Assessment of typhoon induced wind risk under climate change in Japan

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Assessment of typhoon induced wind risk under climate change in Japan

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19.11.2013
Shuoyun Zhang
Abstract

Continuous monitoring of the characteristics of global climate indicates that the global climate has experienced significant change over the past decades. A large amount of scientific work suggests that an irreversible change of climate may occur in the future. In order to ease the pace of climate change, great efforts from various society levels have been devoted in establishing political as well as non-political protocols on the action plans necessary for mitigating the effects of climate change. However, it has been concluded that a promising result is hard to achieve. In order to reduce the impact of climate change, it seems that society has to take adaptation into consideration.

The adaptation under climate change can be regarded as a decision problem under a large amount of uncertainties. The prerequisite for this decision problem is to quantitatively assess the impact of climate change. Presently, this becomes possible for various natural hazards affected by this phenomenon due to the large amount of efforts that have been devoted worldwide to develop credible models for the projection of the future climate. These models often indicate changes in the statistics of climate characteristics which may have a significant influence on various risks associated with natural hazards that are affected by climate change. Among others, the typhoon induced wind risk is of major concern, since significant losses are caused by typhoon/hurricane events worldwide.

Several research works reveal that climate change is likely to affect the transition of typhoon events including their track, intensity and frequency. The frequency of typhoon events is expected to decrease in the future, while the frequency of intense typhoon events is estimated to increase. This statistical change increases the challenge of a reliable estimation of future wind hazards from the probabilistic perspective. In turn it plays a role on the credible estimation of typhoon induced wind risk.

Japan is a region frequently suffering from typhoon events causing among others significant damages to buildings as a result of strong wind. One of the efforts in reducing damage due to a typhoon event concentrates on appropriately upgrading the design code, which may also be the adaptation option in the face of a changing future climate. The building design code in Japan has been upgraded several times historically. Presently it includes a number of requirements on the safety of relevant non-structural elements as well as structural elements. Statistics from over the last half-century indicate a clear decrease in the number of damages inflicted to buildings. However, it is observed that a substantial number of buildings still suffer from minor damages mostly pertaining to non-structural element failures.

Losses due to those non-structural element failures in a typhoon event are often estimated by an empirical vulnerability model developed on the basis of statistical analysis of data from post-disaster investigations. These models generally suffer from
large scatter of data points implying large modeling uncertainty. A fundamental drawback of this approach lies in the inability to assess the efficiency of a potential adaptation of buildings to the climate change. A model with this capability is currently not available for residential buildings in Japan.

Motivated by the above, this dissertation is directed towards developing a methodology to quantitatively assess the impact of climate change and a tool for examining the effectiveness of adaptation of civil infrastructure within the context of typhoon induced wind risk. The purpose for developing such a methodology is to facilitate the selection of adaptive actions for civil infrastructure. The aim is to demonstrate the availability and effectiveness of a general methodology for carrying out such an impact assessment. It also aims at clarifying missing information required for a more precise and reliable impact assessment. The focus is directed towards typical residential buildings in Japan.

More specifically two challenges of the impact assessment are being addressed, i.e. the probabilistic modeling of typhoon transition in the future climate and the development of reliability-based vulnerability modeling. Appropriate treatment of the former challenge can result in a more credible estimation of future wind hazards facilitating at the same time the credible estimation of typhoon induced wind risk. The latter challenge concerns the development of a vulnerability model capable of examining the efficiency of adaptive actions.

The present dissertation consists of six chapters. Chapter 1 introduces the background, motivation, scope, hypothesis and overview of the dissertation. The core consists of four chapters (chapter 2 to 5).

Chapter 2 describes the methodology including the modeling components employed in this dissertation. It follows from (1) the output from a climate model for an assumed climate scenario, (2) a probabilistic typhoon hazard model and (3) a reliability-based vulnerability model. This is built upon the comprehensive review of the state of the art of the current treatment of typhoon induced wind risk.

Chapter 3 describes the probabilistic modeling of typhoon transition in the future climate. It consists of two parts. The first part considers the bias correction of the projected future typhoon events. The second part explores the statistics-based modeling of typhoon transition. The original contribution of the second part is that extensive statistical analysis is employed in order to investigate the plausible modeling of typhoon transition. Specifically, correlation structures of the typhoon transition are estimated in terms of autocorrelation functions (ACF) and partial autocorrelation functions (PACF). This facilitates the specification of a set of plausible models on the basis of autoregressive (AR) models for further investigation. Based on the investigation, it is found that (1) the choice of the functions is generally not sensitive in the transition modeling, (2) the residual terms in the AR model do not follow the
normal distribution and the modeling of the residual terms has significant impact on the fluctuation of the simulated typhoon tracks, (3) the consideration of the spatial inhomogeneity is in general important and (4) the consideration of the seasonality is also important in case the typhoon transition in a specific season is of interest.

Chapter 4 presents an approach for developing a reliability-based vulnerability model for the assessment of typhoon induced wind risk. Following the approach, a provisional version of vulnerability models for typical residential buildings in Japan is developed with available information. The model focuses on three non-structural failures, which account for a large fraction of loss in the historical typhoon events. Based on the developed model, the roof tile resistance and the correlation of trajectories of flying debris seem to play a significant role on the vulnerability. The original contribution of this chapter is: (1) presentation of a reliability-based vulnerability modeling approach for residential buildings in Japan; (2) detailed examinations of the performances of the individual models as well as the vulnerability model, which facilitates to further elaborate the vulnerability model for the considered type of buildings but also provides insights on vulnerability modeling for the other types of structures.

Chapter 5 presents the results of the hazard and risk assessment conducted for 15 locations over the islands of Japan. The typhoon induced wind hazard is assessed based on the probabilistic typhoon hazard model. By using the assessed hazards together with the established vulnerability model, the typhoon induced wind risks under the current and the future climate are calculated for individual locations. It is found that the typhoon induced wind risks for residential buildings in Japan are unlikely to change significantly in the future.

Chapter 6 concludes the work.
Zusammenfassung


Mehrere Forschungsarbeiten deuten darauf hin, dass die Klimaveränderung einen Einfluss auf Häufigkeit, Intensität und Entwicklung von Taifuns hat. Es wird erwartet dass die Häufigkeit abnehmen wird, aber dass die Anzahl Taifuns mit hoher Intensität zunehmen wird. Diese Verschiebung in der Verteilung der Taifun Intensitäten erschwert die probabilistische Modellierung der Windstärken in der Zukunft erheblich.

Japan ist ein Land das sehr oft von Taifuns heimgesucht wird, mit erheblichen Schäden an Gebäude und Infrastruktur als Folgen. Eine Initiative, die in der Vergangenheit immer wieder verwendet wurde, um die Schäden zu reduzieren ist die Anpassung von Baunormen; diese Option könnte auch in Zukunft zur Klimaanpassung verwendet werden. Zurzeit werden in den japanischen Baunormen Sicherheitsbestimmungen sowohl für strukturelle wie auch nicht-strukturelle Bauteile angegeben. Statistiken über die letzten 50 Jahren zeigen, dass die Anzahl Schäden an Gebäuden klar abgenommen
haben. Es wird aber auch beobachtet, dass trotzdem eine grosse Anzahl Gebäude kleine Schäden an nicht-strukturellen Bauteilen erfährt.


Im dritten Kapitel wird das probabilistische Taifunmodell in zukünftigen Klima beschrieben. Es besteht aus zwei Teilen. Im ersten Teil wird die systematische Abweichung der zukünftigen Taifunereignisse korrigiert; im zweiten Teil werden die Statistik basierten Modellierung der Taifunentwicklung beschrieben. Der wissenschaftliche Beitrag des zweiten Teils liegt in der ausführlichen statistischen Analyse die verwendet wurde um eine plausible Modellierung der Taifunentwicklung zu erreichen. Insbesondere werden Korrelationstrukturen in der Taifunentwicklung mit Autokorrelationsfunktionen und partiellen Autokorrelationsfunktion modelliert.
Dies erlaubt die Ermittlung eines Satzes an plausible Modellen durch autoregressive Modelle (AR). Diese Analysen haben unter anderem gezeigt, dass die Wahl der funktionalen Form allgemein keinen Einfluss auf die Taifunentwicklung hat. Weiter wurde festgestellt, dass der residual Term in den AR-Modellen nicht einer Normalverteilung folgt und, dass der residual Term einen signifikanten Einfluss auf die Fluktuationen in den simulierten Taifunzugbahnen hat. Räumliche Inhomogenität und Saisonalität sind allgemein auch zu berücksichtigen.

In Kapitel 4 wird zuerst der Ansatz, der dem Verletzbarkeitsmodell zu Grunde liegt, beschrieben. Danach wird mit dem Ansatz ein Verletzbarkeitsmodell für typische japanische Wohnhäuser entwickelt. Das Verletzbarkeitsmodell berücksichtigt drei nicht-strukturelle Schadentypen, auf die einen grossen Teil der Schäden von vergangenen Taifuns zurückzuführen sind. Der wissenschaftliche Inhalt dieses Kapitel ist (1) das Verletzbarkeitsmodell für Wohngebäude in Japan, das auf der Zuverlässigkeitsmethode aufbaut; (2) eine Detaillierte Untersuchung der Leistung von einzelnen Verletzbarkeitsmodellen und dem hier entwickelten Verletzbarkeitsmodell das eine Weiterentwicklung des Verletzbarkeitsmodelles für japanische Wohnhäuser und für andere Gebäude Typen erlaubt.


Kapitel 6 schliesst die arbeit ab.
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<tr>
<th>Abbreviation</th>
<th>Description</th>
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<tbody>
<tr>
<td>GHG</td>
<td>GreenHouse Gas</td>
</tr>
<tr>
<td>JMA</td>
<td>Japan Meteorological Agency</td>
</tr>
<tr>
<td>WNP</td>
<td>WestNorth Pacific</td>
</tr>
<tr>
<td>FPHLP</td>
<td>Florida Public Hurricane Loss Projection</td>
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<tr>
<td>MHB</td>
<td>Middle High rise Building</td>
</tr>
<tr>
<td>GMST</td>
<td>Global Mean Surface Temperature</td>
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<tr>
<td>IPCC</td>
<td>Intergovernmental Panel Climate Change</td>
</tr>
<tr>
<td>SST</td>
<td>Sea Surface Temperature</td>
</tr>
<tr>
<td>AGCM</td>
<td>Atmospheric General Circulation Model</td>
</tr>
<tr>
<td>CDF</td>
<td>Cumulative Distribution Function</td>
</tr>
<tr>
<td>AR</td>
<td>Autoregressive</td>
</tr>
<tr>
<td>ACF</td>
<td>Autocorrelation Coefficients’ Function</td>
</tr>
<tr>
<td>PACF</td>
<td>Partial Autocorrelation Coefficients’ Function</td>
</tr>
<tr>
<td>cAIC</td>
<td>corrected Akaike Information Criterion</td>
</tr>
<tr>
<td>CAAN</td>
<td>Cumulative Annual Average Number</td>
</tr>
<tr>
<td>COV</td>
<td>Coefficient of Variation</td>
</tr>
<tr>
<td>CDR</td>
<td>Cumulative Damage Ratio</td>
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1 Introduction

1.1 Background

Over the past few decades global climate change has gained a lot of attention from the public as well as the research community. Continuous monitoring of the characteristics of global climate indicates that the global climate has experienced significant change. Large amounts of scientific work suggest that an irreversible change of climate may occur in the future due to emission of GHG caused by anthropogenic activity, see e.g. Solomon et al. (2009). Furthermore, it is not expected that the atmospheric temperature would decrease significantly even if the emissions of GHG were completely ceased (Plattber et al. (2008), Matthews and Caldeira (2008)). Under this situation, two general agreements have been perceived regarding global climate change. Firstly, global climate change will have a profound and long lasting influence on the daily life of the human society and the negative effect will be larger than the positive one in general, see e.g. IPCC (2007a). Secondly, actions that could be categorized into two directions, i.e. mitigation and adaptation, should be undertaken so as to reduce the effect of global climate change acting on the daily life of human beings.

Over the past decade it has been found that mitigation of climate change is difficult to be achieved, whereas at the same time adaptation has been attracting increased attention from both the public society and research community. The adaptation under climate change can be regarded as a decision problem under a large amount of uncertainties. The prerequisite of this decision problem is to quantitatively assess the impact of climate change on, e.g. civil infrastructure, so that it will be possible to quantify the efficiency of adaptive actions. At present, the quantitative assessment of the impact of climate change on the human society has become possible for various types of risks. This is because a large amount of effort has been devoted worldwide to develop models for the projection of the future climate. Consequently, various climate characteristics of the projected future climate have become available. These often show two properties. Firstly, in comparison to statistics based on the observation of current climate, the projection often shows a systematic bias for current climate, see e.g. Ines and Hansen (2006), Piani et al. (2010), Ehret et al. (2012). Secondly, there is also often a change in the statistics of climate characteristics from the projection of the future climate and the current climate. This is the reflection of climate change. This may have a significant influence on various risks due to natural hazards affected by climate change. Among those risks, the typhoon induced wind risk is of major concern, since significant losses are caused by typhoon/hurricane events worldwide.

Several research works reveal that climate change is likely to affect the typhoon events’ transition including their track, intensity and frequency; see e.g. Murakami et
al. (2011) for the general circulation model, Yasuda et al. (2010) and Nishijima et al. (2012) for statistical interpretation. The frequency of typhoon events is projected to decrease in the future, while the frequency of intense typhoon events is estimated to increase, see e.g. Knutson et al. (2010), Yasuda et al. (2010) and Nishijima et al. (2012). This statistical change increases the challenge of a reliable estimation of future wind hazards from the probabilistic perspective. In turn it plays a role on the credible estimation of typhoon induced wind risk.

Japan is a region frequently suffering from typhoon events that cause among others significant damages to buildings. Among the most disastrous typhoon events that challenged modern buildings in Japan is the Typhoon Vera in 1959. It is very likely that even more disastrous typhoons will challenge the buildings in Japan in the future climate. With lessons learnt from historical events, many efforts have been made to construct more wind-resistant structures including advance construction technology and revision of the building code. These efforts, especially the revision of the building code, could be the adaptive actions in the future climate.

The Japanese building design code has been revised several times. At earlier years the efforts of revisions have been concerned with structural performance of buildings. More recently, attention was extended to non-structural elements of buildings such as roof elements, windows and claddings. By 2007 the building design code in Japan included a number of requirements on the safety of relevant non-structural as well as structural elements. Statistics from over the last half-century show clear a decrease in the number of damages to buildings, see e.g. Uyeda (2008). However, it is observed that a substantial number of buildings still suffer from minor damages pertaining to the non-structural element failures.

In the context of risk assessment, e.g. portfolio loss assessment in the insurance industry, a precise assessment of small losses that are often associated with non-structural element failures is important, since these occur usually more frequently than larger losses and thus account for a large fraction of risk when aggregated. Vulnerability models are often developed based on the statistical analysis of data from post-disaster investigations. These models generally suffer from large scatter of data points, something that implies large modeling uncertainty. The validity of the models is sometimes questionable especially for smaller losses. These observations have led academia to an alternative but also complementary approach to developing vulnerability models, i.e. approach considering processes leading to non-structural element failures.

1.2 Motivation

The typhoon transition model in the current probabilistic typhoon hazard models (following the definition in Graf et al. (2009)) often employs an empirical regression approach, see e.g. Vickery et al. (2000), James and Mason (2005), Graf et al. (2009),
Yin et al. (2009), Yasuda et al. (2011). The estimation of coefficients in the regression functions requires sufficient amount of data to ensure the accuracy of the estimation; however, the historical record of typhoon events often cannot satisfy this condition. Hence, there is the challenge of reliably estimating the wind hazards, e.g. 50/100 years return period wind speed. This challenge may become critical in the estimation of wind hazards in the future climate, since the number of typhoon events is projected to decrease in the future. Thus, the modeling approach for the typhoon transition has to be revised. There are two possible ways to resolve this matter. One way is to reformulate the regression functions without loss of capturing the main statistical characteristics of typhoon transition so that fewer samples are required to estimate the coefficients with the same confidence. The other way is to improve the current estimation method. Note that the current estimation method often utilizes the data in the grids of interest. It might be also possible to "borrow" the data in the adjacent grid to perform the estimation, see e.g. Hall and Jewson (2007) and Yonekura and Hall (2011). Nevertheless, these two possible ways require further consistent statistical analysis, whereas such analysis is missing from the state of the art approach. Furthermore, in comparison to the statistics of the best track dataset provided by the Japan Meteorological Agency (JMA), typhoon events extracted from the climate model for the current climate are found to imply the bias, see e.g. Yasuda et al. (2010) and Nishijima et al. (2012).

As aforementioned, climate change has an impact on typhoon induced wind risk. In order to quantify this impact on residential buildings in Japan, Nishijima et al. (2012) conduct a preliminary impact assessment. In their study, the typhoon induced wind risk is assessed using an ad-hoc fragility model, hereafter called empirical fragility model that is developed based on post-disaster statistical loss data. A fundamental drawback of the empirical fragility/vulnerability model, however, is the lack of capability to examine the efficiency of adaptation of buildings to the climate change. A model with this capability is currently not available for residential buildings in Japan. Hence, one of the conclusions in their study is that a more credible fragility model, which together with a cost model constitutes a vulnerability model, is required to perform a more precise assessment of climate change risk and they address the development of such model as a future task.

1.3 Scope

The objective of this dissertation is to present a methodology to assess the impact of climate change while being capable of examining the effectiveness of adaptation on the civil infrastructure in the context of typhoon induced wind risk. The purpose for developing such methodology is to facilitate the selection of adaptive actions for civil infrastructure. The aim is to demonstrate the availability and effectiveness of a general
methodology for carrying out the impact assessment. It also aims at clarifying missing information required for a more precise and reliable impact assessment. The dissertation focuses on typical residential buildings in Japan.

Following the impact assessment framework in Nishijima et al. (2012), this dissertation addresses two challenges:

- Modeling of typhoon transition in the future climate
- Reliability-based vulnerability modeling.

In the first challenge, two aspects are considered, i.e. the bias correction of projected typhoon events and exploration of statistics-based modeling of typhoon transition. In the first aspect, the bias inherited in the climate model is statistically considered in terms of the characteristics of typhoon track and intensity. The bias is quantified and corrected by comparing the statistics of the typhoon events extracted from climate model for the current climate and the observed historical typhoon events in the same period. In the second aspect, the regression function, the method to estimate the coefficients of regression function as well as the modeling of the residual terms are explored based on an extensive statistical analysis. The purpose of this exploration is to identify the critical part of modeling in order to improve the performance of probabilistic typhoon transition modeling for the typhoon event in the future climate.

Several post-disaster surveys and analysis in Japan e.g. Nishimura et al. (2009), find that a large fraction of the wind induced damages to residential buildings in Japan is accounted for by non-structural failures. Thus in the second challenge, three non-structural failures are considered:

- Roof tile failure
- Window failure
- Roof sheathing failure.

The above failure types are modeled in terms of limit state functions with basic random variables and their probabilities are assessed based on the knowledge of wind engineering within the framework of the structural reliability theory, see e.g. Madsen et al. (2006). The vulnerability model developed on this basis is hereafter called reliability-based vulnerability model.

Although the focus of this dissertation is the typhoon induced wind risk for residential buildings in Japan, the philosophy and employed procedure may also be applied into other fields for the assessment of climate change impact as the first step for selection of adaptive actions. Note that there are many similarities in the context of selecting adaptive actions for most types of risks affected by climate change. For instance, it is common to observe the existence of bias in the projection of climate characteristic from climate models, e.g. precipitation (see e.g. Ines and Hansen (2006), Piani et al. (2010)), temperature (see e.g. Wojcik and Buishand (2003)).
1.4 Hypothesis

In order to establish an impact assessment framework for the typhoon induced wind risk for residential buildings in Japan, several hypotheses are employed in this dissertation. These hypotheses concern the fundamentals implied in the methodology as well as those implied in individual modeling components such as the probabilistic typhoon hazard model, climate model and bias correction.

It is assumed that the universe is uncertain and it can be interpreted through a probabilistic view with the support of a probabilistic model. More specifically here the evolution of typhoon transition is modeled by a stochastic process whereas the resistances of the building materials as well as the wind load are described by probabilistic distributions. This hypothesis is the foundation to develop individual modeling components.

A further assumption is that statistical characteristics of climate events such as typhoons are not significantly affected by climate change when looking into a relatively short time period, e.g. as short a period of approximated 20 to 25 years can be assumed, so that the climate indicator in this short time period can be combined as one statistical population. It is also postulated that the climate model is able to capture the effect on climate characteristics due to climate change, although there may exist a systematic bias for the projection of current climate. Furthermore, it is accepted that this effect can be quantified by the statistical change of climate characteristics between the projected future and the current climate. It is assumed that the philosophy and procedure employed in the probabilistic typhoon hazard model, which is verified for the current typhoon events, is also applicable to the typhoon events in the future climate.

It is taken that the resistances of building components are invariable in the examined time periods while the resistances of each building component in two individual time periods are assumed to be identical. Moreover, same model buildings are assumed for the entire region of Japan. Thus, the change of fragility/vulnerability of building only considers the effect from the change of wind load due to climate change. Additionally, only the monetary consequences due to strong wind are accounted for. The loss due to rainfall, which often accompanies a typhoon event, is not modeled.

1.5 Overview of the dissertation

The core of the dissertation consists of four chapters (chapter 2-5). The overview of the structure of the dissertation and the interrelation between individual chapters is illustrated in Figure 1.1. The rest of the chapters are organized as follows.

Chapter 2 presents the methodology describing the modeling aspects employed in this dissertation. It takes basis in (1) the output from a climate model for an assumed climate scenario, (2) a probabilistic typhoon hazard model and (3) a reliability-based
Introduction

vulnerability model. The idea and model components are published in Zhang et al. (2014b) and Zhang et al. (2013). This is built upon the comprehensive review of the state of the art of the current treatment of typhoon induced wind risks.

Chapter 3 describes the probabilistic modeling of typhoon transition in the future climate and it consists of two parts. The first part considers the bias correction of the projected typhoon events. The second part explores the plausibility of the statistics-based modeling of typhoon transition. The original contribution of this part is that extensive statistical analysis is employed to investigate the modeling of typhoon transition. Its main contents and results are published in Zhang and Nishijima (2012).

Chapter 4 presents an approach for developing a reliability-based vulnerability model for the assessment of typhoon induced wind risk. Following this approach, a provisional version of vulnerability models for typical residential buildings in Japan is developed. The original contribution of this chapter is: (1) presentation on a reliability-based vulnerability modeling approach for residential buildings in Japan; (2) detailed examinations of the performance of the individual models as well as the vulnerability model facilitating its further development for the considered type of buildings and providing insights on vulnerability modeling for the other types of structures. The main methodology is published in a peer-reviewed Journal\(^2\), see Zhang et al. (2014a).

Chapter 5 presents the results of the hazard and risk assessment. The assessment is conducted for 15 locations over the islands of Japan. The typhoon wind hazard is assessed based on the probabilistic typhoon hazard model, which is comprised of the occurrence model, the typhoon transition model, the wind field model and the surface

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friction model. The typhoon transition model employed in the assessment is described in chapter 3 while the other model components are according to Graf et al. (2009). Together with the assessed hazards, the typhoon induced wind risks under the current and the future climate are calculated for individual locations employing the vulnerability model established in chapter 4. Part of results are also presented in Zhang et al. (2014b)\(^3\).

At last, chapter 6 presents the conclusion remarks and summarizes the contributions and limitations in the dissertation. Further, future research tasks are addressed.

\(^3\) Reprinted from Civil Engineering and Environmental Systems, 31/2, Shuoyun Zhang, Kazuyoshi Nishijima, Takashi Maruyama, Climate model-based probabilistic assessment of wind risk for residential buildings under projected future climate, Copyright (2014), with permission from Taylor & Francis.
2 Methodology

2.1 Introduction

This chapter presents the methodology employed for carrying out the impact assessment of climate change in the context of typhoon induced wind risk on residential buildings. Firstly, section 2.2 comprehensively reviews the state of the art on the framework of the impact assessment (subsection 2.2.3) as well as the individual model components (subsection 2.2.1 and 2.2.2). The practical application of the aspects presented in subsections 2.2.1 and 2.2.2 is shown in section 3.3 and chapter 4 respectively, where original academic contributions of this dissertation are presented. Secondly, based on the merit of past works, section 2.3 presents in more details on the methodology employed. Lastly, the role of the impact assessment in the adaptation of the relevant building is addressed in section 2.4.

The probabilistic typhoon hazard model employed in this dissertation follows the approach presented in Graf et al. (2009) and Graf (2012). The entire model consists of four components; i.e. the occurrence model, the transition model, the wind field model and the surface friction model, see Figure 2.1. The state of the art associated with the probabilistic typhoon hazard model focuses on the transition modeling part.

![Figure 2.1. Components of the probabilistic typhoon hazard model.](image)

2.2 State of the art

2.2.1 Probabilistic modeling of typhoon hazard

The methodology for probabilistically modeling typhoon hazards and risks has significantly progressed in the last few decades. Presently, a spectrum of probabilistic models is available and widely utilized as a tool to quantify and manage typhoon risks in different contexts. Successful applications include the determination of design wind loads on structures and the pricing of re/insurance portfolio policies. More recently, the methodology and the probabilistic models have been applied beyond these classical applications, i.e. for quantifying the impact of climate change on wind risks due to
typhoons, see e.g. Nishijima et al. (2012). In these applications, among others, the modeling of typhoon transition plays the key role.

Reproducing typhoon events by Monte Carlo simulation is a well-accepted approach for the typhoon induced wind risk assessment. This approach has several advantages over classical approaches. For example, a classical statistical approach for modeling the typhoon induced wind hazard often lacks a sufficient number of observations for reliably estimating the wind speeds of large return periods, whereas the Monte Carlo simulation approach alleviates the statistical problem by best utilizing the observations of historical typhoon tracks in the process of simulating sufficient number of typhoons.

The simulation of typhoon events is pioneered by Russell (1968) and Russell (1971). Since then, this approach has been widely explored and expanded, see Tryggvason et al. (1976), Batts et al. (1980), Georgiou et al. (1983), Neumann (1991), Vickery and Twisdale (1995). These studies share the common idea of applying site-specific probabilistic model. More details on the contribution and the different assumptions made in these studies can be found in Vickery et al. (2009). However, these studies are limited to estimate the typhoon risk for a single site or for a small region. The spatial correlation of wind speeds at different sites cannot be appropriately represented through these models.

The modeling of typhoon transition from its genesis to dissipation, i.e. its whole life, has become the state of the art in the modeling of the typhoon hazard and risk. It facilitates to consider their spatial correlations, which are relevant for the estimation of the portfolio risks. Vickery et al. (2000) present a technique for modeling the full track of typhoon over its life. Since then, various approaches to expand this idea have been developed both by private-sector stakeholders and academia. Generally, the detailed descriptions of the models developed in the private sector are not publicly available. Detailed descriptions of models are found in James and Mason (2005), Emanuel et al. (2006), Hall and Jewson (2007), Rumpf et al. (2007), Graf et al. (2009), Yin et al. (2009), Yasuda et al. (2011), Yonekura and Hall (2011). All these transition models share the basic idea, i.e. the state of typhoon transition is represented by state variables such as the translation speed, translation angle and central pressure, etc., whose necessary statistical information is extracted from historical record and the typhoon transition is simulated on the basis of this extracted statistical information. As a consequence, the simulated typhoon transitions maintain the same statistical characteristics as in the historical record. The main differences among these models are: approaches for formulating the model whether in an explicitly regression function or non-parametric approach; the order of the Markov chain assumed in the model; the assumption/approximation of whether the typhoon transition is spatial and seasonal homogeneous; the treatment of the residual terms in the regression function. Moreover, the aforementioned statistical transition models assume that the evolution of typhoon intensity is independent from the evolution of track. In contrast, in Emanuel et al. (2006) an attempt is made to relate these two evolutions through combining a
statistical track model with a deterministic axi-symmetric balance and a 1-D ocean mixing model. Instead of the central pressure, the wind speed is directly accounted for in their model, hence the wind field model is a part of the transition model. In this dissertation, the probabilistic typhoon hazard model separately includes the wind field model and surface friction model. A comprehensive review of these two components can be found in Vickery et al. (2009).

### 2.2.1.1 Modeling approach

There are two ways of statistics-based modeling of typhoon transition namely the parametric and the non-parametric approach. The parametric approach is initiated in Vickery et al. (2000) for the full track modeling approach and James and Mason (2005), Graf et al. (2009), Yin et al. (2009) and Yasuda et al. (2011) follow this scheme. In the parametric approach a component variable \( y \) of state\(^4 \) of the typhoon transition is assumed to be represented by the following regression function:

\[
y = f(x) + \varepsilon,
\]

where \( f(\cdot) \) is a deterministic function, \( x \) may be the previous states of the typhoon transition and \( \varepsilon \) is a random residual term. On the other hand, Emanuel et al. (2006), Hall and Jewson (2007) and Yonekura and Hall (2011) model the typhoon transition using the non-parametric approach in order to not enforce any preconception associated with the function and distribution family. However, some intermediate steps in their modeling still involve parametric assumptions. In Emanuel et al. (2006), the empirical probability density functions of the transition matrix in regard to translation speed and translation angle are firstly obtained with the non-parametric approach and further smoothed within the space of each spatial-temporal resolution through a three dimensional normalized Gaussian kernel. The serial variance of latitude/longitude displacement is also modeled through the first order autoregressive model in Hall and Jewson (2007) and Yonekura and Hall (2011). On the one hand, with non-parametric modeling the preconception of assigning specific functions can be avoided, whereas the quality of non-parametric modeling depends on the appropriate discretization of the variables of interest, which further relies on the amount of available historical typhoon records. On the other hand, the result from parametric modeling is reliable even with relatively less historical records once the appropriate function is utilized, whereas fitting data with an inappropriate function would result in a systematic bias in the simulated tracks. Simulated results imply that both ways of modeling are capable of reproducing the main features of the typhoons.

