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SINGAPORE

**Application of Remote Sensing for Major Land
Geohazards**

LIM JIE MIN BENJAMIN

SCHOOL OF CIVIL AND ENVIRONMENTAL ENGINEERING

2020

Application of Remote Sensing for Major Land Geohazards

LIM JIE MIN BENJAMIN

School of Civil and Environmental Engineering

A thesis submitted to the Nanyang Technological
University in partial fulfilment of the requirement for the
degree of Doctor of Philosophy

Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

17 January 2020

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Lim Jie Min Benjamin

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I have reviewed the content and presentation style of this thesis and declare it is free of plagiarism and of sufficient grammatical clarity to be examined. To the best of my knowledge, the research and writing are those of the candidate except as acknowledged in the Author Attribution Statement. I confirm that the investigations were conducted in accord with the ethics policies and integrity standards of Nanyang Technological University and that the research data are presented honestly and without prejudice.

17 January 2020

A handwritten signature in black ink, appearing to read 'Leong', with a stylized flourish extending from the end.

Assoc. Prof. Leong Eng Choon

AUTHORSHIP ATTRIBUTION STATEMENT

This thesis contains material from 4 papers published in the following peer-reviewed journal(s) / from papers accepted at conferences in which I am listed as an author.

Chapter 2 (partial) and Chapter 3 is published as Lim, B.J.M., Leong, E.C. & Low, K.S. 2015. Determining volume of failed soil mass in a landslide from satellite images. In: Zhenghan Chen, C.W., De'an Sun, Xongfu Xu (ed.) *6th Asia Pacific Conference on Unsaturated Soils (AP UNSAT 2015)*. CRC Press, Guilin, China, 685 - 690.

The contributions of the co-authors are as follows:

- Assoc. Prof. Leong E.C. provided initial project direction and revised manuscript drafts.
- I performed satellite image processing, data extraction and prepared manuscript drafts.
- Assoc. Prof. Low K.S. made available satellite images from the NTU X-SAT micro-satellite.

Chapter 2 (partial) and Chapter 5 (partial) is published as Lim, B.J.M. and Leong, E.C., 2019. Challenges in the Detection of Ionospheric Pre-Earthquake Total Electron Content Anomalies (PETA) for Earthquake Forewarning. *Pure and Applied Geophysics*, 176(6), 2425-2449.

The contributions of the co-authors are as follows:

- Assoc. Prof. Leong E.C. provided guidance on research paths and revised manuscript drafts.
- I proposed the initial research idea and performed the literature review as basis for the study. I also prepared the manuscript drafts.

Chapter 4 is published as Lim, B.J.M. & Leong, E.C. 2018. Characteristics of landslides induced by the 25 April 2015 M7.8 Nepal earthquake. *5th Geotechnical Earthquake Engineering and Soil Dynamics Conference (GEESD)*. ASCE, Austin, Texas, USA, 64 - 78.

The contributions of the co-authors are as follows:

- Assoc. Prof. Leong E.C. revised manuscript drafts.
- I processed the landslide inventory, analyzed the landslides characteristics and prepared the manuscript drafts.

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The contributions of the co-authors are as follows:

- Assoc. Prof. Leong E.C. provided insights to interpreting the data and results as well as revised manuscript drafts.
- I proposed the analysis method and wrote various automated routines in MATLAB to extract and process satellite GPS data and drafted the manuscripts.

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Lim Jie Min Benjamin

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SUMMARY

In this thesis, the two largest forms of land geohazards were examined, namely, landslides and earthquakes. As they encompass large areas and can cause tremendous damage, remote-sensing methods are therefore of great value. For this research work, the overarching objective is to rely on readily available open-source satellite data alongside new and practical methods to characterize these land geohazards. The objectives are three-fold – 1) to establish a method to estimate landslide volume from two-dimensional imagery, 2) to assess the usefulness of landslide susceptibilities derived from low resolution open-source satellite images, and 3) to deploy an earthquake prediction system using ionospheric precursors.

Firstly, a geometry model was proposed to quantify landslide depth using a varying cut-off plane, with the landslide failure surface being represented as an ellipsoid. This allows for the estimation of landslide volume with spatial information derived from satellite imagery. As compared to other techniques, the proposed approach is not only accurate and convenient to use, but it is also able to explain the theoretical basis behind the commonly observed landslide area-to-volume power law.

Secondly, landslide triggering factors were examined on the basis of a short-term database due to the 25 April 2015 Nepal M_w 7.8 earthquake. While only larger landslides could be identified using low resolution open-source satellite images, it was found that the resulting landslide susceptibility map could adequately capture landslides detected using high resolution images. These results indicate that open-source satellite images are useful for timely landslide risk assessments and does not justify the need for costly but high resolution satellite images.

Thirdly, a new method is proposed to confidently detect pre-earthquake total electron content (TEC) anomalies (PETA). This approach not only overcomes existing difficulties when identifying the effects of solar and geomagnetic activity on TEC, but can also be utilized in an earthquake prediction system. On top of findings related to the non-systematic spatial variations of TEC anomalies, a regional earthquake prediction system was explored and shows promise in approximating the epicentre within a 14 day period before an earthquake.

LIST OF PUBLICATIONS

Journals

1. Lim, B.J.M. and Leong, E.C., 2019. On the detection of anomalous seismo-ionospheric behavior in the presence of space weather stimuli for large earthquakes. *Advances in Space Research*, 63(6), 1961-1978.
2. Lim, B.J.M. and Leong, E.C., 2019. Challenges in the Detection of Ionospheric Pre-Earthquake Total Electron Content Anomalies (PETA) for Earthquake Forewarning. *Pure and Applied Geophysics*, 176(6), 2425-2449.
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2. Lim, B.J.M., Leong, E.C. & Low, K.S. 2015. Determining volume of failed soil mass in a landslide from satellite images. *In: Zhenghan Chen, C.W., De'an Sun, Xongfu Xu (ed.) 6th Asia Pacific Conference on Unsaturated Soils (AP UNSAT 2015)*. CRC Press, Guilin, China, 685 - 690.
3. Lim, B.J.M. & Leong, E.C. 2018. Characteristics of landslides induced by the 25 April 2015 M7.8 Nepal earthquake. *5th Geotechnical Earthquake Engineering and Soil Dynamics Conference (GEESD)*. ASCE, Austin, Texas, USA, 64 - 78.

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LIST OF SYMBOLS

α, β	:	Empirical constants for landslide area-to-volume power law
β_l	:	Latitude of IPP in solar-geomagnetic reference frame
Δ_d	:	Ionospheric delay
Δd_{epi}	:	Epicentral distance error
Δu	:	Epicentral azimuth error
Δ_L	:	Distance between epicentre and predicted epicentre
Δ_x, Δ_y	:	Component lengths of Δ_L
ΔRSV	:	Change in relative search volume
λ	:	Wavelength
$\Lambda(n, m)$	:	Normalization function
ω_o	:	Wavelet's frequency
σ_w	:	Measure of wavelet's support
$\Psi(t)$	:	Analyzing wavelet
$\Psi^*(t)$	:	Complex conjugate of analyzing wavelet
u	:	Epicentral azimuth
u_s	:	Slope angle
u_{IAZ}	:	Angle between boundary of EPZ and IAZ
a	:	semi-major axis (length)
a_l	:	Scaling parameter (Morlet wavelet)
a_n	:	Coefficient of PCs
a_{nm}, b_{nm}	:	Spherical harmonics coefficients of ionospheric model
A	:	Amount or cost of vulnerable elements

A_L	:	Landslide area (actual)
A_L^*	:	Landslide area (projected)
ANN	:	Artificial neural network
$Av\_volumetric\_error$	:	Average volumetric error
b, c	:	semi-minor axis (length)
b_I	:	Translational parameter (Morlet wavelet)
u_s	:	Landslide slope angle
c_L	:	Speed of light
d_{epi}	:	Epicentral distance
DCB_{rcv}	:	Differential code bias (receiver)
DCB_{sat}	:	Differential code bias (satellite)
Dst	:	Dst index
EPZ	:	Earthquake preparation zone
EQ	:	Earthquake
f_1	:	Frequency at 1575.42 mHz
f_2	:	Frequency at 1227.50 mHz
F10.7	:	Solar flux index
h	:	Depth from ellipsoid origin to landslide surface
h/c	:	Depth of cut-off plane (ratio)
H	:	Hazard probability
I	:	Set of training (input) data
IAZ:	:	Ionosphere affected zone
IPP	:	Ionospheric pierce point
O	:	Set of prediction (output) data
J_{LMS}	:	Minimizing cost function

k	:	Aspect ratio between planar and vertical dimensions
k_I	:	Ionosphere refraction coefficient ($\sim 40.3 \text{ m}^3/\text{s}^2$)
k_p	:	Kp index
L	:	Lower quartile
LC	:	Landslide concentration
LC_w	:	Weighted landslide concentration
LI	:	Landslide inventory
LS	:	Landslide
LS_{total}	:	Total number of landslides in given area
M_w	:	Earthquake magnitude
$M_{w,\text{lower}}$	:	Earthquake magnitude lower threshold
n_{pre}	:	No. of days prior to earthquake
N	:	Moving window length
$NDVI$	:	Normalized difference vegetation index
NIR	:	Near infra-red wavelength
P	:	Landslide probability [0 – 1]
PC_n	:	Principal components
P_{nm}	:	Un-normalized Legendre polynomials
$P_{4,\text{sm}}$	:	Carrier-smoothed pseudo-range function
$\tilde{P}_{nm}$	:	Normalized associated Legendre polynomials
r	:	Spherical radius
R	:	Red wavelength
R^2	:	Coefficient of determination
R_{EPZ}	:	Radius of EPZ
R_{IAZ}	:	Radius of IAZ

RSV	:	Relative search volume
s, σ	:	Standard deviation
s_I	:	sun-fixed longitude of IPP
STEC	:	Total electron content (slant)
t	:	Time
TEC	:	Total electron content
TEC $_{\beta}$	:	Reconstructed TEC signal
TEC _{CURRENT}	:	TEC at particular instance
TEC _{MEAN,N}	:	N-day mean TEC
TEC _{LB}	:	Lower bound of TEC signal
TEC _{UB}	:	Upper bound of TEC signal
TEC _U	:	Total electron content units
TTE	:	Time-to-earthquake
UQ	:	Upper quartile
PETA	:	Pre-earthquake total electron content anomalies
x_n	:	Input feature of ANN
volumetric_error	:	Landslide volumetric error
V	:	Vulnerability of elements
V _L		Landslide volume (actual)
V _L [*]	:	Landslide volume (projected)
VTEC	:	Vertical total electron content
w _j	:	Weight of hidden layer (ANN)
W_{Ψ}^y		Continuous wavelet transform (Morlet wavelet)
y	:	Exponent in landslide probability model
$y_{i,j}$	:	Value of input data

$\hat{y}_{i,j}$	:	Value of prediction corresponding to input
$y(t)$	:	Raw and unfiltered TEC signal
Z	:	Z-value (i.e. confidence level)
Z'	:	Zenith angle between satellite, receiver and geocentre

CHAPTER 1 INTRODUCTION

1.1 Land geohazards

Land-based geohazards, which often manifest in the form of landslides and earthquakes, can cause tremendous damage to infrastructure and frequently lead to the destruction of property and loss of human lives. For instance, landslides have led to annual losses up to \$290 million USD between 2000 to 2019 while the losses due to earthquakes are significantly higher, at \$26.5 billion USD annually over the same period (EMDAT 2020). Much of the risks associated with these two major forms of land geohazards stems from the fact that sub-surficial conditions are often ‘unseen’ and are challenging to quantify. This is further exacerbated by the scale of these geohazards which typically encompass large areas, rendering traditional methods, such as in-situ investigations, impractical.

In addition, for a reliable statistical assessment of these land geohazards, a large number of documented cases is necessary. This is especially so in the case of landslides, which entails much time and laborious fieldwork to establish a comprehensive landslide inventory by conventional means. As such, the task of characterizing geohazards coupled with greater demand for up-to-date and accurate spatial information has led the global community to recognise a pressing need for data at scale (Haack et al. 2002).

Consequently, the rapid advancements in remote sensing, such as satellites platforms as well as the availability and accessibility of derived data, is a timely development which could greatly benefit in the understanding of land geohazards, such as landslides and earthquakes.

1.2 Remote sensing

With the advent of space-borne observations, remote-sensing methods serves as a potential avenue in addressing the deficiencies of traditional methods. By observing the earth at great distances, satellites are able to cast new light in understanding geohazards. With a wide field-of-view (FOV) at high altitudes, large spatial coverage is a primary benefit in remote sensing. Typical altitudes of low-earth orbiting (LEO) satellites are within the 160 to 2000 km range. For example, with an orbit altitude of 705 km, the Operation Land Imager (OLI) from the Landsat 8 has a 190 km wide image swath (Barnes et al. 1998). Thus, large swaths of data captured by satellite payloads (e.g. optical imaging sensors) can yield significant amounts of data to understand the occurrences of land geohazards.

Apart from swath-based data (i.e. imagery) which caters to a large observational area, there are also satellites with payloads which utilize processing methodologies capable of capturing discrete, point-based measurements. For example, signals from satellites in the Global Positioning System (GPS) constellation can be exploited to measure ionospheric total electron content (TEC). When paired with ground-based instruments such as GPS stations and modelling methods, these synergistic data sources enable an unprecedented scale of study without compromising accuracy and quality of data used.

It can be appreciated that remote-sensing technology and its derived information are readily available and is a promising avenue in the understanding of land geohazards. As landslides and earthquakes are frequently occurring over the globe and causing huge socio-economic losses on a daily basis, satellite data could be utilized to further understand the occurrences of these natural hazards at scale. This can be achieved by

taking advantage synergistic remote-sensing approaches, both in terms of data sources and processing methods. On this end, it is thus vital to view and study the Earth's system as a whole, where the understanding of its nonlinearly correlated constituents would yield a holistic knowledge on these seemingly stochastic processes (Skinner and Murck 2011).

1.3 Research objective and scope

The primary objective of this study is to examine new and practical ways to quantify the two major forms of land geohazards, namely, landslides and earthquakes, using only open-source satellite data. As compared to commercial data, open-source satellite data is freely accessible in the public domain, is usually lower resolution and unprocessed.

The formulation of three research questions are listed below:

- 1) How can landslide volume be determined accurately from satellite images?
- 2) Are landslide susceptibilities derived from open-source satellite images sufficiently representative?
- 3) Can ionospheric precursors be used for earthquake early warning?

Specifically, the scope of works are as follows:

- i. Review the challenges in quantifying landslide volume with a focus on rationalizing the landslide area-to-volume power-law relationship.
- ii. Propose a technique in estimating landslide volume by means of landslides identifiable in two-dimensional satellite imagery.

