweight structures that are highly vulnerable to heavy snowfall (Lee *et al.*, 2022). Therefore, to prevent damage to agricultural facilities caused by heavy snowfall, it is crucial to determine how long it takes for a snow load of hazardous magnitude to develop on the structure and how much time is available to prepare it (Lee *et al.*, 2020a). In this study, the effective duration of snow load, during which the snow load continuously increases, was calculated. The effective duration refers to the time it takes for the snow load to keep increasing without decreasing or remaining constant. As snow melts, the snow load decreases, and even if snowfall continues, the snow depth may decrease or remain constant if the amount of snowfall is minimal. In this context, snow depth can increase the snow load, but rising temperatures may also lead to an increase in snow load by increasing snow density.

Snow load events may involve both increasing and decreasing phases. Although considering the full variability would be a more physically comprehensive approach, this study focuses on constructing an early-warning framework for situations in which snow loads increase, as these conditions are most critical for structural risk management. When snowfall ceases or snow loads decrease, early-warning activation becomes less relevant. Additionally, snow loads may increase even without active snowfall due to temperature changes; therefore, this study considers the periods during which snow loads increase.

Considering changes in both snow depth and snow density, the effective duration of snow load was calculated using the time-series data where the snow load consistently increased over time. Specifically, only the time-series data showing snow load increases at one-hour intervals were used to calculate the time taken to reach a peak value and the corresponding snow load at that time. For snowfall events exceeding specific reference snow loads (100, 200, 300, 400, 500, and 600 N/m^2), the effective duration and the peak value of snow load were calculated, and statistical analyses were conducted to determine their distribution and the mean of effective duration. In addition, an analysis of the time-series data was conducted for cases where the snow load increased due to rising temperatures, even when the snow depth did not change significantly.

Target agricultural facilities

In this study, the most commonly used agricultural facilities in South Korea, i.e., general-purpose agricultural greenhouses, farmer-advised greenhouses, and disaster-resistant greenhouses, were selected as the target facilities. For these standardised structures, the limit snow depth, which refers to the maximum snow depth that the structures can withstand, has been determined through structural analysis and design. This value, considering the mean unit weight of snow shown in Table 2, represents the maximum snow depth or snow load the structure can endure without structural failure. For each type of facility, standardised designs with varying limit snow depths were selected. In the case of general-purpose A-type greenhouse, a relatively low limit snow depth of 79 mm (or a limit snow load of 79 N/m^2) is specified. For the farmer-advised 1-2W type greenhouse, the most widely adopted multi-span structures in South Korea, the safety design standard specifies a limit snow depth of 190 mm (or a limit snow load of 190 N/m^2). Disaster-resistant greenhouses, developed and promoted by the government to prevent natural disaster damage to agricultural facilities, feature relatively high safety design standards (MAFRA, 2014; 2022). The representative disaster-resistant type of 10-5 single-span greenhouse was selected as the target facility, which is designed to withstand a limit snow depth of 300 mm (or a limit snow load of 300 N/m^2). Their design specifications are shown in Figure 1. It should be noted that this study analysed three representative facilities to demonstrate the applicability of the proposed methodology, and it can be extended to include a wider variety of facility standards and limit snow depths or snow loads.

Markov chain approach for snow load prediction

Theoretical background and formulation

A Markov chain, originally presented by Andrey Markov, is defined as a mathematical system that undergoes transitions between states according to certain probabilities. These probabilities depend solely on the current state, making it a memoryless process. This characteristic is particularly useful for meteorological time series, where future states can be modelled based on present conditions without the need for the entire historical sequence (Gui and Shao, 2017; Ochola and Kerkides, 2003; Zhou *et al.*, 2017). The Markov chain approach provides a robust framework for modelling stochastic processes that evolve over time, particularly in predicting snow load dynamics based on temporal data. In this study, the states of the Markov chain are defined as discrete intervals of snow load magnitudes, i.e., ranges of snow loads in N/m^2. Transitions between these states are governed by transition probabilities, which describe the likelihood of a snow load changing from one state to another over a specific time interval (e.g., hourly). If the state space is finite, the Markov transition matrix, $\boldsymbol{P}$ is a square matrix, as shown in equation 4, where each element P_{ij} represents the probability of transitioning from state i to state j. These probabilities are derived from observed frequency distributions of snow load changes in the collected time-series data. The Markov transition matrix and the transition probability can be formulated as follows in equations 4 and 5.

$$\boldsymbol{P} = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1j} & \cdots & P_{1k} \\ P_{21} & P_{22} & \cdots & P_{2j} & \cdots & P_{2k} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ P_{i1} & P_{i2} & \cdots & P_{ij} & \cdots & P_{ik} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ P_{k1} & P_{k2} & \cdots & P_{kj} & \cdots & P_{kk} \end{bmatrix} \quad \text{(Eq. 4)}$$

$$P_{ij} = \Pr(S_{t+1} = j \mid S_t = i) \quad \text{(Eq. 5)}$$

where k is the cardinality or the number of states, S is the finite state space, and S_t is the state space at time t. Because the sum of transition probability from a state to all other states must be 1 (equation 6),

$$\sum_{j=1}^{k} P_{ij} = 1 \quad \text{(Eq. 6)}$$

and all P_{ij} elements are non-negative, $\boldsymbol{P}$ is a right stochastic matrix. Based on the above, the Markov chain approach for snow load prediction can be formulated as follows:

(1) State space (S)

The snow load range is divided into discrete intervals (states), such as S ={0.0–10.0 N/m^2, 10.1–20.0 N/m^2, $\cdots$}. Each state represents a specific range of snow load magnitudes.

(2) Transition probabilities (P_{ij})

Transition probabilities between states are defined as the likelihood of moving from state i (e.g., 0.0–10.0 N/m^2) to state j (e.g., 10.1–20.0 N/m^2) within a given time interval (e.g., 1 hour). These probabilities are calculated using the observed frequencies from historical snow load data as follows as shown in equation 7:

$$P_{ij} = \frac{\text{Number of transitions from state } i \text{ to state } j}{\text{Total transitions from state } i} \quad \text{(Eq. 7)}$$

(3) Transition matrix ($\boldsymbol{P}$)

The transition matrix $\boldsymbol{P}$ is a square matrix where each element P_{ij} represents the transition probability from state i to state j. The matrix in equation 8 satisfies:

$$\sum_{j} P_{ij} = 1, \ \ \forall i \quad \text{(Eq. 8)}$$

ensuring a valid probability distribution for each state.

(4) Initial state distribution (π_0)

The initial state distribution π_0 represents the probability of the snow load starting in each state at the initial time step. This distribution is derived from the observed data or defined based on specific initial conditions.

(5) Future state prediction (π_t)

The state distribution at any future time t is calculated iteratively using the transition matrix as follows as shown in equation 9:

$$\pi_t = \pi_0 \boldsymbol{P}^t \quad \text{(Eq. 9)}$$

where $\boldsymbol{P}^t$ is the transition matrix raised to the t-th power, and π_t represents the state probabilities at time t.

(6) Snow load exceedance probability

Using the predicted state probabilities π_t, the probability of snow load exceeding a critical threshold S_{crit} can be estimated by summing the probabilities of all states exceeding S_{crit}. These thresholds vary depending on the safety of the target facilities, which will be discussed in detail in the following sub-section. By applying this formulation, the Markov chain approach provides a probabilistic framework for predicting the evolution of snow load over time, enabling the estimation of the structural failure probability under varying climatic conditions.