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\(^4\) The state of typhoon transition is the state of movement and the intensity of typhoon transition at a specific time. It refers to translation speed, translation angle and central pressure in this dissertation if no further clarification is stated.
2.2.1.2 Function on modeling

With respect to the function assumed in the modeling, the Markov representation is the basis for all models mentioned above except the one in Rumpf et al. (2007). Those research works indicate that there is an intrinsic continuity among successive steps of transition along a typhoon track and this continuity can be modeled through a Markov chain. Vickery et al. (2000) model the evolution of translation speed after a logarithmic operation by the first order Markov chain and the evolution of translation angle is modeled by the second order Markov chain. These two state variables are assumed to be interrelated through acting as explanatory variable for each other in the regression function. The modeling approach in Yin et al. (2009) is very similar to the one used in Vickery et al. (2000), although there the evolution of translation speed is modeled with the first order Markov chain without a logarithmic operation and only the translation angle acts as the explanatory variable for the translation speed. In James and Mason (2005), Emanuel et al. (2006) and Yasuda et al. (2011), all of the state variables are modeled by the first order Markov chain and further assume that the state variables are independent. The evolution of typhoon track in Hall and Jewson (2007) is modeled by the first order Markov chain assuming independency between state variables. This assumption on independency is revised in Yonekura and Hall (2011) and a dependency of the variables is thought more appropriate. The characteristic of the Markov chain of typhoon track is not explicitly modeled in the evolution of typhoon track in Rumpf et al. (2007), however, such a characteristic is partially accounted for by splitting the typhoon track into six groups in accordance with the behavior of the typhoon transition. Nevertheless, the systematic statistics-based analysis to explore the sufficient order of the Markov chain and the function is still missing in the state of the art.

2.2.1.3 Modeling of spatial inhomogeneity and seasonality

With respect to the spatial inhomogeneity and seasonality implied by the statistical analysis of historical records, they can be modeled in various ways. The spatial inhomogeneity is accounted for by estimating the coefficients of the function in each predefined longitude by latitude grid, i.e. $5^\circ \times 5^\circ$, over the entire Atlantic Basin in Vickery et al. (2000) and over the West North Pacific (WNP) in Graf et al. (2009) and Yin et al. (2009). This estimation approach results in large discontinuities in the coefficients of the function over two adjacent grids. Consequently, there is a sudden change of the statistical characteristics of simulated typhoon tracks among prescribed adjacent grids, whereas it is more likely that statistical characteristics of historical typhoon tracks change smoothly among adjacent grids. This sudden change included in the simulation may lead to the optimal alternative in the decision making being sensitive to the size of the prescribed grid in case the simulated typhoons are utilized in the typhoon risk management. In James and Mason (2005), where the region of Coral Sea, Australia is considered for a case study, the discontinuity of coefficients of the function among adjacent grids is overcome by not taking into account the spatial
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inhomogeneity. Such compromise might be appropriate for the ocean basin where typhoons are only active within small regions. In Hall and Jewson (2007) the spatial inhomogeneity is taken into account by means of extracting the statistical information for reproducing the typhoon track. In their model all the historical records from the Atlantic Ocean basin are assumed to contribute empirical statistical information for simulating a typhoon track. The extent of contribution of this information depends on the spatial distance between the simulated track and this historical record, i.e. the closer the distance between them, the greater the contribution extent. Hence, the continuity of the coefficients of the function is naturally maintained during the simulation of the full life of the typhoon track. Furthermore, at each step of the simulation, the latitude/longitude displacement consists of the mean part and the residual term part. However, the spatial inhomogeneity of the residual term part is not modeled. The seasonality is modeled in Emanuel et al. (2006) and Graf et al. (2009). The seasonality is modeled by developing the transition matrix of the typhoon track for each spatial-temporal resolution in Emanuel et al. (2006). Graf et al. (2009) accounts for the seasonality by estimating the coefficients of the function separately for each season. No explicit consideration of seasonality is stated in other models. Whether it is necessary to account for the spatial inhomogeneity and seasonality, especially their impact on the simulated tracks, have not been sufficiently addressed in the state of the art.

2.2.1.4 Modeling of the residual terms

In the parametric modeling approach, the state variable representing the typhoon transition consists of a deterministic part and a residual term. The way of modeling the residual terms in Vickery et al. (2000) is not clearly stated. On the other hand, James and Mason (2005) mention that the residual terms follow the normal distribution, whereas they are empirically modeled in their simulation. In Graf et al. (2009) and Yin et al. (2009), the residual terms with respect to translation speed and angle are modeled as normal distributions considering all the data that is used to estimate the coefficients of function in individual grids. The resulted typhoon tracks in Graf et al. (2009) seem over-fluctuated compared to the historical ones. In the non-parametric modeling approach, Emanuel et al. (2006) utilize the normal distribution to fit the empirical transition matrix, for the translation speed and angle, disregarding the fatting tails. This results in over-smoothed simulated tracks. Hall and Jewson (2007) and Yonekura and Hall (2011) observe that the residual terms of the latitude/longitude displacements after the operation of the first order auto-regression are not perfectly normally distributed and they model them empirically at the cost of not accounting for the spatial inhomogeneity. Summarizing, it can be stated that no consensus is achieved in the state of the art on the modeling of the residual terms.
2.2.2  Model of vulnerability

The typical approach for the assessment of typhoon induced wind risk for civil infrastructure is to develop the vulnerability curves for the structures. The vulnerability curve reflects the distribution of damages as a function of a wind hazard index or wind hazard indices. At present, the wind hazard indices in established vulnerability models typically only include the maximum wind speed during a typhoon event.

There are, in general, two types of vulnerability models. The most common approach is to develop the vulnerability model based on the statistical analysis of the aggregated data from post-disaster investigation or from insurance companies, e.g. claim losses. This approach generally suffers in the quality of the collected data, i.e. large scatter of data points. It further results in a modeling uncertainty. The drawback of this approach is circumvented in the second case by developing the vulnerability curve via consideration of the physical process that leads to the damage to the structures. In this approach, the failure of individual structural components is modeled based on the knowledge of wind engineering within the framework of structural reliability theory (see e.g. Madsen et al. (2006)).

2.2.2.1  Empirical vulnerability model

The vulnerability curves are originally drawn based on empirical vulnerability models. These are developed on the basis of statistical data in the regions that suffer most frequently from typhoon catastrophe, e.g. Australia (see e.g. Leicester et al. (1979), Leicester (1981)), the USA (see e.g. Sparks et al. (1994), Bhinderwala (1995)) and Japan (see e.g. Mitsuta et al. (1996)). In those studies, a common characteristic of the vulnerability curve is observed namely the vulnerability of the structure does not linearly increase as a function of the wind speed. For instance, Sparks et al. (1994) observe that the vulnerability curve can be divided into three parts. At the beginning, there is no damage at low wind speeds (less than gradient gust wind speeds of 40 [m/s]); afterwards, the damage ratio, defined as the total amount paid in claims divided by the total insured value, linearly increases with the wind speed until a specific one (gradient gust wind speeds of 70 [m/s]) is reached; in the end, the damage ratio increases rapidly.

These empirical models developed in the earlier stage utilize the gradient wind speed as the hazard index. As a consequence, the effect of the surface roughness category on the damage to structures is not accounted for, see e.g. Sill and Kozlowski (1997). There, the damage is modeled as a function of several variables, among others, including the wind speed at 10 [m] height at a corresponding category converted from gradient wind speed, the mean monetary value of structure and two parameters that determine the rate of damage increase with the wind speed. However, since these two parameters are assigned based on the engineering judgment of the author, their justification should be an aspect of further investigation.
Huang et al. (2001) develop a vulnerability model for single family houses using insurance data from Southeastern USA from Hurricanes Hugo and Andrew. In their model, the damage ratio is modeled exponentially as a function of the effective wind speed which refers to the maximum of surface sustained 10-minute wind speed at the height of 10 [m] in the roughness condition that corresponds to an airport. Since a large amount of data is used to develop the model, the developed vulnerability model and its extended version have found application in several other studies to assess the losses caused by other typhoon events, see e.g. Stewart et al. (2003), Stewart and Wang (2011) and Bjarnadottir et al. (2011) etc.

The vulnerability models in the aforementioned studies are limited to be applicable to a specific region (Leicester et al. (1979) and Leicester (1981) for Australia; Sparks et al. (1994), Bhinderwala (1995), Sill and Kozlowski (1997) and Huang et al. (2001) for USA; Mitsuta et al. (1996) for Japan). Furthermore, the statistical loss after a natural disaster is generally provided by insurance companies lacking of information on building-specific characteristics such as height and material. As a consequence, often aggregate vulnerability curves are developed for a combined portfolio (Leicester et al. (1979), Leicester (1981), Sparks et al. (1994), Bhinderwala (1995), Mitsuta et al. (1996), Sill and Kozlowski (1997)) without having any meaning on the vulnerability of individual building types. In order to generalize the aggregate vulnerability curve, Khanduri and Morrow (2003) develop a conventional approach to disaggregate the aggregate vulnerability curve into several curves representing individual building types. Further, their approach provides a convenient way of translating the vulnerability curves of one region to those for another region by combining them with actuarial data and building inventory information of each region.

The empirical vulnerability models are often developed based on regression methods. These models are capable of estimating or predicting the damage caused by typhoon events, it is however hard to support the estimation of the efficiency of risk reduction measures, e.g. increase of resistance of building component. Note that the efficiency of risk reduction measures is also estimated based on the empirical vulnerability models in several research works, see e.g. Stewart et al. (2003), Bjarnadottir et al. (2011). In these studies, a vulnerability curve, known as standard vulnerability curve, is drawn from the actual statistical loss data and is used for the buildings without undertaking any risk reduction measures or upgrading. The modified, just with engineering judgment, versions of this standard vulnerability curve are assumed for the structures with an individual upgrading type. The efficiency of upgrading is estimated by accounting for the amount of reduced risk calculated from those two versions of the vulnerability curve and the cost used for upgrading. Since there is hardly any supporting statistical data for the justification of engineering judgment for the modification, the extent of accuracy of the modified vulnerability curve requires further investigation.
2.2.2.2 Reliability-based model

A reliability-based fragility model is capable of considering upgrades/downgrades of various buildings' parts. The value of fragility related to individual failure is measured by the failure probability. Different failures are explicitly accounted for by modeling the resistance capacities of individual elements and the wind loads acting on them. Hence, it is possible to examine the effect of upgrading/downgrading on the increase/decrease of the resistance capacity in a quantitative way. Consequently, changes in the probability of failure can be assessed and the efficiency can be assessed in terms of risk change. Therefore, such a model is appropriate for the impact assessment and ultimately risk management of climate change.

Holmes (1996) derives a vulnerability curve for engineering buildings within the framework of structural reliability theory assuming that their resistance capacity follows the lognormal distribution. In this model, the whole building is considered to be a unit without further investigating the failure of each component. In contrast, the vulnerability models developed in Stubbs and Perry (1996), Unanwa et al. (2000) and Unanwa and McDonald (2000) consider separately the failure of individual building components and their probabilities are assessed. In order to reflect the importance of failure of an individual component, a weight is assigned on each of them, e.g. roof covering, roof structure, exterior doors and windows. The fragility/vulnerability is obtained by summing up the weighted damages to individual components. These models do not explicitly consider the causal relationship between failures of individual components. For instance, the failure of a window may affect the failure of the roof structure; the failure of a window may alter the internal pressure and in turn it will change the probability of failure of the roof structure.

This causal relationship of components' failure is incorporated into two well-known reliability-based vulnerability models developed for the buildings in the USA, i.e. the Florida Public Hurricane Loss Projection (FPHLP) model (see Pinelli et al. (2004) and Gurley et al. (2005)) and the FEMA HAZUS-MH Hurricane model (see Vickery et al. (2006a) and Vickery et al. (2006b)), hereafter called FEMA model. More recently, based on the assumptions for the building as well as the pressure damage, i.e. the damage caused directly by gust wind pressure, employed in FPHLP, a new version of reliability-based vulnerability model is developed in Lin and Vanmarcke (2010) and Lin et al. (2010) and Yau et al. (2010), hereafter called Lin-Vanmarcke model. It elaborates the debris damage, i.e. the damage caused by windborne debris, as well as the interdependency of pressure and debris damage. These three models are dedicated to the modeling of vulnerability of buildings during typhoon events and they represent the state of the art in the reliability-based vulnerability modeling. Nonetheless, the models differ in several aspects such as the building and the damage types examined, the ways of calculating the wind loads and the fragility as well as in the modeling of interdependency of pressure and debris damage.
In what concerns the types of considered buildings and failures, the FPHLP model was initially developed to analyze the fragility of single-family buildings located in Florida, USA, including typical one- or two-storey concrete blocks and wood frame buildings with gable and hip roof, see for example Pinelli et al. (2004) for an application of the model for buildings located in Florida, USA. More recently, it has been extended to analyze the fragility of commercial residential MHB comprised of condominiums and multi-storey apartment buildings. The Lin-Vanmarcke model takes basis in the model building in the FPHLP model, i.e. one storey concrete and wood-frame residential buildings with gable and hip roof in Florida, USA. The FEMA model enables the analysis of fragility for typical residential and commercial buildings over the Atlantic and Gulf coasts of the USA, including one- or two-storey single family buildings, up to four storeys of multifamily buildings, manufactured houses, pre-engineered metal buildings, industrial and high rise buildings.

In the FPHLP model, for the analysis of fragility for single-family buildings structural and non-structural failures are modeled including failures of roof cover, roof sheathing, roof-wall connections, walls and openings such as doors, garage doors and windows. For the analysis of fragility for MHB only non-structural failures are considered including the failure of cladding and openings. The damage type considered in the Lin-Vanmarcke model is the same as the damage types considered in the FPHLP model for single-family buildings. The FEMA model also models structural and non-structural failures similar to the FPHLP model.

Coming to the conversion from wind speed to wind load, the FPHLP model utilizes a modified version of the provision in ASCE 7-98 (ASCE (1998)). This modification disregards the so called importance factor, the directionality factor and the topographic effect factor. The pressure coefficients are specified for eight wind directions. Moreover, buildings are assumed to be isolated sufficiently from neighboring buildings and located in an open country terrain corresponding to the exposure category C. In the conversion, the maximum 3-second gust wind speed at roof height is employed as the reference wind speed. In contrast, the FEMA model converts the wind load based on a one-hour sustained wind speed. For the estimation of directionally dependent wind pressure coefficients, an empirical modeling approach has been developed from a large number of boundary wind tunnel tests measuring wind induced pressures on model buildings together with the reference to the counterparts of the British and Australian design codes. The extreme values of the local pressure coefficients resulting from empirical modeling are set equal to agree with those given in the ASCE 7-02 provision (ASCE (2002)) on wind loads. Furthermore, the shielding and interference effects of surrounding buildings are accounted for by modifying the baseline pressures produced for isolated building, following the works by Ho (1992) and Case (1996). The Lin-Vanmarcke model takes basis in the methodology used in the FPHLP model.

For the estimation of fragility, two distinct approaches are employed. In the FPHLP model, the probabilities of structural and non-structural failures are estimated as a
The effect of change of wind direction during an event is not accounted for. In the FEMA model those probabilities are estimated at individual time steps during an event. The cumulative damage over the event is obtained by integrating instantaneous failures over time. Hence, a detailed analysis of the effect of different wind environments on the damage is facilitated, e.g. in terms of the change of wind direction and speed over subsequent steps. The Lin-Vanmarcke model is additionally capable of estimating the probabilities of non-structural failures at instantaneous time steps of an event.

In both the aforementioned models (the FPHLP and FEMA models), the interdependency between debris and pressure damage is modeled considering the effect of debris damage affecting pressure damage. This is achieved by increasing the internal pressure of the building depending on the state (failure/no-failure) of its openings due to the impact of flying debris. Note that the increase in the internal pressure changes the probabilities of failures of several building elements. The mechanism for objects to start flying when they fail due to the gusty wind pressures is not explicitly accounted for; parameters such as the amount of debris of specific types are given as exogenous parameters. In contrast, the effect of pressure damage on debris damage is also modeled in the Lin-Vanmarcke model; by feeding back the output from the pressure damage model as input to the debris damage model. It thus iteratively utilizes the pressure and the debris damage models in the fragility analysis.

The software and tools of FEMA model is publicly available. The descriptions of individual module component and assumptions employed in the FEMA (see FEMA (2006)) and FPHLP (see Gurley et al. (2005)) are well documented in the technical manuals. These models have a broad application in the USA for the impact assessment of typhoon events. For instance, taking the FEMA model as basis, researchers investigated the influence on the typhoon induced wind risk of changes of the building inventory, such as the change of the amount of individual type of buildings (see e.g. Davidson and Rivera (2003), Jain et al. (2005)), the change of building code (see e.g. Davidson et al. (2003), Jain and Davidson (2007)), the change of the building technology (Jain and Davidson (2007)). According to the FPHLP model, the annual risk of hurricane as well as the risk corresponding to given portfolio is predicted and also validated by the actual data, see e.g. Pinelli et al. (2008), Hamid et al. (2010), Hamid et al. (2011).

Several other fragility/vulnerability models for (components of) buildings have been developed in the USA based on the concept of structural reliability theory, such as roof sheathing (Lee and Rosowsky (2005), Li and Ellingwood (2006), Lindt and Dao (2009), Rocha et al. (2010)) and building (Unanwa et al. (2000), Unanwa and McDonald (2000), Rosowsky and Ellingwood (2002)).

Although the methodologies behind these models provide guidance on the development of vulnerability models in general, the models developed for buildings in
the USA are not directly applicable to the case of residential buildings in Japan. This is due to the difference of residential buildings between Japan and USA in several aspects: e.g. geometry of typical residential buildings, characteristics of non-structural elements such as roof shape and roof tile, etc. Note that the building geometry and the roof shape influence the spatial distribution of the wind pressures on the building envelop, which in turn affects the fragility. The geometry and the density of a tile as well as its attachments to the roof frame significantly affect its resistance capacity against wind load as well as its flying trajectory once it becomes wind borne debris. Furthermore, the failure costs of the constituents of residential buildings are different.

2.2.3 Impact assessment under climate change

A direct result of climate change is the rising of the global mean surface temperature (GMST) as stated in the report by the IPCC (IPCC (2007b)). The sea surface temperature (SST) also increases. The causal relationship of whether the increase of GMST leads to the increase of SST or vice versa has been a matter of research, see e.g. Elsner (2006) by statistical analysis of historical temperature records. The conclusion is that the increase of GMST causes the increase of SST and not the other way round. With higher SST, there are two competing processes that in theory may influence the typhoon events, see e.g. IPCC (2007c), Bengtsson et al. (2007). This is also consistent with the observation. On the one hand, the increase in the temperature and water vapour provides more energy when the condition of occurrence of typhoon events is satisfied. As a consequence, the typhoon event intensity increases. This is confirmed by several statistical studies utilizing data from the historical typhoon events. For instance, based on the statistics of 35 years' historical typhoon events worldwide, Webster et al. (2005) find that the number and proportion of intense typhoon events increase in an environment of increasing SST. Emanuel (2005) also confirms that there is a positive correlation between the intensity of typhoon events and the SST based on the statistical analysis of historical typhoon and SST records worldwide. Furthermore, based on the historical record of typhoons occurred in the Atlantic, a similar conclusion is derived, see e.g. Elsner et al. (2008). On the other hand, it is likely to cause greater stabilization of the tropical troposphere, which decreases the number of occurrences of typhoon events. This is also observed in the statistics of historical typhoon events. Webster et al. (2005) also observe that the total number of occurrences of typhoon events decreases in an environment of higher SST.

In recent years researchers pay more attention on aspects such as, e.g. the frequency and the intensity of typhoon events under climate change. This is because a typhoon event is one of the most devastating natural hazards and its understanding thereof is of highly societal importance. At early research stages, Knutson et al. (1998) and Knutson and Tuleya (1999) estimate that in a CO$_2$ warmed climate the intensity of typhoon events will increase 5%-11% if the SST increases by 2.2°C. Recently, more and more research results are made known and large discrepancy exists among the conclusions drawn from various research works. For instance, over the region of WNP, some works
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predict a decreasing trend of occurrence of typhoon events (e.g. Sugi et al. (2002), Oouchi et al. (2006), Bengtsson et al. (2007), Murakami and Sugi (2010), Yasuda et al. (2010)), while others project an increasing trend (e.g. Stowasser et al. (2007), Emanuel et al. (2008)). In addition to that, McDonald et al. (2005) and Murakami et al. (2011) show that the frequency of typhoon events will decrease in the western part of the WNP while having an increasing tendency in the eastern part. Note that simulation of future climate requires the climate scenario as input and boundary condition⁵. Given the same climate scenario, say e.g. SRES A1B scenario, a plausible reason leading to such discrepancy is the difference in resolution and considered scale, i.e. global or regional scale, among the models, see e.g. Murakami and Sugi (2010). With a high resolution global climate model, Knutson et al. (2010) estimate that the typhoon intensity will increase 2-11% by 2100 while the number of their occurrences globally will decrease 6-34% based on the review of existing results.

Research has mainly been focused on the trends of typhoon activity development in the climate change. There is however a limited number of works on the impact assessment of climate change on the civil infrastructure in terms of risk. Recently, this matter started to attract more attention and several published research articles address this issue, such as: Hallegatte (2007), Pielke (2007), Schwierz et al. (2010), Li and Stewart (2010), Emanuel (2011), Mendelsohn et al. (2011), Bjarnadottir et al. (2011), Nishijima et al. (2012). Except Schwierz et al. (2010), who address the impact assessment subject to winter storm damages, all other studies listed above focus on the impact assessment of typhoon events. In all the aforementioned studies, the model components of the assessment framework consist of the hazard and the vulnerability modeling. The empirical vulnerability model derived from the historical typhoon loss/damage data is employed while different empirical functions are assumed in the individual study. Nonetheless, these studies differ in the approach employed for those two modeling parts.

In regard to the hazard modeling, two fundamental approaches are employed. In the first one, the intensities (or together with frequency) of typhoon events are extrapolated by prescribing an increase/decrease with a specific imaginary percentage, examples hereof is Hallegatte (2007), Pielke (2007), Li and Stewart (2010) and Bjarnadottir et al. (2011). For instance, in Hallegatte (2007) and Pielke (2007), the typhoon event intensity for future climate is assumed to increase 10% and 18% respectively. Furthermore, the wind speeds are directly modified and increased according to the current observation and used as the hazard index in the calculation of vulnerability in Pielke (2007). In Hallegatte (2007) on the other hand the intensities of future typhoon events are assumed to increase during the process of artificially synthesizing typhoon events, based on which the wind speed is computed and used as hazard index in the calculation of vulnerability. In Li and Stewart (2010) and Bjarnadottir et al. (2011) the

⁵ For this purpose, IPCC AR4 report specifies six climate scenarios, they are B1, A1T, B2, A1B, A2 and A1FI climate scenarios.
parameters of the annual maximum wind speed distributions are extrapolated by assuming that the mean of the annual maximum wind speed increases by several percentages in the range of -5%-10% in 50 years for different climate scenarios.

In the second approach, the climate model outputs are employed. The typhoon hazard dataset is artificially synthesized by the probabilistic (or hybrid with physical mechanism, see e.g. Emanuel (2011)) hazard model and the computed wind speed is used as hazard index in the calculation of vulnerability. The hazard modeling in Schwierz et al. (2010), Emanuel (2011), Mendelsohn et al. (2011) and Nishijima et al. (2012) is according to the second approach. In Schwierz et al. (2010), the climate scenario for the specification of simulation in the climate model from which output is extracted is A2. Whereas in the other studies, A1B scenario is assumed and it is considered to be the most likely climate scenario in the IPCC AR4 report.

Models based on the first approach, except Li and Stewart (2010) and Bjarnadottir et al. (2011), capture only the change of the intensity of typhoon events in the future climate. In the second approach, the influence of climate change on the intensity, the frequency as well as the trajectory of typhoon events, are captured in the modeling. By utilization of the first approach for the purpose of modeling, the projected typhoon induced wind risk under climate change increases if the typhoon event intensity of future climate is assumed to increase. This relationship does not always hold when the second approach is employed, see e.g. Nishijima et al. (2012). This is because the frequency of typhoon events is considered to decrease in the future climate. It shall also be mentioned that none of the aforementioned studies using the second approach consider the bias that may be present in the projection of typhoon events extracted from the climate model. Note that it is common that there is a bias (Ehret et al. (2012)) implied in the climate model output for the current climate, demonstrated by e.g. for the precipitation by Ines and Hansen (2006) and Piani et al. (2010) and for typhoon events by Yasuda et al. (2010), Nishijima et al. (2012), etc.

A typical drawback of the aforementioned studies is that they are not capable of examining the efficiency of adaptation measures under climate change since the empirical vulnerability models are employed. Note that the effectiveness of risk reduction measures is analyzed in Li and Stewart (2010) and Bjarnadottir et al. (2011) and the procedure to undertake such effectiveness analysis is introduced in the last paragraph of the subsection 2.2.2.1. As aforementioned, the engineering judgment in the process of modifying the vulnerability models lacks the support of statistical loss data. Thus, any conclusions drawn from the application of this approach should be interpreted with caution.
2.3 Modeling methodology in the dissertation

2.3.1 Risk assessment framework

Based on the merits of the aforementioned works, a methodology is presented to assess the impact of climate change on the typhoon induced wind risk for residential buildings. With the proposed methodology the efficiency of adaptation can also be examined. The procedure and the model components for the risk assessment adopted in this dissertation are presented in Figure 2.2. The framework consists of three parts, i.e. climate model part, probabilistic typhoon hazard model part and vulnerability model part. Firstly, the current and a projected future climate are simulated by a climate model for an assumed climate scenario (subsection 2.3.2). The typhoons simulated in the climate model are extracted and serve as the basis for the probabilistic modeling of typhoon events. The biases present in the climate model outputs are accounted for and corrected (subsection 2.3.3, section 3.2 for detailed description) and an "unbiased" dataset is obtained for the projected future climate, referred to hereafter as transformed best track dataset. The probabilistic models for the occurrence and transition of typhoons are developed for the current and the projected future climate based on the best track dataset and the transformed one respectively. Based on the developed occurrence and transition models together with the other components, wind field and surface friction models, of the probabilistic typhoon hazard model, stochastic typhoon event sets are generated for both examined climate situation (subsection 2.3.4 for the introduction of probabilistic typhoon hazard model, section 3.3 for detailed description of the part of probability modeling of typhoon transition). The wind vulnerability models of residential buildings in Japan (subsection 2.3.5, chapter 4 for details) are created consisting of two main elements, namely the fragility model and cost models. The first element is developed by considering physical processes that lead buildings to specific failures. Simplistic failure cost models are formulated considering the prices of building elements as well as execution costs for repair work etc. Finally, the wind hazards as well as risks (chapter 5) under the current and projected future climates are calculated based on the stochastic typhoon event sets and the vulnerability model.

* Individual typhoon event in the transformed best track dataset is transformed from corresponding one in the best track dataset. Therefore, the amount of typhoon events in the transformed best track dataset is the same as that in the best track dataset. Whereas the track and intensity of typhoon events in the transformed best track dataset are considered to be identical to the observational typhoon events in the future climate.
2.3.2 Global climate model with climate change scenario

The current as well as the projected future climate are simulated by the climate model for a chosen climate scenario, known as SRES A1B scenario according to Nakicenovic and Swart (2000), see Kitoh et al. (2009). The climate model outputs include many aspects of information of climatologic characteristics, such as the atmospheric pressure at different height, the wind speed. On the basis of these information and general understanding of typhoon’s forming and evolution mechanism, individual typhoon events are extracted from the climate model output, see e.g. Murakami and Sugi (2010); thus, a dataset of typhoon events extracted from the climate model output for a specific time period, e.g. current and future, is obtained. Specifically, this dissertation utilizes the outputs of the climate model labeled as MRI-AGCM3.2S which is the part of the Kakushin program. Hereafter, the datasets of extracted typhoon events for the current and projected future climate are referred to output from AGCM for current and for future datasets respectively. Specifically, current and future refer to time period of years 1979-2003 and 2075-2099 respectively, see subsection 3.2.1.

The way to describe these extracted typhoon events is identical to that for the typhoon events in the best track dataset, i.e. represented by the intensity in terms of central pressure and track in terms of evolution of movement of typhoon center.
2.3.3 Bias correction

The climatologic characteristics simulated by the climate model, in comparison to the corresponding observational ones, often show that there are biases. These biases are often observed in the climate model output in regard to typical climatologic characteristics, e.g. precipitation (see e.g. Ines and Hansen (2006), Piani et al. (2010), White and Toumi (2013) and Bordoy and Burlando (2013)) and temperature (see e.g. Chen et al. (2011a), Chen et al. (2011b), Thrasher et al. (2012) and Bordoy and Burlando (2013)). The bias prevailing in the output of the climate model is due to the imperfections in the formulation of the climate model, which seems to be irresolvable within a foreseeable time frame, see Palmer and Weisheimer (2011). Whereas the necessity of credible impact assessment under climate change requires a reliable projection of the future climate. Thus, correction of the bias implied in the outputs of the climate model is the prerequisite for the follow-up steps of credible impact assessment. In light of this requirement, various bias correction approaches are developed in recent years.