- iii. Examine the spatial distributions and triggering factors of earthquake-induced landslides from a recent earthquake using a procedure that is translatable to similar inventories and propose a model to represent landslide risk.
- iv. Investigate the differences in results for (iii) when landslides are mapped using high resolution satellite imagery as compared to open-source satellite imagery via a temporal assessment across landslide inventories.
- v. Review of existing methods, concepts and assumptions used in the detection of ionospheric total electron content anomalies prior to earthquakes.
- vi. Highlight critical shortcomings of retrospective analyses in (v) and recommend solutions to facilitate their usability in a prospective scenario.
- vii. Propose a potential earthquake forewarning system using observations of ionospheric total electron content anomalies.

1.4 Organization of thesis

This thesis is organized into five chapters:

Chapter 1 introduces the two themes in this work, land geohazards and remote sensing. The necessity of using remote sensing in the understanding of landslides and earthquakes is presented. The research objective, research questions and scope of works are also outlined.

Chapter 2 provides a literature review for the two land-based geohazard investigated in this thesis. These are landslides, with a focus on volume estimation and

susceptibility models, as well as earthquakes, which touches on the phenomenon of pre-earthquake ionospheric anomalies observations.

Chapter 3 goes into the technical details behind the area-to-volume power law relationship among landslides. Mathematical explanations behind this relationship is derived and presented in the context of computing landslide volume from satellite images without the need for a three-dimensional digital elevation model. Results from the geometry modelling method are presented.

Chapter 4 examines a short-term landslide inventory induced by the 25 April 2015 Nepal (Gorkha) M_w 7.8 earthquake. From readily available open-source satellite imageries, the earthquake-induced landslides are characterized into their respective triggering and predisposing factors. The results are then used to generate a landslide probability risk model corresponding to the landslides from this event. Furthermore, a temporal assessment is conducted to investigate the differences in landslide characteristics when compared against two other inventories published at months to years after the earthquake event.

Chapter 5 addresses the seismo-ionospheric precursory phenomena and attempts to quantify and explain these observations in relation to earthquake prediction. A systematic way of analysing the ionospheric anomalies (i.e. total electron content) is proposed in order to circumvent the shortcomings of previous methods used in literature. The proposed method is subsequently applied on case studies to identify seismo-ionospheric signals to form the basis of an earthquake prediction system (EPS). Challenges in using ionospheric anomalies for the purposes of earthquake prediction are also discussed with several approaches suggested to overcome these issues. Finally, the proposal of an earthquake prediction system applied to the South-

east Asia region is put forward using a large database of earthquakes incorporating recent advances in machine learning.

Chapter 6 provides the overall conclusion and presents the summary of results as well as major findings of the research conducted. Recommendations for future research are also given.

CHAPTER 2 LITERATURE REVIEW

2.1 Landslide volume and susceptibility mapping

2.1.1 Assessment of landslide volume

According to Derron et al. (2005), the preliminary assessment of a landslide event should include geometry and landslide volume, which indicates the destructibility of a landslide (Guzzetti et al. 2006; Malamud et al. 2004). Landslide volume is also one of the critical parameters controlling the amplitude of landslide-generated tsunamis (Geist et al. 2009; Murty 2003; Watts and Grilli 2003). Martha et al. (2010) also stated that information regarding landslide failure volumes are essential for risk mapping (Flentje et al. 2007) and to enable more accurate understanding of landslide processes, such as travel distances and frequency-volume relationships (e.g. Dai and Lee (2001); Okura et al. (2003)). In order to alleviate against the devastating impacts of landslides, geotechnical engineering preventive measures, including the use of retaining walls typically require landslide volume estimates as a primary design parameter (Chen et al. 2014). In this regard, confident methods of evaluating landslide volumes have to be developed to avoid reinforcement failures (under-design) and also for economic reasons (to avoid over-design).

To compute the volume of a landslide, knowledge regarding its three-dimensional extents is necessary. However, it is recognised that accurate landslide volume estimates are hard to obtain (Chen et al. 2014b; Guzzetti et al. 2009; Urgeles et al. 1999). Detailed monitoring of landslides relying on field investigations and instrumentations is time- and resource-consuming and frequently not feasible due to inadequate scientific expertise, insufficient budgets for subsurface investigations or that the size of the monitored landslide is simply too large (Behling et al. 2014;

Martha et al. 2010; Wieczorek and Snyder 2009). The advent of satellite technology has greatly facilitated observations of landslides via remote sensing, thus overcoming the limitations of conventional surveying. Planar dimensions of a landslide can be readily observed through two-dimensional imagery. However, it remains a challenging task to derive an accurate estimate of the volume of a landslide (Guthrie and Evans 2004), mostly due to the difficulty of quantifying the depth of the décollement plane.

As a crude estimation of landslide volume, the landslide depth obtained from methods such as contour interpretation (Korup 2005), ‘envelope’ bounding approach (Arsenault and Meigs 2005), sloping local base level concept (SLBL) (Jaboyedoff et al. 2004) or arbitrary assignment (Martin et al. 2002) could be used. While these approaches allow for a convenient way of approximating landslide volume, they may yield erroneous results (Urgeles et al. 1997, Tseng et al. 2013 and Wang et al. 2014). In contrast, more accurate volumetric assessments could be attained with the use of pre- and post-event digital elevation models (DEM) (Suganthi and Srinivasan 2010). Nevertheless, DEM derived by methods such as stereo photogrammetry or instrumental scanning (e.g. Light Detection and Ranging (LIDAR) and synthetic aperture radar (SAR) interferometry) is time-consuming to generate, requires expert manipulation of point-clouds and is subject to availability of the instrument over the study area (e.g. limited satellite overpass times and/or access to drone-based platforms). Thus, this necessitates the development of a landslide volume estimation method simply from passive satellite observations which optimizes both time and volumetric accuracy.

In particular, the focus in this work is made towards the landslide area-to-volume power law relationship as an alternative means of deriving landslide volume. It is easy to apply the power law relationship for satellite-observed landslide areas, however, there are two issues – 1) volume estimates are erroneous, and 2) the theoretical basis is unclear. The following section further outlines these concerns.

2.1.2 Landslide area-to-volume relationship

Empirical landslide area-to-volume power-law relationships (in the form of Eq. (2.1) and shown in Table 2.1) have been widely used to estimate volume of failed soil mass using landslide area.

$$V_L = \alpha A_L^\beta \quad (2.1)$$

where V_L = landslide volume (km^3); A_L = landslide surface area (km^2); α and β = empirical constants.

As shown in Table 2.2, the ranges of α and β values reported by various authors (e.g., (Chaytor et al. 2009; Guzzetti et al. 2008; Haflidason et al. 2005; Hewitt 2002; Hovius et al. 1997; Kaldaron-Asael et al. 2008; Korup 2005; Larsen et al. 2010; Ten Brink et al. 2006; Tseng et al. 2013) fall within a narrow band. While the underlying basis is unclear, it has been demonstrated that Eq. (2.1) applies regardless of landslide size, location (e.g. failure material), failure process (e.g. rotational and translational) and even trigger mechanism (i.e. earthquake- or rainfall-induced) of the landslide (Guthrie & Evans, 2004; Kalderon-Asael et al., 2008; Guzzetti et al., 2009). As mentioned by Larsen et al. (2010) and Kaldaron-Asael et al. (2008), this is a notable fact considering the many differences in landslide characteristics observed in the literature, and the area-to-volume power-law does not discriminate among them.

Table 2.1 Values of α and β for empirical landslide area-to-volume relationships

Author	α	β	Valid area (km ²)
Simonett (1967)	0.024	1.368	$2.3 \times (10^{-6}) - 0.19$
Abele (1974)	0.017	1.307	0.2 – 60
Whitehouse (1983)	0.024	1.250	0.05 – 3.9
Hovius et al. (1997)	0.050	1.500	$1(10^{-5}) - 1$
Hewitt (2002)	0.020	1.300	$\geq 1(10^{-6})$
Haflidason et al. (2005)	0.027	1.032	0.3 - 39000
Korup (2005)	0.020	1.950	≥ 1
Korup (2006) (i)	0.020	1.550	$\geq 5(10^{-8})$
Korup (2006) (ii)	0.030	1.380	$\geq 1(10^{-6})$
Ten Brink et al. (2006)	0.026	1.292	0.5 – 200
Chaytor et al. (2008)	0.016	1.099	$8.9(10^{-7}) - 0.002$
Guzzetti et al. (2008)	0.033	1.432	$1(10^{-5}) - 1000$
Kalderon-Asael et al. (2008)	0.030	1.380	$3(10^{-12}) - 3(10^{-6})$
Guzzetti et al. (2009)	0.037	1.450	$2(10^{-6}) - 1000$
Larsen et al. (2010) (i)	0.014	1.332	$1(10^{-6}) - 316$
Larsen et al. (2010) (ii)	0.023	1.350	$1(10^{-6}) - 316$
Parker et al. (2011)	0.023	1.388	$3(10^{-5}) - 20$
Tseng et al. (2013)	0.013	1.242	$1.1(10^{-4}) - 0.2$

Table 2.2 Summary of α and β values reported in literature

Parameter (s)	Minimum	Maximum
α	0.013	0.050
β	1.032	1.950
Landslide area (km ²)	3×10^{-12}	4×10^4

Various studies have attempted to provide insights to Eq. (2.1). To account for the variation in β values, Chaytor et al. (2009) stated that it is due to differences in the failed soil mass, landslide processes or presence of saturated or over-pressured sediments. More recently, Klar et al. (2011) pointed out that Eq. (2.1) is independent of slope height, slope angle, physiographical settings and is a result of the self-affine nature of landslides. As opposed to self-affinity, self-similarity (or scale-invariance)

indicates that the aspect ratio of a landslide remains the same at different scales. Thus, this implies that the dimensions of a smaller landslide could simply be stretched by an equal amount in all directions to replicate a larger landslide. As observed by the variability of β values in Table 2.2, deviations from the assumed self-similar behavior seems apparent, suggesting that the aspect ratios are not constant (i.e. larger landslides are relatively thinner compared to smaller landslides). This phenomenon was also discussed by Kalderon-Asael et al. (2008), where the transition of self-similar to self-affine nature of a landslide occurs to account for the different exponent values. In addition, it is generally agreed that the empirical area-to-volume relationships is largely a result of geometrical variations (Kalderon-Asael et al., 2008; Guzzetti et al., 2009). Hence, an implication of these findings is that there could be a possible link between a three-dimensional representation (i.e. geometry) of a landslide and its self-affine characteristic.

For the purposes of estimating volume of a landslide, while the direct use of Eq. (2.1) is convenient, it is error-prone and tends to yield inconsistent results (Brunetti et al. 2009; Guzzetti et al. 2009; Tseng et al. 2013; Wang et al. 2014a). Alternatively, a common geometrical method to calculate the volume of a landslide is to assume that the failed soil mass possess the shape of an ellipsoid (Marchesini et al. 2009; Varnes 1958). Nikolaeva et al. (2014) accounted for a translational component by augmenting the ellipsoidal assumption using two planar constraints. However, in the absence of a ‘truth’ volume, they yielded approximately 50% volumetric error when compared to an empirical area-to-volume power-law relation. Mergili and Fellin (2013) adopted a similar approach, but in their ellipsoid computation technique, several supplementary data were required, such as digital elevation models (DEM),

soil cohesion, friction angle and unit weight. As highlighted earlier, this information may not be readily available depending on the location of the landslides (e.g. inadequate data due to limited instrumental platforms) and soil properties, if available, have a spatial variability.

Therefore, existing techniques used to compute landslide volume typically require information beyond those immediately obtainable from satellite images. If the relationship between the three-dimensional geometrical and mathematical characteristics of landslides could be reconciled with the observed landslide area-to-volume power-law, two advantageous outcomes can be achieved:

- 1) Rationalization of the landslide area-to-volume power-law relationship by means of geometrical and mathematical modelling of landslide failure surface.
- 2) The volume of landslide mass can be readily computed based on landslide areas delineated by pre- and post-event satellite imageries.

Thus, this approach provides a quick volumetric estimation of landslide volume with good accuracy. Additionally, apart from the use of landslide volume as a proxy to damage, regional landslide prone areas may be identified by means of post-event susceptibility mapping. In the following section, an examination is made to understand the triggering characteristics of earthquake-induced landslides using open-source satellite images.

2.1.3 Spatial distribution analyses of earthquake-induced landslides

As compared to landslides, earthquakes as a sub-surface hazard are harder to forewarn against. Furthermore, the fact that large number of landslides may develop during seismic shaking (as opposed to landslides occurring after rainfall events),

means that earthquake-induced landslides are harder to prepare for (Keefer 1984; Martha et al. 2015; Rodriguez et al. 1999; Tian et al. 2013). With the sheer quantity of landslides owing to a particular earthquake, a detailed co- or post-seismic landslide inventory allows comprehensive analyses to be conducted. A landslide inventory typically records, minimally, the locations of landslides, along with other information such as date of occurrence as well as the type of slope failure (e.g. translational or rotational) (Guzzetti et al. 2012). However, preparing such inventories from field investigations alone is unrealistic due to large number of earthquake-induced landslides and can be better supplemented by satellite imagery (Xu et al. 2014). For example, the 2007 M_w 6.6 Niigata Chuetsu-Oki earthquake triggered hundreds of landslides around the coastal city of Kashiwazaki in Japan. The consequences of these landslides were damages to residential areas, transportation routes, pavement, embankment and complete destruction of road and railway sections. Utilizing combinations of ground-based investigations and aerial photography, Collins et al. (2012) studied the spatial distributions of landslides in relation to fault origins (e.g. surface projection of fault planes), peak ground acceleration (PGA), topography (e.g. slope) and geology of the area. Collins et al. (2012) found areas of particularly high landslide concentrations (i.e. landslides per area) not clearly justified by distances to epicentre and PGA, but rather, slope angles and geology. In addition, LIDAR was used to compute and categorise landslide volumes, where they found that most landslides triggered were small (i.e. $< 100 \text{ m}^3$).

Consequently, apart from the direct damages owing to seismic ground motion, landslides are the most significant collateral hazard of earthquake shaking (Bommer and Rodríguez 2002). Indeed, in evaluating landslide risks, one of the most useful

definitions of landslide risk itself was originally presented by Varnes (1984), as shown in Eq. (2.2) (Van Westen et al. 2006). Within Eq. (2.2), the spatial probability of landslides (i.e. landslides in relation to the environment) is an integral part in the assessment of the hazard (H) term.

$$Landslide\_risk = \sum H \sum VA \quad (2.2)$$

where H = hazard probability; V = vulnerability of elements; A = amount or cost of vulnerable elements; $\Sigma(VA)$ = consequences from landslide failures.