Clustering of snow load data

To construct the Markov transition matrix, the time-series data of snow load should be divided into a finite number of states. To define this finite state space, this study employed the K-means clustering algorithm, a widely used unsupervised machine learning method for partitioning data into clusters. This algorithm works by minimising the variance within each cluster while maximising the variance between clusters. It iteratively assigns data points to K predefined clusters based on their proximity to the cluster centroids and updates the centroids by calculating the mean position of all points in each cluster. This process continues until the centroids stabilise or a predefined number of iterations is reached. The set of divided clusters or state space S, and finding the set S that minimises the sum of squared distances between the centroids of each cluster and the objects within the cluster can be formulated as follows in equations 10 and 11:

$$S = \{S_1, S_2, \cdots, S_K\} \quad \text{(Eq. 10)}$$

$$\arg\min_S \sum_{k=1}^{K} \sum_{x_i \in S_k} ||x_i - \mu_k||^2 \quad \text{(Eq. 11)}$$

where S is the set of K clusters or state space, x_i is the data points within the dataset, S_k is the k-th cluster, and μ_k is the centroid of the k-th cluster, calculated as the mean of all data points in S_k.

In the context of this study, the K-means clustering algorithm was applied to the snow load data to identify K distinct states representing ranges of snow load magnitudes. These states form the basis of the state space for Markov chain, where each state corresponds to a specific cluster of snow load values. Multiple candidate values of K were evaluated using the elbow method and silhouette score, and K =10 was selected based on consistent performance across these metrics. This K value was estimated to provide an optimal balance between capturing meaningful variations in snow load behaviour and maintaining computational efficiency. By using K-means clustering, the continuous range of snow load values can be effectively discretised into meaningful states, facilitating the construction of the transition matrix.

Estimation of probability of snow load occurrence

The Markov transition matrix provides a foundational tool for estimating the probability of snow load transitioning between states over time. By constructing this matrix, it becomes possible to determine the likelihood of the current snow load transitioning to another state after a unit time interval (e.g., 1 hour). This process relies on the memoryless property of the Markov chain, where the future state depends only on the current state, not on the sequence of events preceding it. Once the transition matrix is established, it can be used to predict the state distribution of snow load at subsequent time intervals. If the initial state distribution π_t at time t is known, the state distribution at the next time step can be calculated from equation 12 as:

$$\pi_{t+1} = \pi_t \boldsymbol{P} \qquad \text{(Eq. 12)}$$

where π_{t+1} represents the probability distribution of the snow load states at time $t+1$. This recursive relationship allows for predicting the evolution of snow load distributions over time. To predict the snow load state distribution after a specific time interval, the n-squared Markov transition matrix can be utilised as follows in equations 13 and 14:

$$\pi_{t+n} = \pi_t \boldsymbol{P}^n \qquad \text{(Eq. 13)}$$

$$P_{ij}^n = \Pr(S_{t+n} = j \mid S_t = i) \qquad \text{(Eq. 14)}$$

where π_{t+n} is the snow load state distribution after n hours, and P_{ij}^n is the probability that the snow load transitioning from state i to state j after n hours.

Failure probability and risk management strategy

The development of a risk management strategy requires assessing the probability of greenhouse failure under varying snow load conditions. Using the Markov chain framework, this study evaluates the failure probability of agricultural greenhouses by analysing transitions of snow load across predefined states. The limit snow load for each greenhouse standard was used as the threshold criterion for structural failure. Three different criteria were considered in this study, reflecting varying safety standards for different greenhouse specifications. These thresholds can, however, be customised based on additional environmental conditions or design requirements.

To assess the failure probability, the time-series snow load data were divided into K clusters using the K-means algorithm. The uppermost cluster (K-th cluster) was defined as the range exceeding the limit snow load for the greenhouse. Snow loads classified in this cluster were deemed capable of causing structural failure. The probability of transitioning from any current state i to the critical failure state (K-th cluster) within a single time step was represented by P_{iK}, which serves as the failure probability for the greenhouse in that time interval. Furthermore, the Markov chain model allows for the estimation of failure probabilities over longer time intervals by utilising the n-th power of the transition matrix ($\boldsymbol{P}^n$). This enables the calculation of the probability that a snow load value transitions to the critical failure state (K-th cluster) at least once within n hours. Specifically, the cumulative probability of greenhouse failure within n hours (P_f^n) can be derived from equation 15 as:

$$P_f^n = 1 - \prod_{m=1}^{n} (1 - P_{iK}^m) \qquad \text{(Eq. 15)}$$

where P_{iK}^m is the element of the m-th power of the Markov transition matrix, representing the probability of transitioning from state i to state j within m hours. This formulation accounts for the possibility of greenhouse failure due to snow load exceeding the safety threshold over n consecutive time intervals, capturing both direct transitions and cumulative risk.

Meanwhile, the climatic characteristics, snowfall patterns, and structural safety standards of agricultural facilities vary significantly across regions and facility specifications. As a result, even when the same snow load is acting on a structure, the probability of structural failure can differ depending on these factors. Recognising this variability, this study aimed to determine the failure probabilities for each region and facility type under specific snow load conditions. To achieve this, we employed the Markov chain framework to analyse the dynamic progression of snow loads and their impact on the structural safety of various agricultural facilities. By considering the unique climatic conditions of each region and the corresponding structural specifications of facilities, the model provided a detailed assessment of failure probabilities. In addition to regional and facility-specific failure probabilities, a practical outcome of this study was the development of a national-scale failure probability map. This map consolidates the probabilistic risk assessments across all regions and facility types into a single, comprehensive visualisation. By integrating the spatial variability of snowfall and facility vulnerabilities, the map enables stakeholders to quickly identify areas with the highest risks of structural failure due to heavy snowfall.

Results and Discussion

Results of snow load duration analysis

The effective duration of snow load analysed based on meteorological data from 99 weather stations in South Korea over the past 20 years is shown in Figure 2. During this period, a total of 2,584 events exceeded a snow load of 100 N/m^2, with an average effective duration of 6.2 h. Snow loads exceeding

200, 300, 400, 500, and 600 N/m^2 occurred in 910, 477, 277, 177, and 125 events, respectively, with average effective durations of 6.0, 5.9, 5.5, 5.8, and 5.7 h, respectively.

The time required for snow loads to continuously increase is influenced not only by snow depth but also by snow density. Even during continuous snowfall, snow load events experienced partial reductions during daytime hours when temperatures increased, leading to a lack of significant variation in the average effective duration, even for large snow load events. This trend differs from the behaviour of the effective duration of snow depth, which has been shown to increase for events with larger snowfall amounts (Lee *et al.*, 2020a). This distinction highlights the impact of temperature on snow load dynamics, where density fluctuations can offset the effects of sustained snowfall. Consequently, an effective duration of approximately 6 h was observed for snow load events where the snow load continuously increased. This observed duration does not imply a 6-h model time step; rather, it provides a practical forecast horizon for evaluating short-term structural risks. Accordingly, the 6-h probability is utilised as an operationally meaningful indicator within the Markov chain framework, instead of representing the model's inherent temporal resolution.

Figure 3 presents the analysis of hourly changes in snow depth, temperature, and snow load during snowfall events in the Seoul region in 2023. The results show that higher temperatures were associated with increased snow density, leading to greater snow loads for the same snow depth. Conversely, lower temperatures corresponded to lower snow densities and reduced snow loads. These trends align with previous literature demonstrating a positive correlation between temperature and snow density (Hedstrom and Pomeroy, 1998; Jo *et al.*, 2020; Wetzel *et al.*, 2004). This temperature-driven variation in snow density directly affects the loads imposed on structural facilities, with the effect being particularly pronounced during periods of significant snowfall under warmer conditions. These findings underscore the importance of considering temperature-driven changes in snow density when assessing the structural impacts of snowfall events.