A comprehensive review of these bias correction approaches with respect to the precipitation and temperature can be found in Teutschbein and Seibert (2012). In accordance with their classification, there are mainly six groups of approaches, namely (1) linear scaling, see e.g. Lenderink et al. (2007), (2) local intensity scaling, see e.g. Schmidli et al. (2006), (3) power transformation, see e.g. Leander and Buishand (2007), Leander et al. (2008), Leander and Buishand (2007) and Bordoy and Burlando (2013) (4) variance scaling, see e.g. Chen et al. (2011a) and Chen et al. (2011b), (5) distribution transfer, see e.g. Ines and Hansen (2006), Piani et al. (2010), and (6) the delta-change approach, see e.g. Graham et al. (2007) and Moore et al. (2008).

The comparison of typhoons extracted from AGCM for the current dataset, to the ones in the best track dataset provided by JMA, indicates that there are biases in the statistics of typhoon characteristics, i.e. occurrence locations, the number of typhoon occurrences in a given year and typhoon track and intensity (see e.g. Nishijima et al. (2012) and also subsection 3.2.2). However, the aforementioned bias correction approaches designed for the precipitation and temperature are not directly applicable to typhoon events. This is due to the different characteristics of typhoon events, i.e. apart from the frequency of occurrence and intensity, the feature of typhoon track should also be addressed.

Very limited literature is available for the bias correction concerning typhoon events. Nevertheless, an attempt has been made in Yasuda et al. (2010). They quantified the changes of the relevant statistics on the occurrence and dissipation as well as the transition of typhoons between the current and the projected future climate and these changes are added to the statistics of typhoons in the best track dataset to form an "unbiased" dataset of typhoon events in the projected future climate. The bias of occurrence frequency is also accounted for in the simulation of typhoon event dataset. However, the intensity of the typhoon event is not corrected in their study.
The present dissertation follows the idea reflected in Yasuda et al. (2010) for correcting the bias with regard to the typhoon event. Furthermore, this idea is also applied for the minimum central pressure of typhoons during their individual lives, which is considered to account for the bias of the intensity of the typhoon event in the present dissertation. Thus, the transformed best track dataset for the projected future climate is obtained. The transformed best track dataset serves as the input to the probabilistic typhoon hazard model; thus, a stochastic typhoon event set is obtained through simulation. The bias in regard to the occurrence frequency is accounted for in the following. The change of the occurrence number of typhoons between the current and projected future climate is considered by proportionally decreasing the number of typhoon events for the projected future climate in the stochastic typhoon event set generated by Monte Carlo simulation.

2.3.4 Probabilistic typhoon hazard model

The entire model consists of four components, see Figure 2.1. The occurrence model and transition model are probabilistic and the other two are deterministic. In this dissertation, the method proposed by Zhang and Nishijima (2012) (also refer to section 3.3) is employed for the modeling of typhoon transition, which improves the model presented in Graf et al. (2009) and Graf (2012). Note that the evolution of the typhoon's intensity is appropriately modeled by the transition model when moving over the ocean; whereas the filling model is utilized to model the evolution of the typhoon's intensity after its landfall.

In the present dissertation the probabilistic typhoon hazard modeling which proved to be suitable for the typhoon event in the current climate, is assumed to further be applicable for the typhoon event in the future climate. This may be justified since the physical mechanisms that lead to the forming of the typhoon event, the evolution of typhoon track and intensity, as well as the typhoon induced wind are not likely to change. The occurrence models are developed separately for the current climate and future climate based on the best track and the transformed best track datasets. The coefficients in the transition and the filling models for the current and future typhoons are separately estimated based on the corresponding datasets. Note that the typhoon track and intensity may shift in the future. In contrast, the same models are assumed for the wind field and the surface friction for the current and projected future climates. Note that the latter implies that the characteristics of land-use are assumed to not change in the future.

The stochastic typhoon event sets for both of the examined climate situations are generated with Monte Carlo simulation (10000 one-year typhoon events are simulated) by employing the probabilistic typhoon hazard model. In each set, the maximum wind speed at several locations in Japan during individual typhoon events is recorded.
2.3.4.1 Occurrence model

The occurrence model describes the probabilistic characteristics of the initiation of typhoon events. The typhoon event is defined as the part of intensified tropical storm which induces a wind speed not less than 17.2 [m/s], according to the definition in JMA. If this definition applies, a number of track records of tropical storm provided by JMA will be disregarded, which is useful for the transition model. Thus, the initiation of typhoon events in the present dissertation also follows the definition given by Graf (2012). It is defined as the moment at which the central pressure of each tropical storm becomes less than 1000 [hPa] for the first time in the life time of the tropical storm, i.e. if the track record of a tropical storm starts with the central pressure being less than 1000 [hPa] the first record of the tropical storm track is assumed to represent the initiation of the typhoon event. The initial state of the typhoon event includes translation speed and angle and the central pressure of typhoon at the moment of initiation.

The present dissertation utilizes (resample) the historical observation of the initiation of the historical typhoon events, i.e. the location of occurrence represented by the combination of latitude and longitude and the initial state of typhoon events in the generation of stochastic typhoon event set.

2.3.4.2 Transition model

The transition model describes the probabilistic characteristics of the movement of the typhoon event as well as the evolution of typhoon intensity over sea. Specifically, the state variables of typhoon events, i.e. the translation speed and angle and the central pressure, are modeled in the present dissertation. The evolutions of these state variables are generally modeled through regression by accounting for their non-homogeneity with respect to the space and season.

A comprehensive review of existing transition models is given in subsection 2.2.1. A fundamental issue in the state of the art with respect to the probabilistic transition model is that a consistent statistics-based exploration of modeling approach is missing; the existing works simply proposed their individual models while lacking substantial justification. Furthermore, the methodology to account for the spatial and seasonal non-homogeneity has not being sufficiently addressed and there is still discrepancy on the modeling approach for residual terms. These concerns are extensively investigated by statistical analysis in section 3.3. Thereby, a statistics-based transition modeling approach is suggested, which is an improved version of the transition model presented in Graf (2012).

The typhoon track and intensity are estimated in 6-hour time steps when it is over the sea. Note that it is possible that the typhoon crosses the island of Japan within 6 hours. This implies that the simulation will produce a track with two points, both lying in the
sea, and the evolution of typhoon intensity between these two points will not apply the filling model. On the other hand, the information on the typhoon, e.g. wind speed, is generally recorded more frequently when it is close to the island and after it makes landfall. For instance, the JMA meteorological stations record the wind speed every 10 minutes. Thus, in the simulation a typhoon track is generated through linear interpolation, using a 10 minutes time step, of simulated track when it is close to the land and after it makes landfall.

In regard to the criterion of typhoon dissipation, it is assumed that a typhoon dissipate when the central pressure is equal or higher than the peripheral standard pressure, i.e. 1013 [hPa], or if it travels out of the considered region which is bounded by longitude [100°E, 180°E] and latitude [0°N, 60°N].

### 2.3.4.3 Filling model

The filling model describes the evolution of typhoon intensity when the typhoon event makes landfall. In the present dissertation it is modeled as a function of the time $t$ [hour] elapsed after its landfall, see Vickery et al. (2005):

$$\Delta P_t = \Delta P_0 \cdot \exp\left(-\left(d_1 + d_2 \Delta P_0\right) t\right),$$  \hspace{1cm} (2.2)

where $\Delta P_0$ is the difference of the central pressure of a typhoon at the moment of the landfall and the peripheral pressure, i.e. 1013 [hPa], $\Delta P_t$ is the difference of the central pressure of the typhoon at time $t$ and the peripheral pressure. The coefficients $d = (d_1, d_2)$ are constant and are estimated by statistical analyses using the information of track when it is on the island. Note that the coefficients $d$ are estimated separately for two examined datasets, i.e. the best track dataset and the transformed best track dataset.

Note that the amount of data utilized to estimate coefficient $d$ is relatively limited. Thus, there are statistical uncertainties involved in the estimation. Moreover, other studies also proposed different functions for the filling model, see e.g. Vickery et al. (2009), this implies the model uncertainty in regard to the assumed function. These uncertainties are not addressed in the present dissertation.

### 2.3.4.4 Wind field model

The wind field model utilized in this dissertation is a deterministic model describing the wind field as a function of the variables of the state of a typhoon. The variables required to describe the wind field are the central pressure $P_C$, the radius $r_m$ of maximum wind speed, the translation speed $V$ and translation angle $\Gamma$ of the typhoon.
The pressure field is modeled following the formulation proposed by Schloemer (1954) as:

\[ P_r = P_c + \Delta P \cdot \exp\left(\frac{r_m}{r}\right), \tag{2.3} \]

where \( r \) is the distance from the center of the typhoon to the considered location, \( P_r \) is the pressure at the considered location and \( \Delta P = 1013 - P_c \) is the difference between the peripheral pressure and the central pressure. The radius \( r_m \) of maximum wind speed is modeled by a truncated lognormal distribution with a mean value of 136.44 [km] and a standard deviation of 69.70 [km], while the distribution is truncated below 30 [km] and above 400 [km]. The parameters of the distribution are estimated based on the values calculated by using equation (2.3) with the historical observations of \( P_r, P_c \) and \( r \) in regard to typhoons after year 1970. Note that it may not be possible to estimate the value of \( r_m \) by using (2.3) when typhoons are relatively far away from the Japanese islands since the observations for the pressure at the meteorological stations that can be used for the estimation may be unavailable. Therefore, only the records of the typhoons which were close to the Japanese islands (in a radius of 250 [km]) were used to estimate the parameters of distribution of \( r_m \).

The typhoon induced wind field at the time is modeled as proposed by Georgiou et al. (1983), also applied in other studies, see e.g. Meng et al. (1995), as following:

\[ \tilde{u}_g(r,\alpha) = \frac{V \sin \alpha - fr}{2} \sqrt{\left(\frac{V \sin \alpha - fr}{2}\right)^2 + \frac{r}{\rho_a} \frac{\partial P_c}{\partial r}}, \tag{2.4} \]

where \( \tilde{u}_g(r,\alpha) \) is the wind speed at gradient height, hereafter called gradient wind speed, at the location whose distance from the typhoon center is \( r \) and whose angle measured clock-wise relative to the typhoon's translation angle is \( \alpha \). \( \frac{\partial P_c}{\partial r} \) is obtained by using Equation (2.3). \( \rho_a \) is the air density and taken as 1.275 [kg/m³]. The unit used for the variables in Equation (2.4) is [kg] for mass, [m] for length and [s] for time. \( f \) is the Coriolis parameter and it is expressed as \( f = 1.46 \times 10^{-3} \times \sin \phi \) where \( \phi \) is the latitude of the representative location which is assumed as the location of the typhoon center.

### 2.3.4.5 Surface friction model

The surface friction model is utilized to describe the relation between the gradient wind speed and the wind speed at nominal height as well as the relation between the wind directions at gradient height and at nominal height. The definition of the nominal height is explained below.
Based on the model proposed by Davenport (1965) and utilized in Meng et al. (1997), the following expression is assumed to model the relation between gradient wind speed and the wind speed at the nominal height:

\[ u(z) = \tilde{u}_g(r, \alpha) \left( \frac{z}{z_g} \right)^a E_g, \tag{2.5} \]

where \( \tilde{u}_g(r, \alpha) \) is the gradient wind speed calculated by the wind field model using Equation (2.4), \( E_g \) is the topological factor which is taken as 1 in the simulation of stochastic typhoon event set for the roughness category II in the AIJ Load Recommendations (AIJ (2004)) in the present dissertation. \( z_g \) is the gradient height and \( u(z) \) is the one-hour sustained wind speed at the height of \( z \). These heights are measured from the adjusted surface level defined by the following expression, see Simiu and Patel (1976):

\[ d = 0.75h \tag{2.6} \]

where \( h \) is the average height [m] of roughness elements, e.g. buildings, trees, at the considered area, which can be formulated as, see Lettau (1970):

\[ h = A z_0^{0.86}, \tag{2.7} \]

where \( A = 11.4 \), see Meng et al. (1995) and Graf (2012), \( z_0 \) is the roughness length [m] and the value of \( z_0 \) for the roughness category II in the AIJ Load Recommendations (AIJ (2004)) is taken as 0.01 in the simulation of stochastic typhoon event set. The nominal height is defined as the height of 10 [m] from the adjusted surface level. The exponent \( a \) and the gradient height \( z_g \) are assumed to be expressed as, see Meng et al. (1995) and Graf (2012):

\[ a = 0.27 + 0.09\log_{10} z_0 + 0.018(\log_{10} z_0)^2 + 0.0016(\log_{10} z_0)^3, \tag{2.8} \]

\[ z_g = 0.052 \frac{\tilde{u}_g(r, \alpha)}{f_{\lambda}} (\log_{10} R_{\lambda})^{-1.45}, \tag{2.9} \]

where \( R_{\lambda} \) is the modified surface Rossby number and it is expressed as:

\[ R_{\lambda} = \frac{\tilde{u}_g(r, \alpha)}{f_{\lambda} \cdot z_0}, \tag{2.10} \]

where \( f_{\lambda} \) is one of two parameters proposed by Meng et al. (1997) for describing the structure of strong wind in the typhoon boundary layer and the other parameter is \( \xi \). They are expressed as:
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\[
f_\perp = \left( \frac{\partial \bar{u}_z (r, \alpha)}{\partial r} + \frac{\bar{u}_z (r, \alpha)}{r} + f \right)^{\frac{1}{2}} \left( \frac{2 \bar{u}_z (r, \alpha)}{r} + f \right)^{\frac{1}{2}}, \tag{2.11}\]

\[
\xi = \left( \frac{2 \bar{u}_z (r, \alpha)}{r} + f \right)^{\frac{1}{2}} \left( \frac{\partial \bar{u}_z (r, \alpha)}{\partial r} + \frac{\bar{u}_z (r, \alpha)}{r} + f \right)^{\frac{1}{2}}. \tag{2.12}\]

In regard to the relation between the wind direction at gradient height and at nominal height, the inflow angle \( \gamma_z \) at height \( z \) is defined in Meng et al. (1997). It describes the difference between the wind direction at gradient height and at nominal height and it is expressed as:

\[
\gamma_z = \gamma_s \left( 1 - 0.4 \frac{z}{z_g} \right)^{1.11}, \tag{2.13}\]

where \( z_g \) is the gradient height and it can be calculated using Equation (2.9) and \( \gamma_s \) is calculated as:

\[
\gamma_s = (69 + 100 \xi) \left( \log_{10} R_{o, z} \right)^{-1.13}. \tag{2.14}\]

where \( R_{o, z} \) and \( \xi \) can be calculated by Equations (2.10) and (2.12) respectively.

### 2.3.5 Vulnerability model

Losses due to failures of building components in a typhoon event are often estimated by an empirical vulnerability model which is often developed by a statistic-based approach using the post damage data such as the claim data provided by the insurance company. A typical drawback of these models is that they often suffer from the large scatter of the loss data points. This can be clearly seen in several studies, e.g. the Figure 1 in Nishijima et al. (2012). In that figure, there is a large variation on the damage ratio, defined as the ratio of the number of damaged buildings over the total number of residential buildings in a specific region, under a given wind speed. This is due to, on one hand, the estimation of the damage ratio by the aggregated data of the buildings in a region without differentiating the information of percentages of the building characteristics, such as the building type, the construction method as well as the resistance of building components. Note that building characteristics play a significant role on the fragility of the building even under the same wind speed. On the other hand, the wind speed recorded in the meteorological station often utilized as the basis data for the statistical analysis in the vulnerability/fragility model may be not identical to the one that causes the damage in the residential area. This is because the
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roughness of the location where the meteorological station is located may be different from that of the residential region where the damage data is collected. Note that the roughness of the location plays a significant role on the wind speed even under the same typhoon event. Furthermore, apart from the wind speed, as illustrated in chapter 4, other factors of the wind characteristics, e.g. the change of wind direction may also play a role on the fragility of the buildings. Nevertheless, the large scatter implied in the collected damage data will result in a large amount of model uncertainties in the established empirical vulnerability model. This will further lead to large uncertainties involved in the assessment of vulnerability by using an empirical vulnerability model.

The adaptation of civil infrastructure under climate change requires a vulnerability model capable of estimating the efficiency of risk reduction measures. However, the empirical vulnerability model lacks such a capability as stated in subsection 2.2.2.1. Whereas, the reliability-based vulnerability model is capable of estimating the effect of upgrade/downgrade of the building components; thus the efficiency of any risk reduction measures could be examined as stated in subsection 2.2.2.2. However, the established reliability-based vulnerability models in the USA pay more attention on the functionality of assessment rather than in investigating the factors affecting the vulnerability of buildings. Furthermore, those reliability-based vulnerability models are not directly applicable to the residential buildings in Japan. Thus, in order to examine the impact on the residential buildings under climate change, a Japanese version of vulnerability model is required.

An approach to developing a reliability-based vulnerability model for residential buildings in Japan is presented. Following this approach, several provisional reliability-based vulnerability models are developed for several model buildings that represent typical residential buildings in Japan under specific surrounding conditions, see chapter 4, see also Zhang et al. (2014a) for more details. The model buildings are assumed to be surrounded by identical buildings, see section 4.3. The assumed surrounding condition corresponds to the roughness category III in the AIJ Load Recommendations (AIJ (2004)) and the building densities of 0.3 and 0.6, see section 4.3 and TPU (2007). Note that relevant simple assumptions on the surrounding environment and generic building types are assumed in the present dissertation. However, these assumptions do not lose the essence of problem. The primary reason for this consideration is to identify relevant parameters for vulnerability modeling. Such an identification becomes difficult, if the analysis combines several building types and surrounding conditions. Moreover, unavailability of information on the external wind pressure coefficients in the TPU (2007) database, adopted in the present dissertation, for the other combinations of building types and surrounding conditions also prohibits further analysis.

In the present dissertation, three non-structural types of failures, i.e. roof tile failure, window failure and roof sheathing failure, are considered. These failures account for a large fraction of losses in Japan. It is found that the roof tile’s resistance plays a
significant role on vulnerability, see Zhang et al. (2013), Zhang et al. (2014a). For each combination of building type and surrounding condition, the vulnerability curves are developed for a broad range of roof tile’s resistance, from the weakest case to the strongest case in Japan. These developed vulnerability curves can be utilized as the basis for the pursuit of adaptive options.

There are two main contributions in this part of the work. The first one is that a vulnerability modeling approach for residential buildings in Japan is presented, which is based on the mathematical formulation of the Lin-Vanmarcke model, see Lin and Vanmarcke (2010) and Lin et al. (2010), which can be regarded as the state of the art in vulnerability modeling. The present approach not only addresses the adaptability of methodologies developed primarily for residential buildings in the USA, but also improves some aspects of the previous modeling attempts. For instance, the methodology utilized in the Lin-Vanmarcke model implies that the debris flying trajectories in a single time step are independent, which would seem to result in an overestimation of vulnerability; whereas in the present dissertation the fully dependent case which is closer to reality is also investigated. The second contribution is that detailed examinations of the performance of the individual models as well as the vulnerability model are explored, a feature which is often not documented nor investigated. This facilitates to further elaborate the vulnerability model for the considered types of buildings. It also provides insights on vulnerability modeling for other types of structures.

2.4 Role in the framework of adaptation

The pursuit of adaptation alternatives under climate change can be regarded as a decision problem under several uncertainties at the present time. The major source of uncertainty comes from the amount and trajectory of emission of GHG. This is determined by the societal trend of development, e.g. whether people prefer an energy efficient or inefficient driven economy. Consequently, a climate scenario is formed and six climate scenarios are assumed in the IPCC AR4 report (Nakicenovic and Swart (2000)). For each one, its future climate characteristics can be projected based on the climate model, see Figure 2.3. Furthermore, the projection result contains model/epistemic uncertainties due to the imperfection of the recognition of the climate forming mechanisms.
Based on the review of the general decision framework by Nishijima and Faber (2008) and the risk management of typhoon events by Graf and Nishijima (2011), the objective function of the decision problem for adaptation, e.g. in regard to typhoon induced wind risk, is formulated by taking into account the decision variables. It is expressed as:

\[
E[g(X, a, b) | a, b] = E_\Theta \left[ E[g(X, a, b) | \Theta, a] | b \right],
\]

where \( X = (X_1, X_2, \ldots, X_n) \) is the vector of random variables representing aleatory uncertainties characterized by the joint probability distribution function \( F_X(x | \Theta) \) conditional on the vector of the random variables representing epistemic uncertainties \( \Theta = (\Theta_1, \Theta_2, \ldots, \Theta_m) \) which are characterized by the probability distribution function \( F_\Theta(\Theta) \). Within the context of the present dissertation, \( X \) represents the randomness of hazard indices, e.g. maximum wind speed and its consequence, while \( \Theta \) represents the uncertainty in resulting from the choice of the climate scenario and the model uncertainty in the utilized climate model. The expected value \( E[g(X)] \) can refer to e.g. the expected utility (loss) in case where \( g(X) \) is the utility (loss) function. \( a, b \) correspond to two types of distinguished decision variables; action decision \( a \) and test decision \( b \), see e.g. Jensen and Nielsen (2007). Action decisions change the physics or characteristics of the underlying random phenomena. For instance, the upgrading of the design code for wind hazards can change the structural performance in terms of resistance to strong wind. Test decisions change the decision maker’s perception on the uncertainty of underlying phenomena. For instance, the decision to postpone the adaptation may reduce the uncertainty of perception of the climate change trends as well as the model uncertainty in the climate model. The optimal decision for the adaptation problem is identified by employing the objective function (2.15).
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There are three aspects of the decision framework for the adaptation under climate change that may pose a challenge in its application, namely:

- Separation of aleatory and epistemic uncertainties
- Quantification of epistemic uncertainties by an appropriate probability distribution function
- Formulation of the adaptation problem.

The first aspect plays a significant role on probabilistic modeling. As shown in Nishijima and Faber (2008), a violation of this can lead to an erroneous assessment of the objective function. This in turn affects the choice of adaptive actions. In the second aspect that may pose a challenge, the likelihood of occurrence of each climate scenario and the weight of projections from various models should be quantified. In the third aspect, the impact of climate change in terms of utility (loss) has to be defined, in order for the quantitative impact assessment to be possible. The output of the present dissertation may facilitate in enriching the knowledge with respect to the third aspect mentioned above.
3 Probabilistic modeling of typhoon transition in the future

3.1 Introduction

Various climate models are employed to project the future climate and many characteristics of the future climate can be obtained through this output. Among others, typhoon events are of major concern. This chapter describes the probabilistic modeling of typhoon transition in the future climate. Firstly, section 3.2 describes the issues associated with the projection of typhoon events in the future climate. These issues include the methodology to extract the typhoon event, the bias existing in the extracted typhoon events and the approach used in this dissertation to correct the bias. The detailed approach to extract the typhoon event is introduced mainly by the use of appropriate reference, since this part is not the main focus in this dissertation. Then, in section 3.3 the statistics-based modeling of typhoon transition is explored by extensive statistical analysis. Accordingly, a statistics-based modeling approach for the modeling of the typhoon transition in the future climate is suggested.

3.2 Typhoon transition in the future climate

3.2.1 Projection of a typhoon event in the future climate

Several efforts worldwide have been devoted in analyzing the output from the climate models developed for the purpose of projection of future climate represented by climatological characteristics. Among these characteristics, the information of typhoon events is implicitly included and it requires further extraction. One of the approaches for the extraction of information of a typhoon event is to identify each individual event according to some general criteria. These criteria refer to the common understanding of characteristics of typhoon events and its surrounding environment such as sea level pressure, vorticity, maximum wind speed, warm core, upper level wind speed and duration. The details of these criteria can be found in, e.g., Sugi et al. (2002), McDonald et al. (2005), Oouchi et al. (2006), Stowasser et al. (2007), Bengtsson et al. (2007), Gualdi et al. (2008), Yokoi and Takayabu (2009), Murakami and Sugi (2010) and Murakami et al. (2011). By applying this approach, typhoon events are extracted and further statistical analysis can be undertaken.

High resolution climate models are expected to be able to project the typhoon events more realistically and reliably. In order to investigate this hypothesis, Murakami and Sugi (2010) conduct a sensitivity analysis by using the extracted typhoon events from various climate models with four different resolutions ranging from a 180km-mesh to a 20km-mesh. They demonstrate that higher resolutions possess higher skills on the projection in terms of the typhoon intensity, the inter-annual and seasonal variation of
its frequency of occurrence. Furthermore, they also find that the projections from the climate model, when the resolution corresponds to a 60-km mesh or to finer versions, indicate a significant increase of intense typhoon events in the future climate under the SRES A1B climate scenario. This is consistent with the theoretical expectations, see e.g. IPCC (2007c), Bengtsson et al. (2007).

A super-high-resolution (corresponding to 20km-mesh) atmospheric general circulation model (AGCM) has been developed within the research project "Projection of the change in future weather extremes using super-high atmospheric model" (Kitoh et al. (2009)). This project is part of the Kakushin program supported by the Ministry of Education, Culture, Sports, Science and Technology in Japan. Its output is supposed to provide the scientific foundation for the interference actions on the adaptation of climate change in general and contributions for the upcoming IPCC AR5 report in particular. In this dissertation, the output from this super-high-resolution (the highest resolution of global scale climate model up to date) AGCM is used. Specifically, the output from the model labeled as MRI-AGCM3.2S (Mitzuta et al. (2012)) is used.

The simulation of climate with MRI-AGCM3.2S is performed for three different time periods, i.e. 1979-2003 (current), 2015-2039 (near future) and 2075-2099 (future). In the simulation, the SST is used as an input to the AGCM as a boundary condition; observed SST from the UK Met Office Hadley Centre (HadISST) is used for the present climate simulation and the mean of ensemble SSTs from the CMIP3 multi-model projections of the SRES A1B scenario are employed for the future climate simulation, see Murakami et al. (2011).

Typhoon events are extracted from the simulation results by the method applied in Murakami and Sugi (2010), which is tuned from the method used in Oouchi et al. (2006) and is originally in line with those in Sugi et al. (2002) and Bengtsson et al. (1996). In the present dissertation, the datasets of typhoon events for the current climate (time period 1979-2075) and future climate (time period 2075-2099) are used. In accordance with the definition of occurrence of typhoon events, 550 occurrences of typhoon events are extracted for the current climate and 427 occurrences of typhoon events are extracted for the future climate. These are then represented in terms of the central pressure and its location at 6-hour time steps. The tracks of extracted typhoon events both for the current and the future climate are illustrated in Figure 3.1.
3.2.2 Bias of projection

In order to illustrate the effect of bias of projection, this subsection presents the empirical cumulative distribution functions (CDFs) for three variables, i.e. the latitude and longitude of the occurrence location and the minimum central pressure in the life of a typhoon event. These CDFs are shown in Figure 3.2 based on three datasets i.e. the best track one provided by JMA and those from the AGCM for the current and the future climate. It is shown that there are differences in the statistics of those variables between the best track dataset and the output from AGCM for the current dataset, i.e. the corresponding CDFs for individual variables based on these two datasets are not identical. For instance, at the fractile of 0.4 the latitude of occurrence location at 14ºN in the best track dataset shifts to at 15ºN in the output from AGCM for the current dataset. This is understood as the systematic bias in the capability of the AGCM in reproducing the climate characteristics of the current climate. This bias is also observed in other studies, see e.g. Murakami and Sugi (2010), Yasuda et al. (2010), Murakami et al. (2011), Nishijima et al. (2012). Furthermore, it is observed that there is a change in statistics of those variables between the output from AGCM for the current and the future climate datasets, i.e. the corresponding CDFs of individual variable based on these two datasets show difference. For instance, at the fractile of 0.4 the latitude of occurrence location at 15ºN in the output from AGCM for current dataset shifts to at around 15.1ºN in the output from AGCM for future dataset. This change can be understood as the effect of climate change on the typhoon activity. In this dissertation, it is assumed that the AGCM is capable of capturing this change and furthermore this change can be quantified by a statistical approach, see Yasuda et al. (2010).

Apart from the bias and change in the statistics in regard to the occurrence and dissipation location as well as the intensity represented by the minimum central pressure.
pressure in the life of a typhoon, the occurrence frequency also shows the bias and change. Note that the occurrence number of typhoon in the best track dataset for the current time (1979-2003) is 643, whereas these numbers as abovementioned are 550 and 427 from AGCM for the current and future datasets respectively.

3.2.3 Bias correction in regard to the track and intensity

In this dissertation the idea introduced in Yasuda et al. (2010) is employed. Firstly, they quantified the differences of the relevant statistics between the current and the future climate with respect to the occurrence and dissipation location of typhoon tracks. Then, these differences are added to the statistics of typhoons in the best track dataset to form an "unbiased" dataset, i.e. transformed best track dataset, see Figure 3.3 for the whole idea, Figure 3.4 for the illustration of quantified effect $\Delta x$ appearing in the Figure 3.3. Note that Yasuda et al. (2010) apply this idea only for the statistics on the occurrence and dissipation locations of typhoons. In this dissertation, besides these
cases, the idea is applied also for the intensity of typhoon events represented by the minimum central pressure during each typhoon event.

Figure 3.3. Idea of forming an "unbiased" dataset of typhoon events in the projected future climate.

Figure 3.4. Illustration of the quantified effect $\Delta x$ due to climate change between the output from AGCM for current (1979-2003) and future (2075-2099) datasets.
The approach to obtain the transformed best track dataset in the projected future climate is described in the following. Note that the typhoon track as well as the time series of central pressure of typhoon are transformed and the procedures to obtain the transformed track and the time series of transformed central pressure are separately introduced.