As such, an effective and realistic way to mitigate landslides occurring during and after earthquakes is to firstly characterize and understand its spatial distributions. Especially in the case of earthquake-induced landslides, where the number of slope failures are typically numerous, an assessment of locations where these failures occur serve as a means of providing information for rescue efforts. Many of such studies in the literature have alluded to the necessity of employing high to very-high resolution satellite imagery (i.e. meter to sub-meter pixel sampling) in the identification of smaller landslides for the sake of a complete landslide inventory (Ghosh et al. 2012; Guzzetti et al. 2012; Reichenbach et al. 2004; Wiczorek 1984). However, since larger-sized landslides pose a greater risk, the need for such data resolution may not be warranted. This is exacerbated by the costly nature of high resolution imageries, amount of processing time required (i.e. finer sampling resolution results in increased data volume) and limited coverage areas. Thus, the efficacy of open-source satellite imageries for the purposes of quantifying the spatial distributions and triggering factors of landslides remains to be evaluated.

2.2 Ionospheric precursory signatures of earthquake activity

Apart from landslide susceptibility maps, a reliable earthquake warning system based on precursory phenomena can greatly enhance disaster preparedness. For instance, a recent study has shown that landslides could indeed be monitored and even predicted using electromagnetic signals of self-potential and magnetic susceptibility (Yamazaki et al. 2017). Ever since the first reported pre-earthquake ionospheric anomalies on 28 March 1964 (Good Friday Alaska earthquake) by (Moore 1964), much interest has been garnered in the scientific community regarding detailed characterizations and utilizations of these anomalies as earthquake precursors. This is further driven by the pioneering works in the statistical detection of anomalous signals, such as seismo-electromagnetic signals (SEs) of currents, magnetic fields and electric fields, which modify ionospheric plasma, such as electron density and total electron content (Liu et al. 2001; Liu et al. 2000; Oyama et al. 2008).

Pre-earthquake ionospheric anomalies have been recorded by various platforms, such as satellite data (Hsiao et al. 2010; Liu et al. 2009; Sarkar and Gwal 2010; Zhang et al. 2009), ionosondes (Xu et al. 2010; Yu et al. 2009; Zhao et al. 2008), ground-based GPS stations (Yu et al. 2009) and ionospheric maps (Afraimovich and Astafyeva 2008). The origin and reason for such ground processes, more commonly known as ‘seismic preparation or activation’ processes remain unclear, though the reasons have been postulated widely. Several coupling theory includes gravity waves, emanation of warm gases and the positive-holes (Depueva and Ruzhin 1993; Freund 2000; Freund et al. 2006; Hayakawa and Molchanov 2002; Mareev et al. 2002; Pulinets and Ouzounov 2011). Evidently, a consequence of the varied hypotheses regarding seismic preparation and physical mechanism behind these anomalies is a lack of

common opinion and at present, debated theories (Hayakawa 2018; Klimenko et al. 2011). Recently however, Liu and Chao (2017) for the first time present evidence that earthquake-generated electric fields modify ionospheric total electron content near the epicentre area. Therefore until further and more detailed evidence is present, the mechanism for generation of these anomalies is by and large not well understood, even though its existence has been observed in numerous case studies (Liu et al. 2004).

Several agencies, including the GeoCosmo team from USA, PRE-EARTHQUAKES project from Europe and Russia, Earthquake Integrated Frontier Research project from Japan as well as the iSTEP project from Taiwan, have even embarked on goal-oriented studies to employ multi-faceted precursors, data sources (e.g. ground and remote sensing methods) and analysis procedures to improve knowledge on pre-earthquake anomaly manifestations and for the possible deployment of a system for earthquake prediction (Liu et al. 2016; Tsai et al. 2006). For a successful earthquake prediction, time frame for occurrence, location and strength (i.e. when, where, what) of the earthquake have to be made in a sufficiently accurate and deterministic fashion (i.e. in contrast to a probabilistic or stochastic assessment) (De Santis et al. 2018; Jordan et al. 2011; Monroe et al. 2007; Ouzounov et al. 2018). Recently, Bouta et al. (2019) published a comprehensive cost-benefit analysis on earthquake warning systems. The authors concluded that such implementations not only help to reduce mortality rates during earthquakes, but the overall economic gain is substantial (i.e. approximately \$289 million USD over a 50-year period). Even though present warning systems utilising the detection of P and S waves can only provide up to a 15 second warning (i.e. lead time) window, the social and economic benefits of earthquake warning are expected to increase with accurate alarm signals and also with

a longer warning time. Thus, the detection of ionospheric anomalies may serve to address these issues.

In this work, the focus is given to ionospheric-based pre-earthquake total electron content anomalies (hereafter known as PETA) and issues that have to be addressed and resolved prior to using it as an earthquake (EQ) prediction parameter. Certainly, a concurrent analysis of the various types of precursors and even other ionospheric parameters would yield more confident results especially when it pertains to something as capricious as earthquakes (e.g. Figure 2.1). However, with the current state of knowledge in PETA, especially when it comes to data analysis procedures, it does not readily facilitate an actual earthquake prediction system. Thus, it is of great interest to develop a framework to predict earthquakes by means of PETA. In the subsequent sections, the ionospheric total electron content is first introduced, followed by a statistical examination of PETA case studies in the literature.

Figure 2.1 An overview of earthquake precursors and associated measurement platforms (adapted from Hayakawa (2018)); ionospheric perturbations are of interest in this research

2.2.1 PETA case studies and challenges

Case studies on earthquake precursors up till 2015 were compiled based on precursor types and summarized in Figure 2.2 which shows that total electron content (TEC) as well as radon, thoron and groundwater-related anomalies were the most widely studied. It should be noted that the calculation of TEC from measurements of ground-based GPS receivers have been developed over 20 years ago (Liu et al. 1996). More information regarding the computation of TEC is provided in Appendix – A. Comparing TEC and radon/thoron/groundwater studies in Figure 2.3, studies on radon/thoron/groundwater observations were generally more than those involving ionospheric TEC before and during the early 2000s. The trend was subsequently reversed with a remarkable increase in ionospheric TEC studies since 2007. This was

perhaps due to the launch of the FORMOSAT-3/COSMIC-1 constellation of six polar-orbiting satellites on April 2006 (Fong et al. 2008). These satellites carried payloads essential for ionospheric TEC, electron density and atmospheric (i.e. using the radio occultation technique) measurements, providing vast quantities of data and opportunities to study earthquake precursors at a global scale.

Figure 2.2 Number of publications classified by nature of precursor; ULF and VLF represent ultra- and very-low frequencies

Figure 2.3 Comparison of number of publications between ionospheric TEC and radon/thoron/groundwater

As with the majority of earthquake precursor studies, PETA case studies are retrospective in nature (i.e., post-event). For example, recent publications within the past six years (e.g., Chauhan et al. (2009); Fuying and Yun (2011); Liu et al. (2010); Nenovski et al. (2015); Sánchez-Dulcet et al. (2015); Singh et al. (2009); Tojiev et al. (2013) were undertaken based on past significant earthquakes. A search through the database for relevant publications (i.e. seismic effects on TEC) further reveals that there is an overall increasing number of case studies conducted on PETA from 2010 onwards. This observation was similarly reflected in Figure 2.3. Plausible reasons for the trend may be due to increasing availability of TEC data especially space-based sources, such as low-earth orbiters (LEO) from European satellite constellation SWARM, USA/Taiwan FORMOSAT-7/COSMIC-2 constellation mission as well as the near-equatorial orbiter (NEO) climate research satellite VELOX-CI from Singapore. In view of increasing global development and urbanization, it will be very useful to have an earthquake prediction system to lessen the impact of an earthquake (Boughazi et al. 2014; Islam et al. 2015). Figure 2.3 also shows a gradual decline of earthquake precursory studies from 2012 onwards which may be attributed to a general stagnation of research in this area.

Figure 2.4 summarizes the common methodology for a PETA analysis and considerations that should be taken into account. Earthquake prediction (or forewarning) is differentiated from earthquake forecasting in that the former typically involves the establishment of the time, location and magnitude of an earthquake on the basis of one or more precursors whereas the latter involves the establishment of the occurrence probability of an earthquake. For the purposes of this study which relies on ionospheric TEC as an earthquake precursor, the term ‘earthquake

prediction' and 'earthquake prediction system' (EPS) were adopted according to conventional definition.

In an early study, Tong (1988) conducted an investigation in earthquake prediction involving anomalous animal behavior and posed a series of questions regarding data analysis procedures which should be addressed for pre-earthquake anomaly detection. These questions are equally relevant for PETA and are presented below with modifications where appropriate:

- 1) What is the nature of data and its reliability?
- 2) What is the 'normal' behaviour of ionospheric total electron content in the absence of seismic influences?
- 3) Can a particular geophysical or geochemical change be shown to cause the observed ionospheric total electron content perturbations?
- 4) Can non-seismic noise factors be eliminated from the data set?
- 5) How wide is the spatial range of ionospheric total electron content that will be affected by the pre-earthquake stimuli and what are the limits of detection by ionospheric total electron content to different stimuli (e.g. nature of earthquake)?

The above questions shall be addressed in this thesis. Furthermore, solutions will be proposed in order to circumvent specific issues (i.e. Points (2), (4) and (5)) which are imperative to allow the translation of these observations into a prospective earthquake prediction system.

Figure 2.4 Typical processing flow and consideration for a retrospective (backward-looking) statistical PETA analysis (topics highlighted in bold are addressed in the current study)

2.2.2 Relevance of earthquake preparation zone to seismo-ionospheric precursors

Apart from the difficulty in confidently detecting seismo-ionospheric signals, another major challenge pertains to the utilization of ionospheric anomalies to forewarn an impending earthquake. The time of occurrence, geographic location and seismic strength have to be determined in earthquake forewarning (as in the case of classical earthquake prediction) (Devi et al. 2012; Wallace et al. 1984). This implies that quantitative estimations of these three factors have to be inferred from observations of ionospheric anomalies. Assuming that systematic associations between anomalous

ionospheric manifestations and seismic TLS (i.e. time, location and strength) do indeed exist, an observation-driven prognosis for potential seismic activity can be made consequently. A methodology dependent on deterministic parameters (e.g. TEC) significantly differs from conventional statistical assessments of earthquake risk (e.g. probabilities) as it will be more valuable and relevant in the (very) short- and medium-term scenario (Blaunstein and Hayakawa 2009; Pulinets et al. 2015). The ensuing discussion (and objective of this study) elaborates on the link (or to a certain degree, the lack of) between earthquake location and the appearance of localized ionospheric anomalies. While a temporal analysis simply detects a possible anomaly, a spatial analysis is needed to collocate the anomaly at a particular geographic position (Su and Liu 2014).

Early works in earthquake prediction uses the ‘earthquake preparation zone’ or EPZ as a basis for seismo-ionospheric studies (Crampin 1987). Essentially, the EPZ presents itself as a region of cracked rocks due to the influence of tectonic stresses, which forms within the site of an earthquake focus. As a result, it is presumed that various seismic precursory signatures are likely to originate from this neighbourhood. In the absence of an alternative indicator, an examination of previous case studies involving earthquakes and ionospheric anomalies reveals that the notion of EPZ serves as a convenient approach for spatial collocation and is frequently used to imply causality (Aggarwal 2015; Akhoondzadeh and Saradjian 2011; Chauhan et al. 2009; Choi et al. 2012; Pulinets and Ouzounov 2011). Furthermore, various studies have pointed out that these pre-earthquake anomalies should be localised within the EPZ (Krankowski et al. 2006; Namgaladze et al. 2013).

Determining the size (i.e. radius) of EPZ (i.e. R_{EPZ}) typically adopts the formulation proposed by Dobrovolsky et al. (1979) and is presented in Eq. (2.3),

$$R_{EPZ} = 10^{0.43M_w} \quad (2.3)$$

where M_w refers to earthquake magnitude.

Figure 2.5 and Table 2.3 additionally illustrate other EPZ relations which were proposed in the literature. However, most of these are not applicable to ionosphere or space weather analyses as their radii are too small to detect ionospheric variabilities. For example, Kondratenko and Nersesov (1962) is only valid for earthquakes with $M_w \leq 3.0$ while Rikitake (1975) yielded small EPZ values as compared to the others, and hence insignificant on Figure 2.5. As for Dobrovolsky et al. (1979) (i.e. Eq. (2.3)), it is clearly observed that the EPZ radius scales exponentially with earthquake magnitude, especially from $M_w \geq 6.0$ onwards and gives ample coverage at larger magnitudes to examine ionospheric TEC anomalies. It ought to be noted that Eq. (2.3) was not established by means of ionospheric observations, which are extremely dynamic in nature, but rather on the first and second states of solid and liquid (i.e. mechanical processes) (Chen et al. 2011). It incorporates in-situ precursory phenomena such as resistivity, radon emissions and light effects (Su and Liu 2014). As a result, Eq. (2.3) was derived from the optimization of pattern recognition to identify earthquake-prone areas with assumptions made regarding thickness of the fractured (critical) region (i.e. surrounding inclusion, tectonic stress and surface deformation) (Gelfand et al. 1976; Keilis-Borok and Soloviev 2011). Nonetheless, there appears to be no physical reason justifying the inscription of a perfect circle (implied by Eq. (2.3)) centred on the epicentre for a stochastic process such as

earthquake (Bowman et al. 1998). Furthermore, the geographical extent of any ionospheric anomalies is potentially confounded by dynamic interactions between the atmosphere and ionosphere as well as space weather phenomenon such as the equatorial ionization anomaly (EIA) and solar rotation. Thus, usage of the EPZ for seismo-ionospheric studies could be problematic when defining it as a region for anomaly detection (Akhoondzadeh 2015; Akhoondzadeh and Saradjian 2011; Astafyeva and Heki 2011). For instance, previous works by Wang et al. (2009) and Marshall et al. (2013) have shown that the actual earthquake preparation area is potentially much smaller than the size described by Eq. (2.3), while Dogan et al. (2011) stated that the perturbed region of the ionosphere is in the same order of magnitude as EPZ. In general, there are inconsistent approaches when it comes to locating the anomaly with respect to the epicentre. While some studies stated greatest anomalies were found near the epicentre, others reported otherwise (e.g. edge of the EPZ) (Nenovski et al. 2015; Yiyan et al. 2009). Pulinets et al. (1994) recognized that a wide ionospheric extent in terms of geographical latitude and longitude could be perturbed by earthquake activity, thus posing a significant challenge in collocating the epicentre for a prospective earthquake forewarning scenario.