Cluster analysis of snow loads

Prior to performing cluster analysis on the snow load data, it was observed that the raw data were heavily skewed toward smaller values, as shown in Figure 4 a,c. This skewness can pose significant challenges in separating the data into appropriate states during clustering, as the majority of data points are concentrated near zero, leading to an imbalance in the state distribution. To address this issue, this study applied a log transformation to the snow load data. The log transformation effectively reduced the skewness of the data, as shown in Figure 4 b,d. By redistributing the data more evenly across the range of snow load values, this transformation enhanced the suitability of the dataset for clustering analysis. The log-transformed data allowed for a more balanced division of states, facilitating the identification of distinct clusters that better represent the variability in snow loads.

The cluster analysis results for the six representative regions selected in this study, considering the farmer-advised 1-2W type greenhouse facility with a structural safety threshold of 190 N/m^2 for snow load, are presented in Figure 5. This figure illustrates how snow load states were defined using clustering, with each colour representing a state. The red state indicates snowfall events that exceed the structural safety threshold, specifically the limit snow load for the facility. Regions more vulnerable to snowfall exhibited a greater number of events in which the snow load exceeded the safety threshold. In addition to the six representative regions mentioned in the paper, the cluster analysis was also performed for all 99 weather stations across the country.

The snow load data in regions such as Seoul and Gunsan showed that most snow loads remain below the safety threshold, with only a small portion of events classified into the red state. Regions like Sokcho and Daegwallyeong demonstrated a significantly higher proportion of snow loads in the limit snow load state, indicating more frequent exceedance of the structural safety threshold. In the case of Yeosu, which is a region with relatively low snowfall, no snow load events exceeding the limit snow load for the given facility specification were observed. This indicates that the region is not subject to significant risks associated with heavy snowfall under the considered conditions. Particularly in the case of Daegwallyeong, this region demonstrated the highest proportion of snow load events in the red state, indicating frequent heavy snowfall and significant risks for greenhouse facilities.

The results underscore the need for region-specific risk management strategies. While facilities in Seoul, Gunsan, and Yeosu may require lower safety standards for snow load mitigation, regions like Sokcho and Daegwallyeong demand more robust structural reinforcements to withstand higher snow loads. In addition, the clustering of snow loads into distinct states enabled a probabilistic approach to assessing the likelihood of exceeding critical thresholds. The clustering results provided a foundation for integrating the Markov chain framework to analyse transitions between snow load states over time.

The cluster analysis results in

demonstrate how snow load clustering varies within the same region when different agricultural facility specifications are considered. For the general-purpose greenhouse (Figure 6a), a significant number of snow load events exceeded the structural safety threshold of 100 N/m^2, with frequent occurrences in higher states (red clusters), indicating substantial risk under heavy snowfall conditions. For the farmer-advised greenhouse (Figure 6b), the safety threshold is set at 190 N/m^2, resulting in fewer events exceeding the limit, with most data points concentrated in lower states. In contrast, for the disaster-resistant greenhouse (Figure 6c), which has a much higher safety threshold of 300 N/m^2, snow load events rarely exceeded the structural limit, demonstrating the enhanced resilience of this design. These results highlight the importance of selecting appropriate facility specifications tailored to the expected snow load conditions of a given region.

Derivation of Markov transition matrix

The derived Markov transition matrices for each representative region considering the farmer-advised 1-2W type greenhouse facility are presented in Tables 3 and 4. The transition probabilities calculated from historical snow load data exhibited clear patterns of progression across snow load states. For lower snow load states, the probabilities of remaining in the same state or transitioning to an adjacent higher state were relatively high. This reflects the gradual accumulation of snow under normal conditions. For higher snow load states, particularly those near or exceeding the structural safety threshold, the probabilities of remaining in the adjacent state decreased. This indicates a higher likelihood of transitioning to lower states due to melting or snow removal interventions.

To evaluate disaster risk, the data utilised the snowfall events during which snow loads continuously increased. As a result, the transition matrices exhibited an upper triangular structure, as transitions were predominantly observed from lower states to higher states. The values of 1.0000 in diagonal elements of the Markov transition matrices represent absorbing states, specifically the highest state corresponding to snow load exceeding structural thresholds. Once entered, these states imply that the snow load has surpassed the limit, and transitions to other states are not considered in our conservative estimation framework. In the case of Yeosu, where no snowfall events exceeded the limit snow load for the target facility, all transition probabilities corresponding to state 10 were found to be zero. This reflects the low risk of experiencing significant structural snow loads. For Seoul, the Markov transition matrix revealed a high likelihood of snow loads remaining in lower states, aligning with the relatively mild snow conditions. In contrast, Daegwallyeong displayed transition probabilities that frequently shifted into higher snow load states, highlighting the heavy snowfall patterns of the region. These results emphasise the variability of snow load dynamics across regions, underscoring the importance of location-specific risk assessments for disaster prevention.

Failure probability of facilities

The failure probabilities of agricultural facilities under varying snow load conditions were estimated using the Markov transition matrix. Table 5 shows the failure probability of farmer-advised 1-2W type greenhouse facility considering various current snow loads. The failure probability represents the likelihood of a snow load exceeding the structural safety threshold for a specific facility within a defined time interval. In the cases of Seoul and Gunsan, the failure probabilities remained low, with snow loads predominantly confined to lower states. However, occasional transitions into higher states reflect the need for monitoring during rare heavy snowfall events. For Yeosu region, the failure probability for the given facility specification was determined to be zero because no snowfall events exceeding the limit snow load were observed.

In regions with heavy snowfall, such as Pohang, Sokcho, and Daegwallyeong, the failure probabilities were significantly higher. Frequent transitions into higher states highlighted the elevated risk of structural failure in these areas, emphasising the need for more robust facility designs and proactive snow load management strategies. Especially in the cases of Pohang and Sokcho, the failure probability of the facility exceeded 90% within 6 hours when snow loads corresponding to state 9 occurred, indicating extreme vulnerability to heavy snowfall. For Daegwallyeong, while the failure probability under state 9 snow loads was slightly lower compared to Pohang and Sokcho, the region still exhibited a high probability of failure. This was consistent with the frequent occurrence of heavy snowfall in the area, highlighting the significant vulnerability of the facility to such conditions.

The analysis of failure probabilities for various agricultural facility specifications within the same region is presented in Table 6. The failure probability varied significantly depending on the structural specifications of the facility. The general-purpose greenhouse facilities exhibited the highest failure probabilities due to their lower safety thresholds, making them particularly vulnerable in regions prone to frequent heavy snowfall. In the case of farmer-advised 1-2W type facilities, while they are more resilient than the general-purpose facilities, these structures exhibited moderate failure probabilities in high-risk regions. The disaster-resistant facilities demonstrated minimal failure probabilities, even in regions with heavy snowfall, emphasising the importance of adopting robust designs.

The calculated failure probabilities revealed significant variability across regions and facility types, emphasising the importance of tailored risk management strategies. By incorporating probabilistic predictions from the Markov transition matrix, this study provides a robust framework for assessing and mitigating structural risks posed by heavy snowfall. In addition, the failure probabilities derived from this analysis provide valuable insights for disaster risk management by enabling early warning systems, resource allocation, and policy recommendations. High failure probabilities can trigger alarms for preventive actions, such as snow removal or facility reinforcement. Regions and facilities with elevated failure probabilities can be prioritised for risk mitigation measures, while the findings also support the adoption of higher safety thresholds for facilities in regions prone to heavy snowfall.

Failure probability map for risk management

The failure probabilities derived from the Markov chain model form the basis for a practical risk management strategy aimed at mitigating structural damage caused by heavy snowfall. Figure 7 presents failure probability maps generated using this framework, which estimate the likelihood of structural failure by modelling the dynamic progression of snow load over time. These maps provide an intuitive overview of nationwide risks for various facility specifications. The framework not only quantifies the likelihood of structural failure but also provides actionable insights to reduce the risk of damage to agricultural greenhouses. By integrating probabilistic modelling with operational strategies, the proposed methodology offers a robust tool for disaster risk management in regions prone to heavy snowfall.