The procedure to obtain the transformed track is illustrated in Figure 3.5. Two steps are essentially involved in transforming the track of a typhoon event. The first step is to obtain the transformed occurrence and dissipation location of the typhoon track. The second step is to transform the track points between the occurrence and dissipation points.

In order to achieve the first step, the typhoon occurrence and dissipation locations should firstly be identified. Note that in the present dissertation the occurrence/dissipation location is represented by the combination of latitude and longitude. Therefore, the transformation of occurrence/dissipation location refers to the transformation of relevant latitude and longitude. The approaches to transform the occurrence and dissipation locations are identical and the transformation of latitude and longitude are independent. In order to illustrate this approach, the procedure to transform the latitude of occurrence location is introduced in the following. The relationship between the value \(x_{BT}\) of relevant variable, here is the latitude of occurrence location, in the best track dataset and the transformed one \(x_{un}\) in the transformed best track dataset can be expressed as:

\[
x_{un} = x_{BT} + \Delta x(x_{BT}),
\]

where \(\Delta x(x_{BT})\) is the statistical change at the value of \(x_{BT}\) and it is calculated as:

\[
\Delta x(x_{BT}) = F^{-1}_2(F_{BT}(x_{BT})) - F^{-1}_1(F_{BT}(x_{BT})),
\]

where \(F_{BT}(\cdot)\) is the empirical CDF of the variable relevant to the best track dataset, \(F^{-1}_1(\cdot)\) and \(F^{-1}_2(\cdot)\) are the inverse empirical CDFs of the variable relevant to output from the AGCM for current and future datasets respectively.

The transformed longitude of occurrence location as well as the latitude/longitude of dissipation location is also obtained by Equation (3.1) and (3.2). Note that in the process of using these two equations for transformation for different variables, \(x_{BT}\) and \(x_{un}\) refer to corresponding variable and \(F_{BT}(\cdot), F^{-1}_1(\cdot)\) and \(F^{-1}_2(\cdot)\) are obtained accordingly.
After obtaining the transformed occurrence and dissipation locations, the latitude/longitude of track points between those two points are proportionally transformed and formulated as:

\[ x_{\text{un}}^{j} = x_{\text{occ}}^{\text{un}} + \frac{x_{\text{dis}}^{\text{occ}} - x_{\text{occ}}^{\text{un}}}{x_{\text{BT}}^{\text{BT}} - x_{\text{occ}}^{\text{BT}}} (x_{\text{occ}}^{j} - x_{\text{occ}}^{\text{BT}}), \]

where \( x_{\text{BT}}^{\text{occ}} \) and \( x_{\text{BT}}^{\text{dis}} \) correspond to the values of variable, i.e. latitude/longitude, of occurrence and dissipation point in the best track dataset respectively, \( x_{\text{un}}^{\text{occ}} \) and \( x_{\text{un}}^{\text{dis}} \) represent the values of variable referring to transformed occurrence and dissipation points respectively. Note that the superscripts "occ", "dis" refer to the occurrence and dissipation points, which is also utilized for the minimum central pressure. \( x_{\text{BT}}^{j} \), \( x_{\text{un}}^{j} \) represent the values of the variable of the \( j^{\text{th}} \) step of a typhoon in the best track and transformed best track datasets respectively. Thus, the track in the transformed best track dataset is obtained.

The approach to obtain the time series of transformed central pressure of a typhoon event in the transformed best track is similar to the one to obtain its track and it is also carried out in two steps, as illustrated in Figure 3.6. The first step is to obtain the transformed minimum central pressure and it is identical to the first step of the approach to obtain the transformed track. The transformed minimum central pressure of each individual typhoon event is also obtained following the Equation (3.1) and
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(3.2) and corresponding variables $x_{BT}$ and $x_{un}$ refer to the minimum central pressure and associated functions $F_{BT}^{-1}(\cdot)$, $F_{1}^{-1}(\cdot)$ and $F_{2}^{-1}(\cdot)$ are obtained accordingly. However, in comparison to the second step of the approach to proportionally transform the track points between the occurrence and dissipation points, there is a small variation in the second step for obtaining the time series of transformed central pressure.

Time series of central pressure of typhoon in the best track dataset

Central pressure at occurrence point

Minimum central pressure in a life of typhoon

Modeling of transformation of minimum central pressure

Modeling of time series of central pressure between occurrence point and the point minimum central pressure achieved

Transformed minimum central pressure

Time series of transformed central pressure

Central pressure at dissipation point

Statistical change $\Delta x$ with respect to minimum central pressure

Modeling of transformation of time series of central pressure between dissipation point and the point minimum central pressure achieved

Figure 3.6. The procedure to obtain the time series of transformed central pressure for the transformed best track dataset in the future climate.

The minimum central pressures of a typhoon event in both datasets are denoted as $x_{min,P}^{BT}$ and $x_{min,P}^{un}$, with the indices "BT" and "un" denoting, as previously, the best track and the transformed best track datasets respectively. If there are several identical minimum central pressures in a life of typhoon event, then $x_{min,P}^{BT}$ and $x_{min,P}^{un}$ refer to the first ones occurring in the time series. Note that $x_{min,P}^{un}$ is calculated according to Equation (3.1) and (3.2). The value $x_{occ,P}^{un}$ of central pressure of occurrence point in the time series of a typhoon event in the transformed best track dataset is assumed to be equal to the corresponding value $x_{BT}^{occ,P}$ in the best track dataset. In analogy, the value $x_{dis,P}^{un}$ of central pressure of dissipation point in the time series of a typhoon event in the transformed best track dataset is assumed to be equal to the corresponding value $x_{BT}^{dis,P}$ in the best track dataset. The central pressure of each track point between $x_{occ,P}^{un}$ and $x_{min,P}^{un}$ is obtained by proportionally transforming the corresponding central pressure in the best track dataset according to the following expression:

-55-
where \( x_{BT}^{j,P}, x_{un}^{j,P} \) represent the central pressure of the \( j^{th} \) step of a typhoon in the best track and transformed best track datasets respectively. The central pressure of each track point between \( x_{un}^{min,P} \) and \( x_{un}^{dis,P} \) in the transformed best track dataset is obtained by a proportional transformation of the corresponding central pressure in the best track dataset, such as:

\[
x_{un}^{j,P} = x_{un}^{min,P} + \frac{x_{un}^{occ,P} - x_{un}^{min,P}}{x_{BT}^{occ,P} - x_{BT}^{min,P}} \left( x_{BT}^{j,P} - x_{BT}^{min,P} \right).
\]  (3.5)

By applying the approach described above, the time series of central pressure of each typhoon in the best track dataset is transformed; thus, the time series of central pressure in the transformed best track dataset is obtained.

An example of transformation of track and time series of central pressure of a typhoon, typhoon Bart, in the best track dataset is illustrated in Figure 3.7. In Figure 3.7 (a), the occurrence and dissipation location are transformed by using Equation (3.1) and (3.2), while the other track points are transformed by using Equation (3.3). In Figure 3.7 (b), the minimum central pressure in the time series is transformed by using Equation (3.1) and (3.2), the central pressures of the track points before and after the track point of the minimum central pressure are transformed by using Equation (3.4) and (3.5) respectively.

![Figure 3.7. An example of transformed typhoon track and central pressure.](image-url)
3.2.4 Bias correction in regard to occurrence frequency

The change of the number of occurrences of typhoons between the current and the projected future climate is considered as follows. The occurrence rate of typhoons in the projected future climate is assumed to decrease to 78% (=427/550) of that in the current climate. The number of typhoon events in the stochastic event set for the projected future climates is decreased accordingly.

3.2.5 Discussion

The correction of biases in the outputs from the climate model are in general controversial issues, see e.g. Ehret et al. (2012). Some researches argue that correction of biases fundamentally depends on the improvement of capability of climate model on simulating the climate, which relies on the improvement of understanding of climate forming mechanism. However, the urgency of credible impact assessment under climate change cannot just wait for the outputs from credible climate models. Thus, the existing various statistics-based bias correction approaches may be a reasonable expedient.

The present dissertation presents an ad-hoc statistics-based bias correction approach with respect to the typhoon events extracted from AGCM, which is originally utilized in Yasuda et al. (2010). However, other issues beyond impact assessment are not addressed. Among others, the quantitative measurement of the bias of climate model output is not defined and investigated. This concerns the measurement of the capability of climate model on reproducing the current climate, which is out of the scope of the present dissertation. However, this is relevant to the selection of utilization of outputs of climate model which is considered to simulate the current climatologic characteristics with the least bias. Note that there are many existing climate models and thus many simulated climatologic characteristic datasets are available. This selection may be achieved by implementing the validation of outputs from climate model for the current climate. The climate model can be regarded as a large-scale computational model and it consists of many sub-models simulating specific climatologic index, e.g. temperature and precipitation. Thus, the existing methodologies, see e.g. Mahadevan and Rebba (2004) and Rebba et al. (2006), designed for the validation of outputs of large-scale computational model may serve for this purpose.

A fundamental assumption implicitly accepted in the adopted bias correction approach in the present dissertation and also often in the other bias correction approach is that the climate model is capable of capturing the effect affected by climate change and it can be quantified by statistical change. The adequacy of this assumption may be able to be checked with respect to other climatologic characteristics such as the temperature by comparing the relative difference of observations in the two different time periods, say e.g. 1900-1925 and 1979-2003, affected by climate change and that of outputs from climate model for corresponding time periods. Note that the record of
climatologic characteristic such as the temperature and precipitation is generally available in the meteorological station for long time, say e.g. more than 100 years. However, the credible observation of typhoon event is not available for early old time, say e.g. before 1970s. Thus, it is hardly to check the correctness of this assumption with respect to typhoon event. Nevertheless, this can become possible in the near future, say e.g. in 20 years, when sufficient long time of observation of typhoon becomes available. Thus, it should keep in caution on applying the results based on this assumption.

In order to collect sufficient amount of typhoon events for the statistical analysis, the typhoon events in a specific time period should be combined as one statistical population; thus, the homogeneity of statistical characteristics in this time period is assumed. Note that the typhoon activity may also be affected by the climate change so that the statistical characteristics of typhoon events among different years in an examined time period may vary. The length of time period must be determined by the balance between the amount of typhoon activities available and the homogeneity of statistical characteristics of typhoon events in the time period. In the present dissertation, the typhoon events in 25 years (time period of 1979-2003 and 2075-2099) are assumed to have the same statistical characteristics. This choice may be justified since 25 years even longer time period of typhoon events are often utilized as input dataset in the probabilistic typhoon hazard model, see e.g Vickery et al. (2000), Graf et al. (2009) with assuming the homogeneity of statistical characteristics of typhoon events among the assumed time period.

When the new observations of typhoon activities are available, they may be incorporated in the best track dataset and the bias correction approach described in the present dissertation is also applicable. However, before the incorporation of these new observations, homogeneity of the statistical characteristics among the new observations and the existing best track dataset requires to be checked e.g. by statistical analysis. Assume that their statistical characteristics are homogeneous; thus, new best track dataset with more amount of typhoon activities can be obtained. This will reduce the statistical uncertainties in the utilization of probabilistic typhoon hazard model.

The present dissertation addresses the bias correction on the full track of typhoon events rather than the landfall events. This is because the modeling of full track of typhoon is the state of the art in the modeling of typhoon hazard as adopted in the present dissertation. Note that this modeling approach can capture the correlation of wind speeds among spatial regions; whereas the hazard modeling approach focusing on the landfall event is lack of this capability. Moreover, since the part of track referring to landfall is part of full track, the bias correction of the full track of typhoon also includes the bias correction of landfalls, see Figure 3.7.
3.3 Exploration of statistics-based modeling of typhoon transition

3.3.1 General statistical characteristic of present transitions

For the typhoon event in the best track for the WNP provided by the JMA, the typhoon state, including the typhoon position and its central pressure, is available at a time interval of 6-hours when the typhoon is far from Japan. The typhoon state is recorded more frequently as the typhoon approaches Japan. In accordance with the trajectory of historical typhoons, most of them initiate at the Pacific Ocean east of Philippine and they could be generally categorized into three groups. One group of typhoons heads west towards China south sea and Vietnam; another group sweeps northwest and lands on the southeast coastal line of China; the last group firstly heads northwest and then veers northeast. Apart from these three typhoon groups, many typhoons may show complicated trajectories. Assuming that the evolution behavior of a typhoon is considerably random, its transition could be modeled using the statistical characteristics of the best track dataset.

In order to discover the statistical characteristics of the best track dataset, the successive translation speeds, translation angles and central pressures are plotted, see Figure 3.8. $V_i$, $\Gamma_i$, $P_i$ represent these parameters at time step $i$ respectively. Note that the translation angle of a typhoon is 0º when traveling north and positive clockwise. It is observed that there are nearly linear relationships between successive translation speeds and so is translation angle. This agrees with the observation made in Emanuel et al. (2006), where the historical typhoons in the North Atlantic ocean are examined. A similar relationship is observed between successive central pressures. Furthermore, by developing these scatter plots for different areas and seasons, it is observed that the statistical characteristics of these three state variables show, on one hand, differences among the various seasons for a specific spatial region, known as seasonality, e.g. see the comparison between Figure 3.8 (a) and Figure 3.8 (b). On the other hand, there is a difference among the various spatial regions within the same time period, known as the spatial inhomogeneity, e.g. see the comparison between Figure 3.8 (b) and Figure 3.8 (c).
Figure 3.8. Scatter plots showing relationships between successive translation speeds, successive translation angles and successive central pressures. Typhoon tracks are those travelling within the region: (a) bounded by longitude [124°E, 132°E] and latitude [24°N, 28°N] and occurred in the month July; (b) bounded by longitude [124°E, 132°E] and latitude [24°N, 28°N] and occurred in the month September; (c) bounded by longitude [132°E, 140°E] and latitude [32°N, 36°N] and occurred in the month September.

3.3.2 Modeling approach

A typhoon is assumed to be represented by realizations of stochastic processes with due consideration of the influence of the typhoon statistical characteristics resulting from the spatial inhomogeneity and seasonality. In these stochastic processes, the transition state $S_{t+1|Z_{i}}$ at time step $i+1$ during a seasonal time frame $t_{q}$ within a spatial region $Z$ is a function of previous states expressed in the following form:

$$S_{t+1|Z_{i}} = f_{Z_{i}}\left(S_{t_{q}i_{q}}, S_{t_{q}-1|Z_{i}}, \ldots, S_{t_{q}q_{t_{q}}}\right) + e_{t+1|Z_{i}},$$  \hspace{1cm} (3.6)
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where $f_{Z,t_g}(\cdot)$ is a deterministic function within the spatial region $Z$ during the seasonal time frame $t_g$, $q$ is the order of the previous states and $\varepsilon_{i+1,Z,t_g}$ is the residual term at time step $i+1$ within the spatial region $Z$ during the seasonal time frame $t_g$. The modeling process includes:

- Exploration of the function $f_{Z,t_g}(\cdot)$
- Estimation of the coefficients in $f_{Z,t_g}(\cdot)$
- Modeling of the residual term $\varepsilon_{i+1,Z,t_g}$.

Note that in regard to the evolution of typhoon intensity, the present dissertation focuses only on the period when the typhoon is over the sea. The modeling of the typhoon after it reaches land is carried out using the so called filling model, see e.g. Vickery et al. (2005).

### 3.3.2.1 Exploration of the function

This subsection explores several plausible models. It starts by observing the relationship drawn from the scatter plots, which suggests that the autoregressive (AR) model is appropriate to represent typhoon transition. Therefore, the autocorrelation coefficients’ function (ACF) and the partial autocorrelation coefficients’ function (PACF) are estimated in order to identify the necessary and sufficient orders of the AR models. Considering for example the area bounded by the longitudes [124°E, 132°E] and the latitudes [24°N, 28°N] and the area bounded by the longitude [140°E, 148°E] and the latitude [28°N, 32°N] in the month September and assuming that the typhoon transition is stationary therein, ACF’s and PACF’s are estimated for the state variables as functions of the time lag, see Figure 3.9. Here, the unit of the time lag is 6 hours, at which interval the JMA best track dataset is available. Since the ACF’s decay as a function of time lag and the PACF’s show a cut off at a time lags of appropriately a value of 2, the autoregressive models of the second order, denoted as AR(2), can be plausible. Similar observations are made for other seasons and areas. Therefore, the first plausible transition models for the state variables are:

\[
V_{i+1} = a_1 + a_2 V_i + a_3 V_{i-1} + \varepsilon_{V,j+1}, \quad (3.7)
\]

\[
\Gamma_{i+1} = b_1 + b_2 \Gamma_i + b_3 \Gamma_{i-1} + \varepsilon_{\Gamma,j+1}, \quad (3.8)
\]

\[
P_{i+1} = c_1 + c_2 P_i + c_3 P_{i-1} + \varepsilon_{P,j+1}. \quad (3.9)
\]

Here, $\varepsilon_{V,j+1}$, $\varepsilon_{\Gamma,j+1}$ and $\varepsilon_{P,j+1}$ are the random residual terms for the state variables $V_{i+1}$, $\Gamma_{i+1}$ and $P_{i+1}$ respectively. The residual terms for each individual time step are modeled as identically independent distributed random variables. For some seasons
and areas, the estimated PACF for the translation speed and angle differs significantly from zero only at time lags equal to 1; hence, the autoregressive models of the first order, denoted as AR(1), are also plausible and are expressed as follows:

\[ V_{i+1} = a_1 + a_2 V_i + \epsilon_{V_{i+1}}, \]  
\[ \Gamma_{i+1} = b_1 + b_2 \Gamma_i + \epsilon_{\Gamma_{i+1}}. \]

As the third class of plausible models, regression models including the possible interrelations between the translation speed and angle are assumed:

\[ V_{i+1} = a_1 + a_2 V_i + a_3 V_{i-1} + a_4 \Gamma_i + \epsilon_{V_{i+1}}, \]  
\[ \Gamma_{i+1} = b_1 + b_2 \Gamma_i + b_3 \Gamma_{i-1} + b_4 V_i + \epsilon_{\Gamma_{i+1}}. \]

Vickery et al. (2000) indicate that the typhoon intensity is subject to SST. Here, the following function is assumed as one of possible plausible models:

\[ P_{i+1} = c_1 + c_2 P_i + c_3 P_{i-1} + c_4 T_i + \epsilon_{P_{i+1}}, \]

where \( T_i \) represents the SST at step \( i \).
The goodness of fits of these possibly plausible models are explored. The investigation is performed with respect to: AR(1) model vs. AR(2) model; whether or not the interrelation needs to be considered between the translation speed and the translation angle; whether the SST is necessarily included in the regression model. To achieve that, the corrected Akaike information criterion (cAIC), see Appendix A for details, is employed. Note that the cAIC is capable of accounting for the non-normality of the residual terms, see Yanagihara (2006). It favors the model with a smaller value of cAIC. The cAIC is calculated for each grid (latitude 4° × longitude 8°) and for each month that contains at least 20 samples of the historical typhoon track record. Typhoons heading westward and eastward are separately treated in this calculation.

The numbers of the grids (and directions in case of the translation) with the smaller cAIC value are counted. In Figure 3.10, the corresponding histograms are shown for
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the month September as an illustrative example. The number of grids are compared for the following cases: (a) AR(1) vs. AR(2) for translation speed; (b) AR(1) vs. AR(2) for translation angle; (c) AR(2) for translation speed vs. interrelation model (Equation (3.12)); (d) AR(2) for translation angle and interrelation model (Equation (3.13)); (e) AR(2) for central pressure vs. model including SST (Equation (3.14)). In the x-axis, AR(1) and AR(2) are indicated by "1" and "2" respectively while "3" corresponds to the interrelation models for translation speed and translation angle and the model including SST for central pressure.

The results indicate that for all months more grids favor the suitability of AR(1) over AR(2), see histograms (a) and (b); more grids favor the employment of non-interrelation translation models, see histograms (c) and (d); more grids support the exclusion of SST in the model, see histograms (e).

### 3.3.2.2 Estimation of coefficients

In order to reflect the seasonality and spatial inhomogeneity, the regression models are developed separately for predefined time frames and spatial grids. The grids’ size must be determined by considering the balance between the amount of samples available and the homogeneity of the characteristics of the samples in the grids. In terms of seasonality, it is postulated that the statistical characteristics of typhoons do not significantly differ within one-month periods; hence, the time frame is set to one month. The average movements of the historical typhoons are approximately 0.4° in latitude and 0.8° in longitude in one time step (i.e. 6 hours). Considering that the explored models include the AR(2) model in the regression form, a grid size that can include two steps of typhoon transitions is required; hence, 0.8° in latitude and 1.6° in longitude at minimum. The models for eastward and westward translations (speed and angle) are developed separately in order to take into account the underlying difference in the statistical characteristics of the typhoon translation. The above form the base line for estimating the coefficients of the regression models.
With respect to the amount of samples for the coefficients estimation, it is proven that the more samples the smaller associated statistical uncertainty. Samples in adjacent grids and time frames might possess part of homogeneity of the statistical characteristic compared to those within the grid and time frame of interest. If this is the case, these samples are considered for estimating the regression models’ coefficients for the grid and time frame of interest. To achieve that, a procedure is designed to borrow the samples from the adjacent grids and time frame. In this procedure, the approach developed in Butler and Rothman (1980), see Appendix B for details, is utilized to identify suitable samples that can be borrowed. Note that this utilized approach is capable of accounting for the case of non-normality of the residual term. The identification of borrowable samples proceeds from those samples in the near adjacent to the far adjacent and the identification continues until the sample in the adjacent grids and time frame is not borrowable. In the present dissertation, those borrowable samples are defined as those falling in the predictive interval of a statistical level, i.e. 95%, that is estimated by the samples in the grid and time frame of interest in accordance with the regression mechanism described in Butler and Rothman (1980). The outcome is that, with respect to a one month period, the samples included in the previous and next month could be merged to estimate the coefficients of interest and this further confirms the existence of seasonality. Furthermore, the spatial grid size varies with the spatial region as well as the month.

3.3.2.3 Modeling of residual term

Based on the explored functions, statistical characteristics of the residual terms are investigated. As illustrated in Figure 3.11 (Equations (3.9), (3.10) and (3.11) are utilized), it is found that the residual terms for the state variables do not follow the normal distributions. This is consistent with the observation in Hall and Jewson (2007). Moreover, it is also found that this non-normality of the residual terms cannot be eliminated, either by simply adding explanatory variables in the function or by utilizing a logarithmic operation of the state variables. In Figure 3.11, the normalized histograms of the frequencies of the residuals are shown, together with the probability density functions of the two normal distributions that are fit to the histograms in two ways. The histograms are obtained by examining typhoons traveling in the month September within the area bounded by the longitudes [124°E, 132°E] and the latitudes [24°N, 28°N] and histograms (a) and (b) are obtained by using those typhoons heading westward. One of the two fitted normal distributions is obtained by accounting for all the data, exaggerating maybe such as variability (e.g. Graf et al. (2009) and Yin et al. (2009)). The other one is obtained by neglecting both tails at quantiles larger than 1.5 times of the standard deviations resulting most likely in an underestimation of the variability (e.g. Emanuel et al. (2006)).
Figure 3.11. The normalized histograms of the frequencies of residual terms for: (a) translation speed with the model of Equation (3.10); (b) translation angle with the model of Equation (3.11); (c) central pressure with the model of Equation (3.9).

The modeling of the residual terms becomes critical e.g. for the case when the typhoon transition model is utilized to predict the future transition of emerging typhoons. The consequences of the two approximations of the normal distributions on the simulated typhoon tracks are discussed in the next subsection. It should be mentioned here that it is not generally suggested to model the residual terms by a normal distribution; their empirical modeling, similar to the way proposed by James and Mason (2005) not accounting though for the spatial inhomogeneity and seasonality, or more flexible modeling such as mixture models are suggested as more suitable.

**3.3.3 Performance of modeling**

Based on the statistical investigation in the previous subsections, the following transition modeling is proposed: Equations (3.9), (3.10) and (3.11) for modeling the evolution of the state variables, estimation of the coefficients by the method described in subsection 3.3.2.2 and employment of the empirical distributions of the residual terms. The performance of the proposed modeling is investigated by simulating typhoons by Monte Carlo techniques and then comparing several statistics of the typhoon transition with those of the historical typhoons. In the Monte Carlo simulation, the initial typhoon states are re-sampled from the initial states of the historical typhoons. Then, the typhoons' transition is simulated using the transition model. Note that the evolution of the typhoon intensity after landfall is simulated using a filling model, which takes basis in the proposals of Vickery et al. (2005) and the coefficients in the model are estimated in accordance with the data provided by the JMA for Japan.
Probabilistic modeling of typhoon transition in the future

Figure 3.12. (a) Historical tracks that occurred in September during 1951-2006; (b), (c) and (d) are the simulated tracks for the typhoon which occurred in September over the same period. (b) is the result of the proposed modeling; (c) is the result by modeling all the residual terms with a normal distribution; (d) is the result by modeling the residual term with a normal distribution disregarding both tails at quantiles larger than 1.5 times of the standard deviation.

Figure 3.12 (a) shows the tracks of the historical typhoons for the month September in the period between 1951 and 2006. Note that the other plots show the tracks of the simulated typhoons in the same month and period. The simulated typhoon tracks are illustrated in Figure 3.12 (b) when the proposed modeling approach is employed, in Figure 3.12 (c) when modeling the residual terms by the normal distribution considering all the data and in Figure 3.12 (d) when modeling the residual terms by the normal distribution considering the data only within the 1.5 times of the standard deviation. It can be seen that the tracks in Figure 3.12 (d) are smoother than the ones in Figure 3.12 (a) and the tracks in Figure 3.12 (c) are more fluctuated than the ones in Figure 3.12 (a). The two approaches for modeling the residual terms using normal distributions result in either overly fluctuated or overly smoothed tracks. In contrast, it seems that the modeling of the residual terms using empirical distributions succeeds in reproducing an accurate fluctuation in the historical typhoon tracks.
The statistics of the transitions of the typhoons simulated with the proposed model are calculated. These are compared to the statistics of the historical typhoons. Moreover, for comparison two competing (not proposed) models are developed and the statistics of the typhoons simulated by these models are also calculated. These competing models are, based on the proposed modeling, the ones whose regression models’ are estimated either by assuming spatial homogeneity or by assuming no seasonality.

In Figure 3.13, cumulative annual average numbers (CAAN’s) of typhoons are shown as a function of the translation speed, translation angle and central pressure respectively. These statistics are obtained by counting the typhoons traveling at the latitude of 20°N or 35°N and at longitudes between 120°E and 160°E. CAAN’s for translation speed and angle are the measures of the typhoons’ movements and CAAN’s for central pressure are the measures of the typhoons’ intensity. The figure shows that the proposed model, as well as the second competing model (no seasonality), perform well agreeing with the statistics obtained by historical records at both latitudes. On the other hand, the simulation with the first competing model (spatial homogeneity) fails to generally reproduce the statistics obtained from the historical record.

In Figure 3.14, the statistics are shown for the month of September only. It is seen that the simulated results from the proposed model fit the historical statistics for all three state variables at both latitudes. On the other hand, the first competing model fails to reproduce the statistics obtained from the historical record especially at 35°N, which
may be reasoned by the accumulation of errors in the simulation starting from lower latitudes. The second competing model also fails notably at $35^\circ$N, where the seasonality is more dominant.

Figure 3.14. Cumulative average numbers of typhoons in September calculated with the historical records and the Monte Carlo simulations as a function of the translation speed, translation angle and central pressure at latitudes $20^\circ$N and $35^\circ$N. Results correspond to 10000 one-year typhoon events generated by Monte Carlo simulation.

In order to examine the sensitivity on the choice of the function, alternative models based on various combinations of functions are investigated. A summary of them is provided in Table 3.1. For those alternative models, the coefficients are estimated through the method described in subsection 3.3.2.2 and the residual terms are all empirically modeled. In Figure 3.15, the statistics obtained by the historical typhoon as well as by the simulations based on alternative models are shown. It can be seen that the statistics obtained by all the models fit the one obtained by the historical typhoon.

Table 3.1. Summary of alternative models.

<table>
<thead>
<tr>
<th>Modeling</th>
<th>Functional form utilized</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Translation speed</td>
</tr>
<tr>
<td>0</td>
<td>(3.10)</td>
</tr>
<tr>
<td>1</td>
<td>(3.7)</td>
</tr>
<tr>
<td>2</td>
<td>(3.12)</td>
</tr>
<tr>
<td>3</td>
<td>(3.10)</td>
</tr>
</tbody>
</table>
Probabilistic modeling of typhoon transition in the future

3.3.4 Discussion remarks

Plausible functions are explored by means of cAIC. It is found that for many of the grids and months examined simpler functions for the modeling of the typhoon transition are more suitable. By the simulation, it is found that the choice of the functions among different versions of a model does not play a significant role in the statistical characteristics of the typhoon transition as long as the necessary order of autoregressive explanatory variables is included. On the one hand, the functions with a lesser number of explanatory variables require lesser amount of historical records to estimate the coefficients at the same confidence level. This suggests employing simpler functions in cases with a limited number of typhoon records. This is useful for modeling the typhoon events under climate change, since research works indicate that the frequency of their occurrence will decrease under climate change in the future, see e.g. Bengtsson et al. (2007) and Knutson et al. (2010). On the other hand, if more accurate prediction of typhoon transition is required, e.g. the forecasting of an emerging typhoon is of interest, models having more explanatory variables could be advantageous since they facilitate the use of more information.