Pertaining to this aspect, an attempt is made in this research to evaluate the consistency in locations of these TEC anomalies with respect to the epicentre and the EPZ. A database of earthquakes is assembled, with several of them studied by others previously. In order to detect the presence of anomalies, a frequency-based approach based on wavelet analyses is proposed to circumvent the inherent assumptions made in existing statistical methods. Consequently, relying on a data-driven approach, an assessment is made if the ionospheric anomalous zone (IAZ) do indeed appear over

the epicentre and within the EPZ (i.e. Eq. (2.3)) using published ionospheric data. Furthermore, an attempt is made to quantify the geometry of the IAZ. The overarching objective of the study is to verify if geographic location and extent of IAZ could be a precursor to potential seismic activity.

Figure 2.5 Various EPZ formulations proposed in literature

Table 2.3 Relations for EPZ radius proposed in literature

Reference	EPZ radius, R (km)	Remarks
Kondratenko and Nersesov (1962)	$R = \frac{8.1M_w - 1.8}{2}$	Anomalous crustal deformation; events $\leq M_w 3.0$
Rikitake (1969)	$R = 10^{\frac{11.4 + 1.1M_w}{3} - 5}$	Anomalous geomagnetic changes
Anderson and Whitcomb (1975)	$R = \frac{10^{0.26M_w + 0.46}}{2}$	Extrapolation of Kondratenko and Nersesov (1962) for large magnitude earthquakes
Rikitake (1975)	$R = 10^{\frac{M_w - 4.45}{1.96}}$	Anomalous crustal deformation; events $\leq M_w 7.0$
Dobrovolsky et al. (1979)	$R = 10^{0.43M_w}$	Anomalous in-situ precursors; events $\geq M_w 4.0$
Bowman et al. (1998); Kanamori and Anderson (1975)	$R \propto 10^{0.5M_w}$	Deformation of critical region
Afraimovich et al. (2004)	$R = \frac{4L^2}{\lambda}$	Ionospheric response to gravity waves

2.2.3 Developments in earthquake prediction, forecasting and precursors

Till now, earthquake prediction seems impossible and elusive. One-off successes such as the medium-term prediction of the 1975 M_s 7.3 Haicheng earthquake in China which saved many lives could not be repeated to predict a devastating M_s 7.8 earthquake that occurred 18 months later in the Tangshan province and optimism in earthquake prediction quickly waned (Chen 1988; Wang et al. 2006). There has been several international and national efforts devoted to earthquake prediction since the 1960s, such as the International Commission on Earthquake Prediction, China's Earthquake Bureau (CEA) and USA's National Earthquake Hazards Reduction Program (NEHRP). While reasons for the concurrent commencements of these projects are uncertain, none of these initiatives nor predictive methods put forward were ultimately found to be successful (Suzuki 1982). For instance, the seismological community in Japan failed to predict the disastrous 2011 Tohoku M_w 9.1 earthquake even with nationally-driven efforts and projects, which eventually led to the complete abandonment of research in earthquake prediction (Uyeda 2013). In general, it has been acknowledged that earthquake prediction is impossible (Geller et al. 1997; Richter 1958). Charles Richter, inventor of the Richter scale, famously said, "Only fools and charlatans predict earthquakes" (Elkin 2012; Hasian Jr et al. 2014).

Earthquake early warning systems utilize real-time measurements (e.g. seismic waves as well as variabilities in ground motion such as peak ground accelerations (PGA) and velocities (PGV)) to provide very short-term (i.e. seconds to minutes) earthquake alerts (Böse et al. 2008; Juhel et al. 2018; Lin 2011d; Minson et al. 2019).

To further elucidate the discussion, big data collected by internet query platforms, such as Google Trends, could be prodded to reveal social perceptions of earthquake

prediction. Similar approaches has been previously applied to other research domains, such as healthcare, medicine, politics and population diversity (Huang 2015; Mavragani and Tsagarakis 2016; McLean et al. 2016; Sampri et al. 2016; Troumbis 2017). Google Trends is a free and publicly accessible database which analyses users' search terms (or keywords) and offers insights to temporal and geographical patterns based on the volume of searches (Google 2017; Jun et al. 2018). Due to the sheer amount of global queries it handles (i.e. 5.5 billion per day, up to 2 trillion in 2016), it is insightful to infer the interest in earthquake prediction since it is a representative source of big data (Jun et al. 2018; Sullivan 2016). Interest is quantified in terms of the change in relative search volumes (ΔRSV) between time t and time $t+I$, where RSV is a normalized value between 0 and 100 (i.e. peak number of searches within that period). Here, several keywords were examined in Google Trends, namely, 'earthquake prediction', 'earthquake forecast' and 'earthquake precursor'. It should be noted that there is a distinction between *prediction* (i.e. deterministic) and *forecast* (i.e. probabilistic) (Wang 2014).

As illustrated in Figure 2.6 which shows ΔRSV for a span of 14 years (i.e. between 2004 and 2018; Google Trends do not provide results earlier than 2004), there were only a handful of occasions corresponding to significant earthquake events where the keywords registered values above 80 (i.e. extremely high increase) (Durmuşoğlu 2017). For example, a clear spike in searches of 'earthquake prediction' and 'earthquake forecast' was recorded on March 2011. On 11 March 2011, a disastrous M_w 9.1 megathrust earthquake occurred off the coast of Japan which triggered a massive tsunami, resulting in widespread destruction to human lives and infrastructure (Norio et al. 2011). Furthermore, long-term harmful effects and indirect

health implications from the Fukushima Daiichi nuclear disaster due to the induced tsunami are still being investigated till this day (Fukunaga et al. 2017; Sawano et al. 2018). As mentioned earlier, failure of the earthquake prediction projects ongoing in Japan at the time leading up to the Tohoku earthquake in 2011 had yielded much pessimism in its (i.e. deterministic earthquake prediction) prospects since then. The fallout of this may be observed from the next spike in ΔRSV over 80, which occurred on April 2015. Whereas searches in both earthquake prediction and forecasting were significant for the 2011 Japan earthquake, a clear dominance of queries involving ‘earthquake forecast’ was found for the April 2015 increase, likely attributed to the large M_w 7.8 earthquake in Gorkha, Nepal on 25 April 2015. This suggests a more favourable stance (whether public or the scientific community) being placed on medium- to long-term probabilistic assessments (i.e. seismic return periods and recurrence behaviour which are in the order of years, if not decades) instead of deterministic predictions (Ouzounov et al. 2018). Yet, within the field of conventional seismology, the validity of probabilistic seismic hazard assessment (PSHA) models has long been debated (Castaños and Lomnitz 2002; Kossobokov 2014; Wyss et al. 2012). Nonetheless, in light of the seeming disappointments and impossibilities, two facts remain clear from the search trends – 1) people are interested in the capabilities for earthquake prediction or forecast, though only retrospectively, and, 2) the public is still seeking or hoping for a potential solution in expecting the next earthquake before it happens.

Figure 2.6 Monthly global increase of interest in earthquake prediction and related keywords for 14 years based on searches indexed by Google Trends

An EPS, typically built upon earthquake precursors, can mitigate coseismic risks to humans and infrastructure (Böse et al. 2008). In Google Trends, the keyword, ‘earthquake precursor’, has an exponentially declining trend since 2004. However, given that early works confirming the occurrences of seismo-ionospheric anomalies started around the early 2000s along with the proposal of physical mechanisms causing the TEC perturbations, it is plausible that the interest in earthquake precursors before 2004 was significant (e.g. Afraimovich et al. (2004); Chen et al. (2004); Freund (2000); (Hayakawa and Molchanov 2002); Liu et al. (2001); Liu et al. (2000); Pulinets et al. (2002); Pulinets et al. (2003)).

A strong M_w 9.1 – 9.3 Sumatra-Andaman earthquake, which was deemed the largest seismic event on earth within a 40 year period, occurred on 26 December 2004 (Lay et al. 2005). As this event occurred after the spikes in ΔRSV on June and September 2004 (Figure 2.6), it could not have been a contributing factor to their high values.

Interestingly though, ‘earthquake forecast’ searches for the subsequent period of December 2004 and January 2005 (i.e. after the earthquake) only received a moderate increase with ΔRSV between 20 and 40, with the number of ‘earthquake prediction’ searches even lower. To account for the lower adoption of internet search engines in the earlier years, the ΔRSV values were normalized against the total number of searches recorded across time. So based on these findings, a general pessimistic outlook on earthquake prediction as a whole may be reasonably inferred.

The interest in earthquake precursors following 2004 saw a marked increase on two separate occasions – July 2008 and April 2009. For the former occurrence, it was also accompanied by an increase in ‘earthquake forecast’ searches and is likely due to the M_w 7.9 Wenchuan (China) earthquake on 12 May 2008. For this event, there was a large number of retrospective studies conducted in assessing ionospheric anomalies as part of seismic precursory investigations (Hsiao et al. 2010; Jhuang et al. 2010; Liu et al. 2009; Zhang et al. 2009; Zhao et al. 2008; Zhao et al. 2010). Although the broad ‘earthquake precursor’ search term could refer to precursors other than seismo-ionospheric anomalies, these figures were likely boosted by the new source of ionospheric data from the FORMOSAT-3/COSMIC-1 constellation of six polar-orbiting satellites launched on April 2006 (Fong et al. 2008). As for the latter occurrence, the M_w 6.3 L’Aquila earthquake on 6 April 2009 placed the entire study of earthquake prediction under intense scrutiny due to its controversy from the trials of seismologists and public officials being held responsible in giving contradicting and misinformation prior to the earthquake (Alexander 2010; Hasian Jr et al. 2014). Even though they were subsequently acquitted from the indictment, this particular

incident suppressed further scientific interest in the pursuit of earthquake prediction in light of severe social repercussions (Benessia and De Marchi 2017).

From Figure 2.6, the exponential decrease in interest for earthquake precursors since 2004 have been marked by general stagnation of research into translatable EPS. While numerous retrospective studies on seismic-induced ionospheric anomalies have been reported and evidenced, there is a clear disconnect when it comes to exploiting this knowledge into a prospective scenario. Therefore, it is worth taking a closer look into the pitfalls of current methodologies inspecting pre-earthquake ionospheric signatures and examine ways of exploiting occurrences of such phenomenon into a prospective EPS.

Till date, complexities in seismic processes, especially with incomplete knowledge about earthquake mechanisms, difficulty of measurements as well as non-linearities, render traditional forms of analyses (e.g. correlations and statistical approaches) ineffective since they typically only capture linear correlation structures and overlook important underlying relationships (Alarifi et al. 2012; Narejo and Pasero 2018). Few early research has attempted to incorporate artificial intelligence in the understanding of earthquake precursors and EPS (Itai et al. 2005; Negarestani et al. 2002; Ozerdem et al. 2006; Panakkat and Adeli 2007; Plagianakos and Tzanaki 2001). For example, Böse et al. (2008) estimated earthquake source parameters (e.g. focal depth and magnitude) using seismic wave characteristics and shallow two layer neural networks (NN), named PreSEIS. Külahcı et al. (2009) employed ANNs to study the non-linear relationships between earthquakes and the observed radon gas precursors. They highlighted that ANNs could avoid the need for complex mathematical operations owing to a large number of causative and inter-related factors, especially

when a complex geological phenomenon such as an earthquake is being studied. Lately, the opportunity for EPS has seen new light due to improved developments within the domain of artificial intelligence such as machine learning and deep neural network topologies. Inter-disciplinary efforts in other fields integrating machine learning methods have yielded significant breakthroughs, such as in weather forecasting, churn prediction, traffic modelling and disease diagnosis (Cosma et al. 2017; Idris et al. 2012; Narejo and Pasero 2018; Nayak et al. 2013). Similarly, there has been a recent effort being placed into examining the synergy of conventional earthquake research with computerized intelligent algorithms. These studies, though limited in quantity at present, exemplify the benefits of machine learning models (i.e. non-parametric, data-driven and self-adaptive) (Narejo and Pasero 2018). For instance, Rouet - Leduc et al. (2017) applied a Random Forest (RF) model to examine a previously unidentified earthquake precursor (i.e. acoustic emissions from shearing layers). The authors discovered that the underlying characteristics of a continuously recorded acoustic signal could accurately determine the time (though, not strength) of an upcoming earthquake in a laboratory experiment. Asim et al. (2018) employed a combination of computational intelligence methods (i.e. support vector regression, hybrid neural network and particle swarm optimization) on 60 seismic features which are either non-parameteric (i.e. independent variables) or parametric (i.e. dependent variables) in nature. Though these features were selected empirically, the accuracy of their technique was reported to be approximately 90.6% for a binary classification problem (i.e., whether there is an earthquake or not). The results from these recent developments in earthquake prediction research thus appear to show great promise of artificial intelligence in undertaking this challenge, especially during

this period when data, instrumentations, accessibility and analytical methods have proliferated.

In this thesis, an investigation is conducted into establishing a prospective EPS by means of seismo-ionospheric observations (i.e. PETA) at three PETA pseudo-observation stations (PPOS) to capture the spatial variations of PETA prior to earthquakes. A region of frequent seismic activity (i.e. Sumatran fault zone) is selected to constitute a large catalogue of earthquakes. To uncover the link between potential seismic activity and the ionosphere, a machine learning framework is then formulated on the basis of PPOS which are used to approximate epicentral distance, magnitude, azimuth and time-till-earthquake (TTE) as the main outputs. By varying the combinations of these outputs, their accuracies are evaluated in the context of establishing an EPS.

CHAPTER 3 LANDSLIDE VOLUME ESTIMATION

3.1 Geometry modelling of the décollement plane

In this study, it is hypothesized that the upper and lower bounds of the various reported landslide area-to-volume relationships (Table 2.2) could possess underlying geometrical characteristics. First, the décollement plane of the failed soil mass in a landslide is assumed to lie between a spherical and oblate ellipsoidal surface. This assumption is made as a real sliding surface may be approximated by the arc of an ellipse, which is hence frequently used in slope stability analyses (Baker and Yoder 1958; Michel et al. 2020; Taylor et al. 2018). Figure 3.1 provides such an illustration for the case of an ellipsoidal décollement plane, where the surface of a landslide is at a distance h below the point of origin of the sphere, in an oblique plane (defined by the slope angle B). Therefore, the orientation of the ellipsoid is aligned such that its horizontal axes (x - y plane) are parallel to the inclination of the slope surface. A typical representation of V_L is denoted by the shaded region in Figure 3.1, where it is bounded by the surface of the landslide and the presumed ellipsoidal décollement plane.

Figure 3.1 Ellipsoidal approximation for décollement plane

The volume of the displaced soil material in a landslide can be subsequently computed using Eq. (3.1), which is the equation for volume of an ellipsoidal cap.

$$V_L = \frac{ab(c-h)^2(2c+h)\pi}{3c^2} \quad (3.1)$$

where a = length of semi-major axis; b, c = length of semi-minor axes; and h = depth from ellipsoid origin to landslide surface. For a spherical décollement plane, $a = b = c$.