Previous studies have primarily estimated heavy snowfall risks based on static or average snow depth and density, often without incorporating the dynamic progression of snow accumulation over time. In contrast, our approach uniquely integrates the Markov chain method with temperature-dependent snow density to capture the temporal evolution of snow loads. This enables probabilistic forecasting of structural risk, offering a significant advancement over static threshold models (Lee *et al.*, 2020a; Yu *et al.*, 2017).

The national-scale failure probability maps developed in this study provide actionable insights into regional risks, supporting early warning systems and disaster risk mitigation strategies. By enabling region- and structure-specific risk assessments, the framework facilitates informed decision-making for disaster prevention and resource allocation. Policymakers and facility managers can use the maps to prioritise interventions such as snow removal operations, reinforcement of vulnerable greenhouses, and the issuance of emergency warnings. Ultimately, this methodology offers a practical tool for managing the risks posed by heavy snowfall to agricultural, contributing to enhanced disaster resilience in the agricultural sector under changing climate conditions.

Meanwhile, there are several limitations to this study. First, the snow density model used, although calibrated for Korean conditions, still relies on generalised empirical equations and may not fully capture localised microclimatic variations. Second, this study considered standardised greenhouse designs only, and did not address potential structural irregularities, construction errors, or aging effects. Future research should aim to refine snow load estimation using AI-based real-time data assimilation and expand the applicability to other agricultural infrastructure.

Conclusions

This study aimed to assess the probabilistic behaviour of snow loads and their implications for the structural safety of agricultural facilities using the Markov chain model to identify regional and facility-specific vulnerabilities. The findings confirmed that snow load patterns vary substantially by region, leading to significant differences in structural risk. Areas with heavier snowfall showed distinctly higher failure probabilities, while regions with milder conditions exhibited relatively low risk levels. These results demonstrate that regional climatic characteristics strongly influence snow load-related hazards.

The study also found that structural vulnerabilities differ across facility types. General-purpose greenhouses showed the highest failure probabilities due to their lower safety thresholds, whereas disaster-resistant greenhouses exhibited minimal risk even in snowfall-prone regions. These outcomes directly support the study's objective of evaluating how facility specifications affect their susceptibility to snow load failure. This capability allows planners to prioritise resources and interventions based on probabilistic predictions of snow load evolution.

The nationwide failure-probability maps developed in this study provide practical value by enabling stakeholders to identify high-risk areas and prioritise mitigation efforts accordingly. These maps serve as a basis for informed decision-making, guiding resource allocation, structural reinforcement, and emergency planning to enhance the resilience of agricultural systems.

Overall, this study highlights the importance of considering both regional snowfall characteristics and facility-specific safety standards when managing snow load risks. The findings offer meaningful insights for the development of targeted disaster management strategies and contribute to improving the long-term safety and sustainability of agricultural facilities in snow-prone regions. Meanwhile, in this study, snow load was estimated solely from snow depth and air temperature, and although we adopted one of the most widely used formulations for this purpose, this approach does not fully capture other meteorological and physical processes that may influence the evolution of snow load. Future research may expand this framework by incorporating additional climatic variables or applying the approach to other infrastructure types.

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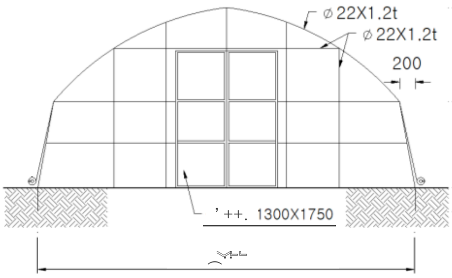
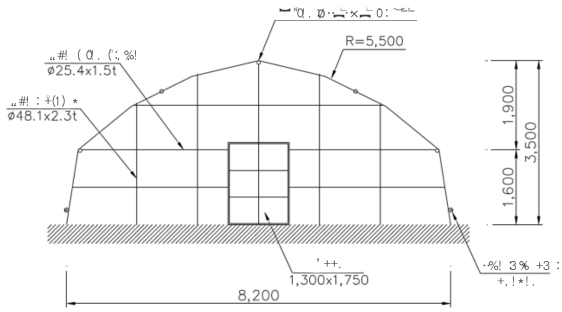
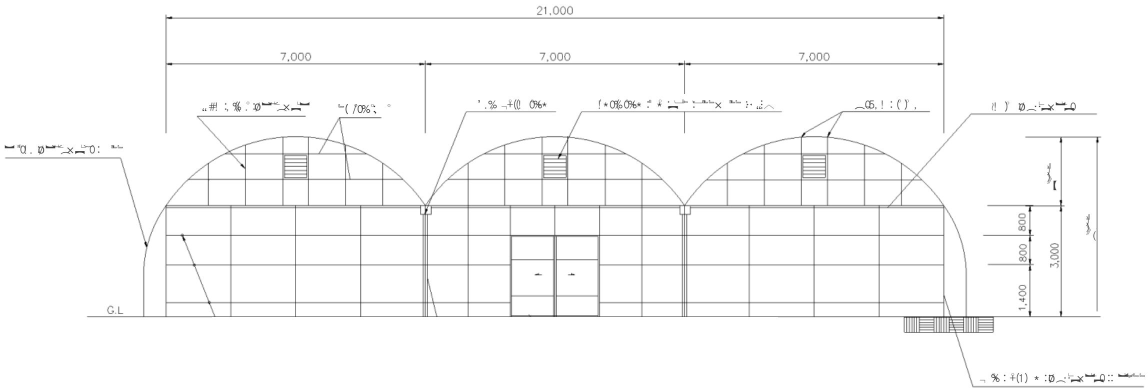


(a) General-purpose A-type



(b) Disaster-resistant 10-5 single-span type



(c) Farmer-advised type (1-2W multi-span type)

Figure 1. Design specifications of target greenhouse facilities (unit: mm).