The method utilized in the present dissertation accounts for the spatial inhomogeneity and seasonality, reflecting the visual observation of the scatter plots. The simulation results show that the spatial inhomogeneity has to be appropriately taken into account in the modeling of the typhoon transition. The simulated results in Figure 3.13 show

Figure 3.15. CAAN’s calculated with the historical records and the Monte Carlo simulations as a function of the translation speed, translation angle and central pressure at latitude 20°N, 35°N. 0, 1, 2, 3 represent the corresponding modeling. Results correspond to 10000 one-year typhoon events generated by Monte Carlo simulation.
that the statistics are not too sensitive to the consideration of the seasonality, as long as
the annual statistics are accounted for. This is consistent with the conclusions of Graf
and Nishijima (2011), where the annual maximum wind speed is examined. However,
results illustrated in Figure 3.14 also indicate the importance of modeling the
seasonality in the case that the typhoon transition in a specific season is of interest.
However, the seasonality has not attracted sufficient attention in the statistic-based
modeling of typhoon transition, except modeling in Emanuel et al. (2006) and Graf et
al. (2009).

The residual terms are found not to follow the normal distribution. The fluctuation of
the simulated tracks is sensitive to the modeling of the residual terms. Appropriate
modeling of the residual terms can succeed in reproducing the fluctuation of the
typhoon tracks facilitating a more precise assessment of typhoon hazards and risks of
geographically large-scale portfolios. The reason for that is that either overly fluctuated
or overly smoothed tracks might lead to a systematic bias of spatial correlation in the
estimation of typhoon hazards and risks.

The quality of statistic-based transition modeling crucially relies on the amount of
available typhoon data. Therefore, the quality of simulated results at regions with very
few historical records is questionable since the statistical information of transition is
borrowed from other regions. This obstacle might be overcome by modeling the
intrinsic mechanism of typhoon transition, say e.g. by modeling the impact of
climatological and surrounding environment. Emanuel et al. (2006) make an initial
effort towards this direction, which may serve to resolve this matter.

3.3.5 Conclusion

The modeling of the typhoon transition is investigated by means of an extensive
statistical analysis. Firstly, the estimated ACF’s and PACF’s for the state variables of
the typhoon indicate that the second order of the autoregressive models is sufficient.
Secondly, by the cAIC, it is found that for many of the grids and months examined,
simpler functions for the modeling of the typhoon transition are more suitable. Thirdly,
the choice of the functions is not significant in the transition modeling; however,
modeling of the residual terms has a significant impact on the fluctuation of the
simulated typhoon tracks. Finally, the consideration of the spatial inhomogeneity is
important and the consideration of the seasonality is also of importance if the typhoon
transition in a specific season is of interest. Based on these statistical analyses, the
modeling of typhoon transition is proposed accordingly.
4 Reliability-based modeling of vulnerability

4.1 Introduction

With a reliability-based vulnerability model it is possible to estimate the efficiency of risk reduction measures intended for parts of building elements. However, such a model is not available in Japan and the one developed and used in the USA is not applicable to Japan for the reasons mentioned in chapter 2. This chapter aims at presenting an approach for developing reliability-based vulnerability models for residential buildings in Japan, taking basis on the merits of the state of the art of reliability-based vulnerability modeling. Based on that, a provisional version of vulnerability models is proposed. By throughout examination of the model, information and data necessary for developing a more credible vulnerability model are identified and discussed.

4.2 The modeling components

For the development of a reliability-based fragility model for residential buildings in Japan three non-structural failures, see section 1.3, are considered in this dissertation. These account for a large fraction of the wind induced damages to residential buildings in Japan. Several post-disaster surveys and analysis, e.g. Nishimura et al. (2009), find that windborne debris is the major cause of windows' failures especially in urban areas. Therefore, this dissertation concentrates on windows' failures by flying debris and wind pressure. It is however assumed that roof tiles are the only source of flying debris. In order to account for the causal relationship between the roof tiles' failure and the windows' failure caused by debris impact, a debris flying model is employed.

In this dissertation two failure scenarios are considered. The first one is: roof tiles fail at first, then some of them may hit windows as flying debris and cause the failure of windows increasing the internal building pressure and eventually roof sheathings of the building may fail. The other failure scenario is: windows fail due to gusty wind pressures at first and then the same failure process as in the first failure scenario follows.

The detailed modeling approach is described in the following sections. Firstly, the model building and the surrounding conditions are introduced in section 4.3. Secondly, the modeling of wind load is described in section 4.4. Thirdly, the modeling of three failures is described in sections 4.5 to 4.7 respectively. Then, simplistic failure cost models, described in section 4.8, are developed taking into account the prices of building materials as well as execution costs for repair work etc. This together with the developed fragility models constitutes the vulnerability model. The components of the
vulnerability model are illustrated in Figure 4.1. Note that the aforementioned components are developed to describe failures at an instantaneous point in time. The estimation of the fragility over the entire period of a typhoon event is thus obtained by integrating the failures at the instantaneous times. The integration is performed through Monte Carlo simulation. The procedure for this is described in subsection 4.9.1. Lastly, subsection 4.9.2 explains the way for developing the vulnerability model.

![Figure 4.1. Components of vulnerability model.](image)

### 4.3 Model building and surrounding condition

The vulnerability model is developed considering model buildings representative of typical residential buildings in Japan. The model buildings are a two-storey wood-frame building with a gable roof, see Figure 4.2 also for their components. Specifically, two model buildings, denoted as building type 1 and type 2 in the present dissertation, are considered. In the figure, \( w \) and \( h \) are the width and height respectively of a roof tile, \( w_{\text{eff}} \) and \( h_{\text{eff}} \) are the effective width and height respectively taking into account the overlaps of roof tiles, \( a \) and \( b \) are the width and height respectively of a roof sheathing. The assumed roof tile is a typical Japanese tile, and its density is denoted as \( \rho_t \). The roof sheathing element is assumed to be made of plywood. The building geometry and the other parameters of the roof tiles and sheathings are provided in Table 4.1. In accordance with the assumed building geometry and parameters of the roof tiles and sheathings, the roof of building type 1 is covered by 1152 pieces of roof tiles and 24 sets of roof sheathings and the roof of building type 2 is covered by 1440 pieces of roof tiles and 30 sets of roof sheathings. The area of the window in the first floor (defined as the area between the heights \( H_3 \) and \( H_2 \) in Figure 4.2) is assumed to be 15% of the area of the wall of the first floor for each building side. Note that it is assumed that only the first floor windows can be hit by flying debris. Thus, the area of the windows in the ground floor is not modeled. This assumption is based on the observation in Japan that the window failure of this
two-storey building often occurs on the first floor rather than on the ground floor. This may be explained by the fact that the residential buildings are generally closely located and between the adjacent buildings there are cars, trees etc. which can protect the window on the ground floor. Furthermore, it is assumed that there is only a single (aggregated) window on each side of the building.

Figure 4.2. Geometries of model building and building elements.
Table 4.1. Parameter of model building, roof tile and roof sheathing.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Type 1</th>
<th>Type 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>$H_1$</td>
<td>7.0 [m]</td>
<td>7.7 [m]</td>
</tr>
<tr>
<td>$H_2$</td>
<td>6.2 [m]</td>
<td>6.2 [m]</td>
</tr>
<tr>
<td>$H_3$</td>
<td>3.5 [m]</td>
<td>3.5 [m]</td>
</tr>
<tr>
<td>$B$</td>
<td>6.2 [m]</td>
<td>6.2 [m]</td>
</tr>
<tr>
<td>$D$</td>
<td>9.3 [m]</td>
<td>9.3 [m]</td>
</tr>
<tr>
<td>$\beta$</td>
<td>26.7°</td>
<td>45°</td>
</tr>
</tbody>
</table>

Roof tile

| $h$            | 0.315 [m]    |
| $w$            | 0.295 [m]    |
| $h_{\text{eff}}$ | 0.275 [m]   |
| $w_{\text{eff}}$ | 0.225 [m]   |
| $\rho$         | 3000.0 [kg/m³] |

Roof sheathing

| $a$            | 1.22 [m]     |
| $b$            | 2.44 [m]     |

The model building is assumed to be surrounded by buildings that are identical to the model building. The spatial building density $C_A$ (hereafter, building density) is defined upon the database developed by the research group at the Tokyo Polytechnic University (TPU (2007)), see Figure 4.3, which is defined as:

$$C_A = \frac{B \cdot D}{B' \cdot D'}.$$  \hspace{1cm} (4.1)

where $B'$ and $D'$ are the distances of adjacent buildings along the breadth and depth of the building respectively, see Figure 4.3. The surrounding conditions for $C_A = 0.1, 0.3, 0.6$ are illustrated in Figure 4.4. The assumed surrounding condition corresponds to the roughness category III in the AIJ Load Recommendation (AIJ (2004)).

Figure 4.3. Illustration of the definition of building density.
4.4 Wind load modeling

The gust wind load $L$ is defined using a 3-second gust wind. It is assumed to be modeled as:

$$L = \frac{1}{2} \rho_a U_{10\text{min}}^2 (1 + 2 I_u G_a)(C_{p,\text{out}} - C_{p,\text{in}}),$$  \hspace{1cm} (4.2)

where $\rho_a$ is the air density taken equal to 1.29 [kg/m$^3$], $U_{10\text{min}}$ is the reference 10-minute sustained wind speed which corresponds to the AIJ roughness category III at the roof height, i.e. $H_i = 7.0$ [m], $I_u$ is the turbulence intensity, $G_a$ is the peak factor and assumed to follow the lognormal distribution with a median of 3.2 and a coefficient of variation (COV) of 0.125, see the JCSS Probabilistic Model Code (JCSS (2001)). In the following this is denoted as $LN(\ln(3.2),0.125)$. $C_{p,\text{out}}$ and $C_{p,\text{in}}$ are respectively the external and internal pressure coefficients, which are functions of the location of the building surface. The value of $C_{p,\text{out}}$ for a window is approximated by the average of the external pressure coefficients on the wall of the first floor. Note that it is found that the values of the external pressure on the first floor of building are rather close, while one aggregated window on each side of wall is assumed in this dissertation. There may be pressure in the cavity beneath the tile. However, the research on this aspect is very limited and corresponding value is hardly available. In this dissertation $C_{p,\text{in}}$ is assumed to be zero for the modeling of wind load acting on roof tile. For the modeling of window failure due to wind pressure and roof sheathing failure, the value of $C_{p,\text{in}}$ is determined depending on the state of the windows. If no window fails, $C_{p,\text{in}}$ is assumed to be zero. If one or more windows are in the state of failure, $C_{p,\text{in}}$ is assumed to be the average of the external pressure coefficients at the locations of the failed window(s), see Vickery et al. (2006a).

The surrounding condition and relative wind direction affect the external pressure coefficients. The values of the external pressure coefficients utilized for the model buildings are adopted from the database developed by TPU (2007). The database was developed based on wind tunnel experiments. It contains the external pressure coefficients for different building orientations and wind directions.
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coefficient distributions over the entire building envelop under various surrounding conditions for 16 relative wind directions, see Figure 4.5. As an example, Figure 4.6 illustrates the contours of the external pressure coefficients of a gable roof for the cases $C_A = 0.1, 0.3, 0.6$ and relative wind directions 1 and 5. It should be mentioned that the wind tunnel experiment undertaken by TPU (2007) used the wind with turbulence intensity of 0.25 for all these three building densities, whereas in reality the turbulence intensity may vary. In the following, the analysis of vulnerability model is undertaken for the building densities of 0.3 and 0.6, which is in the range of building density of residential area in Japan and the turbulence intensity is assumed to $I_u = 0.25$ in the calculation of wind load in this dissertation.

Figure 4.5. Numbering of the wind direction relative to the building orientation.

Figure 4.6. Contours of external wind pressure coefficients for building densities equal to 0.1, 0.3, 0.6 and relative wind directions 1 and 5 for the gable roof (reproduced by the numerical data in TPU (2007)). The black dots are the measurement points in the wind tunnel experiment.
4.5 Roof tile failure modeling

The failure of a roof tile is defined to occur when the gust wind load \( L_{rt} \) acting on the roof tile exceeds its resistance \( R_{rt} \), see Figure 4.7. Thus, the probability \( P_{F,rt} \) of a roof tile failure is written as:

\[
P_{F,rt} = P[R_{rt} - L_{rt} < 0].
\]

The gust wind load \( L_{rt} \) is calculated from Equation (4.2). The resistance \( R_{rt} \) of a roof tile can be formulated as:

\[
R_{rt} = R_{G,rt} + R_{F} = R_{G,rt} \left(1 + R_{F}/R_{G,rt}\right) = R_{G,rt} \times \zeta,
\]

where \( R_{G,rt} = F_{rt} \cos \beta \), \( F_{rt} \) is the gravity force, \( \beta \) is the angle of roof slope, \( R_{F} \) is a part of roof tile’s resistance that excludes the gravity force, e.g. due to mechanical attachments of the roof tile to the roof structure and locking by adjacent roof tiles. \( \zeta \) is the index accounting for the resistance of the roof tile as the times of its gravity force. \( R_{G,rt} \) is assumed to follow the lognormal distribution with a COV of 0.05. Based on the assumptions on the geometry and density of the roof tile, the median of \( R_{G,rt} \) is obtained to be 392 [Pa]; hence, \( R_{G,rt} \sim LN(\ln(392),0.05) \).

Okada and Kikitsu (2005) have conducted experiments to estimate roof tile resistances of different tile types (normal, wind-resistant), means of attachments (simple nail, screwed nail etc.), size and depth of nails, attachments ratios (all, staggered and every other/three rows) and wood types (plywood, cedar board etc.). According to the experimental results, for example, the mean value of normal roof tiles with simple nail/50[mm]/20[mm]/staggered/plywood respectively is 657 [Pa] and the mean value of normal roof tiles with simple nail/50[mm]/20[mm]/all/plywood respectively is 1394 [Pa]. In case more resistant tiles and attachment methods are adopted the resistance becomes higher and up to 10000 [Pa]. In this dissertation it is estimated that the average value of the resistance ranges approximately between 600-2400 [Pa] depending on the regions of Japan. In the development of the vulnerability model in subsection 4.10.3, the cases of \( \zeta = 1,2,4,6,25 \) are illustrated, corresponding to...
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medians of 392, 784, 1568, 2352, 9800 [Pa] respectively. These values cover the roof tile’s resistance from the weakest to the strongest case. The corresponding attachments are given in Table 4.2.

Table 4.2. Attachments for various roof tile’s resistance.

<table>
<thead>
<tr>
<th>ζ</th>
<th>Median of resistance [Pa]</th>
<th>Attachment</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>392</td>
<td>Normal tile/no attachment</td>
</tr>
<tr>
<td>2</td>
<td>784</td>
<td>Normal tile/simple nail (13xL55) with 55[mm] and 25[mm]/staggered/plywood</td>
</tr>
<tr>
<td>4</td>
<td>1568</td>
<td>Normal tile/simple nail(13xL55) with 55[mm] and 25[mm]/all/plywood</td>
</tr>
<tr>
<td>6</td>
<td>2352</td>
<td>Wind resistant tile/simple nail (13xL65) with 65 [mm] and 35 [mm]/staggered/plywood</td>
</tr>
<tr>
<td>25</td>
<td>9800</td>
<td>Wind resistant tile/screwed nail (12xL65) with 65 [mm] and 35 [mm]/all/plywood</td>
</tr>
</tbody>
</table>

It should be mentioned that in the practice the resistances of roof tiles at roof edges are likely to be significantly higher than others located elsewhere, since they are often attached to the roof structures with (more resistant) mechanical attachments. However, the information on the difference between the resistance of roof tiles at edges and other regions is hardly available in the literature. Since the percentage of roof tile having higher resistance is relative small in general, in the modeling of roof tile failures the resistances of roof tiles are assumed to be identical regardless its location. Thus, assuming that these roof tiles having higher resistance do not fail, the effective number of the roof tiles that fail can be smaller; hence, the vulnerability assessment in subsection 4.10.3 for the roof tile’s resistance of ζ = 1, 2, 4, 6 can be considered to be conservative.

4.6 Window failure modeling

4.6.1 Window failure by wind pressure

The failure of a window by wind pressure is defined by the wind load $L_w$ acting on the window exceeding the window’s resistance $R_w$. Thus, the probability $P_{F_{w,w}}$ of window failure due to wind pressure can be formulated as:

$$P_{F_{w,w}} = P[R_w - L_w < 0].$$

The calculation of $L_w$ follows from Equation (4.2). The distribution of the window’s resistance defined in this manner is quantified in Vickery et al. (2006a) and this is employed in this dissertation. Thus, the resistance $R_w$ follows the Weibull distribution with a scale parameter of 2628 [Pa] and a shape parameter of 4.7. The 5%-quantile of the assumed resistance is 1397 [Pa]. No systematic survey is publicly available on the
resistance of standard window glasses used for residential buildings in Japan; however, by referring to the minimum requirement in the Japanese design code and its associated documents (Notification No. 1454 and 1458 of the Ministry of Construction as of 2000) as well as catalogues of window glasses provided by manufacturers the value seems comparable to that in Japan.

4.6.2 Debris flying modeling

The flying trajectory of a roof tile is modeled on the basis of the model proposed by Lin and Vanmarcke (2010). This is a probabilistic hybrid model developed upon kinematic consideration and experimental and field observations. The flying debris is assumed to fly along with a gust wind speed $U_{3sec, max}$:

$$U_{3sec, max} = U_{10min} + G_u \sigma_u = (1 + G_u I_u) U_{10min}, \quad (4.6)$$

where $\sigma_u$ is the standard deviation of the gust wind speed.

The landing position of the flying debris, with coordinates $(x, y)$, is modeled by a two dimensional normal distribution and its probability density function $\mu(x, y)$ is expressed as:

$$\mu(x, y) = \frac{1}{(2\pi \sigma_x \sigma_y)} \exp \left[ -\frac{1}{2} \left( \frac{(x-m_x)}{\sigma_x} \right)^2 + \left( \frac{y}{\sigma_y} \right)^2 \right]. \quad (4.7)$$

Here, the coordinate is such that $x$ is along-wind direction, $y$ is across-wind direction and the origin $O$ is the projection of the center of the roof of the source building onto the effective ground (defined later), see Figure 4.8. Obviously, the landing position and the parameters in Equation (4.7) are functions of the gust wind speed; however, for the sake of simplicity this is not signified and mentioned in the following unless necessary. $\sigma_x, \sigma_y$ are the standard deviations of the along-wind and across-wind flying distances respectively and $m_x$ is the mean of the along-wind flying distance. The COV of the along-wind flying distance is denoted as $\eta_x$, i.e. $\sigma_x = \eta_x m_x$. In Lin and Vanmarcke (2010), the value of $\eta_x$ is assumed to be 0.35, which is estimated based on the field debris observations provided in the post-damage survey of Twisdale et al. (1996). Their estimation of $\eta_x$ included roof tiles and sheathing as the debris type. In contrast, this dissertation only considers roof tiles as the source of debris. Thus, the uncertainties implied in the modeling of trajectory of flying debris are expected to be smaller and it is postulated that $\eta_x = 0.3$. Moreover, it is assumed that the standard deviations of along-wind and across-wind flying distances are equal, i.e. $\sigma_y = \sigma_x$. This assumption follows from the observation that the variation of the debris trajectory in the along-wind and across-wind directions is nearly symmetrical, see Tachikawa (1983), Lin et al. (2006), Lin and Vanmarcke (2010). The mean along-wind flying distance $m_x$ is modeled as a function of the gust wind speed in accordance
with the numerical experiment described in Holmes et al. (2005). Table 4.3 shows several correspondences between the gust wind speed and the mean along-wind flying distance \( m_x \) for building type 1. Note that the mean along-wind flying distance is the travel distance until a flying debris reaches the effective ground level, which is defined as \( H_1 \) [m], see Figure 4.8, above the ground level. In the numerical experiment for obtaining the value of \( m_x \), the initial kinematic conditions on the flying debris is required. These conditions are assumed in this dissertation as follows: a roof tile starts flying at the center of the roof in a perpendicular direction to it. The roof slope is taken equal to \( \beta \). Given a specific wind speed and direction, together with the initial conditions, the flying debris trajectory is obtained; hence, \( m_x \) is estimated. Hereafter, this trajectory is called the most likely trajectory.

Table 4.3. Vaule of \( m_x \) as a function of 3-second gust wind speed for building type 1.

<table>
<thead>
<tr>
<th>3-second gust wind speed [m/s]</th>
<th>( m_x ) [m]</th>
</tr>
</thead>
<tbody>
<tr>
<td>30</td>
<td>5.2</td>
</tr>
<tr>
<td>35</td>
<td>6.5</td>
</tr>
<tr>
<td>40</td>
<td>7.8</td>
</tr>
<tr>
<td>45</td>
<td>9.1</td>
</tr>
<tr>
<td>50</td>
<td>10.3</td>
</tr>
<tr>
<td>55</td>
<td>11.5</td>
</tr>
<tr>
<td>60</td>
<td>12.6</td>
</tr>
</tbody>
</table>

For a given gust wind speed: \( U_{3sec} \)

![Diagram of flying debris trajectories and criterion for debris hitting on the wall.](image)

Figure 4.8. Flying debris trajectories and criterion for debris hitting on the wall.

The mathematical expression that flying debris hits a wall of the target building is obtained by projecting the wall on the effective ground level along with a trajectory that crosses the eave, i.e. at a height of \( H_2 \) [m] of the target wall. Note that this
trajectory is a function of the wind speed and direction as well as of the relative positions between the target and the source building.

Consider the hypothetical case that the target and the source building are located in such a way that the most likely trajectory crosses exactly the eave of the target building, see Figure 4.8. The area $S_m$ and the position $Pos_m$ of the projected wall refer to the size and shape of the projected wall and the coordinate of its center respectively. The area and position together frame the projected wall on the plane at the effective ground level. Hence, the probability $\pi_m$ that debris hits the wall in this hypothetical case is calculated as:

$$\pi_m = \int_{S_m,Pos_m} \mu(x, y) \, dx \, dy. \quad (4.8)$$

In the following a general case is considered. Denoting by $S$ and $Pos$ the area and position respectively of the projected wall on the effective ground, the probability $\pi$ that debris hits a wall is defined and calculated by:

$$\pi = \int_{S,Pos} \mu(x, y) \, dx \, dy. \quad (4.9)$$

In principle the area $S$ and the position $Pos$ can be determined in accordance with the numerical model by Holmes et al. (2005) for different combinations of the relative positions of the target and the source buildings, different wind speeds and directions, in the same manner as the case of the most likely trajectory. However, this is computationally expensive and not feasible for Monte Carlo simulation. Therefore, a simplified approach for evaluating the integral in Equation (4.9) is employed by an approximation such that $S = S_m$. Thereby, $\pi$ is computed as:

$$\pi = \int_{S,Pos} \mu(x, y) \, dx \, dy. \quad (4.10)$$

The approximation of $S = S_m$ is justified by the fact that the value of $\pi$ becomes less sensitive to $S$ as the position of the projected wall is located farther from the most likely landing position of flying debris.

### 4.6.3 Window failure by debris

This subsection describes the way to calculate the probability that a window on the target building fails due to the impact of debris from the surrounding buildings. Assume that the $l^{th}$ window ($l = 1, 2, 3, 4$) of the target building may be impacted by the debris from a surrounding building $i$ ($i = 1, 2, \ldots, I$), where $I$ is the number of the considered surrounding buildings. The probability that one tile as flying debris from building $i$ hits the wall of the target building can be calculated using Equation (4.10).
It is denoted hereafter as $\pi_i$. Then, the probability $\pi_{i,j}$ that one tile from building $i$ hits the $l^{th}$ window can be written as:

$$\pi_{i,j} = \pi_i \cdot \pi_{ij},$$  \hspace{1cm} (4.11)

where $\pi_{ij}$ is the conditional probability that the debris will hit the window given that the debris hits the wall. It is assumed that the window always fails if the debris hits the window. Therefore, the probability that debris from one tile from the building $i$ causes the failure of the $l^{th}$ window is equal to $\pi_{i,j}$.

In case debris from two or more tiles fly from one source building it is assumed that the individual probabilities of causing the failure of a window are identical. Assume that the number of failed roof tiles from building $i$ is $n_i$. If the trajectories of these tiles are assumed to be independent, the probability $p_{i,j}$ that the $l^{th}$ window of the target building fails by the impacts of these tiles is calculated as:

$$p_{i,j} = 1 - \left(1 - \pi_{i,j}\right)^{n_i}.$$  \hspace{1cm} (4.12)

Note however that it is unlikely that the trajectories of these tiles from one building in a same gust event are fully independent. This is because often a cluster of roof tiles fail simultaneously by the same wind gust and become debris that fly along with the same path. Thus, the trajectories of the failed tiles are actually correlated to some extent. For that reason, the other extreme case is also considered in this dissertation, i.e. the trajectories of the flying tiles are fully dependent. Under this assumption, $p_{i,j}$ is calculated as:

$$p_{i,j} = 1 - \left(1 - \pi_{i,j}\right)^1 = \pi_{i,j}.$$  \hspace{1cm} (4.13)

In this dissertation both cases are investigated. Furthermore, it is assumed that the trajectories of flying debris from different surrounding buildings are independent. Thus, the probability $P_l$ that the $l^{th}$ window of the target building fails by the impact of the flying debris from all the surrounding buildings is calculated as:

$$P_l = 1 - \prod_{j=1}^{I} (1 - p_{i,j}).$$  \hspace{1cm} (4.14)

In order to calculate the probability $P_l$ the probability $\pi_{ij}$ has to be estimated. The method to estimate $\pi_{ij}$ is adapted from the approach used in Lin et al. (2010). The probability $\pi_{ij}$ is the product of (i) the probability that debris hits the wall at which the $l^{th}$ window is located and (ii) the conditional probability that the debris that hits the wall hits the window, which is computed as follows. The way to the computation of $\pi_{ij}$ is discussed in the following.
The two sides of the target building facing the source building, namely the normal and the closest side face, as well as the relative angle $\theta_i$ between the source building $i$ and the target building are defined as in Figure 4.9. The probability that debris hits each of the four building faces is assigned as being equal to: $\cos \theta_i$ for the normal face, $\sin \theta_i$ for the closest side face, and zero for the other two faces.

The probability $r$ that debris hits a window on one of the four building faces conditional on that the debris hits the building face is assumed to be the ratio of the window area to the wall areas as $\sum A_i/(B \cdot (H_3 - H_2))$ or $\sum A_i/(D \cdot (H_3 - H_2))$. As mentioned earlier these are equal to 0.15. Hence, if the window is located on the normal face, $\pi_{ij} = r \cos \theta_i$; if window is located on the closest side face, $\pi_{ij} = r \sin \theta_i$; otherwise $\pi_{ij} = 0$.

Figure 4.9. Relative position between the source and the target building for the calculation of the probability that debris hits the window conditional on that it hits the wall, after Fig.1 in Lin et al. (2010).

### 4.7 Roof sheathing failure modeling

The safety margin of a roof sheathing is modeled as:

$$ M_{rs} = R_{G,rt} + R_{rs}' - L_{rs} = R_{G,rt} + R_{rs}' - (W_{out} + W_{in}), $$

(4.15)

where $R_{G,rt}$ is defined in section 4.5, $R_{rs}'$ is the resistance of roof sheathing. Here, $R_{rs}' \sim LN(\ln(2598),0.11)$ [Pa] is assumed which is adopted from Vickery et al. (2006b). $L_{rs}$ is the wind load acting on the roof sheathing, which in turn is the sum of the external wind pressure $W_{out}$ and the internal wind pressure $W_{in}$, see Figure 4.10. These are calculated from Equation (4.2). The probability $P_{F,rs}$ of a roof sheathing failure is written as:

$$ P_{F,rs} = [M_{rs} < 0]. $$

(4.16)
Fragilities of roof sheathing for residential buildings in Japan are estimated in Kikitsu and Kawai (2009). They have conducted experiments for estimating the resistances of typical joints among roof sheathing elements and on this basis they have estimated the relevant resistances. According to the experiments the median of the resistance of a rafter at the roof edge is in the range of 50-110 [m/s] at 3-second gust wind speed, depending on the type of joints among the roof sheathing elements. For comparison the median value of the resistance assumed in this dissertation is approximately converted into 3-second gust wind speed using Equations (4.2) and (4.6) and substituting median values for the random variables and representative values for the other parameters. The calculated median corresponds to approximately 70 [m/s], which is in the range mentioned above; however, less vulnerable roof sheathing is plausible.

### 4.8 Failure cost modeling

In this dissertation only monetary costs are considered as a consequence of the failures. The failure cost models are developed for the roof tile and window failure. A failure cost model for the roof sheathing failure is not proposed or utilized, since it is found that with the present assumptions on the fragility modeling and the scale of wind speed considered in the dissertation, the probability of the roof sheathing is negligibly small, see subsection 4.10.2; hence, not significantly contributing to the overall risk. Note that in this dissertation the considered maximum wind speed is only 32.7 [m/s] in terms of 10-minute sustained wind speed at the AIJ roughness category III at the height of 7 [m], see the following section for how the time series are employed in the development of the vulnerability model using Monte Carlo simulation.

The roof tile failure cost $C_{Tile}$ consists of the setup cost $C_S$, material cost $C_M$, execution cost $C_E$, decommission cost $C_D$ and overhead cost $C_O$. These cost components are estimated as:

$$C_M = x \cdot C_{M,\text{ref}},$$

(4.17)
Reliability-based modeling of vulnerability

\[
C_E = r_E (C_S + C_M), \quad (4.18)
\]

\[
C_D = x \cdot C_{D,u}, \quad (4.19)
\]

\[
C_O = r_O (C_S + C_M + C_E + C_D) \quad (4.20)
\]

where \(x\) is the amount of square meters of failed roof tile, \(C_{M,u}\) and \(C_{D,u}\) are the unit (\(m^2\)) cost of material cost and decommission cost respectively and \(r_E\) and \(r_O\) are the rate of execution cost and overhead cost respectively. These values are estimated for individual roof tile’s resistance corresponding to a specific attachment. They are shown in Table 4.4, Table 4.5, Table 4.6, Table 4.7 and Table 4.8 respectively for the roof tile’s resistance of \(\zeta = 1, 2, 4, 6, 25\). In addition to abovementioned cost components, the window failure cost also includes the property damage and they are shown in Table 4.9.