For a given landslide, the factors determining volume of the displaced material are the semi-axis lengths (a, b, c) as well as the distance h (defined in terms of h/c). For the case of décollement plane modelling using a presumed spherical surface, semi-major axis a (or radius r) can be computed conveniently, since it is equal to semi-minor axes b and c . For an ellipsoid, the aspect ratio between its axes (a, b, c) is not 1: 1: 1. In this study, the aspect ratios utilized for the ellipsoid varies according to k : 1: 1, where $8 \leq k \leq 125$ (note: these values correspond to the ellipsoidal décollement planes corresponding to the lower bounds of reported area-to-volume relationships in literature, as shown in Figure 3.2). The aspect ratio of k : 1: 1 describes the simplest form of an ellipse. In this manner, the variability of the vertical dimension, $c-h$ (i.e. position of the décollement plane), is only dependent on the ratio h/c , where increasing values of h/c would correspondingly result in decreasing landslide volume. To obtain the geometries of the spheres and ellipsoids which bound the empirical area-to-volume relationships found in the literature, values between 0.1 to 1.5 km (i.e. with regular intervals of $\Delta a = 0.1$ km) were assigned to the semi-major axis (a), covering approximately $0.01 \text{ km}^2 \leq A_L \leq 10 \text{ km}^2$. In addition, h/c values varied within $0 \leq h/c < 1$ (i.e. with regular intervals of $\Delta h/c = 0.1$), where values greater than 1 are

physically meaningless. The parameters for the geometrical modelling study are summarized in Table 3.1.

Table 3.1 Parameters defined in the geometrical modelling approach

Parameter	Description	Value(s)
h/c	Depth of cut-off plane	$0.1 \leq h/c \leq 0.9$ ($\Delta h/c = 0.1$)
k	Aspect ratio between planar and vertical dimensions (k : 1: 1)	1 (Spherical) $8 \leq k \leq 125$ (Ellipsoidal)
a	Length of semi-major axis	0.1 to 1.5 km ($\Delta a = 0.1$ km)

3.2 Rationalizing the landslide area-to-volume relationship by h/c method

Firstly, in order to investigate the upper bounds of the area-to-volume relations, the spherical décollement plane was utilized. For each set of spherical (i.e. $a = b = c$) geometry, ten regularly spaced intervals (i.e. nine data points per set) at $\Delta h/c (= 0.1)$ between $0.1 \leq h/c \leq 0.9$ was used to compute the corresponding area and volume. Thus, with the spherical semi-axis lengths ranging between 0.1 to 1.5 km at intervals of $\Delta a = \Delta b = \Delta c = 0.1$ km, a total of 15 spherical geometry sets were obtained. The spherical geometry parameters used to describe the upper bounds of the area-to-volume relationships are further summarized and detailed in Table 3.2. Figure 3.2 illustrates the results from the upper and lower bounds of the area-to-volume power-law relations reported in the literature (Table 2.1). The landslide area-to-volume trend of increasing sets in Table 2.1 is further depicted within Figure 3.2, where the area-to-volume relationship given by Sets 1 and 2 are enveloped by ellipses (i.e. yellow and red, respectively).

Table 3.2 Spherical geometry modelling parameters

Set No. ¹	Semi-axis length (km) ²	h (km)		
		Min. ³	Max. ⁴	Interval ⁵
1	0.10	0.01	0.09	0.01
2	0.20	0.02	0.18	0.02
3	0.30	0.03	0.27	0.03
4	0.40	0.04	0.36	0.04
5	0.50	0.05	0.45	0.05
6	0.60	0.06	0.54	0.06
7	0.70	0.07	0.63	0.07
8	0.80	0.08	0.72	0.08
9	0.90	0.09	0.81	0.09
10	1.00	0.10	0.90	0.10
11	1.10	0.11	0.99	0.11
12	1.20	0.12	1.08	0.12
13	1.30	0.13	1.17	0.13
14	1.40	0.14	1.26	0.14
15	1.50	0.15	1.35	0.15

1 For each spherical geometry set, there are a total of nine data points

2 Semi-axis length applies for semi-major (a) and semi-minor (b , c) dimensions (i.e. spherical)

3 Min. values correspond to $h/c = 0.1$

4 Max. values correspond to $h/c = 0.9$

5 Interval is computed using axis length divided by ten (i.e. $\Delta h/c = 0.1$)

Figure 3.2 Upper and lower bounds of reported power laws with data points from the proposed h/c method; typical sets for spherical $k = 1$ are highlighted

As shown in Figure 3.2, when the spherical décollement plane was assumed, it is able to encompass the upper limit of the empirical area-to-volume relationships using $h/c \leq 0.9$ at increasing axis lengths (i.e. increase values of $a = b = c$).

Subsequently, to examine the lower bounds of the area-to-volume relationships, the ellipsoidal décollement plane was utilized. Beginning with ellipsoidal aspect ratio $k = 2$, the general formulations of the various dimensions for the ellipsoidal surface geometry are shown in Table 3.3. Here, a maximum ellipsoidal aspect ratio of $k = 125$ was applied to limit the landslide area to 10 km^2 .

Table 3.3 Ellipsoidal (k : 1: 1) geometry modelling parameters

k^1	Semi-axis length (km)		h (km)		
	Major (a) ²	Minor (b, c) ³	Min. ⁴	Max. ⁵	Interval ⁶
2	0.10	0.05	0.005	0.045	0.005
⋮	⋮	⋮	⋮	⋮	⋮
2	1.50	0.75	0.075	0.675	0.075
⋮	⋮	⋮	⋮	⋮	⋮
k	0.10	$0.10 / k$	$0.01 / k$	$0.09 / k$	$0.01 / k$
⋮	⋮	⋮	⋮	⋮	⋮
k	1.50	$1.50 / k$	$0.15 / k$	$1.35 / k$	$0.15 / k$

1 Starts from $k = 2$ (i.e. ellipsoidal); used in this study is $k = 8, 20, 50$ and 125

2 For each k , semi-major (i.e. a) lengths are from 0.1 to 1.5 km (i.e. $\Delta a = 0.1$ km)

3 Corresponds to semi-minor axes (i.e. b and c); computed as semi-major length divided by k

4 Min. values correspond to $h/c = 0.1$

5 Max. values correspond to $h/c = 0.9$

6 Interval is computed using axis length divided by ten (i.e. $\Delta h/c = 0.1$)

From Figure 3.2 (which plots landslide areas and volumes for ellipsoidal geometry at $h/c = 0.9$), when h/c ratio of 0.9 was applied on the ellipsoidal décollement plane, the aspect ratio k varies (depending on A_L) in order to cater to the lower bounds of reported power laws. As shown in Figure 3.2, the aspect ratios (at $h/c = 0.9$) of the ellipsoids used to demarcate the lower bound of the empirical area-to-volume relationships are 8, 20, 50 and 125: 1: 1 corresponding to the landslide areas of 0.01, 0.1, 1 and 10 km² respectively. Note that using the ellipsoidal décollement plane, an upper bound could alternatively be obtained by decreasing the value of h/c , which yields larger landslide volume at a particular k . The corresponding ellipsoidal data points for $k = 8$ and $k = 20$ are shown in Figure 3.3, which shows the demarcation of the lower bound of the power-laws using $h/c = 0.9$ (i.e. $k = 50$ and $k = 125$ are derived

in the same manner). Consequently, the results of the geometrical modelling approach clearly suggest that the empirical area-to-volume relationships observed by various authors could be explained by the inherent geometry of the failure mass, which takes on the shape between a spherical and an ellipsoidal décollement plane. A further mathematical justification which sheds light on the theoretical basis of the observed landslide area-to-volume relationships is given in APPENDIX – B.

Figure 3.3 Ellipsoidal data points for $k = 8$ and $k = 20$; lines of $h/c = 0.9$ to demarcate lower bounds of reported power laws; $k = 50$ and $k = 125$ are determined in the same manner; typical sets for ellipsoidal $k = 8$ are highlighted

3.3 New method of estimating landslide volume from aerial or satellite images

3.3.1 Landslide area and equivalent ellipsoidal aspect ratio

As the décollement plane for any landslide may be modelled as a spherical or ellipsoidal surface, it is therefore possible to compute individual landslide volumes from orthogonal aerial or satellite images without the use of DEMs. With reference

to Figure 3.2, in order to estimate landslide volume, three parameters have to be determined beforehand – 1) landslide area, 2) landslide ellipsoidal aspect ratio, k , and 3) h/c value. Among the three, landslide area and aspect ratio may be conveniently determined from 2-D imagery and are interlinked (note that there are slight differences between the actual and observed landslide area, which is further discussed in APPENDIX – C). For example, landslide areas are routinely measured and reported in field investigation reports as well as in scientific journal publications. In the literature, some reports with more in-depth analyses may also reveal further characteristics of the landslide, such as dimensions of the source area. Several landslides, such as the Hattian Bala, Campo Vallemaggia and Ischia events, possess large source areas which are useful in the subsequent analyses.

In this study, for each landslide listed in Table 3.4, the ellipsoidal aspect ratio was computed via an *equivalent area* method. Landslide scars can be delineated using either a single satellite image (e.g. RGB compositions) or via the change detection technique (e.g. Normalized Difference Vegetation Index) using multi-temporal satellite images (Schlögel et al. 2011; Tsai et al. 2010). Thus, with accurate georeferencing or topographical scale, landslide surface area and length (i.e. Figure 3.4) can be quantified using a suitable GIS (i.e. Geographic Information System) program. For this purpose, the software application Global Mapper 18 from Blue Marble Geographics was utilized for all landslide georeferencing and measurement (i.e. landslide area and dimensioning) works. Once the area and length (in the sliding direction) have been determined for each landslide, the *equivalent area* method employs Eq. (3.2) to compute its width.

$$A_L = \pi \cdot a \cdot b \quad (3.2)$$

where A_L = landslide area; a = semi-major axis (length); b = semi-minor axis (width)

Some landslides generally have elliptical surface area, similar to the example shown in Figure 3.5 (e.g. Ischia landslide). Note that it is possible for the landslide width to be larger than its length, depending on the failure geometry. For some cases however, the landslide surface geometry may be more complicated, where a distinct elliptical surface may be problematic to circumscribe. A typical example of a landslide with complicated surface geometry is illustrated in Figure 3.6 (e.g. Salna landslide). Nevertheless, the proposed approach is a consistent technique to fit an ellipsoid to describe each landslide in order to compute its volume using the geometry modelling method, regardless if the landslide is generally elliptical (i.e. Figure 3.5) or having more complicated surface geometry (i.e. Figure 3.6 and Figure 3.7). The primary benefit of measuring the landslide length according to the overall flow direction and landslide boundary is that it offers an unambiguous way to define the dimensions of the equivalent ellipsoid. Once the landslide aspect ratio k has been defined, the final landslide volume may then be computed after determining the h/c value (discussed in the following section). Several more examples of the equivalent ellipses used in the proposed approach are further illustrated in Figure 3.8.

Figure 3.4 Determining the landslide length from orthographic satellite (or aerial) images; boundary is demarcated based on flow direction

Figure 3.5 Landslides with approximately elliptical areas; a) Collinabos landslide; b) Higashi-Takezawa landslide; c) Hsiaolin landslide; equivalent ellipse shown in red dashed line

Figure 3.6 Landslide with complicated surface geometry; length is measured based on flow direction and landslide boundary (dotted line)

Figure 3.7 Landslides with complicated area geometries demarcated within black dashed lines; a) Valpola landslide; b) Rosone landslide; c) Corvara landslide; equivalent ellipse shown in red dashed line

a)

b)

c)

d)

e)

f)

Figure 3.8 Equivalent ellipses (red dashed lines) on several landslides in the current study; a) Maierato landslide; b) Koba landslide; c) Guinsaugon landslide; d) Os landslide o; e) Hope landslide; f) Attabad landslide; g) Jovac landslide; h) Saidmarreh landslide

Once the landslide length and width have been calculated using Eq. (3.2), the corresponding aspect ratio k is derived according to Eq. (3.3).

$$k = \frac{a}{b} \quad (3.3)$$

where a is the length of semi-major axis; b is the length of semi-minor axis

At this point, the only remaining parameter to be establish in order to compute landslide volume is the h/c value, and is covered in Section 3.4.2.

3.4 Calibration of $h/c - A_L^*$ relationship

3.4.1 Description of landslide inventory

Global landslide morphometric datasets (Table 3.4) collected for calibration of h/c and validation of the proposed volume estimation method were obtained from single event mapping, multiple landslides inventories as well as reported statistics by geologists and relevant authorities (e.g. United States Geological Survey). Among

the 58 landslide case studies, about half of the case studies involved the use of digital elevation (DEM) or terrain models (DTM) and LIDAR for volume estimation. Other approaches to determine landslide volume incorporated information and derivations from field investigations (e.g. boreholes), differential GPS (DGPS) measurements, seismic reflection profiles or multi-beam swath bathymetry data. Among the 58 landslide cases, a random separation according to 80:20 ratio was conducted to split the dataset into training/testing (i.e. 48 cases) and validation (i.e. 10 cases) landslides. The training/testing dataset was used in model generation while the validation dataset was utilized exclusively to validate the model.