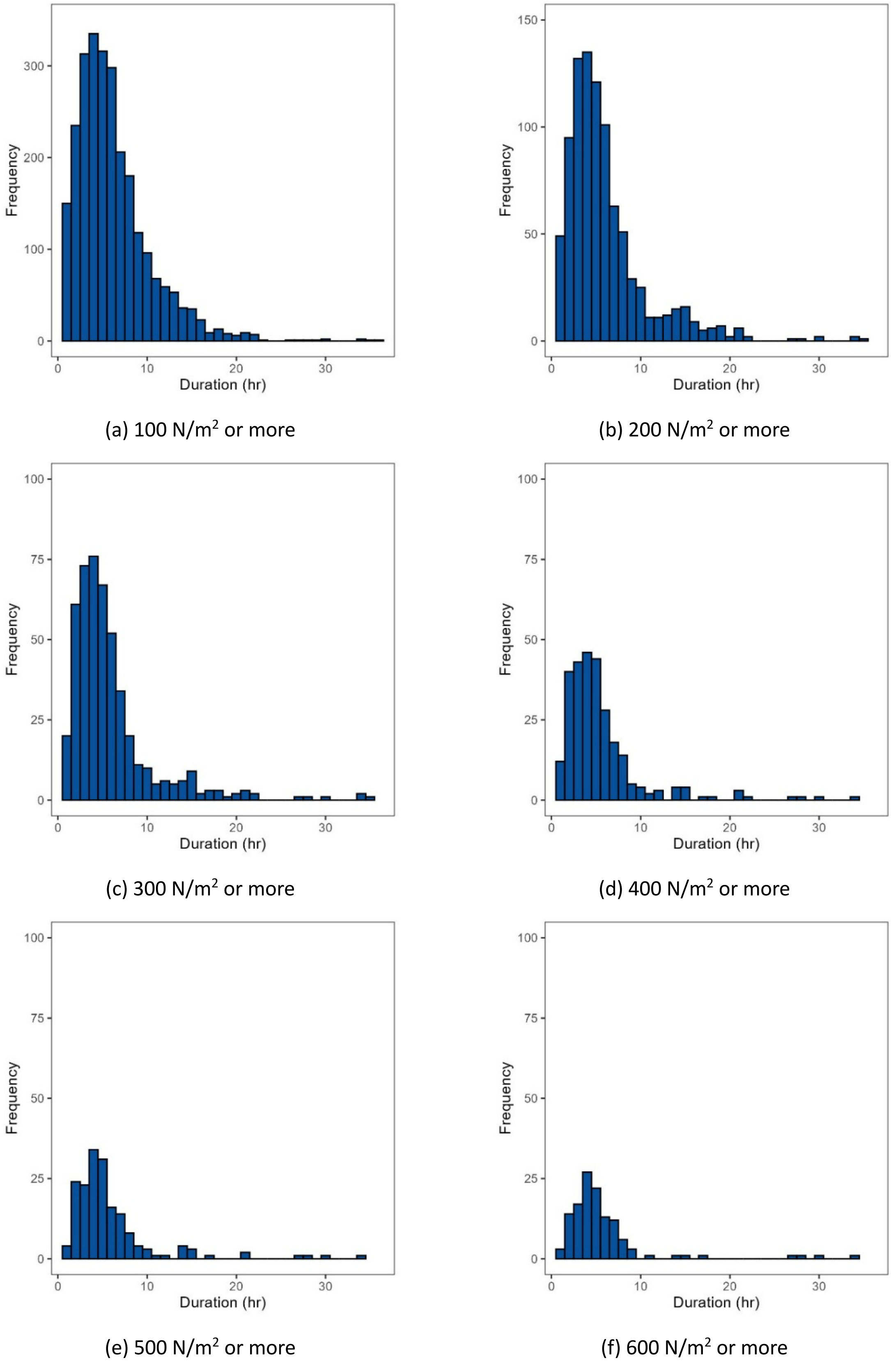


Figure 2. Histogram of effective snow load duration according to reference snow load conditions across all 99 weather stations in South Korea.

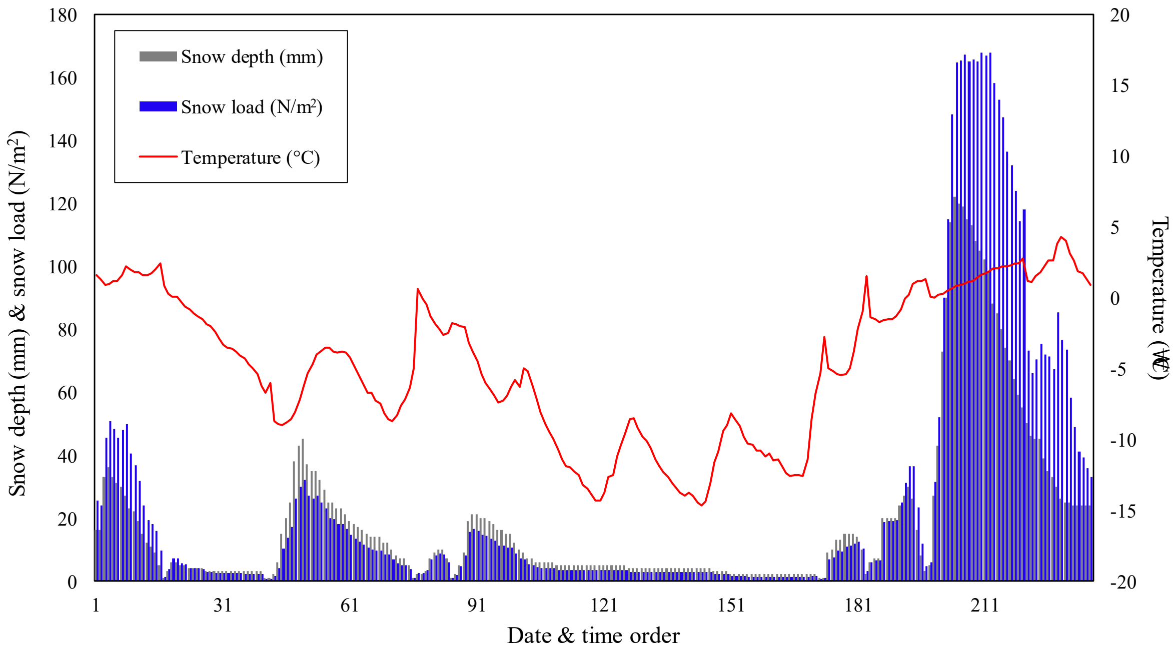
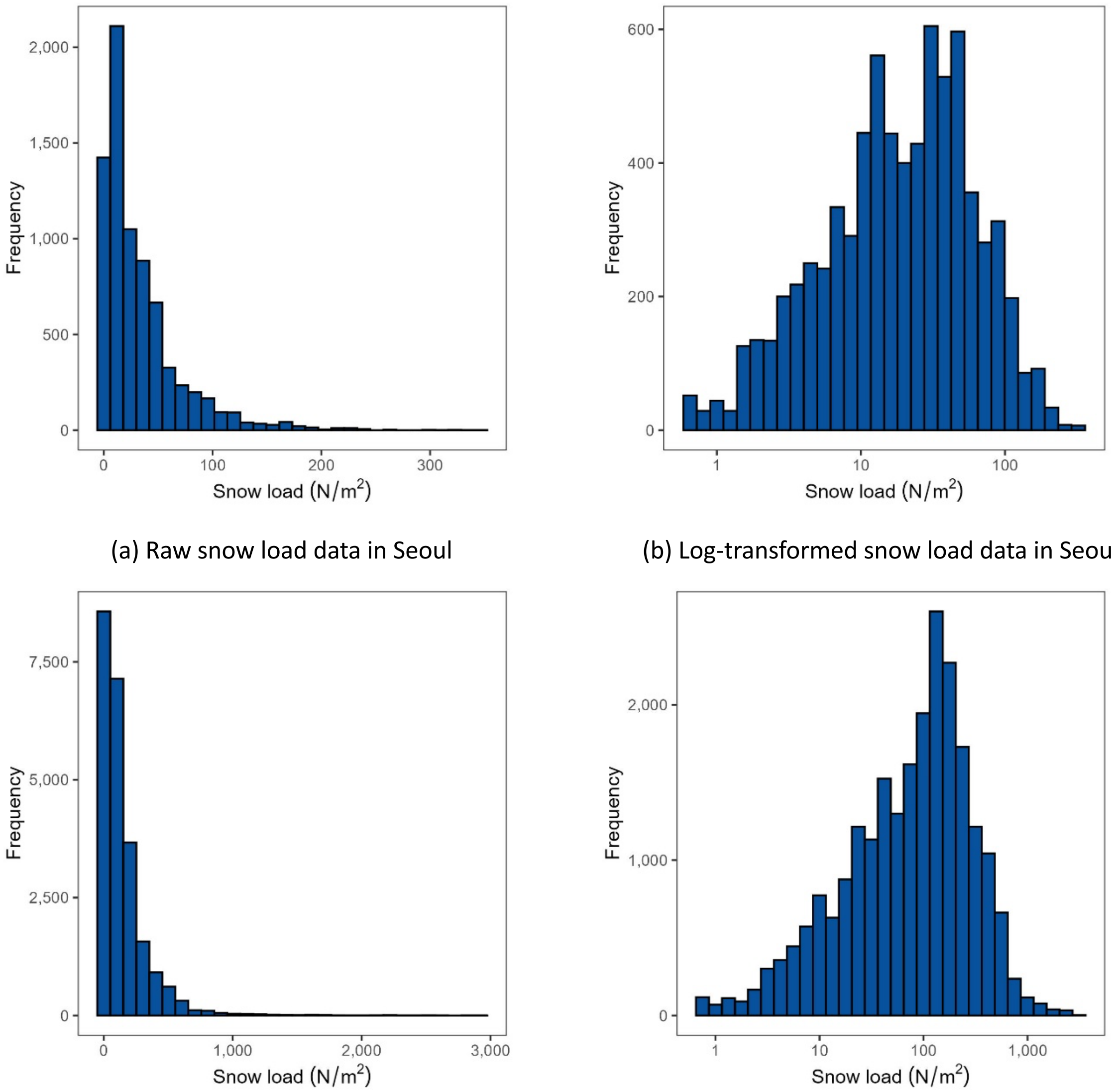


Figure 2. Comparison of snow depth and snow load considering snow type variations with temperature during the winter of 2023 in Seoul.