### Table 4.4. Roof tile failure cost for roof tile’s resistance of \(\zeta = 1\).

<table>
<thead>
<tr>
<th>Roof tile failure cost</th>
<th>Quantity</th>
<th>Unit</th>
<th>Price [JPY]</th>
<th>Subtotal [JPY]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Setup cost</td>
<td>1</td>
<td>set</td>
<td>10000</td>
<td>10000</td>
</tr>
<tr>
<td>Material cost</td>
<td>1</td>
<td>m(^2)</td>
<td>6000</td>
<td>6000</td>
</tr>
<tr>
<td>Execution cost (15%)</td>
<td></td>
<td></td>
<td></td>
<td>2400</td>
</tr>
<tr>
<td>Decommission cost</td>
<td>1</td>
<td>m(^2)</td>
<td>3000</td>
<td>3000</td>
</tr>
<tr>
<td>Overhead cost (50%)</td>
<td></td>
<td></td>
<td></td>
<td>10700</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td></td>
<td></td>
<td><strong>32100</strong></td>
</tr>
</tbody>
</table>

### Table 4.5. Roof tile failure cost for roof tile’s resistance of \(\zeta = 2\).

<table>
<thead>
<tr>
<th>Roof tile failure cost</th>
<th>Quantity</th>
<th>Unit</th>
<th>Price [JPY]</th>
<th>Subtotal [JPY]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Setup cost</td>
<td>1</td>
<td>set</td>
<td>10000</td>
<td>10000</td>
</tr>
<tr>
<td>Material cost</td>
<td>1</td>
<td>m(^2)</td>
<td>6000</td>
<td>6000</td>
</tr>
<tr>
<td>Execution cost (30%)</td>
<td></td>
<td></td>
<td></td>
<td>4800</td>
</tr>
<tr>
<td>Decommission cost</td>
<td>1</td>
<td>m(^2)</td>
<td>5000</td>
<td>5000</td>
</tr>
<tr>
<td>Overhead cost (50%)</td>
<td></td>
<td></td>
<td></td>
<td>12900</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td></td>
<td></td>
<td><strong>38700</strong></td>
</tr>
</tbody>
</table>

### Table 4.6. Roof tile failure cost for roof tile’s resistance of \(\zeta = 4\).

<table>
<thead>
<tr>
<th>Roof tile failure cost</th>
<th>Quantity</th>
<th>Unit</th>
<th>Price [JPY]</th>
<th>Subtotal [JPY]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Setup cost</td>
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<td>set</td>
<td>10000</td>
<td>10000</td>
</tr>
<tr>
<td>Material cost</td>
<td>1</td>
<td>m(^2)</td>
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<td>6000</td>
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<tr>
<td>Execution cost (60%)</td>
<td></td>
<td></td>
<td></td>
<td>9600</td>
</tr>
<tr>
<td>Decommission cost</td>
<td>1</td>
<td>m(^2)</td>
<td>6000</td>
<td>6000</td>
</tr>
<tr>
<td>Overhead cost (50%)</td>
<td></td>
<td></td>
<td></td>
<td>15800</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td></td>
<td></td>
<td><strong>48400</strong></td>
</tr>
</tbody>
</table>
Table 4.7. Roof tile failure cost for roof tile’s resistance of $\zeta = 6$.

<table>
<thead>
<tr>
<th>Roof tile failure cost</th>
<th>Quantity</th>
<th>Unit</th>
<th>Price [JPY]</th>
<th>Subtotal [JPY]</th>
</tr>
</thead>
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<tr>
<td>Setup cost</td>
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<td>set</td>
<td>10000</td>
<td>10000</td>
</tr>
<tr>
<td>Material cost</td>
<td>1</td>
<td>m$^2$</td>
<td>8000</td>
<td>8000</td>
</tr>
<tr>
<td>Execution cost (40%)</td>
<td>1</td>
<td>m$^2$</td>
<td>6000</td>
<td>2400</td>
</tr>
<tr>
<td>Decommission cost</td>
<td>1</td>
<td>m$^2$</td>
<td>6000</td>
<td>6000</td>
</tr>
<tr>
<td>Overhead cost (50%)</td>
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<td>m$^2$</td>
<td>8000</td>
<td>4000</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td></td>
<td></td>
<td>47800</td>
</tr>
</tbody>
</table>

Table 4.8. Roof tile failure cost for roof tile’s resistance of $\zeta = 25$.

<table>
<thead>
<tr>
<th>Roof tile failure cost</th>
<th>Quantity</th>
<th>Unit</th>
<th>Price [JPY]</th>
<th>Subtotal [JPY]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Setup cost</td>
<td>1</td>
<td>set</td>
<td>10000</td>
<td>10000</td>
</tr>
<tr>
<td>Material cost</td>
<td>1</td>
<td>m$^2$</td>
<td>8000</td>
<td>8000</td>
</tr>
<tr>
<td>Execution cost (100%)</td>
<td>1</td>
<td>m$^2$</td>
<td>8000</td>
<td>8000</td>
</tr>
<tr>
<td>Decommission cost</td>
<td>1</td>
<td>m$^2$</td>
<td>8000</td>
<td>8000</td>
</tr>
<tr>
<td>Overhead cost (50%)</td>
<td>1</td>
<td>m$^2$</td>
<td>8000</td>
<td>4000</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td></td>
<td></td>
<td>66000</td>
</tr>
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Table 4.9. Window failure cost.

<table>
<thead>
<tr>
<th>Window failure cost</th>
<th>Quantity</th>
<th>Unit</th>
<th>Price [JPY]</th>
<th>Subtotal [JPY]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Material cost (Glass)</td>
<td>3.1</td>
<td>m$^2$</td>
<td>1200</td>
<td>3720</td>
</tr>
<tr>
<td>Material cost (Glass sealing)</td>
<td>3.1</td>
<td>m</td>
<td>290</td>
<td>899</td>
</tr>
<tr>
<td>Execution cost (30%)</td>
<td>3.1</td>
<td>m$^2$</td>
<td>5000</td>
<td>15500</td>
</tr>
<tr>
<td>Decommission cost</td>
<td>3.1</td>
<td>m$^2$</td>
<td>5000</td>
<td>10752.4</td>
</tr>
<tr>
<td>Overhead cost (50%)</td>
<td>200000</td>
<td></td>
<td></td>
<td>200000</td>
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<tr>
<td>Total</td>
<td></td>
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<td>232257.1</td>
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### 4.9 Vulnerability modeling

#### 4.9.1 Procedure of estimating fragility

The failure models explained above facilitate the estimation of the probabilities of failures at instantaneous points in time during a typhoon event. In order to obtain the fragility during a typhoon event, these failures must be integrated over time. This is performed by Monte Carlo simulation. The time interval between subsequent time steps assumed in the Monte Carlo simulation is 10 minutes.

As a basis for the Monte Carlo simulations, 30 time series of wind speed and direction of historical typhoon events in Japan are selected, see Appendix D for the information of these time series. Their selection accounts for various ranges of typhoon characteristics. These characteristics include the maximum wind speed during a
typhoon event, the change of wind direction and the duration of critically high wind speeds.

The Monte Carlo simulation is executed following the procedure illustrated in Figure 4.11. Therein, the random resistances of individual objects (roof tiles, windows and roof sheathings) are assumed to be independent. It is worth mentioning that it is necessary to choose a sufficiently long time interval at which the sustained wind speed in adjacent time period can be considered as independent, otherwise the wind speed in the adjacent time intervals are correlated, which will result in overestimation of fragility/vulnerability unless treated appropriately. 10-minute is supposed to be an appropriate option, while it is also the time interval for producing the quasi-steady pressure coefficients obtained by TPU (2007) and at which the time series of wind speed and direction is available in the Japan Meteorological Agency. A 10-minute sustained wind speed at the AIJ roughness category III at the height of 7 [m] is utilized as the input to the Monte Carlo simulations. Thus, the 10-minute sustained wind speeds measured at meteorological stations are converted employing the power laws for the vertical wind profile described in the Load Recommendation by AIJ (2004), see the Appendix C for the details. The peak factors at individual locations of the roof tiles are assumed to be fully dependent. All the buildings considered are aligned to the same orientation as shown in Figure 4.4; however, the orientation of these buildings is uniformly randomly generated. The fragilities for roof tiles and windows are estimated by crude Monte Carlo simulation. In contrast, the fragility for roof sheathing is estimated by conditional Monte Carlo simulations since the failure probability of each piece of roof sheathing is found to be small (see subsection 4.10.2) under the assumptions employed in this dissertation. This follows from the following formulation.
Figure 4.11. Flowchart with the steps for performing the simulation for estimating the fragility.
The probability $P_{F_{rs},q}(k)$ of the $q^{th}$ roof sheathing failure until time step $k (1, 2, \cdots, K)$, where $K$ is the number of discretized time steps during a typhoon event, is formulated as:

$$P_{F_{rs},q}(k) = P\left[ \bigcup_{t=1}^{k} R_q - L_{q,t} < 0 \right] = P\left[ R_q - \max_{t=1,2,\cdots,k} L_{q,t} < 0 \right],$$

(4.21)

where $R_q$ is the resistance of the $q^{th}$ roof sheathing and $L_{q,t}$ is the wind load at the location of the $q^{th}$ roof sheathing at time step $t (t = 1, 2, \cdots, k)$. Then, an estimator of $\hat{P}_{F_{rs},q}(k)$ can be written as:

$$\hat{P}_{F_{rs},q}(k) = \frac{1}{N} \sum_{i=1}^{N} F_{R_q}(L_{q,max,k}^{(i)}), L_{q,max,k}^{(i)} = \max_{t=1,2,\cdots,k} L_{q,t}^{(i)},$$

(4.22)

with $N$ being the number of simulations, $F_{R_q}(\cdot)$ being the cumulative distribution function of the resistance of the $q^{th}$ roof sheathing and $L_{q,t}^{(i)}$ being the $i^{th}$ realization of the wind load at the location of the $q^{th}$ roof sheathing at the time step $t$.

A substantial part of the losses due to the failure of roof sheathing is the property loss because of rain entering into the building through one of failed roof sheathings, it is meaningful to investigate also the case that at least one roof sheathing fails. The probability $P_{F_{rs}}(k)$ that at least one roof sheathing fails until time step $k$ is formulated as:

$$P_{F_{rs}}(k) = P\left[ \bigcup_{q=1}^{Q} R_q - \max_{t=1,2,\cdots,k} L_{q,t} < 0 \right].$$

(4.23)

Then, an estimator of $\hat{P}_{F_{rs}}(k)$ can be written as:

$$\hat{P}_{F_{rs}}(k) = \frac{1}{N} \sum_{i=1}^{N} P\left[ \bigcup_{q=1}^{Q} R_q - L_{q,max,k}^{(i)} < 0 \right], L_{q,max,k}^{(i)} = \max_{t=1,2,\cdots,k} L_{q,t}^{(i)} = \frac{1}{N} \sum_{i=1}^{N} \left( 1 - \prod_{q=1}^{Q} \left( 1 - P\left[ R_q - L_{q,max,k}^{(i)} \right] \right) \right)$$

(4.24)
4.9.2 Development of vulnerability model

The vulnerability is estimated based on the Monte Carlo simulation for the fragility together with the failure cost models; namely, realizations of the loss are obtained as a function of the states (failure/non-failure) of all considered elements of the building. The vulnerability model is then developed by curve-fitting of the expected losses caused by individual typhoon events as a function of the maximum wind speed during each typhoon event.

The individual models described in the previous sections facilitate to estimate the vulnerability of the model building for broader ranges of surrounding conditions and other parameters in the modeling. However, in subsection 4.10.3 the vulnerability model is presented only for a few representative cases for example one with building densities of 0.3 and 0.6. This is firstly because the building density of residential areas in Japan is often in the range between 0.3 and 0.6. Secondly it is also due to the restriction of the availability of the wind pressure coefficient in the database provided by TPU, i.e. the wind pressure coefficients are only available for building densities of 0.1, 0.3 and 0.6 with some specific conditions. Note that a high building density, say e.g. building density of 0.6, results in a short distance between adjacent buildings (as shown in Figure 4.4) and in such a situation the validity of the debris flying model and the developed debris-hit criterion is questionable. Thus, the developed vulnerability model for the building density of 0.6 should be kept in high caution.

4.10 Results

4.10.1 Individual modeling

The expected percentages of failed roof tiles are illustrated in Figure 4.12 as functions of the wind speed for three building densities, i.e. $C_d = 0.1, 0.3, 0.6$ and for two directions, i.e. directions 1 and 5 for building type 1 under the building density of 0.3. The illustrated results are calculated based on the assumption that the roof tile's resistance is equal to its gravity force, i.e. $\zeta = 1$. The expected percentage of failed tiles increases as the wind speed increases; however, below specific wind speeds no roof tiles are likely to fail. It is also observed that the relative wind direction plays a significant role. For example, at a wind speed of 35 [m/s] for $C_d = 0.1, 0.6$, all the roof tiles are likely to fail under direction 1, whereas only around 60% of them are expected to fail under direction 5.
Figure 4.12. Expected percentage of failed roof tiles as a function of wind speed for building type 1 with roof tile’s resistance of \( \zeta = 1 \) under building density of 0.3.

In Figure 4.12, it also illustrates several characteristics worth mentioning. For example, for the direction 1 the expected percentage of failed roof tiles for \( C_a = 0.6 \) at a wind speed less than 25 [m/s] is smaller than that for \( C_a = 0.3 \). This can be explained by the "protecting effect" present at high building densities; i.e. a building located in a dense building area tends to experience lower external wind pressures. In contrast, for direction 1 the expected percentage of failed roof tiles for \( C_a = 0.6 \) at a wind speed of 30 [m/s] is larger than that for \( C_a = 0.3 \). This sounds contradictory to the former observation; however, it is the reflection of the measured external pressure coefficients employed in this dissertation. In order to explain the reason for this, the cumulative numbers of measurement points of external pressure coefficients for \( C_a = 0.1, 0.3, 0.6 \) for the direction 1 are presented in Figure 4.13 (a). It is seen that the cumulative number for \( C_a = 0.3 \) is larger than that for \( C_a = 0.6 \) when the external pressure coefficient is less than a specific value which is between -0.30 and -0.25, and vice versa. The two curves of the cumulative numbers intersect at the value of the external pressure coefficient. The probabilities of failure of a roof tile as a function of the wind speed with the external pressure coefficients of -0.30, -0.29, -0.28, -0.27, -0.26, -0.25 are shown in Figure 4.13 (b). It is observed that the corresponding wind speed at which the tiles are more likely to start flying is around 25 [m/s]. This is why the curves of the expected percentages of failed roof tiles intersect at a wind speed slightly above 25 [m/s].
Figure 4.13. Illustration of (a) cumulative number of measurement point as a function of pressure coefficients for $C_d = 0.1, 0.3, 0.6$ in direction 1, (b) the failure probability of a roof tile as a function of 10-minute sustained wind speed with the external pressure coefficients between -0.30 and -0.25 under the roof tile’s resistance of $\zeta = 1$.

Figure 4.14 illustrates the probability that at least one window fails due to the impact of debris as a function of a 3-second gust wind speed. It presents the cases for $C_d = 0.1, 0.3, 0.6$ and directions 1 and 5 for building type 1. Note that the calculated probability considers flying debris only from adjacent buildings for illustrative purposes. However, in the estimation of the fragility by Monte Carlo simulation flying debris from all surrounding buildings is taken into account. It is observed that the building density plays a significant role on the probability of window failure due to the impact of debris. The probability of failure for $C_d = 0.3, 0.6$ is significantly higher than that for $C_d = 0.1$. This is due to the relationship between the distances among the buildings and the flying distance of the debris. The distance between the centers of adjacent buildings are 24.0, 13.9 and 9.8 [m] for $C_d = 0.1, 0.3, 0.6$ respectively, see also the relative distance illustrated in Figure 4.4. The most likely flying distance $m_x$ is, on the other hand, not more than 12.6 [m] when the 3-second gust wind speed is less
than 60 [m/s], see Table 4.3. In general the smaller the difference between the value of \( m_s \) and the distance between the adjacent buildings, the higher the probability of failure. The difference between the value of \( m_s \) and the distance between adjacent buildings under \( C_A = 0.1 \) is significantly larger than the difference between the value of \( m_s \) and the distance between the adjacent buildings both for \( C_A = 0.3 \) and \( C_A = 0.6 \) at the 3-second wind speed being less than 60 [m/s]. However, as the wind speed increases, the probability of window failure decreases if the flying distance of debris is likely to exceed the distance between the adjacent buildings, see e.g. the case of wind direction 1 at wind speed larger than 35 [m/s] for \( C_A = 0.6 \).

![Figure 4.14](image)

Figure 4.14. Probability that at least one window fails due to the impact of debris as a function of the wind speed for \( C_A = 0.1, 0.3, 0.6 \) and wind directions 1 and 5 for building type 1.

### 4.10.2 Cumulative fragility during a typhoon event

Figure 4.15 shows an example of the accumulation of the instantaneous failures over a typhoon event. The time series of wind speed and direction in this event are generated based on the observations at the Kagoshima meteorological station during typhoon Bart in 1999. The plots in the figure are for building type 1 under the case of \( C_A = 0.3 \). The time series of the mean value of the cumulative damage ratio (CDR)\(^7\) for each roof tile and window is presented for three cases. In case (a) the trajectories of flying debris from a source building at one time step are assumed to be independent and the roof tile’s resistance is taken equal to its gravity force, i.e. \( \zeta = 1 \). In case (b) the trajectories are assumed to be fully dependent and the roof tile’s resistance is assumed to be equal to its gravity force, i.e. \( \zeta = 1 \). In case (c) the roof tile’s trajectories are assumed to be fully dependent and its resistance is considered to be twice its gravity force, i.e. \( \zeta = 2 \). The plots in the figure show that the roof tile and window fragilities

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\(^7\) The damage ratio is defined as ratio of number of damaged building elements, e.g. roof tiles to the total number of building element.
Reliability-based modeling of vulnerability

are highly sensitive to $\zeta$ and the dependency of the trajectories. Note that the probability of window failure due to gust wind pressure is small ($\approx 1.8 \times 10^{-4}$) in this example, therefore, the window failure is virtually accounted for by the flying debris impact. In the time series of wind speed and direction illustrated in Figure 4.15, the wind speed increases from the time step 21 to 23, at which the maximum wind speed is achieved. It is observed that there is a significant increase in the mean CDRs for all three cases from the time step 22 to 23 relative to their increase from the time step 21 to 22. This is partly explained by the increase of the wind speed, however, also by the change of wind direction. This is explained in the following.

Figure 4.15. Cumulative fragility as a function of time for case (a): the trajectories of flying debris from a source building at one time step are independent and $\zeta = 1$, (b): the trajectories of flying debris from a source building at one time step are fully dependent and $\zeta = 1$, (c): the trajectories of flying debris from a source building at one time step are fully dependent and $\zeta = 2$.

The CDRs at each time step follow specific distributions. The estimated distributions for roof tile are illustrated in Figure 4.16 for the time steps 21, 22 and 23 in case (c). The aforementioned observation about the increase in the mean CDR is also reflected in the change of distribution of the CDR. There are two non-zero peaks for each of those distributions of the CDR at the time step 21, 22 and 23. From the time step 21 to
22, one peak at around the CDR value of 0.04 is strengthened and the other peak at around the CDR value of 0.075 shifts to around 0.125. From the time step 22 to 23 two peaks shift to the right; the peak at around the CDR value of 0.04 shifts to a CDR value of around 0.08 and the peak at around the CDR value of 0.125 shifts to around 0.14. It is remarkable that the peak at a CDR value of zero disappears. This shift of the CDR distribution is largely accounted for by the change of the wind direction, which alters the spatial distribution of the external pressure distribution on the roof. As a consequence, roof tiles once located at an area of lower external wind pressures may now be subjected to higher external wind pressures.

![Figure 4.16. Probability density function of damage ratio of roof tiles (which approximates the probability mass of the discrete damage ratio) cumulative up to time step 21, 22 and 23 for case (c) in Figure 4.15.](image)

The probability that at least one roof sheathing fails is also estimated and it turns out that under the assumptions made in this dissertation it is small (\( \approx 10^{-8} \)) at the wind speed of 28 [m/s], which corresponds to approximately 35 [m/s] at 10 [m] height in the AIJ roughness category II. Furthermore, the exceedance probability of this wind speed is fairly small; thus, the expected losses due to the failure of roof sheathing may be considered to be negligible.

Based on the presented results together with engineering judgment, in the following analysis flying debris trajectories are assumed to be fully dependent.
4.10.3 Vulnerability model

The developed vulnerability models for the target building (i.e. building type 1) under the building densities of 0.3 and 0.6 are presented in Figure 4.17 and Figure 4.18 respectively for the roof tile’s resistance of $\zeta = 1, 2, 4, 6, 25$. In Figure 4.19 and Figure 4.20, the vulnerability models for the building type 2 are given for the case of building densities of 0.3 and 0.6. Each point in the plot corresponds to the expected loss computed for a typhoon event and its maximum 10-minute sustained wind speed during the event. The correspondences between the expected loss and the maximum 10-minute sustained wind speed are fitted by a vulnerability curve which is often characterized by an exponential function in the empirical vulnerability model, see e.g. Huang et al. (2001), Hallegatte (2007), Bjarnadottir et al. (2011) and Nishijima et al. (2012). Especially, the empirical vulnerability model presented and used in Nishijima et al. (2012) are developed based on loss data after typhoon Songda in Japan. In the present dissertation, the exponential function is also used to fit expected losses. However, it is found that one exponential function is hard to fit well the expected losses over the entire range of wind speed. It seems that the piecewise exponential function is an appropriate option to fit these losses by trial and error and it is expressed by the following functional form:

$$c(x) = \begin{cases} 
0 & x \leq x_0 \\
 a \left(x - x_0\right)^b & x_0 < x \leq x_i \\
 \min\left(c\left(x - x_2\right)^d, e\right) & x > x_i.
\end{cases} \quad (4.25)$$

Here, $c(x)$ is the expected loss when the maximum 10-minute sustained wind speed in the time series is $x$ [m/s]. $e$ is the upper limit of the failure cost, which corresponds to the failure of all the roof tiles and windows. The estimated coefficients for these cases by curve fitting are presented in the Table 4.10, Table 4.11, Table 4.12 and Table 4.13 respectively.

It can be seen in the figures that the expected consequence of a building type under a specific surrounding condition decreases as the roof tile’s resistance increases. This is mainly because the increase of roof tile’s resistance can largely reduce the expected percentage of failed roof tile and the expected consequence due to roof tile failure decreases. Thus, the number of flying debris decreases, as a consequence the window failure due to flying debris also decreases. Note that the failed roof tile is assumed to be only source of flying debris. It may happen that the expected consequence from the window failure due to pressure is the major one. In an extreme case that the roof tile’s resistance is sufficient large, the consequence due to the roof tile failure and window failure due to flying debris may be negligible. In the present dissertation, it is found that for the two considered building types under two surrounding conditions no roof tile is found to be failure under the roof tile’s resistance of $\zeta = 25$ in $10^5$ times of
simulation and the expected consequences in these cases under the roof tile’s resistance of $\zeta = 25$ come from the window failure due to pressure.

It should be mentioned that expected losses might be different even if the maximum wind speeds of the two time series are equal, as seen in Figure 4.17, Figure 4.18, Figure 4.19 and Figure 4.20. This is because, in addition to the maximum wind speed, other factors such as the duration of critical wind speeds and wind direction changes during a typhoon event also play a role on the amount of damage and hence on the resulting losses. In more sophisticated models these parameters may be considered as additional hazard indices.

![Graph](image-url)

Figure 4.17. Developed vulnerability model for building type 1 under building density of 0.3 for various roof tile’s resistances (cases: $\zeta = 1, 2, 4, 6, 25$).
Table 4.10. Coefficients in the vulnerability models for building type 1 under building density of 0.3.

<table>
<thead>
<tr>
<th>$\zeta$</th>
<th>$x_0$</th>
<th>$x_1$</th>
<th>$x_2$</th>
<th>$a$</th>
<th>$b$</th>
<th>$c$</th>
<th>$d$</th>
<th>$e$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>10</td>
<td>14</td>
<td>0</td>
<td>$7.62 \times 10^{-4}$</td>
<td>11.7</td>
<td>11.13</td>
<td>3.33</td>
<td>$2.02 \times 10^6$</td>
</tr>
<tr>
<td>2</td>
<td>14</td>
<td>21.1</td>
<td>0</td>
<td>$6.96 \times 10^{-4}$</td>
<td>9.25</td>
<td>2.46 $\times 10^{-4}$</td>
<td>6.29</td>
<td>$2.33 \times 10^6$</td>
</tr>
<tr>
<td>4</td>
<td>27</td>
<td>20</td>
<td>0</td>
<td>$9.55 \times 10^{-4}$</td>
<td>7.26</td>
<td>2.89</td>
<td>4.27</td>
<td>$2.64 \times 10^6$</td>
</tr>
<tr>
<td>6</td>
<td>16</td>
<td>24</td>
<td>0</td>
<td>0.39</td>
<td>2.51</td>
<td>1.13 $\times 10^{-2}$</td>
<td>4.23</td>
<td>$2.81 \times 10^6$</td>
</tr>
<tr>
<td>25</td>
<td>16</td>
<td>24</td>
<td>0</td>
<td>0.43</td>
<td>2.21</td>
<td>1.18 $\times 10^{-2}$</td>
<td>3.72</td>
<td>$3.34 \times 10^6$</td>
</tr>
</tbody>
</table>

Figure 4.18. Developed vulnerability model for building type 1 under building density of 0.6 for various roof tile’s resistances (cases: $\zeta = 1, 2, 4, 6, 25$).
Table 4.11. Coefficients in the vulnerability models for building type 1 under building density of 0.6.

<table>
<thead>
<tr>
<th>ζ</th>
<th>Coefficients</th>
<th>Coefficients</th>
<th>Coefficients</th>
<th>Coefficients</th>
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<td>x₀ = 16</td>
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<td>x₀ = 16</td>
<td>x₀ = 16</td>
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<tr>
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<td>x₁ = 27.5</td>
<td>x₁ = 21</td>
<td>x₁ = 24</td>
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<tr>
<td></td>
<td>x₂ = 0</td>
<td>x₂ = 0</td>
<td>x₂ = 16</td>
<td>x₂ = 16</td>
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<td>a = 2.73·10⁻⁸</td>
<td>a = 7.26·10⁻²</td>
<td>a = 6.57·10⁻²</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>b = 13.57</td>
<td>b = 3.13</td>
<td>b = 3.00</td>
<td>b = 3.00</td>
<td></td>
</tr>
<tr>
<td></td>
<td>c = 6.57·10⁻²</td>
<td>c = 0.11</td>
<td>c = 0.37</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>d = 4.89</td>
<td>d = 3.13</td>
<td>d = 3.00</td>
<td>d = 2.19</td>
<td></td>
</tr>
<tr>
<td></td>
<td>e = 2.02·10⁶</td>
<td>e = 2.33·10⁶</td>
<td>e = 2.64·10⁶</td>
<td>e = 2.81·10⁶</td>
<td>e = 3.34·10⁶</td>
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</table>

Figure 4.19. Developed vulnerability model for building type 2 under building density of 0.3 for various roof tile’s resistances (cases: ζ = 1, 2, 4, 6, 25).
Table 4.12. Coefficients in the vulnerability models for building type 2 under building density of 0.3.

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<th>Coefficients</th>
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<th>ζ = 6</th>
<th>ζ = 25</th>
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<tr>
<td>x₀</td>
<td>10</td>
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<td>16</td>
<td>16</td>
<td>16</td>
</tr>
<tr>
<td>x₁</td>
<td>18</td>
<td>20</td>
<td>24</td>
<td>27</td>
<td>30</td>
</tr>
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<td>x₂</td>
<td>0</td>
<td>0</td>
<td>18</td>
<td>16</td>
<td>16</td>
</tr>
<tr>
<td>a</td>
<td>1.60</td>
<td>5.02</td>
<td>9.78E-2</td>
<td>5.93E-2</td>
<td>7.24E-2</td>
</tr>
<tr>
<td>b</td>
<td>5.95</td>
<td>5.09</td>
<td>4.65</td>
<td>4.05</td>
<td>3.75</td>
</tr>
<tr>
<td>c</td>
<td>6.36E3</td>
<td>3.82E-4</td>
<td>5.32E-2</td>
<td>1.4E-3</td>
<td>3.5E-3</td>
</tr>
<tr>
<td>d</td>
<td>1.47</td>
<td>6.29</td>
<td>5.66</td>
<td>5.62</td>
<td>4.89</td>
</tr>
<tr>
<td>e</td>
<td>2.28E6</td>
<td>2.68E6</td>
<td>3.06E6</td>
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<td>3.93E6</td>
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</table>

Figure 4.20. Developed vulnerability model for building type 2 under building density of 0.6 for various roof tile’s resistances (cases: ζ = 1, 2, 4, 6, 25).
Table 4.13. Coefficients in the vulnerability models for building type 2 under building density of 0.6.