Table 3.4 Information of landslide inventory compiled for volume assessment

Reference(s)	Landslide name (Location)	No. ¹	Trigger ²
Wieczorek et al. (2003)	Tidal Inlet (Alaska)	1	E
Brückl et al. (2006)	Gradenbach (Austria)	1	R
Bruce and Cruden (1977)	Hope (Canada)	1	E
Van Den Eeckhaut et al. (2007)	Collinabos (Belgium)	1	R
Oppikofer (2012)	Punta Cola (Chile)	2 (1)	E
Weifeng and Biliang (2009)			
Xu et al. (2009)			
Chigira et al. (2010)			
Tang et al. (2010)			
Wu et al. (2010)	Wenchuan-related (China)	12 (2)	E, R
Dai et al. (2011)			
Zhang et al. (2011)			
Chen et al. (2012)			
Clague and Stead (2012)			
Huang et al. (2012b)			

Zhang et al. (2012)			
Ren et al. (2014)			
Wang et al. (2014b)			
Martha et al. (2010)	Salna (India)	1	R
Peart (1991)	Saidmarreh (Iran)	1	E
Azzoni et al. (1992)	Valpola (Italy)	1	R
Nicoletti and Parise (2002)	Sicily (Italy)	1	E
Corsini et al. (2005)	Corvara (Italy)	1	R
Baldi et al. (2008)	Sciara del Fuoco (Italy)	1 (1)	E
Borgatti et al. (2008)			
Corsini et al. (2009)	Ca' Lita (Italy)	1	R
Ronchetti et al. (2009)			
Cervi et al. (2012)			
Alonso et al. (2010)	Vajont (Italy)	1	R
John (2010)	Maierato (Italy)	1	R
Pisani et al. (2010)	Rosone (Italy)	1 (1)	R
Corominas and Mavrouli (2011)	Ruinon (Italy)	1 (1)	R
De Alteriis et al. (2014)	Ischia (Italy)	1 (1)	E
Tsutsui et al. (2007)	Mid-Niigata, Dajia River (Japan, Taiwan)	5	E, R
Chigira (2009)	Koba (Japan)	2	R
Corominas and Mavrouli (2011)	Higashi-Takezawa (Japan)	2	E
Derron et al. (2005)	Oppstadhornet (Norway)	1	R
Oppikofer et al. (2009)	Aknes (Norway)	1	R
Schneider et al. (2013)			
Petley et al. (2010)	Hattian Bala, Attabad (Pakistan)	2 (1)	E
Tariq and Gomes (2017)			

Catane et al. (2007)	Guinsaugon (Phillipines)	1	E
Lóczy et al. (2012)	Jovac (Serbia)	1	E
Laloui et al. (2004)			
Jaboyedoff and Derron (2015)	La Frasse (Switzerland)	1	R
Bonzanigo et al. (2006)	Campo Vallemaggia (Switzerland)	1 (1)	R
Bonzanigo et al. (2007)			
Chen et al. (2011)	Hsiaolin (Taiwan)	3	E, R
Kuo et al. (2013)			
Duman (2009)	Tortum (Turkey)	1	E
Hadley (1978)	Madison Canyon (U.S.A.)	1	E
Johnson (1978)	Blackhawk (U.S.A.)	1	R
McAdoo et al. (2000)	Continental slopes (U.S.A.)	2	E
Wartman et al. (2016)	Oso (U.S.A.)	1	R
Randall (2012)	Red Bluff (U.S.A)	2 (1)	R

1 No. of landslides in parentheses are included in the validation dataset and excluded during training

2 E – Earthquake-triggered; R – Rainfall-triggered

As shown in Figure 3.9 to Figure 3.11, many landslides occur in tectonically active countries, such as Italy, China and Japan and hence, are earthquake-induced (i.e. triggered by ground motion). Notable landslides arose from single catastrophic earthquake events, such as from the M_w 7.7 Chi-Chi (Taiwan) earthquake in 1999, M_w 7.6 Kashmir (Pakistan) earthquake in 2005, M_w 7.9 Wenchuan (China) earthquake in 2008 as well as the 2011 Tohoku (Japan) earthquake. On the contrary, some of the landslides were also rainfall-induced (e.g. 2007 Salna (India) landslide and 2010 Maierato (Italy) landslide), which are generally due to decrease in soil shear strength due to increased water content (i.e. greater pore water pressures). Among the

rainfall-induced landslides include several severe weather events such as the 2004 Typhoon Mindulle (Taiwan) and 2009 Typhoon Morakot (Phillipines), where tremendous amount of rainfall triggered numerous landslides. Two broad classification of landslide triggers were also examined, with the proportion of earthquake- and rainfall-induced landslides further illustrated in Figure 3.12 and Figure 3.13. Among the 58 cases in total, half of them (i.e. 29 cases) were earthquake-induced landslides, while the remaining half (i.e. 29 cases) were rainfall-induced landslides. In addition, the number of translational and rotational landslides for each type of landslide (i.e. earthquake- and rainfall-induced) were 20 and 9, respectively.

Figure 3.9 Significant landslides in continental America; landslides names are in parentheses

Figure 3.10 Significant landslides in continental Europe and Middle-East; landslides names are in parentheses

Figure 3.11 Significant landslides in continental Asia; landslides names are in parentheses

Figure 3.12 Proportion of landslides (i.e. earthquake- vs. rainfall-induced) considered in this study

Figure 3.13 Proportion of landslides (i.e. translational vs. rotational) considered in this study

3.4.2 $h/c - A_L^*$ relationship

The aforementioned approach fulfils the requirements of determining landslide area and ellipsoidal aspect ratio from orthogonal (i.e. nadir-looking) aerial or satellite images. Once the landslide area and aspect ratios have been defined, the only parameter that remains is h/c . Since h/c is an adjustable parameter (which causes landslide volume to vary within the reported power laws shown in Figure 3.2), it can be calibrated using the previously mentioned large set of landslide cases (48 landslides) with reported area and volume measurements or estimates ('truth'). Therefore, calibration of h/c allows the landslide décollement plane to be obtained on the basis of its area observable by satellite images (i.e. A_L^*).

As shown in Figure 3.14, the range of A_L^* for the landslide dataset is between 0.02 km² and approximately 170 km² (corresponding landslide volumes ranging from 0.0003 km³ to 20 km³). Majority of the larger landslides were triggered by earthquakes. For the combined landslide inventory consisting of both earthquake- and rainfall-induced landslides, it is observed that h/c approaches unity (i.e. theoretical limit) when A_L^* is approximately 10 km² and thereafter appears to be insensitive to further increases in A_L^* (i.e. $h/c = 1$ for $A_L^* > 10$ km²). Therefore, based on Figure 3.14, overall R^2 is 0.86 between h/c values and landslide area (i.e. $A_L^* \leq 10$ km²) for the combined landslide inventory. A sensitivity analysis was further conducted by separating the landslides into their respective trigger (i.e. either earthquake- or rainfall-induced) and repeating the analysis. As shown in Figure 3.14, the best-fit line remains consistent to the combined landslide inventory, although the degree of fit appears to be better for earthquake-induced landslides (i.e. $R^2 = 0.89$) as compared to rainfall-induced landslides (i.e. $R^2 = 0.85$).

Figure 3.14 Correlations between h/c and landslide area; landslides are separated into: combined inventory, earthquake-induced and rainfall-induced; shaded areas correspond to limits of the $h/c - A_L^*$ bilinear functions

From these findings, the relationship between h/c and A_L^* is described using a bilinear function obtained from the combined landslide inventory, as shown in Eq. (3.4).

$$\frac{h}{c} = \begin{cases} 0.06 \ln A_L^* + 0.86, & A_L^* \leq 10 \text{ km}^2 \\ 1.0, & A_L^* > 10 \text{ km}^2 \end{cases} \quad (3.4)$$

where c = length of semi-minor axis (perpendicular to slope surface); and h = depth from ellipsoid origin to landslide surface. Note that the value of h/c must be less than 1 to yield a logical solution.

In summary, the overall workflow employed to estimate landslide volume using landslide area observed by satellite imagery with the geometry modelling method is presented in Figure 3.15. A separation h/c calibration method using machine learning and artificial neural networks (ANN) is explored in APPENDIX – D with results therein.

Figure 3.15 Overall workflow for determining landslide volume using satellite images and geometry modelling method

3.4.3 Validating the geometry modelling method

Using Eq. (3.4) to estimate h/c values from A_L^* , the predicted landslide volumes for the validation dataset consisting of 10 landslides were obtained based on Eq. (3.1). Figure 3.16 shows the variation of volumetric error with landslide area for the landslide cases. Here, it is shown that the bounding volumetric error using the h/c regression model shown in Eq. (3.4) is within $\pm 13.3\%$. From Figure 3.17, it further shows that while the actual and predicted volumes are within the bounds of landslide area-to-volume relationship, a single power-law would not provide accurate estimate of landslide volume. Also, there does not appear to be a significant difference in landslide volume errors between earthquake- and rainfall-induced landslides.

Figure 3.16 Volume estimation errors for validation dataset based on $h/c - A_L^*$ bilinear function

Figure 3.17 Plot of actual and predicted landslide volumes against area

Based on these results, it appears that the proposed bilinear model performs well, as its use is relatively straightforward and provides more consistent landslide volume estimates than existing regression-based area-to-volume power-law equations. As compared to empirical area-to-volume relations yielding errors greater than 30% and algorithm-based approaches (e.g. Wang et al. (2014a)) which obtained volumetric error of 25%, the benefits of the proposed h/c method is its theoretical basis and better accuracy, along with its simplified computation procedures.

3.5 Summary

Landslides frequently result in the destruction of property and in the worst-case, loss of lives. In post-event assessments and recovery works, landslide volume is a valuable parameter. While remote sensing via satellite imagery has greatly facilitated the identification of landslide events, however the landslide volume remains a variable that is tough to quantify.

The current research proposes a geometry modelling method to estimate the volume of a landslide using observations from aerial or satellite imagery. Formulation of the proposed volume computation framework was initially based on deriving an explanation for the area-to-volume power-laws, where the upper and lower bounds of literature power-law approximations could be obtained by assuming that the décollement plane of a landslide was either spherical or ellipsoidal.

Using this discovery, a general ellipsoidal assumption regarding the shape of the décollement plane was employed for landslide volume computation. The only information required is aerial or satellite images providing planar measurements of the landslide scar dimensions. After obtaining the aspect ratio of the landslide, an adjustable parameter, h/c , was incorporated to vary the depth of the décollement plane. The dependency of h/c on landslide area was subsequently calibrated using 48 landslide cases with resulting $R^2 \sim 0.86$ and valid for $A_L^* \leq 10 \text{ km}^2$ from a bilinear function. Volume of a landslide can then be calculated by finite integration of the region bounded by the landslide surface and décollement plane. Finally, the proposed method yielded a bounding error of $\pm 13.3 \%$. A machine learning artificial neural network method was also explored, where the value of h/c was predicted using A_L^* in a shallow neural network architecture. The optimized model yielded only marginal improvements, with a bounding volumetric error of 10.4% . Consequently, the bilinear function method is favoured in computing landslide volume as it is more straightforward to apply than using a machine learning model.

Therefore, the proposed geometry modelling method technique used to compute landslide volume has shown to yield reasonable estimates and can be effectively used in place of empirical area-to-volume relations which tend to be inconsistent and error-

prone. In addition, it requires less computational time compared to methods incorporating computer algorithms or the generation of digital elevation models. Thus, the proposed approach provides a good alternative when a rapid and accurate assessment of landslide volume is required.

CHAPTER 4 ANALYSIS OF EARTHQUAKE-INDUCED LANDSLIDE INVENTORY

In this section, the characteristics and distribution of landslides mapped over the three temporal periods induced by the Nepal Mw 7.8 earthquake on 25th April 2015 (note: the background of the earthquake is given in APPENDIX – E) were analysed to understand the differences in landslide trigger. Also, the accuracy of landslide susceptibilities based on a short-term landslide inventory mapped using open-source satellite images was examined. While there were further landslides induced by an aftershock on 12th May 2015 as well as rainfall from the ensuing monsoon season, the landslides studied here were only due to the main shock on 25th April 2015. The analyses were conducted via statistical comparisons between landslides mapped in the short-term (i.e. this study), medium-term (i.e. Kargel et al. 2016) and long-term (i.e. Roback et al. 2018). The short-term landslide inventory was first independently verified against the literature using a region located in Langtang Valley (where the largest landslide occurred along with numerous smaller landslides). Thereafter, lithological groups accounting for the greatest number of landslides were identified and trivariate analyses incorporating the weighted landslide concentration were subsequently conducted on each landslide variable per lithological group. To address possible issues of multicollinearity between the identified variables, a principal component analysis (PCA) approach was conducted to infer critical parameters in triggering landslides during the 2015 Nepal event. Within each dataset, interaction between landslide variables was investigated by a multivariate assessment in order to obtain landslide probability models. Subsequently, parallel analysis was used to retain significant components which served as inputs to the binomial logistic

regression. The parsimonious landslide models are finally derived and validated by true positive prediction rates and area under the receiver-operator-characteristic (ROC) curve.

4.1 Short-term landslide inventory

Due to the limitations of satellite overpass times and presence of clouds which would hinder earth surface observations in some imagery acquisitions, all coseismic landslides mapped by open-source satellites (i.e. short-term inventory), such as Landsat-7 and Landsat-8, before the major aftershock on 12th May were attributed to the main shock on 25th April. In order to illustrate the process of deriving the short-term landslide inventory from open-source images, an examination was conducted on a section in the Langtang Valley region of central Nepal, where the largest landslide induced by the main shock and numerous smaller landslides could be found. For the verification, two Landsat-8 acquisitions were used: one pre-event image on the 5th Nov 2014 (Scene ID: LC81410412014309LGN00) and one post-event image on the 1st June 2015 (Scene ID: LC81410412015152LGN00). For each acquisition, atmospheric correction (i.e. haze and cloud masking, conversion to ground reflectance) was first applied to the panchromatic and multispectral channels. The panchromatic band was then used in pan-sharpening to generate a 15 m multispectral image and further cropped to the Langtang Valley region. The Normalized Difference Vegetative Index (NDVI) for each acquisition was computed using the near-infrared (NIR) and red (R) reflectance obtained from the multispectral image (i.e. Eq. (4.1)) (Tucker 1979):

$$NDVI = \frac{NIR - R}{NIR + R} \quad (4.1)$$

Once the NDVI values have been derived, landslides can be detected on the basis of vegetative change (i.e. removal of vegetative cover during slope erosion) indicated by the deviation in NDVI values on a pixel-by-pixel basis with a minimum landslide area of 15 m. The NDVI differencing and NDVI ratio methods between pre- and post-NDVI images were both evaluated for landslide detection; however, it was found that the NDVI ratio approach yielded results which corresponded best with COMET's landslide inventory (Figure 4.1) (BGS/Durham 2015; Williams et al. 2018). Figure 4.1 further shows that the locations of detected landslides agree with the landslide identification efforts of Lacroix (2016), who used an earlier pre-event acquisition on the 21st April 2014. In general, the landslide polygons correspond well to the inventories published by COMET and Lacroix (2016). As for the medium-term and long-term landslide inventories utilized for comparisons against the short-term inventory, their corresponding databases were made available from the published reports of Kargel et al. (2016) and Roback et al. (2018), respectively.

Figure 4.1 Comparison between identified landslides in Langtang Valley

4.2 Study area

Landslide concentration (LC), defined as the number of landslide occurrences (LS) normalized by a set area boundary, was used to describe quantitatively the relative spatial distribution of landslides (Collins et al. 2012). As observed in Figure 4.2, the clustering of landslides was densest towards the east of the epicentre, which is in agreement with the SAR line-of-sight surface displacements and eastward directed fault rupture of the main shock. Further in-situ investigations revealed that landslides were most significant to the east of the epicentre (Collins and Jibson 2015). In order to quantify these observations, a directional distribution ellipse with standard deviation of 1σ was generated to encompass majority of the landslides in the short-

term inventory. The resulting ellipse shown in Figure 4.2, which was oriented southward at an angle of 15° from east of the epicentre with a length (major axis) of approximately 194 km, was able to capture close to 80% of the landslides, hence confirming the observations.