(d) Log-transformed snow load data in Daegwallyeong

Figure 4. Distribution of snow load data in Seoul and Daegwallyeong: before log transformation and after log transformation.

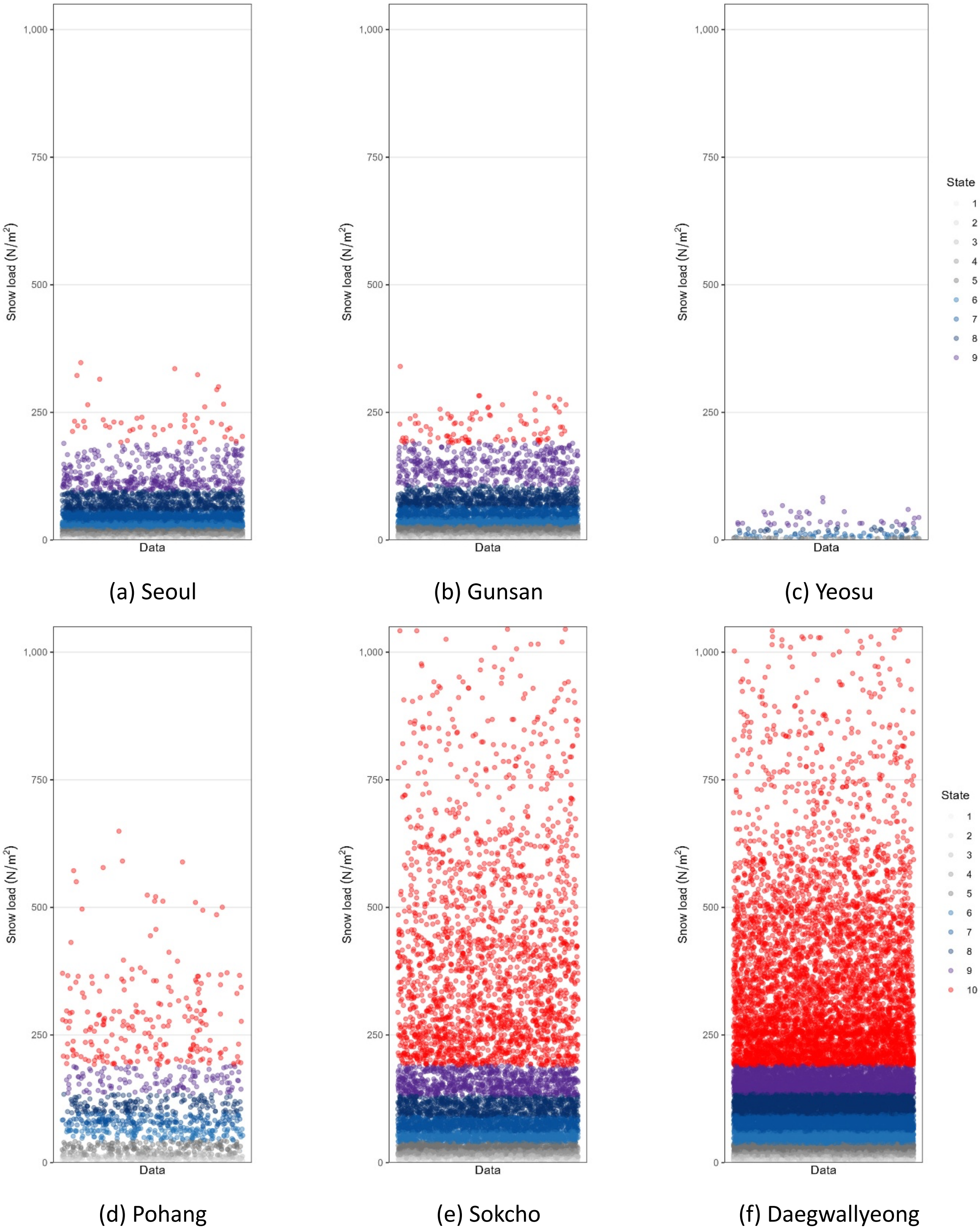
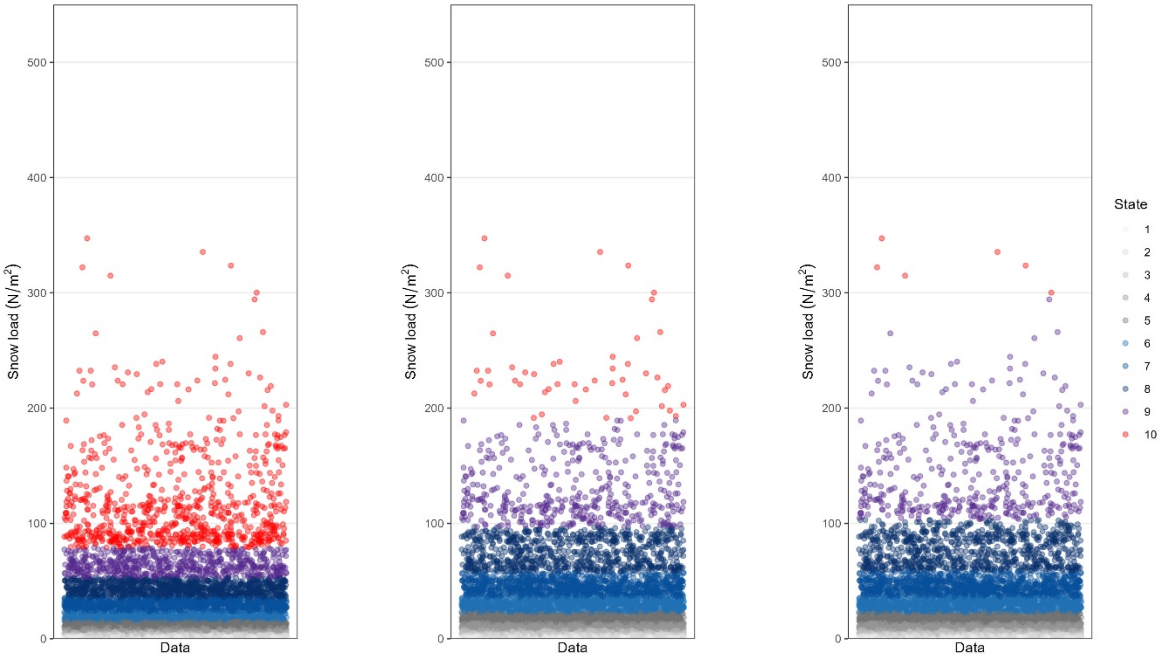
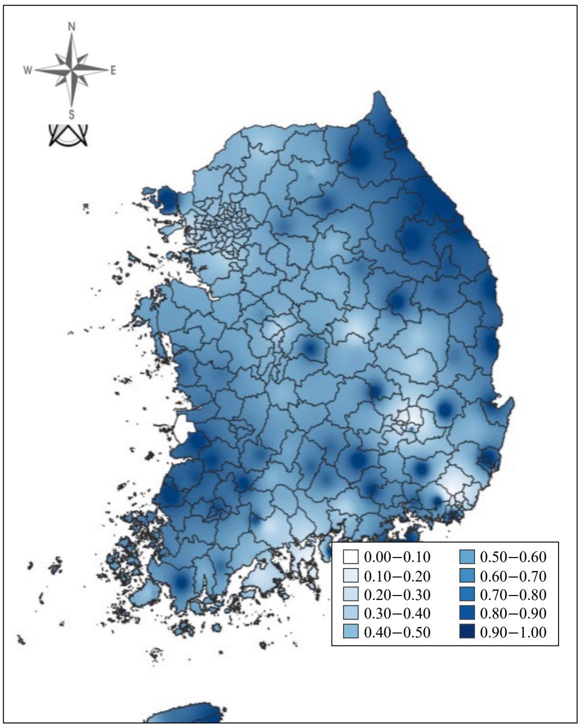


Figure 5. Cluster analysis results for snow load data considering farmer-advised 1-2W type greenhouse facility.