<table>
<thead>
<tr>
<th>Coefficients</th>
<th>$\zeta = 1$</th>
<th>$\zeta = 2$</th>
<th>$\zeta = 4$</th>
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<th>$\zeta = 25$</th>
</tr>
</thead>
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<td>14.0</td>
<td>16.0</td>
</tr>
<tr>
<td>$x_1$</td>
<td>17.0</td>
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<td>21.7</td>
<td>28.5</td>
<td>22.0</td>
</tr>
<tr>
<td>$x_2$</td>
<td>0.0</td>
<td>0.0</td>
<td>14.0</td>
<td>22.0</td>
<td>16.0</td>
</tr>
<tr>
<td>$a$</td>
<td>1.63</td>
<td>2.98$\cdot 10^2$</td>
<td>6.3$\cdot 10^{-3}$</td>
<td>6.46$\cdot 10^{-2}$</td>
<td>2.97</td>
</tr>
<tr>
<td>$b$</td>
<td>5.85</td>
<td>2.80</td>
<td>5.46</td>
<td>3.46</td>
<td>1.15</td>
</tr>
<tr>
<td>$c$</td>
<td>38.93</td>
<td>1.11$\cdot 10^{-2}$</td>
<td>1.77$\cdot 10^{-4}$</td>
<td>8.2$\cdot 10^{-3}$</td>
<td>3.99$\cdot 10^{-2}$</td>
</tr>
<tr>
<td>$d$</td>
<td>3.05</td>
<td>5.24</td>
<td>7.27</td>
<td>5.99</td>
<td>3.63</td>
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<tr>
<td>$e$</td>
<td>2.28$\cdot 10^6$</td>
<td>2.68$\cdot 10^6$</td>
<td>3.06$\cdot 10^6$</td>
<td>3.27$\cdot 10^6$</td>
<td>3.93$\cdot 10^6$</td>
</tr>
</tbody>
</table>

4.11 Discussion

4.11.1 Critical assumptions

The assumptions in modeling vulnerability are intended to be simple in this dissertation. The developed vulnerability model depends on several critical assumptions. Among others, the following assumptions play crucial roles on the estimated vulnerability:

- Surrounding conditions
- Roof tile’s resistance
- Dependency of trajectory of flying debris.

The assumption in regard to the surrounding conditions of the target building plays a crucial role on the failure of the building at a specific wind speed, see Figure 4.12. In reality there are cases where the surrounding building conditions are more complicated: e.g. the heights of surrounding buildings are different; the alignments of the surrounding buildings are irregularly arrayed. On the other hand, however, the analysis for more complicated surrounding conditions is constrained by the availability of the pressure coefficients of these complicated case in the database of wind pressure developed by TPU (2007). For instance, the wind pressure coefficients for these two aforementioned more complicated surrounding conditions are not currently available from the database. Furthermore, it is observed that the fragility under $C_a = 0.3$ is not always larger than the fragility under $C_a = 0.6$ at the same wind speed, see Figure 4.12. This is due to the measured external pressure coefficients, see Figure 4.13 (a). Since this observation is not conforming to our prior understanding, further numerical and field experiments may be required to clarify it.
For the purpose of verifying the developed model, annual typhoon induced wind risks at various locations in Japan are calculated using the developed vulnerability model. It is found that the calculated risk is unreasonably high for the case $\zeta = 1$, see Chapter 5 and also in Zhang et al. (2013) for detail. As abovementioned, the expected consequence comes from the window failure due to pressure when the roof tile’s resistance is sufficient high, e.g. $\zeta = 25$. In such situation, the assumption that the failed roof tile is the only source of flying is not valid anymore and the vulnerability may be largely underestimated.

The trajectories of the flying debris from one building at a time step are considered to be correlated to a certain extent, if not fully dependent. However, availability of the information that facilitates to the trajectory correlation modeling is limited in the literature. In this dissertation two extreme cases, i.e. fully dependent and independent, are examined. It is shown that there is a large variation among the results from these two extreme cases, see Figure 4.15 (a, b). The result for the real case should lie between the results from these two extreme cases. Furthermore, the trajectories of debris from different buildings are assumed to be fully independent in the present dissertation; the discrepancy between this assumption and the reality will overestimate the fragility due to the failure of window due to roof tile as flying debris. The author tends to believe that the assumptions that the trajectories of debris at one time step within one building and between buildings are respectively fully dependent and fully independent are very close to the reality for the assumed model buildings in the present dissertation. Note that the distance, around 7 [m] see e.g. AIJ (2004), affected by a gust wind is in the range of depth and breadth of model building adopted in the presented dissertation. Moreover, the simulated result on the basis of these assumptions conforms to the engineering judgment. Nevertheless, the assumption on the correlation modeling should be further investigated with more field data as well as the sensitivity analysis.

4.11.2 Other aspects

The time interval at which failures are evaluated with the Monte Carlo simulation is chosen as 10 minutes in this dissertation and the failures and flying debris trajectories are evaluated with the wind corresponding to a 3-second gust. The former implicitly assumes that the change of wind direction within this period is not significant, while the latter implicitly supposes that the resistance of the objects considered in the dissertation and the flying debris trajectory is most sensitive to a 3-second gust, which is yet to be investigated. It is possible that different combinations of the choices of the time interval and gust period may result in different vulnerability estimations. This has to be further investigated.

Although under the assumption made for the roof sheathing and the wind speeds considered in this dissertation the probability of failure of roof sheathing is found to be negligible, it could become significant under other reasonable assumptions and/or higher wind speeds.
The vulnerability model is developed in the present dissertation for strong wind events, which are dominated by horizontal wind such as typhoons and winter storms. Other strong wind events such as tornadoes, in which vertical component of wind and suction by pressure difference are not negligible, is inappropriate for applying the model developed in this dissertation.

The quality of workmanship can affect the fragility/vulnerability. This can be reflected in the modeling of resistance capacity of building components. The good quality of workmanship tends to have higher resistance capacity which will result in lesser fragility/vulnerability. However, the information on the quantitative relationship between the quality of workmanship and the resistance is hardly available. Therefore, the quantitative evaluation of influence on the fragility/vulnerability from the quality of workmanship is not performed in the present dissertation. This is addressed as a future task.

The modeled vulnerability suffers from the model uncertainties. Apart from the abovementioned critical assumptions with respect to the surrounding conditions, the roof tile’s resistance and the dependencies of trajectories of flying debris, the source of model uncertainties also comes from the selection of model building, e.g. different geometry as seen in the presented results (see the difference between Figure 4.17 and Figure 4.19) and cost model which will be discussed in the last chapter. Besides these, more sophisticated debris flying modeling may also result in different estimated vulnerability.

The fitted vulnerability curves also suffer from the model uncertainties due to the selection of functional form. The vulnerability curves are fitted by a piecewise exponential function in the present dissertation. Selection of other functional form may result in different vulnerability curves. This in turn may lead to a different typhoon induced risk assessment result. Furthermore, the fitted vulnerability curves also suffer from statistical uncertainty, since only 30 time series of wind speed and direction are used as input to generate the expected losses. This statistical uncertainty can be reduced by generating more expected losses once more time series of wind speed and direction become available.

4.12 Conclusion

An approach for developing a reliability-based vulnerability model for residential buildings in Japan is presented. A provisional version of a vulnerability model is developed. Based on the investigation of the performance of the established models together with sensitivity analysis, critical assumptions significantly affecting the modeled vulnerability are clarified. Out of many model parameters it is found that the roof tile’s resistance and the correlation of flying debris trajectories are relevant. Future research efforts should be directed towards the development of a more credible model and the main aspects of concern that should be further investigated are identified.
Although the current version of the vulnerability model needs several updates and a verification, the presented approach and the model provide a basis for further development of the vulnerability model of residential buildings in Japan.
5 Assessment of typhoon induced wind hazard and risk

5.1 Introduction
This chapter presents the assessment results of typhoon induced wind hazard and risk for the current climate (period 1979-2003) as well as the projected future climate (period 2075-2099). The assessment is conducted in accordance with the model presented in chapters 3 and 4. The rest of the chapter is organized as follows. The procedure to conduct the assessment is described in section 5.2. The results of the hazard assessment are presented in section 5.3. The results of risk assessment are discussed in section 5.4. The adaptation and issues relevant to it are described in section 5.5.

5.2 Assessment procedure
The hazard assessment is conducted for the current and the future climate situation for 15 locations over the islands of Japan, see Figure 5.1. The hazard assessment for the current climate is conducted employing the probabilistic typhoon hazard model, see subsection 2.3.4, with the typhoon transition model from section 3.3. In regard to the hazard assessment for the future climate, the unbiased dataset in the future climate is first obtained following the approach described in subsection 3.2.3.

Figure 5.1. Locations of the cities where the typhoon wind hazard and risk are computed.
The hazard assessment is conducted by Monte Carlo simulation. In the simulation, 400 times of 25 years, corresponding to 10000 one-year, typhoon events are generated. For individual generated typhoons, the induced wind speeds at individual locations are computed for at a 6-hours interval when the typhoon is over the sea and a 10 minutes interval after reaching land. Among these computed wind speeds, the maximum wind speed in a life of typhoon at individual locations is recorded. Based on the recorded maximum wind speed in the individual life of a typhoon at an individual location, the annual maximum wind speed is selected over that of typhoon occurred in a year. Note that 10000 one-year typhoon events’ induced wind speeds are computed, an approximated annual maximum wind speed distribution is obtained and its statistical characteristics, e.g. 99%, 98% quantiles and its median are derived.

The annual risk of one building for a specific building in a given condition, hereafter called a combination, at a location \( j \) is estimated as:

\[
E[C^j_k] = E\left[ \sum_{i=1}^{N_j} C^k(TS_{i,j}) \right],
\]

(5.1)

where \( E[C^j_k] \) is the expected value of the consequence in a year conditional on the \( k^{th} \) combination, \( N_j \) is the number of typhoon events in a year affecting location \( j \), \( TS_{i,j} \) is the time series of wind speed and relative wind direction at location \( j \) in the \( i^{th} \) typhoon event. \( C^k(\cdot) \) is the consequence incurred by a time series of a typhoon event conditional on the \( k^{th} \) combination, which can be obtained by estimating the vulnerability for individual typhoon events by means of Monte Carlo simulation for fragility, see subsection 4.9.1, together with the failure cost model. However, this can be proved to be computationally expensive (several months of computation in the standard personal computer). Therefore, \( C^k(TS_{i,j}) \) is approximated by \( c^k(V_{\max_{i,j}}) \), where \( c^k(\cdot) \) refers to Equation (4.25) and the coefficients in the Table 4.10, Table 4.11, Table 4.12 and Table 4.13 developed in subsection 4.10.3 and \( V_{\max_{i,j}} \) is the maximum 10-minute sustained wind speed at location \( j \) in the \( i^{th} \) typhoon event. Here, it corresponds to the one measured at 7 [m] height in the AIJ roughness category III. Thus, the annual risk of one building at a location \( j \) is rewritten as:

\[
E[C^j_k] = E\left[ \sum_{i=1}^{N_j} c^k(V_{\max_{i,j}}) \right].
\]

(5.2)

The annual risks of one building conditional on a combination for those 15 locations are computed based on the above equation. Note that the wind speed obtained from the probabilistic typhoon hazard model corresponds to 10-minute sustained wind speed at 10 [m] height in the AIJ roughness category II. Thus, the wind speed is first converted to the one corresponding to a 10-minute sustained wind speed at 7 [m] height in the AIJ roughness category III by applying the approach described in Appendix C.

The average of annual risks of one building for those 15 locations can be estimated as:
\[ E(C_j) = E\left(E[C_j^k]\right) = \sum_{k=1}^{K} p_k E[C_j^k], \]

where \( K \) is the amount of combinations, \( p_k \) is the probability that a building belongs to the \( k^{th} \) combination.

### 5.3 Hazard assessment

Statistical change of the typhoon events in the projected future climate with respect to the occurrence frequency, the intensity as well as the track are modeled in the present dissertation. In order to investigate the effect of individual statistical change on the wind speeds, besides the model accounting for all three statistical changes which is hereafter called standard model, the other three alternative models not considering either one of three statistical changes are also examined. The summary of these models are given in Table 5.1. In the table, the bias correction with respect to frequency concerns whether the amount of typhoon event are considered to decrease by 78\% of that in the present time and the bias correction in regard to the intensity and track concerns whether the intensity and track are transformed based on the approach described in subsection 3.2.3.

<table>
<thead>
<tr>
<th>Model</th>
<th>Frequency?</th>
<th>Intensity?</th>
<th>Track?</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>1</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>2</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>3</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
</tr>
</tbody>
</table>

The 99\% quantiles of annual maximum wind speed distribution for the current climate and for the future climate under model 0, 1, 2 and 3 are presented in Table 5.2. The 98\% quantiles and medians of those are presented in Table 5.3 and Table 5.4 respectively. Note that the 99\% and 98\% quantiles of the annual maximum wind speed distribution correspond to the 100 and 50-year wind speeds respectively. The presented wind speeds are 10-minute sustained wind speeds at 10 [m] height in the AIJ roughness category II.

For the purpose of validation, the estimated 100-year wind speeds for all those 15 locations for the current climate are compared to the one specified in the wind hazard map over Japan in AIJ (2004). This hazard map is developed based on the outputs from several probabilistic models for both typhoon and non-typhoon induced strong winds, incorporating the historical observation as well as engineering judgment and it is developed for the purpose of designing buildings. This hazard map can be used as a
Assessment of typhoon induced wind hazard and risk

benchmark for the validation. Note that the value of 100-years wind speed can be considered to be mainly due to the wind speed from typhoon events in these regions. It is found that at the majority of locations, the estimated 100-year wind speeds are very close to the one specified in the hazard map; in Oita, Hiroshima, Osaka and Toyama, the estimated 100-year wind speeds tend to be higher than the one specified in the hazard map. The overestimated 100-year wind speeds at these locations are understood to be a result of the imperfection of the filling model used to describe the evolution of typhoon event intensity in terms of the central pressure after its landfall. It should be mentioned that this overestimation is also observed in the result obtained by Graf et al. (2009).

Table 5.2. 99% quantiles of annual maximum wind speed distribution at 15 locations for the current climate as well as for the future climate under model 0, 1, 2 and 3.

<table>
<thead>
<tr>
<th>Location</th>
<th>Current [m/s]</th>
<th>Future [m/s]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Current [m/s]</td>
<td>0</td>
</tr>
<tr>
<td>Minamidaito</td>
<td>44.12</td>
<td>45.18</td>
</tr>
<tr>
<td>Ishigaki</td>
<td>43.72</td>
<td>45.15</td>
</tr>
<tr>
<td>Naha</td>
<td>43.79</td>
<td>45.06</td>
</tr>
<tr>
<td>Kagoshima</td>
<td>40.49</td>
<td>41.44</td>
</tr>
<tr>
<td>Oita</td>
<td>38.24</td>
<td>38.89</td>
</tr>
<tr>
<td>Kumamoto</td>
<td>38.87</td>
<td>39.60</td>
</tr>
<tr>
<td>Nagasaki</td>
<td>39.15</td>
<td>40.06</td>
</tr>
<tr>
<td>Fukuoka</td>
<td>38.30</td>
<td>38.67</td>
</tr>
<tr>
<td>Hiroshima</td>
<td>36.92</td>
<td>37.51</td>
</tr>
<tr>
<td>Osaka</td>
<td>38.14</td>
<td>37.51</td>
</tr>
<tr>
<td>Tokyo</td>
<td>37.76</td>
<td>37.32</td>
</tr>
<tr>
<td>Chiba</td>
<td>38.08</td>
<td>38.04</td>
</tr>
<tr>
<td>Toyama</td>
<td>36.73</td>
<td>36.54</td>
</tr>
<tr>
<td>Niigata</td>
<td>36.78</td>
<td>35.29</td>
</tr>
<tr>
<td>Sapporo</td>
<td>33.94</td>
<td>31.97</td>
</tr>
</tbody>
</table>
Table 5.3. 98% quantiles of annual maximum wind speed distribution at 15 locations for the current climate as well as for the future climate under model 0, 1, 2 and 3.

<table>
<thead>
<tr>
<th>Location</th>
<th>Current [m/s]</th>
<th>Future [m/s]</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minamidaito</td>
<td>42.29</td>
<td>43.59</td>
<td>43.90</td>
<td>41.55</td>
<td>43.07</td>
<td></td>
</tr>
<tr>
<td>Ishigaki</td>
<td>42.18</td>
<td>43.22</td>
<td>43.79</td>
<td>41.19</td>
<td>44.08</td>
<td></td>
</tr>
<tr>
<td>Naha</td>
<td>42.11</td>
<td>43.52</td>
<td>44.14</td>
<td>41.39</td>
<td>43.51</td>
<td></td>
</tr>
<tr>
<td>Kagoshima</td>
<td>38.80</td>
<td>39.50</td>
<td>40.10</td>
<td>38.20</td>
<td>39.34</td>
<td></td>
</tr>
<tr>
<td>Oita</td>
<td>36.53</td>
<td>37.04</td>
<td>37.46</td>
<td>35.08</td>
<td>36.43</td>
<td></td>
</tr>
<tr>
<td>Kumamoto</td>
<td>37.11</td>
<td>37.58</td>
<td>38.51</td>
<td>36.37</td>
<td>37.44</td>
<td></td>
</tr>
<tr>
<td>Nagasaki</td>
<td>37.21</td>
<td>37.97</td>
<td>38.50</td>
<td>36.53</td>
<td>37.37</td>
<td></td>
</tr>
<tr>
<td>Fukuoka</td>
<td>36.23</td>
<td>36.51</td>
<td>37.24</td>
<td>35.46</td>
<td>36.03</td>
<td></td>
</tr>
<tr>
<td>Hiroshima</td>
<td>35.21</td>
<td>35.34</td>
<td>35.78</td>
<td>33.95</td>
<td>35.31</td>
<td></td>
</tr>
<tr>
<td>Osaka</td>
<td>36.19</td>
<td>35.69</td>
<td>36.32</td>
<td>34.63</td>
<td>36.06</td>
<td></td>
</tr>
<tr>
<td>Tokyo</td>
<td>35.82</td>
<td>35.57</td>
<td>35.64</td>
<td>34.69</td>
<td>35.89</td>
<td></td>
</tr>
<tr>
<td>Chiba</td>
<td>36.18</td>
<td>36.23</td>
<td>37.08</td>
<td>35.03</td>
<td>36.22</td>
<td></td>
</tr>
<tr>
<td>Toyama</td>
<td>34.56</td>
<td>34.38</td>
<td>34.84</td>
<td>33.26</td>
<td>34.96</td>
<td></td>
</tr>
<tr>
<td>Niigata</td>
<td>34.80</td>
<td>33.68</td>
<td>34.63</td>
<td>32.77</td>
<td>34.41</td>
<td></td>
</tr>
<tr>
<td>Sapporo</td>
<td>31.98</td>
<td>30.46</td>
<td>30.99</td>
<td>30.03</td>
<td>30.90</td>
<td></td>
</tr>
</tbody>
</table>

Table 5.4. Medians of annual maximum wind speed distribution at 15 locations for the current climate as well as for the future climate under model 0, 1, 2 and 3.

<table>
<thead>
<tr>
<th>Location</th>
<th>Current [m/s]</th>
<th>Future [m/s]</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minamidaito</td>
<td>30.69</td>
<td>30.33</td>
<td>31.87</td>
<td>29.22</td>
<td>30.23</td>
<td></td>
</tr>
<tr>
<td>Ishigaki</td>
<td>29.94</td>
<td>29.85</td>
<td>31.13</td>
<td>28.84</td>
<td>29.93</td>
<td></td>
</tr>
<tr>
<td>Naha</td>
<td>30.14</td>
<td>29.66</td>
<td>31.04</td>
<td>28.59</td>
<td>30.03</td>
<td></td>
</tr>
<tr>
<td>Kagoshima</td>
<td>26.60</td>
<td>25.57</td>
<td>27.03</td>
<td>24.92</td>
<td>26.06</td>
<td></td>
</tr>
<tr>
<td>Oita</td>
<td>24.67</td>
<td>23.97</td>
<td>25.13</td>
<td>23.15</td>
<td>23.78</td>
<td></td>
</tr>
<tr>
<td>Kumamoto</td>
<td>25.11</td>
<td>24.19</td>
<td>25.54</td>
<td>23.50</td>
<td>24.33</td>
<td></td>
</tr>
<tr>
<td>Nagasaki</td>
<td>24.70</td>
<td>23.74</td>
<td>25.10</td>
<td>23.11</td>
<td>23.87</td>
<td></td>
</tr>
<tr>
<td>Fukuoka</td>
<td>23.73</td>
<td>22.88</td>
<td>24.12</td>
<td>22.25</td>
<td>22.75</td>
<td></td>
</tr>
<tr>
<td>Hiroshima</td>
<td>23.27</td>
<td>22.56</td>
<td>23.59</td>
<td>21.91</td>
<td>22.25</td>
<td></td>
</tr>
<tr>
<td>Osaka</td>
<td>23.72</td>
<td>22.78</td>
<td>24.00</td>
<td>22.24</td>
<td>23.05</td>
<td></td>
</tr>
<tr>
<td>Tokyo</td>
<td>23.74</td>
<td>22.78</td>
<td>23.82</td>
<td>22.34</td>
<td>22.97</td>
<td></td>
</tr>
<tr>
<td>Chiba</td>
<td>23.95</td>
<td>22.96</td>
<td>23.97</td>
<td>22.60</td>
<td>23.16</td>
<td></td>
</tr>
<tr>
<td>Toyama</td>
<td>21.50</td>
<td>20.84</td>
<td>21.86</td>
<td>20.36</td>
<td>20.55</td>
<td></td>
</tr>
<tr>
<td>Niigata</td>
<td>20.73</td>
<td>19.87</td>
<td>20.93</td>
<td>19.44</td>
<td>19.85</td>
<td></td>
</tr>
<tr>
<td>Sapporo</td>
<td>17.18</td>
<td>16.78</td>
<td>17.72</td>
<td>16.20</td>
<td>15.59</td>
<td></td>
</tr>
</tbody>
</table>
It is observed in Table 5.4 that the medians of the annual maximum wind speeds distributions decrease at all locations in the future when the standard model is utilized for the future climate. This is consistent with the result obtained in Nishijima et al. (2012). There, the hazard assessment is conducted without the bias correction of the typhoon events extracted from the AGCM model. Furthermore, their hazard assessment shows that the 100/50-year wind speeds increase over most of the locations in Japan in the future. In contrast, as seen in Figure 5.2, 100/50-year wind speeds tend to increase in the south/western part of Japan, whereas these wind speeds tend to decrease in the north/eastern part of Japan in the future. This is due to the approach of bias correction employed in this dissertation which is explained in the following.

![Figure 5.2. Changes of 100/50-year wind speeds at 15 locations in Japan. The wind speed for the future climate is calculated based on model 0.](image)

It can be seen that the reduction of occurrence frequency leads to the decreases of 99%, 98% and the median of the annual maximum wind speed distribution, see the comparison between the presented results for the model 0 and the model 1 in Table 5.2, Table 5.3 and Table 5.4. It is also shown that the bias correction with respect to typhoon intensity lead to the increases of 99%, 98% and the median of the annual maximum wind speed distribution, see the comparison between the presented results for the model 0 and the model 2. This is the reflection that the frequency of strong typhoon event in the future climate is projected to increase. This statistical change is added to the best track dataset by the approach described in subsection 3.2.3 to form the unbiased dataset in the future climate. It results in that for each typhoon event the minimum central pressure in its life decreases; consequently, the time series of all central pressures decrease as the approach adopted in the present dissertation. Thus, high quantiles of annual maximum wind speed distribution increase as long as the occurrence frequency is the same. In contrast, the bias correction with respect to the typhoon track result in the different change trends of wind speed at various locations.
For instance, for the 99% quantile, this aspect of bias correction will result in the increase of annual maximum wind speed distribution at Minamidaito, Hiroshima and the locations in Kyushu island including Kagoshima, Oita, Kumamoto, Nagasaki and Fukuoka and the decrease of that at Ishigaki, Naha, Osaka, Tokyo, Toyama, Niigata, Sapporo and not significant change at Chiba, see the comparison between the model 0 and model 3 in Table 5.2. Note that the results from the standard model (model 0) are the aggregated effect by accounting for all three aspects of bias correction and the hazard assessment result from the standard model will be utilized for the risk assessment.

5.4 Risk assessment

The annual risks of building type 1 and type 2 in the building densities of 0.3 and 0.6 based on the roof tile’s resistance of $\zeta = 1$ at the considered 15 locations under the current climate with corresponding developed vulnerability models, as presented in subsection 4.10.3, are presented in Table 5.5. It can be seen that these computed annual risks are unreasonably high. This is because the resistance of normal roof tile in Japan is in general larger than the value of $\zeta = 1$ as mentioned in the section 4.5. Furthermore, the roof tile’s resistance of $\zeta = 25$ (corresponding to median value of 9800 [Pa]) is highly larger than the normal roof tile’s resistance which is between 600 – 2400 [Pa] and with this resistance the other assumptions in the vulnerability modeling to develop the vulnerability curve is not valid anymore. Thus, the developed vulnerability model with $\zeta = 1, 25$ is not employed to investigate the change in risk between the current and the future climate.

The annual risks of two building types, building type 1 and 2, in the two building densities, 0.3 and 0.6, based on the roof tile’s resistance of $\zeta = 2, 4, 6$ at the considered 15 locations under the current and future climate are given in Table 5.6, Table 5.7, Table 5.8 and Table 5.9. It can be seen that the annual risk is not to change significantly in the future for each case.
Table 5.5. The annual wind risks at 15 locations under various developed vulnerability models for the roof tile’s resistance of $\zeta = 1$ for the current climate.

<table>
<thead>
<tr>
<th>Location</th>
<th>Current [JPY]</th>
<th>Building type 1</th>
<th>Building type 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$C_a = 0.3$</td>
<td>$C_a = 0.6$</td>
<td>$C_a = 0.3$</td>
</tr>
<tr>
<td>Minamidaito</td>
<td>1.05·10^6</td>
<td>8.41·10^5</td>
<td>1.53·10^6</td>
</tr>
<tr>
<td>Ishigaki</td>
<td>9.49·10^5</td>
<td>7.43·10^5</td>
<td>1.38·10^6</td>
</tr>
<tr>
<td>Naha</td>
<td>9.70·10^5</td>
<td>7.71·10^5</td>
<td>1.41·10^6</td>
</tr>
<tr>
<td>Kagoshima</td>
<td>5.89·10^5</td>
<td>4.02·10^5</td>
<td>9.08·10^5</td>
</tr>
<tr>
<td>Oita</td>
<td>4.31·10^5</td>
<td>2.62·10^5</td>
<td>6.89·10^5</td>
</tr>
<tr>
<td>Kumamoto</td>
<td>4.61·10^5</td>
<td>2.92·10^5</td>
<td>7.29·10^5</td>
</tr>
<tr>
<td>Nagasaki</td>
<td>4.34·10^5</td>
<td>2.75·10^5</td>
<td>6.85·10^5</td>
</tr>
<tr>
<td>Fukuoka</td>
<td>3.70·10^5</td>
<td>2.21·10^5</td>
<td>5.87·10^5</td>
</tr>
<tr>
<td>Hiroshima</td>
<td>3.40·10^5</td>
<td>1.92·10^5</td>
<td>5.43·10^5</td>
</tr>
<tr>
<td>Osaka</td>
<td>3.74·10^5</td>
<td>2.20·10^5</td>
<td>5.97·10^5</td>
</tr>
<tr>
<td>Tokyo</td>
<td>3.72·10^5</td>
<td>2.16·10^5</td>
<td>5.93·10^5</td>
</tr>
<tr>
<td>Chiba</td>
<td>3.89·10^5</td>
<td>2.29·10^5</td>
<td>6.18·10^5</td>
</tr>
<tr>
<td>Toyama</td>
<td>2.53·10^5</td>
<td>1.38·10^5</td>
<td>3.95·10^5</td>
</tr>
<tr>
<td>Niigata</td>
<td>2.23·10^5</td>
<td>1.22·10^5</td>
<td>3.43·10^5</td>
</tr>
<tr>
<td>Sapporo</td>
<td>1.10·10^5</td>
<td>5.64·10^4</td>
<td>1.68·10^5</td>
</tr>
</tbody>
</table>
Table 5.6. The annual wind risks for building type 1 under building density of 0.3 at 15 locations based on the developed vulnerability models for roof tile’s resistance of $\zeta=2,4,6$ for the current and the future climate.