Figure 4.2 Map of landslide clusters (short-term landslide inventory) with the overall directional distribution; the Eurasian-Indian (EU-IN) fault line is demarcated

Thus, a study area was defined from the epicentre in the eastern direction within a 20° sector. Furthermore, the choice of sector as the study area (as opposed to a regular or arbitrary area) was chosen to reflect the radial propagation of seismic waves from the epicentre during earthquake initiation and serves as the basis in understanding landslide occurrences in relation to seismic origin (e.g. epicentre) (Datta 2010). Epicentral distance intervals of 20 km were generated within the study area and bounded at a radial distance of 200 km from the epicentre. The location of the defined study area and landslides considered in analyses are illustrated in Figure 4.3.

Figure 4.3 Location of study area and short-term landslide inventory

While LC is useful in determining the density of landslides, however it may cause erroneous interpretations. This occurs in the case when LC is high, while in reality, landslide count is low and the representative area is comparatively smaller. Thus, a high LC value may yield a false impression of increased landslide risk even though the quantity of landslides may be considered low or otherwise, insignificant. Hence, an additional parameter, landslide inventory (LI) percentage, was utilized to aid in the interpretation of landslide risk for each parameter (Table 4.1). The parameter LI accounts for the proportion of landslides with respect to the entire inventory. To facilitate the concurrent interpretation of both LC and LI values in the trivariate analyses, a *weighted landslide concentration* (LC_w) (Eq. (4.2)) is introduced. The LC_w corrects the LC value by accounting for the variation of LI so that a high LC_w would reflect a high degree of landslide risk as indicated in Table 4.1. The LS_{total} in Eq. (4.2) represents the total number of landslides for a given bounded area.

$$LC_w = LC / LI^{-1} = \frac{LS^2}{LS_{total} \cdot km^2} \quad (4.2)$$

Table 4.1 Qualitative assessment of landslide risk based on LC and LI

Qualitative assessment of landslide risk		LC (landslides/km ²)	
		Below average	Above average
LI (%)	Below average	Low	Low
	Above average	Low	High ¹

¹ High LC_w value implies high risk of landslide

4.3 Seismic source, lithology and terrain variables

There is a myriad of landslide susceptibility variables studied in the literature. Figure 4.4 summarizes the frequency of common landslide variables considered in 23 other similar studies involving earthquake-induced landslides. They arise from various seismic events around the world, including the 1929 M_w 7.7 Buller (Parker 2013), 1968 M_w 7.1 Inangahua (Parker 2013), 1989 M_w 6.9 Loma Prieta (Keefer 2000), 1992 M_w 6.7 Erzincan (Akgun 2012), 1992 M_w 7.3 Suusamyr (Havenith et al. 2006), 1994 M_w 6.7 Northridge (Kritikos et al. 2015; Parker 2013), 1999 M_w 7.7 Chi-chi (Kritikos et al. 2015; Lee et al. 2008; Parker 2013), 1999 M_w 7.0 Luzon (Lee and Evangelista 2006), 2003 M_w 6.3 Lefkada (Papathanassiou et al. 2013), 2005 M_w 7.6 Kashmir (Sato et al. 2007), 2007 M_w 6.6 Niigata (Collins et al. 2012), 2008 M_w 7.9 Wenchuan (Kritikos et al. 2015; Parker 2013; Qi et al. 2010; Su et al. 2010), 2010 M_w 6.9 Yushu (Xu et al. 2013a), 2008 and 2013 M_w 7.0 Lushan (Huang et al. 2013; Liu et al. 2015) earthquakes. It can be observed that slope angle (i.e. Figure 3.1) as a fundamental slope stability parameter is present in almost all of the studies, followed by source-related fault distances and local soil conditions characterized by lithology. While

ground motion parameters such as PGA, PGV (i.e. peak ground velocities) and MMI (i.e. modified Mercalli intensity) are often included in analyses, these estimates are typically modelled values, such as from maps published under the USGS ShakeMap system (e.g. Kritikos et al. 2015, Liu et al. 2015). In the USGS ShakeMap methodology, topographic amplification effect is usually approximated by slope angle, unless detailed geological information is available (Wald et al. 2006). Goda et al. (2015) examined various ground motion models and have found that USGS PGA estimates for the M_w 7.8 Nepal main shock possess biases due to source-to-site distance discrepancies. Consequently, PGA (and PGV) values were not used in this study.

Figure 4.4 Frequency of landslide susceptibility variables studied in literature

In order to quantify the effects of seismic source and possible site amplifications, epicentral distances and lithology are chosen as proxies, since there is a strong link between PGA, epicentral distance and underlying soil (Dhanya et al. 2017; Pétursson 2009; Podany 2008). Epicentral distance is a useful representation of the source and

seismic attenuation of earthquakes and is frequently used in place of more complex source-to-site measures such as the Joyner-Boore distance. The location of an earthquake's epicentre is also relatively easier to pinpoint as it does not require fault models (as is the case for Joyner-Boore distance) and is easily translatable across such studies (Akkar and Bommer 2007).

To further quantify source-to-site effects, differential interferometric analysis (DinSAR) was used to derive surface trace of the Main Frontal Thrust (MFT) fault in order to examine seismogenic fault influences (i.e. fault distances). However, it should be noted that in the 25th April mainshock, there was no surface rupture associated with the seismogenic fault (Angster et al. 2015; Kobayashi et al. 2015; Lindsey et al. 2015). Differential interferometric analysis (DinSAR) of the 25 April earthquake was conducted based on single-look-complex (SLC) images on 17 and 29 April acquired from Sentinel-1A. After mosaicking the SLC images in slant range, the DinSAR processing flow consists of interferogram generation, Goldstein phase filtering, phase unwrapping, orbit refinement as well as phase to displacement conversion and geocoding. The resulting displacement map served as input to fault modeling. A regular mesh grid based on sampling spacing of 500 m was used for the inversion. The inversion process was initialized using values from the Global Centroid-Moment-Tensor (CMT) database and constrained by strike (295°), dip (11°) and rake (108°) using the elastic dislocation approach (Okada 1985). As shown in Figure 4.2, the resulting fault line (i.e. intersection of the dipping fault plane with earth surface) obtained from the inversion is approximately at the same location as the tectonic plate boundaries delineated by Bird (2003) and the Eurasian-Indian fault line (Okamura et al. 2015).

Apart from epicentral and fault distances, ground motion and amplification effects during an earthquake are also governed by near-surface geology (Kumar et al. 2016). The most important parameter in evaluating seismic soil response is the average shear wave velocity for a depth of 30 m (i.e. V_{s30}), but investigations for V_{s30} in Nepal (e.g. Kathmandu Valley) remain inadequate (Paudyal et al. 2012). In the 25th April event, most landslides were found to be shallow and occurred in fractured, weathered and surficial material (Collins and Jibson 2015). To account for the occurrences of slope failures on shallow soils and influences of soil type on seismic amplification, surficial lithological classifications of the study area were utilized (Dijkshoorn and Huting 2009). The major lithology groups are cambisols (CM), leptosols (LP), regosols (RG), luvisols (LV) and glaciers (GG). The finer divisions of each group include eutric cambisols (CMe), gleyic cambisols (CMg), gelic cambisols (CMi), humic cambisols (CMu), chromic cambisols (CMx), eutric leptosols (LPe), gelic leptosols (LPi) or cryosols, mollic leptosols (LPm), eutric regosols (RGe), haplic luvisols (LVh).

For the trivariate analyses with LC_w and epicentral distances, landslide predisposing factors were extracted from the pre-earthquake digital elevation model (DEM) of the Cartosat-1 satellite (CartoDEM) due to its recent acquisitions (within the period 2005 to 2014 – year before the earthquake) as well as its better accuracy over the Indian landmass (Muralikrishnan et al. 2013). From the DEM, fundamental terrain parameters including slope angle, aspect and elevation were computed. In addition, more complex DEM-derived parameters such as slope curvature (i.e. surface concavity/convexity), topographic openness (i.e. degree of enclosure) as well as topographic position (i.e. slope position relative to its surroundings) were generated.

For interpretation of the results, variables were separated into intervals (i.e. bins) as shown below in Table 4.2.

Table 4.2 Binning intervals for each variable considered in this study

Variable	Interval ¹	Min	Max
Epicentral distance (km)	20 (10)	0	200
Fault distance (km)	10 (6)	60	120
Slope angle (°)	5 (10)	0	> 45
Slope aspect ² (°)	45 (8)	0	360
Elevation (m)	200 (9)	800	2600
Curvature	0.1 to 1 ³ (12)	< -2	> 2
Openness ⁴ (°)	10 (8)	0	90
Position	Various ³ (6)	Valleys	Ridges

¹ Value in parenthesis indicate total number of intervals

² Clockwise from north (0°); binning according to direction (e.g. 90° means east)

³ Refer legend in figure for the binning interval

⁴ Openness is defined according to Yokoyama et al. (2002)

4.4 Landslide probability by multivariate analysis

In order to understand the interplay and relative importance between seismic source, terrain and lithological parameters in landslides that occurred during the 2015 Nepal earthquake, an assessment via multivariate analysis was conducted. As there remains a possibility that these parameters may be correlated to one another (especially those derived from DEM), a dimension reduction technique using principal components analysis (PCA) was conducted to address the issue of multicollinearity and transform them into a set of uncorrelated variables (i.e. principal components) with associated eigenvalues. In PCA, a critical decision involves selecting the number of components

to be retained, where an incorrect choice would lead to under-extraction (i.e. loss of information) or over-extraction (i.e. inclusion of spurious components) (Franklin et al. 1995). These choices, such as the Kaiser's greater-than-one rule or simple eyeball searches for the 'elbow-point' of a scree plot, would likely result in an unreliable selection of components (Jackson 1993). Hence, the parallel analysis (PA) approach originally proposed by Horn (1965) was adopted. The PA approach involves comparing the actual eigenvalues with random data eigenvalues generated by a Monte Carlo simulation process that reflects the observed data in terms of sample size and number of variables. Principal components (PC) from the outcome of the PCA are only retained if the i th eigenvalue from the actual data is greater than the corresponding i th eigenvalue from the random data at the 95th percentile (O'Connor 2000). Various studies have concluded that PA is an ideal method to determine the number of components in a PCA in terms of accuracy and robustness to different components (Crawford et al. 2010). To identify the major landslide variable(s) influencing each PC, a loading threshold of 0.70 is employed (Jolliffe and Morgan 1992). The retained PCs are subsequently employed in a stepwise binomial logistic regression (LR) in order to derive the landslide susceptibility model. As input to the LR necessitates dichotomous landslide responses, a similar-sized, randomly distributed dataset of non-landslides (i.e. negative response) and their associated parameters were generated. Based on the logit transformation of landslide response from the LR procedure, landslide probability can be expressed by Eqs. (4.3) and (4.4):

$$Landslide\_probability(P) = \frac{1}{1 + e^y} \quad (4.3)$$

$$y = a_1PC_1 + a_2PC_2 + a_3PC_3 + \dots + \gamma \quad (4.4)$$

where P = probability of landslide response between 0 – 1; a = coefficients of PCs; γ = constant. Subsequently, the model (Eq. (4.3)) was assessed based on prediction accuracies and the receiver-operator-characteristic (ROC) plot. An illustration of the overall methodology used in the current study is shown in Figure 4.5.

Figure 4.5 Overall methodology in this study

4.5 Results from short-term landslide inventory

4.5.1 Overall variations of LC and LI with lithology

The overall variations of LC and LI with lithological classifications (Figure 4.6) for landslides within the study area are shown in Figure 4.7 and Figure 4.8. Lithological groups exhibiting LC and LI above their respective averages were highlighted in the respective plots. From Figure 4.7 and Figure 4.8, six lithological groups presented LC values above the average LC value of 0.45 LS/km² while only two groups (i.e.

CMu and RGe) possessed LI above the average LI value of 9.1%. As described previously, analysis of LC alone may be problematic and is evident in Figure 4.7, where LPm appears to have a significantly higher LC value (approximately twice that of CMg and RGe). This is due to the low area composition of the LPm group within the study area. Moreover, LPm comprised of only 5.6% of the overall landslide inventory (Figure 4.8) and thus do not reflect an area of significant landslide risk. Furthermore, it is observed that the LPi group (located mostly northwards of Nepal in the high elevation areas of Himalayas) has very low LC value of 0.07 LS/km² (even though its area composition is the highest among all lithology groups) and is a region of low landslide susceptibility due to the extension of rock material close to the surface (Nachtergaele 2010). Since the soils in the LPi group are a result of weathering from in-situ rock formations, these mostly shallow soils would have likely experienced lesser seismic ground amplification.

Conversely, following the landslide risk assessment matrix shown in Table 4.1, only the groups of CMu (LC = 0.57 LS/km²) and especially RGe (LC = 1.02 LS/km²) fall within the high risk category. Humic cambisols (CMu) are medium to fine-textured materials (i.e. loamy to clayey textured soils) while the regosols (RGe) group are largely composed of weakly developed fine grained soils and generally unconsolidated (low shear strength) in nature (Chesworth 2007; Driessen et al. 2000; Lagacherie et al. 2006). The high tendency for shallow landslide occurrences in these generally weak soils during the mainshock is reflected in the LI values. In total, landslides in the CMu (LI = 29.9%) and the RGe (LI = 50.3%) groups constituted over 80% of the current landslides within the study area. Since they represent the locations of the majority of slope failures (i.e. high landslide risk) induced by the 25th

April earthquake, subsequent trivariate analyses in relation to seismic source and topographical properties are conducted for two lithological groups to avoid confounded results from other lithologies.

Figure 4.6 Lithological map

Figure 4.7 Variations of LC and area composition with lithology

Figure 4.8 Variations of LI with lithology

4.5.2 Overall variations of LC_w with fault distance

Figure 4.9 shows the variation of LC_w with distances from the fault line. Estimated fault geometry from the non-linear inversion process was approximately 160 km by 40 km and at a focal depth of 13 km, yielding a mean slip of 2 m. The modelled fault line is well-represented by the EU-IN plate boundary given by Bird (2003). From Figure 4.9, majority of landslides were situated at a distance of approximately 70 to 100 km from the fault line. Due to dip angle (11°) of the rupture plane, the fault trace is not located within the study area and the closest landslide is about 62 km away. This is however different from the works of Keefer (2000) and Collins et al. (2012) where responsible seismogenic faults were near or within the region bounded by the respective study areas. For example, Xu et al. (2014) reported that the largest

landslide concentration was found at the furthest distance from the fault. Nonetheless, their interval for fault distances was only at 100 m and the extents considered in their study are comparatively smaller than those employed here.