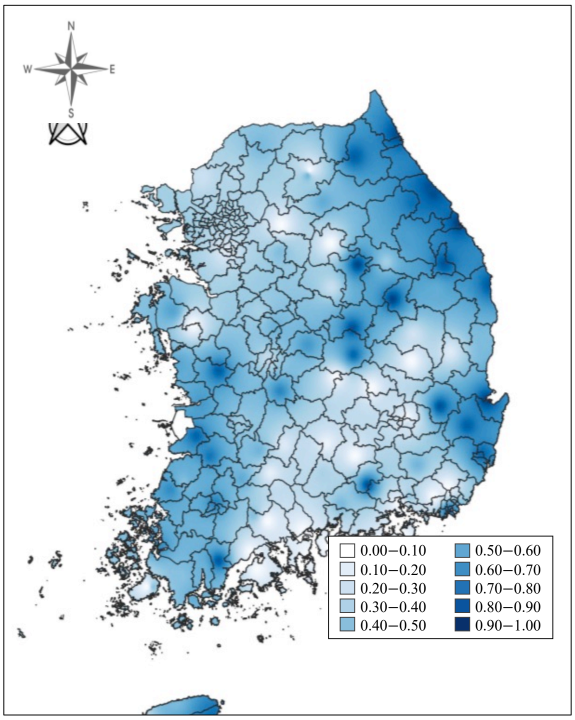


(a) General-purpose A-type (b) Farmer-advised 1-2W type (c) Disaster-resistant 10-5 type

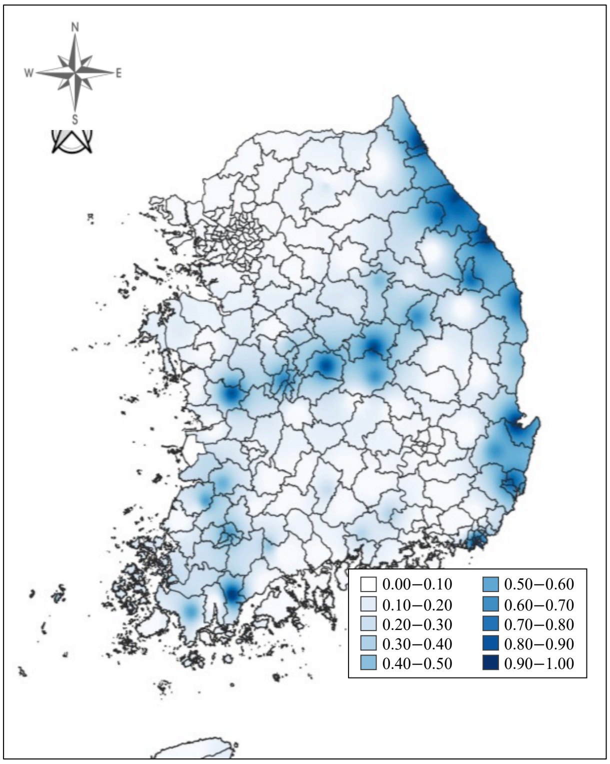
Figure 6. Cluster analysis results for snow loads in Seoul, considering various agricultural facility specifications.



(a) General-purpose A-type greenhouse under a current snow load of 70 N/m^2



(b) Farmer-advised 1-2W type greenhouse under a current snow load of 150 N/m^2



(c) Disaster-resistant 10-5 type greenhouse under a current snow load of 250 N/m^2

Figure 7. Nationwide failure probability map for different types of greenhouse facilities under various current snow load conditions.

Table 1. Descriptive statistics of snow depth and temperature data for the six representative weather stations.

Station	Snow depth (mm)		Temperature (℃)		
	Maximum	Mean	Maximum	Minimum	Mean
Seoul	285.0	36.1	9.5	-18.5	-4.5
Gunsan	284.0	47.2	9.9	-16.6	-3.2
Yeosu	68.0	11.2	6.6	-9.1	-2.0
Pohang	287.0	70.6	11.9	-12.7	-0.2
Sokcho	835.0	118.2	15.8	-15.8	0.1
Daegwallyeong	1,262.0	169.8	15.8	-26.2	-4.8

Table 2. Mean unit weight of snow.

Snow depth (m)	Unit weight (N/m^3)
0.5 or less	1,000
1.0	1,500
1.5	2,000
2.0 or greater	3,000

Table 3. Markov transition matrix for farmer-advised 1-2W type greenhouse facility in Seoul, Gunsan, and Yeosu.

State	Seoul									
	j									
i	1	2	3	4	5	6	7	8	9	10
1	0.8251	0.0852	0.0583	0.0179	0.0135	0.0000	0.0000	0.0000	0.0000	0.0000
2	0.0000	0.9107	0.0601	0.0120	0.0103	0.0052	0.0017	0.0000	0.0000	0.0000
3	0.0000	0.0000	0.9178	0.0587	0.0209	0.0013	0.0013	0.0000	0.0000	0.0000
4	0.0000	0.0000	0.0000	0.9248	0.0643	0.0079	0.0030	0.0000	0.0000	0.0000
5	0.0000	0.0000	0.0000	0.0000	0.9233	0.0665	0.0101	0.0000	0.0000	0.0000
6	0.0000	0.0000	0.0000	0.0000	0.0000	0.9178	0.0783	0.0039	0.0000	0.0000
7	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.9345	0.0645	0.0010	0.0000
8	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.9624	0.0376	0.0000
9	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.9780	0.0220
10	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000
	Gunsan									
State	j									
i	1	2	3	4	5	6	7	8	9	10
1	0.8265	0.1173	0.0255	0.0153	0.0051	0.0102	0.0000	0.0000	0.0000	0.0000
2	0.0000	0.7922	0.1247	0.0701	0.0104	0.0026	0.0000	0.0000	0.0000	0.0000
3	0.0000	0.0000	0.8326	0.1360	0.0230	0.0063	0.0021	0.0000	0.0000	0.0000
4	0.0000	0.0000	0.0000	0.8385	0.1292	0.0262	0.0062	0.0000	0.0000	0.0000
5	0.0000	0.0000	0.0000	0.0000	0.8890	0.1048	0.0049	0.0012	0.0000	0.0000
6	0.0000	0.0000	0.0000	0.0000	0.0000	0.8855	0.1094	0.0051	0.0000	0.0000
7	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.8835	0.1149	0.0016	0.0000
8	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.9336	0.0664	0.0000
9	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.9468	0.0532
10	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000
	Yeosu									
State	j									
i	1	2	3	4	5	6	7	8	9	10
1	0.9091	0.0000	0.0000	0.0000	0.0909	0.0000	0.0000	0.0000	0.0000	0.0000
2	0.0000	0.4000	0.0000	0.2000	0.0000	0.2000	0.0000	0.2000	0.0000	0.0000
3	0.0000	0.0000	0.5714	0.0714	0.0714	0.1429	0.1429	0.0000	0.0000	0.0000

4	0.0000	0.0000	0.0000	0.9524	0.0000	0.0476	0.0000	0.0000	0.0000	0.0000
5	0.0000	0.0000	0.0000	0.0000	0.7143	0.1905	0.0952	0.0000	0.0000	0.0000
6	0.0000	0.0000	0.0000	0.0000	0.0000	0.7222	0.2222	0.0556	0.0000	0.0000
7	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.7692	0.1538	0.0769	0.0000
8	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.8235	0.1765	0.0000
9	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
10	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 4. Markov transition matrix for farmer-advised 1-2W type greenhouse facility in Pohang, Sokcho, and Daegwallyeong.