<table>
<thead>
<tr>
<th>Location</th>
<th>$\zeta=2$ [JPY]</th>
<th>$\zeta=4$ [JPY]</th>
<th>$\zeta=6$ [JPY]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Current</td>
<td>Future</td>
<td>Current</td>
</tr>
<tr>
<td>Minamidaito</td>
<td>2.96 · 10^5</td>
<td>3.00 · 10^5</td>
<td>2.62 · 10^4</td>
</tr>
<tr>
<td>Ishigaki</td>
<td>2.58 · 10^5</td>
<td>2.72 · 10^5</td>
<td>2.26 · 10^4</td>
</tr>
<tr>
<td>Naha</td>
<td>2.71 · 10^5</td>
<td>2.70 · 10^5</td>
<td>2.44 · 10^4</td>
</tr>
<tr>
<td>Kagoshima</td>
<td>1.22 · 10^5</td>
<td>1.17 · 10^5</td>
<td>7.43 · 10^3</td>
</tr>
<tr>
<td>Oita</td>
<td>7.04 · 10^4</td>
<td>6.92 · 10^4</td>
<td>3.40 · 10^3</td>
</tr>
<tr>
<td>Kumamoto</td>
<td>8.23 · 10^4</td>
<td>8.11 · 10^4</td>
<td>4.37 · 10^3</td>
</tr>
<tr>
<td>Nagasaki</td>
<td>7.80 · 10^4</td>
<td>7.86 · 10^4</td>
<td>4.23 · 10^3</td>
</tr>
<tr>
<td>Fukuoka</td>
<td>5.91 · 10^4</td>
<td>5.93 · 10^4</td>
<td>3.10 · 10^3</td>
</tr>
<tr>
<td>Hiroshima</td>
<td>4.89 · 10^4</td>
<td>4.81 · 10^4</td>
<td>2.52 · 10^3</td>
</tr>
<tr>
<td>Osaka</td>
<td>5.77 · 10^4</td>
<td>5.28 · 10^4</td>
<td>2.59 · 10^3</td>
</tr>
<tr>
<td>Tokyo</td>
<td>5.65 · 10^4</td>
<td>5.00 · 10^5</td>
<td>2.93 · 10^3</td>
</tr>
<tr>
<td>Chiba</td>
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Table 5.7. The annual wind risks for building type 1 under building density of 0.6 at 15 locations based on the developed vulnerability models for roof tile’s resistance of $\zeta=2,4,6$ for the current and the future climate.

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<tr>
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<th>$\zeta=4$ [JPY]</th>
<th>Current</th>
<th>Future</th>
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<td></td>
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</tr>
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</tr>
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Table 5.8. The annual wind risks for building type 2 under building density of 0.3 at 15 locations based on the developed vulnerability models for roof tile’s resistance of $\zeta=2,4,6$ for the current and the future climate.

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<td>$7.17 \cdot 10^2$</td>
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<td>$4.41 \cdot 10^2$</td>
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Table 5.9. The annual wind risks for building type 2 under building density of 0.6 at 15 locations based on the developed vulnerability models for roof tile’s resistance of $\zeta=2,4,6$ for the current and the future climate.

<table>
<thead>
<tr>
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<td>3.76 $\cdot 10^{5}$</td>
<td>4.81 $\cdot 10^{4}$</td>
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<td>3.70 $\cdot 10^{5}$</td>
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<td>6.65 $\cdot 10^{4}$</td>
<td>2.28 $\cdot 10^{3}$</td>
<td>3.21 $\cdot 10^{3}$</td>
</tr>
<tr>
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<td>1.74 $\cdot 10^{5}$</td>
<td>1.55 $\cdot 10^{4}$</td>
<td>1.94 $\cdot 10^{4}$</td>
<td>5.82 $\cdot 10^{2}$</td>
<td>8.34 $\cdot 10^{2}$</td>
</tr>
<tr>
<td>Oita</td>
<td>1.17 $\cdot 10^{5}$</td>
<td>1.11 $\cdot 10^{5}$</td>
<td>6.85 $\cdot 10^{3}$</td>
<td>8.68 $\cdot 10^{3}$</td>
<td>2.94 $\cdot 10^{2}$</td>
<td>4.41 $\cdot 10^{2}$</td>
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<td>3.64 $\cdot 10^{2}$</td>
<td>4.98 $\cdot 10^{2}$</td>
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</table>

Figure 5.3. Changes in annual risk at 15 locations in Japan
In the Table 5.6, Table 5.7, Table 5.8 and Table 5.9, 12 different vulnerability curves are utilized for the calculation of annual risk of one building conditional on each of 12 combinations in the present dissertation. Assume that individual residential building in Japan belongs to one of these 12 combinations. Without knowing the further information on the percentage of building belonging to each combination, it is assumed that the probability that a building belongs to each combination is equal; thus $K = 12$ and $p_k = 1/12$. The average of annual risks of one building for 15 considered locations under the current climate and future climate are estimated by using Equation (5.3), the result is presented in Figure 5.3. The results show that at 5 locations the risks increase; at the other locations the risks decrease; in both cases though, the changes are not significant.

Table 5.10 presents the contributions of individual wind speed intervals to the annual risk for the current and the future climate. The wind speed is the 10-minute sustained wind speed at a height of 7 [m] in the AIJ roughness category III. In the table, the contribution is represented by a percentage. It shows that for the locations along the south/western part of Japan the percentage shifts from low wind speed to high wind speed in the future climate, for example in the following locations Minamidaito, Ishigaki, Naha, Kagoshima, Oita, Kumamoto, Nagasaki, Fukuoka, Hiroshima, Osaka, Tokyo, Chiba. In contrast, for the locations along the north/eastern part of Japan the percentage shifts from high wind speed towards low wind speed, e.g. Toyama, Niigata, Sapporo.
Table 5.10. The contributions from each wind speed interval to the annual risk of one building in terms of percentage (%) for the current and the future climate.

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<th>Future</th>
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<td>20-25</td>
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</tr>
<tr>
<td>Current</td>
<td>7.29</td>
<td>45.22</td>
<td>32.82</td>
</tr>
<tr>
<td>Future</td>
<td>6.69</td>
<td>42.80</td>
<td>36.56</td>
</tr>
<tr>
<td>Chiba</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Current</td>
<td>6.80</td>
<td>43.55</td>
<td>33.34</td>
</tr>
<tr>
<td>Future</td>
<td>6.10</td>
<td>40.12</td>
<td>36.97</td>
</tr>
<tr>
<td>Toyama</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Current</td>
<td>8.36</td>
<td>41.21</td>
<td>34.57</td>
</tr>
<tr>
<td>Future</td>
<td>7.69</td>
<td>43.50</td>
<td>33.02</td>
</tr>
<tr>
<td>Niigata</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Current</td>
<td>7.75</td>
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<td>36.07</td>
</tr>
<tr>
<td>Future</td>
<td>7.94</td>
<td>43.28</td>
<td>34.32</td>
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<td>Sapporo</td>
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<tr>
<td>Current</td>
<td>8.96</td>
<td>41.93</td>
<td>33.69</td>
</tr>
<tr>
<td>Future</td>
<td>12.66</td>
<td>50.75</td>
<td>25.21</td>
</tr>
</tbody>
</table>
5.5 Consideration of adaptation

In chapter 4, it is observed that the increase of roof tile resistance can reduce the fragility/vulnerability of a building. Thus, the increase of roof tile resistance can be considered as an adaptation alternative, which not only can reduce the fragility of one building directly, it can also achieve that through an indirect way, i.e. reduce the loss due to window failure. Because the window's failure is mainly due to the impact of flying debris and the increase of roof tile resistance results in less number of flying debris which reduces the failure probability of window due to the impact of flying debris. As a consequence, the fragility due to window failure reduces. Another point is that the failure of a window will lead to the increase of internal building pressure and the failure probability of roof sheathing will increase. Another adaptation alternative is to take the risk reduction measures to protect the window directly such as installation of a window shield, e.g. window shutter, or installation of high impact resistance glass. Since the owner of the building can benefit by taking these risk reduction measures from their investment directly, these risk measures are often undertaken.

Due to the nature of the vulnerability model presented in this dissertation, it is possible to examine the efficiency of various risk reduction measures in a quantitative way. However, it should be said, as aforementioned in chapter 2, that a formal efficiency assessment requires consideration of, among others but most importantly, uncertainty of the future climate and uncertainty of the climate models. In this dissertation assessment is based on one climate scenario, i.e. the SRES A1B and one particular climate model, i.e. model MRI-AGCM3.2S. Therefore, the efficiency assessment of the risk reduction measures shall be considered as a future matter of research.
Conclusions and outlook

6 Conclusion and outlook

6.1 Conclusion

In the present dissertation, the impact assessment of typhoon induced wind risk under climate change is addressed. In the impact assessment, the best track dataset provided by the JMA and the extracted typhoon events from a climate model for an assumed climate scenario, i.e. A1B, are utilized as the basis dataset. The systematic bias in the extracted typhoon events is accounted for by an ad-hoc approach. The best track dataset and the "unbiased" best track dataset in the future climate are treated as the input datasets to the probabilistic typhoon hazard model and 10000 one-year typhoon events are artificially generated and corresponding wind speeds are calculated and they form a wind hazard dataset. The decrease of frequency of typhoon events in the future climate is accounted for by proportionally reducing the number of typhoon events in the simulated wind hazard dataset. By using the wind hazard dataset together with the developed reliability-based vulnerability model in this dissertation, the impact of typhoon induced wind risk for residential buildings in Japan is assessed both for the current and the future climate.

Chapter 2 comprehensively reviews the past contributions in the typhoon hazard modeling focusing on the probabilistic modeling of typhoon transition, the vulnerability modeling under wind hazard and the impact assessment under climate change. With respect to the typhoon transition modeling, it is found that the main differences among various works for the probabilistic modeling of typhoon transition lie in the formulation of the model either in an explicitly regression function or in a non-parametric way, the assumption of the order of the Markov process, the assumption whether the typhoon transition is spatial and seasonal homogeneous and finally the treatment of the residual terms in the regression function. However, a consistent and systematic statistics-based analysis is missing from all works that are considered to be the state of the art. With respect to the vulnerability modeling, it is found that no model capable of estimating the efficiency of risk reduction measures for residential buildings in Japan is available. In what concerns the impact assessment of typhoon induced wind risk for residential buildings, it is observed that current models are limited to the functionality of the assessment and are not able to assess the efficiency of adaptation. Based on the merit of the existing impact assessment models, chapter 2 presents a methodology to assess the impact of climate change and being capable of examining the efficiency of adaptation on residential buildings in the context of typhoon induced wind risk. The methodology consists of the climate model and an assumed climate scenario, the modeling of the bias correction, the probabilistic typhoon hazard model and a reliability-based vulnerability model.
Chapter 3 investigates the probabilistic modeling of typhoon transition in the future climate. It consists of two parts. The first part considers the correction of bias in the extracted typhoon events. The idea employed in Yasuda et al. (2010) is utilized to correct the bias. In their study, this idea is only applied to the correction of bias in regard to the track trajectory and occurrence frequency of typhoon events. In contrast, the track trajectory, the occurrence frequency as well as the intensity of typhoon events are all considered in this dissertation. The second part explores the probabilistic modeling of typhoon transition by extensive statistical analysis. Firstly, the correlation structures of the typhoon transition are estimated in terms of ACF and PACF. This facilitates the specification of a set of plausible models for further investigation. Then, cAIC is applied to investigate the relative goodness of fit of these models. The spatial inhomogeneity and the seasonality are taken into account by developing the models for different spatial grids and seasons separately. An appropriate size of spatial grids is investigated. The statistical characteristics of the random residual terms in the models are also examined. Finally, Monte Carlo simulations are performed to investigate the overall performance of the proposed model. It is found that the choice of the functions is generally not relevant in the transition modeling; however, modeling of the residual terms has significant impact on the fluctuation of the simulated typhoon tracks. Furthermore, the consideration of the spatial inhomogeneity is in general important and that of the seasonality is important in the case that the typhoon transition in a specific season is of interest.

Chapter 4 presents an approach for developing a reliability-based vulnerability model for the assessment of typhoon induced wind risk of residential buildings in Japan. Following the approach, a provisional version of a vulnerability model is developed based on available information. By examining the model, it is found that the roof tile resistance and the correlation of trajectories of flying debris play a significant role on the vulnerability. Critical assumptions made in the modeling requiring further investigation and thus concerning the updating of the vulnerability model are identified and discussed.

Chapter 5 presents the results of the hazard assessment as well as the risk assessment following the methodology presented in chapter 2 and the individual model component in chapters 3 and 4. In the hazard assessment, the sensitivity analysis with respect to change of the typhoon occurrence frequency, typhoon track and intensity are performed. In the risk assessment, 12 conditional annual risks of one building are performed for the current and future climate for 15 locations. Upon the employed climate model, assumed climate scenario and vulnerability model and other assumptions made in the present dissertation, it is found that the 100/50 year wind speeds in the south/western part of Japan tend to increase, whereas a decrease tendency is observed in the north/eastern part of Japan; typhoon induced wind risk for residential buildings in Japan is unlikely to change significantly in the future.
6.2 Scientific achievements and limitations

The scientific achievements of the present dissertation work are: (1) introduction of an impact assessment methodology being capable of evaluating the efficiency of adaptation under climate change; (2) application of extensive statistical analysis to explore the statistics-based modeling of typhoon transition; (3) presentation of a reliability-based vulnerability modeling approach for residential buildings in Japan.

However, these scientific achievements have their limitations. Regarding (1), the impact is assessed in terms of monetary loss or its equivalence in this dissertation. In general, many aspects of civil infrastructure failures, e.g. the fatalities caused by the failure of a structure, may be affected by climate change that is difficult to be quantified in terms of monetary loss. Concerning (2), the function is explored by comparing the relative goodness of fit of several plausible models by cAIC. However, a more consistent and systematic statistical analysis is to explore the function by looking into the necessity of adding an individual explanatory variable in the function at each step. Regarding (3), only three non-structural failures are considered in the modeling, consideration of other failures may result in a different vulnerability model. Furthermore, in order to comprehensively understand the performance of the residential buildings, further sensitivity analyses are necessary; in what concerns the trajectories of flying debris from one building at a time step, the presented approach only considers two extreme cases, i.e. fully dependent and independent. Finally, model verification has not been made. This should be done in the future as long as the post disaster survey of typhoon event in Japan is available.

6.3 Outlook

6.3.1 Climate scenario and climate model

The present dissertation relies on a single climate model and considers a single climate scenario (SRES A1B). The sensitivity of these assumptions to the impact assessment results is not investigated in the present dissertation. Therefore, it should be emphasized that the conclusion drawn is conditional upon, among all other assumptions, the employed climate model and scenario.

6.3.2 The surface friction model and development of society

In the present dissertation, the same surface friction models are assumed for the current and the projected future climate, i.e. the same roughness length are used. This implies that the characteristics of land-use are assumed not to change in the future. However, the development of the human society may change the pattern of the land-use and building density resulting in a different surface roughness length. Thus, the surface wind speeds may change even when experiencing the same typhoon event. Consequently, the wind risk may also change. Furthermore, the development of the
Conclusions and outlook

Society affects the risks associated with climate change through the society's consumption behavior and this refers to the climate scenarios assumed in the climate model.

6.3.3 Vulnerability model

In regard to the vulnerability modeling, following aspects are addressed as future tasks:

- Consideration of more failure types and more building geometries
- Updating of debris flying modeling
- Sophistication of failure cost model
- Verification of the vulnerability model.

In this dissertation only three non-structural failures types are considered. Consideration of more failure types may be required. The fragility modeling is based on two specific building geometries that affects the spatial distribution of external wind pressure, which eventually influences the vulnerability. Although the model buildings considered in the present dissertation are typical, buildings in different regions are designed and constructed differently; not only with respect to the requirements by the design code and its associated documents, but also reflecting traditional design practices devised for specific wind environments in regions. In assessing the risk for a country-wide portfolio of residential buildings it is necessary to develop a set of vulnerability models for buildings of other geometries and parameters that envelops most relevant types of buildings and surrounding conditions.

The three failure types considered in the dissertation are all static in the sense that failures occur when the load exceeds the resistance. However, these and other failure types may occur as a result of the accumulation of wind load over a period of time. For instance, a roof tile may experience and resist fluctuating wind load until it fails. If some failure types are to be modeled as the accumulation of wind load or wind load effect over a period of time this requires a hazard index that accounts for, e.g. the duration of the critical wind speed, see Matsui et al. (2012). As described in the previous section it is found that apart from the wind speed the change of wind direction also affects the vulnerability. Thus, updated versions of the vulnerability model may include several hazard indices.

The modeling of flying debris and its trajectory in this dissertation is simplistic: roof tiles are considered as the only source of debris; the departure point of a flying debris is assumed to be the center of the roof, which might be erroneous if the distances between the adjacent buildings are relatively short; the vertical characteristic of the flying debris trajectory are not fully modeled; and the wind flow with flying debris is assumed to be steady. These are addressed as a task in the future development of the debris flying model in which the debris flying trajectory will be modeled by a 3-D model which can capture the vertical characteristics. Furthermore, the wind turbulence
Conclusions and outlook

will be incorporated in the simulation of trajectory of flying debris and the trajectory of flying debris failed at different location of roof will be modeled separately.

The assumed failure cost model is simplistic, which requires adjustments case-by-case. The failure cost in general depends not only the structural performance of the roof elements, but also other parameters such as esthetics and cosmetics. The failure cost model presented here does not include indirect cost such as property damages due to debris strike and water penetration etc. These highly depend on buildings in consideration - modeling failure costs for anonymous buildings and collecting statistics on them is a challenge. The impacts on the human safety are not considered in the present dissertation, which should be addressed as a future task.

Finally, but not least, the verification of the developed vulnerability model is required. This can be achieved by comparing the collected post disaster damage data and the estimated vulnerability for a given geographical region. Note that the vulnerability of one building are estimated based on specific conditions in the present dissertation, whereas the collected post damage data are in general available as an aggregated form for a given geographical region. In order to verify the developed vulnerability model, the information on the number of buildings locating in each specific condition for this given region should also be required. Given this type of information, the loss of all buildings in this region can be estimated by summing up the vulnerability of buildings locating in each specific condition.
Appendix

Appendix A: corrected Akaike Information Criterion (cAIC)

Let \( Y = (y_1, \ldots, y_n)' \) be an \( n \times 1 \) observation vector and \( X = (x_1, \ldots, x_n)' \) be an \( n \times k \) matrix of realizations of explanatory variables \( x_1, \ldots, x_k \) with full rank \( k \), where \( n \) is the sample size. For the selection of variables in the linear regression of response variable \( Y \) on a subset of \( k \) explanatory variables \( x_1, \ldots, x_k \) as:

\[
Y = X^M \beta + \epsilon,
\]

where \( X^M \) is the \( n \times m \) matrix of realizations of \( m (m \leq k) \) selected explanatory variables over \( k \) explanatory variables. \( \beta = (\beta_1, \ldots, \beta_n)' \) is the vector of regressional coefficients and \( \epsilon = (\epsilon_1, \ldots, \epsilon_n)' \) is the vector of residual terms. If \( \epsilon = (\epsilon_1, \ldots, \epsilon_n)' \) are assumed to be independently and identically distributed (IID) normal distribution \( N(0, \sigma^2) \), the goodness of fit of Equation (A.1) between \( Y \) and \( X^M \) can be examined by the well known Akaike Information Criterion (AIC). It favors the model with a smaller value and it is expressed as:

\[
AIC = n \log \left( \hat{\Sigma} \right) + n \left\{ \log (2\pi) + 1 \right\} + 2m + 2.
\]

where

\[
\hat{\Sigma} = \frac{1}{n} Y \left( I_n - X^M \left( X^M \right)' \left( X^M \right)^{-1} \left( X^M \right)' \right) Y
\]

If \( \epsilon = (\epsilon_1, \ldots, \epsilon_n)' \) are assumed to be IID following an unknown nonnormal distribution, Yanagihara (2006) propose a corrected version of Akaike Information Criterion (cAIC) which is constructed partially based on the jackknife method. It is described as following.

Let \( Y_{(-i)} \) and \( X^M_{(-i)} \) be obtained from \( Y \) and \( X^M \) by deleting \( y_i \) and \( x_i \) respectively and \( \hat{\beta}_{(-i)} \) and \( \hat{\epsilon}_{(-i)} \) be Maximum Likelihood Estimations (MLEs) of \( \beta \) and \( \epsilon \) under a normal assumption. \( \hat{\beta}_{(-i)} \) and \( \hat{\epsilon}_{(-i)} \) can be expressed as:

\[
\hat{\beta}_{(-i)} = \left( \left( X^M_{(-i)} \right)' X^M_{(-i)} \right)^{-1} X^M_{(-i)} Y_{(-i)},
\]

\[
\hat{\epsilon}_{(-i)} = \frac{1}{n-1} \left( Y_{(-i)} \right) \left( I_{n-1} - X^M_{(-i)} \left( X^M_{(-i)} \right)' \left( X^M_{(-i)} \right)^{-1} \left( X^M_{(-i)} \right)' \right) Y_{(-i)}.
\]
Appendix

The cAIC in the candidate model $M$, which is partially constructed by the predicted residuals. It is given as:

$$
cAIC = n \log(\hat{\Sigma}) + n \log(2\pi) + c_1 \sum_{i=1}^{n} \left( y_i - \left(\hat{\beta}_{[-i]} \right)^\prime x_i \right)^\prime \left( \hat{\Sigma}_{[-i]} \right)^{-1} \left( y_i - \left(\hat{\beta}_{[-i]} \right)^\prime x_i \right), \quad (A.6)
$$

where coefficient $c_1$ is defined as:

$$
c_1 = \frac{n(n+m)(n-m-3)}{(n-1)(n-m-2)} \sum_{i=1}^{n} \frac{1}{1-(P_M)_{ii}}, (n > m + 3). \quad (A.7)
$$

where

$$
P_M = X^M \left( \left( X^M \right)^\prime X^M \right)^{-1} \left( X^M \right)^\prime,
$$

(A.8)

and $(A)_{ij}$ denotes the $(i, j)^{th}$ element of matrix $A$.

By using the formulas for cross-validation in Fujikoshi et al. (2003), cAIC can be rewritten as a simple form which can avoid the calculation of $\hat{\beta}_{[-i]}$ and $\hat{\epsilon}_{[-i]}$. It is expressed as:

$$
cAIC = n \log(\hat{\Sigma}) + n \log(2\pi) + c_2 \sum_{i=1}^{n} \frac{\left( \hat{\epsilon}_i \right)^\prime \hat{\epsilon}_i}{\left(1 - (P_M)_{ii}\right) \left(1 - (P_M)_{ii} - \left( \hat{\Sigma} \right)^{-1} \hat{\epsilon}_i / n \right)}, \quad (A.9)
$$

where $\hat{\epsilon}_i$ is an ordinary least-squares residual given as:

$$
\hat{\epsilon}_i = \hat{\Sigma}^{-1/2} \left( y_i - \hat{\beta} x_i \right), \quad (A.10)
$$

and coefficient $c_2$ is defined as:

$$
c_2 = \frac{(n+m)(n-m-3)}{(n-m-2)} \sum_{i=1}^{n} \frac{1}{1-(P_M)_{ii}}, (n > m + 3). \quad (A.11)
$$

In the Equation (A.10), $\hat{\beta}$ is estimated as:

$$
\hat{\beta} = \left( \left( X^M \right)^\prime X^M \right)^{-1} \left( X^M \right)^\prime Y. \quad (A.12)
$$
Appendix B: Predictive interval based on reuse of the sample

Butler and Rothman (1980) propose a methodology to construct the predictive interval for a future observation within the framework of linear regression model based on the reuse of the sample. For the linear regression model:

\[ Y = \mathbf{X}\theta + \epsilon \]  

where \( Y = (y_1, \cdots, y_n)' \), \( \mathbf{X} = (\mathbf{x}_1, \cdots, \mathbf{x}_n)' \) are the realization of vector of response variable \( y \) and realization of matrix of explanatory variables \( x_1, x_2, \cdots, x_k \), \( \theta = (\theta_1, \cdots, \theta_k)' \) is a \( k \times 1 \) vector coefficients, \( n \geq k + 1 \). All \( (n-1) \times k \) sub-matrices of \( \mathbf{X} \) are of full rank \( k \) and \( \epsilon = (\epsilon_1, \cdots, \epsilon_n)' \). \( \epsilon_i (i = 1, 2, \cdots, n) \) are assumed to be IID.

Given the value of \( \mathbf{x}_f (k \times 1) \), the concern is to construct the predictive interval which is believed that the forecasted value \( y_f \) will not fall in this interval with the probability not larger than \( \beta (0 < \beta < 1) \), i.e. the significance level of \( \beta \). Assume that \( \epsilon_f \), the residual term of the forecast, is symmetric distributed. This predictive interval (PI) can be expressed as:

\[
PI = \left\{ (\mathbf{x}_f)' \hat{\theta} \pm \alpha s \left[ 1 + (\mathbf{x}_f)' (\mathbf{X}\mathbf{X})^{-1} \mathbf{x}_f \right]^{\frac{1}{2}} \right\},
\]

where \( \hat{\theta} = (\mathbf{X}\mathbf{X})^{-1} \mathbf{X} Y \) and \( s = \left( \mathbf{Y} (\mathbf{I} - \mathbf{A}) \mathbf{Y} / (n - k) \right)^{\frac{1}{2}} \) and \( \mathbf{A} = \mathbf{X}(\mathbf{X}\mathbf{X})^{-1} \mathbf{X}' \). \( \alpha \) is given as:

\[
\alpha = \left( \frac{n - k - 1}{n - k} \right)^{\frac{1}{2}} \frac{\tau_{(n-[\alpha\beta])}}{\left( 1 - \left( \tau_{(n-[\alpha\beta])} \right)^2 / (n-k) \right)^{\frac{1}{2}}}.
\]

where \( \{ \tau_i = (1 - (A)_{ii})^{-\frac{1}{2}} | y_i - (\mathbf{x}_i)' \hat{\theta} | / s \} \) is the set of absolute Studentized residuals, \( \{ \tau_{(i)} \} \) is their set of order statistics, \( \lceil \cdot \rceil \) is the greatest integer function and \( (A)_{ii} \) represents the \( i^{th} \) diagonal element of \( \mathbf{A} \).

The derivation and proof of effectiveness of this approach can be found in Butler and Rothman (1980).
Appendix

Appendix C: Conversion of wind speeds

10-minute sustained wind speeds in two different roughness categories at two heights are converted in this dissertation by the power law. The measured and targeted wind speed are denoted as $V_{\text{mea}}$, $V_{\text{tar}}$ respectively. The conversion follows:

$$V_{\text{tar}} = \left( \frac{Z_{\text{mea},G}}{f(Z_{\text{mea}})} \right)^{\alpha_{\text{mea}}} \cdot \left( \frac{f(Z_{\text{tar}})}{Z_{\text{tar},G}} \right)^{\alpha_{\text{tar}}} \cdot V_{\text{mea}},$$

(C.1)

where $Z_{\text{mea},G}$ and $Z_{\text{tar},G}$ are the gradient heights in the roughness categories that correspond to the measured and target wind speed respectively. $\alpha_{\text{mea}}$ and $\alpha_{\text{tar}}$ are the exponents in the power law for the roughness categories that corresponds to the measured and target wind speed respectively. $Z_{\text{mea}}$ and $Z_{\text{tar}}$ are the heights of measured and target wind speed respectively and $f(Z)$ is the function of height $Z$ as:

$$f(Z) = \begin{cases} Z_{G} & Z_{G} \leq Z \\ Z & Z_{b} \leq Z < Z_{G} \\ Z_{b} & Z < Z_{b}, \end{cases}$$

(C.2)

where $Z_{G}$ is the gradient heights, $Z_{b}$ is the height below which 10-minute sustained wind speed is assumed to be invariant along the height. The value of $Z_{G}$, $Z_{b}$ and exponent used in Equations (C.1), (C.2) are given in Table C.1.

Table C.1. The value used in the power law for the conversion of wind speed, following AIJ (2004).

<table>
<thead>
<tr>
<th>Roughness category</th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>IV</th>
<th>V</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Z_{b}$ [m]</td>
<td>5</td>
<td>5</td>
<td>10</td>
<td>20</td>
<td>30</td>
</tr>
<tr>
<td>$Z_{G}$ [m]</td>
<td>250</td>
<td>350</td>
<td>450</td>
<td>550</td>
<td>650</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>0.1</td>
<td>0.15</td>
<td>0.2</td>
<td>0.27</td>
<td>0.35</td>
</tr>
</tbody>
</table>
Appendix D: Information on 30 selected time series

The information on 30 selected time series of wind speed and direction is given in Table D.1. It presents the corresponding information of the typhoon ID, the meteorological station to measure the wind speed, the height to measure wind speed, the roughness category at which the meteorological station is located and the maximum wind speed during the typhoon event. The wind speed presented in the table is already converted to the 10-minute sustained wind speed in roughness category III at the height of 7 [m].
## Table D.1. The information of 30 selected time series of wind speeds.

<table>
<thead>
<tr>
<th>Typhoon ID</th>
<th>Meteorological station</th>
<th>The height to measure wind speed [m]</th>
<th>Roughness category</th>
<th>Maximum wind speed [m/s]</th>
</tr>
</thead>
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<tr>
<td>199918</td>
<td>Aburazu</td>
<td>18.6</td>
<td>III</td>
<td>24.2</td>
</tr>
<tr>
<td>199918</td>
<td>Kagoshima</td>
<td>44.8</td>
<td>IV</td>
<td>28.3</td>
</tr>
<tr>
<td>199918</td>
<td>Kumamoto</td>
<td>23.7</td>
<td>III</td>
<td>19.9</td>
</tr>
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<td>199918</td>
<td>Naga</td>
<td>10.3</td>
<td>II</td>
<td>19.0</td>
</tr>
<tr>
<td>199918</td>
<td>Saga</td>
<td>56.1</td>
<td>IV</td>
<td>20.8</td>
</tr>
<tr>
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<td>Miyakojima</td>
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<td>II</td>
<td>29.2</td>
</tr>
<tr>
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<td>Aburazu</td>
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<td>III</td>
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</tr>
<tr>
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<td>Kagoshima</td>
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<td>IV</td>
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</tr>
<tr>
<td>200416</td>
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<td>17.5</td>
</tr>
<tr>
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<td>Tanegashima</td>
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<td>II</td>
<td>19.5</td>
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<td>28.2</td>
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<td>IV</td>
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<td>II</td>
<td>13.9</td>
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<tr>
<td>200418</td>
<td>Yakushima</td>
<td>15.9</td>
<td>III</td>
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