State	Pohang									
	j									
i	1	2	3	4	5	6	7	8	9	10
1	0.7692	0.1923	0.0385	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2	0.0000	0.7561	0.1707	0.0366	0.0366	0.0000	0.0000	0.0000	0.0000	0.0000
3	0.0000	0.0000	0.8493	0.1096	0.0411	0.0000	0.0000	0.0000	0.0000	0.0000
4	0.0000	0.0000	0.0000	0.8608	0.1139	0.0253	0.0000	0.0000	0.0000	0.0000
5	0.0000	0.0000	0.0000	0.0000	0.8807	0.1101	0.0092	0.0000	0.0000	0.0000
6	0.0000	0.0000	0.0000	0.0000	0.0000	0.8794	0.1135	0.0071	0.0000	0.0000
7	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.8397	0.1603	0.0000	0.0000
8	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.8421	0.1579	0.0000
9	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.7347	0.2653
10	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000
State	Sokcho									
	j									
i	1	2	3	4	5	6	7	8	9	10
1	0.7576	0.1212	0.0505	0.0404	0.0202	0.0101	0.0000	0.0000	0.0000	0.0000
2	0.0000	0.7617	0.1745	0.0383	0.0213	0.0043	0.0000	0.0000	0.0000	0.0000
3	0.0000	0.0000	0.7903	0.1548	0.0355	0.0161	0.0032	0.0000	0.0000	0.0000
4	0.0000	0.0000	0.0000	0.8081	0.1682	0.0237	0.0000	0.0000	0.0000	0.0000
5	0.0000	0.0000	0.0000	0.0000	0.8044	0.1758	0.0132	0.0066	0.0000	0.0000
6	0.0000	0.0000	0.0000	0.0000	0.0000	0.8395	0.1489	0.0116	0.0000	0.0000
7	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.8481	0.1364	0.0156	0.0000
8	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.8211	0.1584	0.0205
9	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.8504	0.1496
10	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000
State	Daegwallyeong									
	j									
i	1	2	3	4	5	6	7	8	9	10
1	0.7889	0.1554	0.0381	0.0147	0.0029	0.0000	0.0000	0.0000	0.0000	0.0000
2	0.0000	0.8554	0.1133	0.0205	0.0086	0.0022	0.0000	0.0000	0.0000	0.0000
3	0.0000	0.0000	0.8948	0.0878	0.0159	0.0015	0.0000	0.0000	0.0000	0.0000
4	0.0000	0.0000	0.0000	0.8880	0.0994	0.0105	0.0021	0.0000	0.0000	0.0000
5	0.0000	0.0000	0.0000	0.0000	0.8965	0.0968	0.0055	0.0012	0.0000	0.0000
6	0.0000	0.0000	0.0000	0.0000	0.0000	0.9157	0.0810	0.0029	0.0005	0.0000
7	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.8992	0.0952	0.0052	0.0005
8	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.8979	0.0937	0.0084
9	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.9111	0.0889
10	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000

Table 5. Failure probability of farmer-advised 1-2W type greenhouse facility according to current snow load.

Seoul		Gunsan		Yeosu	
Current snow load (N/m^2)	P_f within 6 hours, P_f^6	Current snow load (N/m^2)	P_f within 6 hours, P_f^6	Current snow load (N/m^2)	P_f within 9 hours, P_f^9
0.1−1.7	0.0000	0.1−2.3	0.0000	0.1−0.9	0.0000
1.8−3.9	0.0000	2.4−5.4	0.0000	1.0−1.3	0.0000
4.0−7.8	0.0000	5.5−10.1	0.0000	1.4−1.9	0.0000
7.9−13.7	0.0000	10.2−17.7	0.0001	2.0−2.8	0.0000
13.8−22.4	0.0000	17.8−28.1	0.0003	2.9−4.6	0.0000
22.5−36.1	0.0002	28.2−42.8	0.0016	4.9−8.6	0.0000
36.2−57.7	0.0024	42.9−64.9	0.0147	8.8−14.4	0.0000
57.8−97.0	0.0270	65.0−106.4	0.1054	15.7−26.6	0.0000
97.1−189.4	0.3737	106.7−190.0	0.6827	28.7−82.9	0.0000
191.3−347.3	1.0000	190.2−340.0	1.0000	190.1−190.2	0.0000

Pohang		Sokcho		Daegwallyeong	
Current snow load (N/m^2)	P_f within 6 hours, P_f^6	Current snow load (N/m^2)	P_f within 6 hours, P_f^6	Current snow load (N/m^2)	P_f within 9 hours, P_f^9
0.1−2.9	0.0000	0.1−3.2	0.0005	0.7−2.2	0.0000
3.4−7.9	0.0000	3.4−7.7	0.0005	2.3−6.1	0.0000
8.2−14.1	0.0000	7.8−14.7	0.0015	6.2−12.7	0.0000
14.2−24.6	0.0003	14.8−24.9	0.0022	12.8−22.7	0.0003
25.0−42.8	0.0021	25.0−39.6	0.0141	22.8−37.0	0.0015
43.5−68.5	0.0198	39.7−60.9	0.0403	37.1−60.6	0.0079
68.9−96.1	0.1549	61.1−90.2	0.1986	60.7−94.8	0.0661
96.8−133.8	0.6695	90.5−130.6	0.6458	94.9−135.0	0.3366
135.6−188.7	0.9985	130.8−190.0	0.9667	135.1−190.0	0.8585
191.3−649.1	1.0000	190.4−1,466.3	1.0000	190.1−2,925.3	1.0000

Table 6. Failure probability of various agricultural facility specifications in Seoul.

General-purpose A-type		Farmer-advised 1-2W type		Disaster-resistant 10-5 type	
Current snow load (N/m^2)	P_f within 6 hours, P_f^6	Current snow load (N/m^2)	P_f within 6 hours, P_f^6	Current snow load (N/m^2)	P_f within 9 hours, P_f^9
0.1−1.6	0.0002	0.1−1.7	0.0000	0.1−1.7	0.0000
1.7−3.4	0.0007	1.8−3.9	0.0000	1.8−3.9	0.0000
3.5−6.0	0.0002	4.0−7.8	0.0000	4.0−7.8	0.0000
6.1−9.7	0.0017	7.9−13.7	0.0000	7.9−13.7	0.0000
9.8−15.1	0.0008	13.8−22.4	0.0000	13.8−22.4	0.0000
15.2−23.3	0.0082	22.5−36.1	0.0002	22.5−36.2	0.0000
23.4−35.6	0.0299	36.2−57.7	0.0024	36.3−58.7	0.0002
35.7−52.6	0.2055	57.8−97.0	0.0270	58.8−103.0	0.0029
52.7−79.0	0.7832	97.1−189.4	0.3737	103.8−294.3	0.0574
79.2−347.3	1.0000	191.3−347.3	1.0000	300.2−347.3	1.0000