Figure 4.9 Variation of LC_w with fault distance

4.5.3 Variations of LC_w with epicentral distance and terrain variables

Spatial distance correlations of landslides occurrences with seismic source and terrain parameters provide a first order indication regarding the distribution of earthquake-induced landslides within the affected region. The results from the trivariate analyses of LC_w, epicentral distance and the relevant terrain variables are presented in the following sections.

4.5.3.1 Slope angle

Figure 4.10 presents the slope angle map of Nepal while Figure 4.11 and Figure 4.12 show the variations of LC_w with epicentral distance and slope angle for the RGe and CMu lithological groups, respectively. Overall, the distributions of LC_w are observed

to approximate a normal distribution with respect to epicentral distance. This suggests a site amplification effect, since more landslides would be expected to be found near the epicentre if ground conditions are similar (Dahal et al. 2013; Zhang et al. 2014). For both lithologies, LC_w is small near the epicentre up to a distance of 60 km regardless of slope angle. Kargel et al. (2016) attributed the occurrences of landslides at low slope angles to materials which were already near failure and only required slight stress increase to fail. Further away from the epicentre, there is a significant increase in LC_w which peaks at the epicentral distances of 80 to 100 km (bin 5) and constitutes 33% of the landslides observed. However, the slope angles corresponding to these peaks are different for the two lithologies. The RGe lithology registered more slope failures within the slope angles of 35° to 40° and the LC_w was markedly higher (close to five times) than the same slope angle bin (8) located further away from the epicentre. This suggests a strong preference for slope failures in the RGe group to occur within this slope angle range. Within this epicentral distance, CMu had more landslides occurring within the slightly higher slope angle range of 40° to 45° , but LC_w is only up to twice the LC_w for the same slope angle range further away (between epicentral distances 100 to 140 km). For both lithologies, LC_w decreases further away from the peak value at epicentral distance bin 5, and appears to reach a threshold at 140 km, beyond which very few landslides were observed. This findings point to a possible attenuation limit of the seismic waves generated during the 25th April mainshock in relation to its magnitude (Nuttli 1973).

Figure 4.10 Slope angle map

Figure 4.11 Variations of LC_w with epicentral distance and slope angle (RGe)

Figure 4.12 Variations of LC_w with epicentral distance and slope angle (CMu)

4.5.3.2 Slope aspect

Figure 4.13 Slope aspect map

Figure 4.13 presents the slope aspect map of Nepal. Lee (2013) mentioned that landslides were found to be more frequent if the slope aspect is concurrent with the movement direction of the seismogenic fault and thrusting direction of the blocks. From finite fault models developed for the 25 April Nepal main shock, rupture

propagated from the hypocentre in the southeasterly direction (Goda et al. 2015). This is reflected in Figure 4.14 and Figure 4.15, where landslides occur mostly on slopes facing the southeastern direction for both lithologies. This relation is however more compelling for the CMu group, where the LC_w is approximately twice the LC_w value in the RGe group. Corresponding LI values for landslides in the southeastern (eastern) direction are 18.9% (14.0%) for RGe and 26.9% (21.7%) for the CMu groups. On the contrary, slopes facing the northern direction (i.e. north, northeast and northwest) which are virtually perpendicular to the rupture propagation direction registered significantly lower LC_w values and thus exhibit least slope failure tendencies.

Figure 4.14 Variations of LC_w with epicentral distance and slope aspect (RGe)

Figure 4.15 Variations of LC_w with epicentral distance and slope aspect (CMu)

4.5.3.3 Topographical elevation

Figure 4.16 presents the elevation map of Nepal with respect to mean sea level. Figure 4.17 shows that regions with elevations between 1600 – 2000 m for RGe constitute the highest LC_w values and accounted for 36.3% of the landslide inventory. For the CMu group (Figure 4.18), LC_w was distinctly higher at elevations of 2000 – 2400 m and comprised 30.1% of the landslides. As compared to RGe, there was a marked absence of landslides at elevations below 1800 m. Within the Nepal region, Bäumler and Zech (1998) previously reported high clay fractions for elevations between 2000 to 3000 m. The presence of clay layers at these elevations are likely to amplify seismic ground motion (i.e. high PGA), resulting in the higher landslide concentrations. Furthermore, Bussmann et al. (2008) found that metamorphosed clay and sand sediments located at these elevations (i.e. up to 2600 m) transits to stronger quartzite

rich substrates at higher elevations, thus explaining the lack of slope failures at those elevations.

Figure 4.16 Elevation map

Figure 4.17 Variations of LC_w with epicentral distance and elevation (RGe)

Figure 4.18 Variations of LC_w with epicentral distance and elevation (CMu)

4.5.3.4 Slope curvature

Figure 4.19 presents the general slope curvature map of Nepal and the study area was found to be dominated by moderately concave (i.e. curvature between -2 to -1) and moderately convex (i.e. curvature between 1 and 2) slopes. A clear preference for articulated (either concave or convex) slopes was observed which accounted up to 52.5% of the landslide inventory. However, the LC_w values were greater for concave slopes than for convex slopes. To describe finer variations of the slope, cross-sectional and longitudinal curvatures were also evaluated (not shown here). For both CMu and RGe groups shown in Figure 4.20 and Figure 4.21, respectively, the highest LC_w values were obtained in concave (i.e. between -2 to -0.5) (for cross-section curvatures) and convex (i.e. between 0.2 to 1) (for longitudinal curvatures) slopes. Combining the results, Figure 4.19 further illustrates the most probable surface slope configuration most prone to failure (Kimerling et al. 2016).

Figure 4.19 Slope curvature (general) map; most probable slope configuration for landslides (inset)

Figure 4.20 Variations of LC_w with epicentral distance and general curvature (RGe)

Figure 4.21 Variations of LC_w with epicentral distance and general curvature (CMu)

4.5.3.5 Topographical openness

Figure 4.22 Topographical openness map

Figure 4.22 illustrates the topographic openness map covering the study area in Nepal while Figure 4.23 and Figure 4.24 present the results for positive openness derived at fine-scale (90 m), which characterizes the openness relative to higher elevations on the surface (Lollino et al. 2014). It should be noted that negative openness ('below

ground’) is not simply the positive openness (‘above-ground’) attached with a negative sign, but refers to nadir angles (as compared to zenith angles for positive openness) (Yokoyama et al. 2002). The results obtained for both positive and negative openness are strikingly similar and consequently only the positive openness results are shown. As seen in Figure 4.23 and Figure 4.24, LC_w are highest at positive openness between 50° to 60° . However, since the openness values fall below 90° , the landslides would mostly be located in areas of low terrain exposure such as valleys and canyons, where anthropogenic influences may have led to increased slope instability (Doneus 2013).

Figure 4.23 Variations of LC_w with epicentral distance and topographic openness (RGe)

Figure 4.24 Variations of LC_w with epicentral distance and topographic openness (CMu)

4.5.3.6 Topographic position

Figure 4.25 presents the topographic position map which accounts for the relative height along a hillside slope. Topographic position influences climatic conditions (e.g. solar radiation) and soil formation processes. Furthermore, moisture content in soils at the lower portions of slopes are typically higher, increasing the likelihood of slope instability (Clark et al. 1999; Eisenlohr et al. 2013). From the results shown in Figure 4.26 and Figure 4.27, LC_w in both lithologies were highest for topographic position corresponding to valleys and close to six times more than that for ridges. Other position classes have considerably low LC_w values. Landslides located on valleys (ridges) comprised 60.6% (32.5%) and 60.3% (33.4%) of the total inventory for RGe and CMu, respectively. As mentioned previously, the predominant mode of landslide failure is translational. Layers of loose deposits and weathered materials typically found on valleys would likely have been destabilized by the seismic shaking,

resulting in higher landslide concentration in these areas (Xu et al. 2014). These observations further reflect the results found from the openness analysis.

Figure 4.25 Topographical position map

Figure 4.26 Variations of LC_w with epicentral distance and topographic position (RGe)

Figure 4.27 Variations of LC_w with epicentral distance and topographic position (CMu)

4.6 Analysis using Kargel et al. (2016) medium-term landslide inventory

As shown in Figure 4.28 to Figure 4.32, analysis on the medium-term landslide inventory for the dominant RGe and CMu (Figure 4.28 and Figure 4.29) lithological groups from Kargel et al. (2016) reveals very similar landslide trigger characteristics as the short-term landslide inventory presented in the previous section. To aid comparisons with the short-term landslide inventory, the following figures present the results in the medium-term inventory: (i) variations of LC and LI with lithology - Figure 4.28 and Figure 4.29, (ii) fault distance - Figure 4.30, (iii) slope angle, slope aspect and elevation - Figure 4.31, and (iv) general curvature, openness and position - Figure 4.32.

The similarities between the short- and medium-term landslide inventories were likely due to similar data sources (i.e. open-source satellite images) being used along with the short time difference between the two inventories (i.e. only a few months).

As such, more explanations were placed on the more comprehensive long-term landslide inventory from Roback et al. (2018) instead.

Figure 4.28 Kargel et al. (2016) landslide inventory - variations of LC with lithology

Figure 4.29 Kargel et al. (2016) landslide inventory - variations of LI with lithology

Figure 4.30 Kargel et al. (2016) landslide inventory - variations of LC_w with fault distance

Figure 4.31 Kargel et al. (2016) landslide inventory – variations of slope angle (a, b), slope aspect (c, d) and elevation (e, f) with epicentral distance

Figure 4.32 Kargel et al. (2016) landslide inventory – variations of general curvature (a, b), openness (c, d) and topographic position (e, f) with epicentral distance

4.7 Analysis using Roback et al. (2018) long-term landslide inventory

The study sector as defined in Figure 4.3 was likewise retained, as well as the adoption of similar classifications for each variable to ensure consistency and interpretability during the analysis of Roback et al. (2018)'s landslide inventory. Figure 4.33 and Figure 4.34 shows the variations of LC_w and LI with lithology. Here the major difference lies in the number of lithological groups identified, which had 7 groups (i.e. less CMi, LPe, LPm, LVh) instead of 11. Due to the possible

amalgamation of imagery pixels registered as change (i.e. landslide), more lithological groups may be identified in the earlier analysis. As expected, significant differences in landslide densities between the two datasets (i.e. short- and long-term) may be observed, with the average LC here as 2.35 LS/km², compared to 0.45 LS/km² in the short-term inventory. Nonetheless, since LC (note, not LC_w) requires the concurrent interpretation with LI (as shown in Figure 4.34), it is revealed that the conclusion regarding lithological groups with highest landslide clusters remain the same (i.e. CMu and RGe). Likewise, Figure 4.35 corroborates the earlier observation that most landslides occurred approximately 70 to 100 km from the EU-IN fault line.

Figure 4.33 Roback et al. (2018) landslide inventory - variations of LC with lithology

Figure 4.34 Roback et al. (2018) landslide inventory - variations of LI with lithology

Figure 4.35 Roback et al. (2018) landslide inventory - variations of LC_w with fault distance

Figure 4.36 illustrates the variations of slope angle, slope aspect and elevation for the two lithological groups, RGe and CMu, for the long-term inventory. Here, Figure 4.36 (a) to (d) show that landslides which faced southeast with slope angles higher than 35° were most susceptible to failure, which is in line with the earlier findings

using the short-term inventory. Else, landslides in the long-term inventory generally registered a higher elevation with milder slope curvature and were located on gentle slopes (i.e. topographic position) as illustrated in Figure 4.37 (a), (b), (e) and (f). As for openness depicted in Figure 4.37 (e) and (f), the highest LC_w values were found on terrain pixels with openness of 50° to 60° , which were consistent with the earlier analysis. In general, it is observed that there is no significant difference in landslide predisposing and trigger factors when employing a markedly denser landslide inventory.

From these results, the use of open-source satellite imagery may be sufficient for relief efforts by first emergency responders. Potential landslide locations can be rapidly identified through these imagery archives. While the landslide inventory is generally coarser, these readily available satellite images are also useful to understand landslide failures in scientific research without the need for exorbitant high-resolution commercial images which entails long processing times. For instance, the Roback et al. (2018)'s inventory took three years after the earthquake in 2015 to be mapped and finally published.

Figure 4.36 Roback et al. (2018) landslide inventory – variations of slope angle (a, b), slope aspect (c, d) and elevation (e, f) with epicentral distance

Figure 4.37 Roback et al. (2018) landslide inventory – variations of general curvature (a, b), openness (c, d) and topographic position (e, f) with epicentral distance

4.8 Multivariate analysis

Landslide parameters considered in the multivariate analysis for the short-term landslide inventory were slope angle, aspect, elevation, curvature, openness, position, lithology as well as epicentral and fault distances. The multivariate analysis was conducted using the landslide inventory identified from open-source imagery. Topographic openness and position were derived at fine and coarse scales to represent the variations with respect to the surroundings. Figure 4.38 presents the scree plot showing the eigenvalues for each PC and the cut-off values derived via parallel analysis. Based on the 95th percentile eigenvalues, only five PCs (Pearson's correlation coefficient, $r < 0.3$) were retained. The variables which loaded most (i.e. loading > 0.7) on the five PCs include slope angle, curvature, elevation, epicentral distance, fault distance and to a lesser extent, openness. The five PCs were subsequently entered into the stepwise binomial LR procedure with the resulting coefficients (as in Eq. (4.4)) shown in Eq. (4.5). Finally, values obtained by Eq. (4.5) for each landslide observation can be used to generate the landslide probability using Eq. (4.3).

$$y = 0.01 \cdot PC1 + 0.15 \cdot PC2 - 0.12 \cdot PC3 - 0.004 \cdot PC4 - 0.002 \cdot PC5 - 8.45 \quad (4.5)$$

The eventual landslide probability model from the short-term landslide inventory was able to obtain a true positive prediction for landslide occurrence at an accuracy of 95.4%.

Figure 4.38 Scree plot with eigenvalue cut-offs

To assess the overall performance of the model, a receiver-operator-characteristic (ROC) plot (Figure 4.39) which plots the probability between true and false positively identified landslides was utilized. *Sensitivity* refers to the probability of correct classification while *1-specificity* indicates false classification. Area under the ROC curve, which evaluates overall accuracy of the model, is 0.983 units² and equivalent to 98.3% model accuracy. Thus, the landslide probability model from the short-term landslide inventory is strongly validated by the multivariate analysis.

Figure 4.39 Receiver-operator-characteristic (ROC) plot

4.8.1 Validating the short-term landslide probability model using medium- and long-term landslide inventories

In order to ascertain whether the landslide probability model obtained from the short-term landslide inventory adequately represents landslide prone areas as identified by the medium- and long-term inventories, Eqs. (4.4) and (4.5) was used. Here, the coefficients of the PCs derived from the short-term inventory shown in Eq. (4.5) was used to compute landslide probabilities using the five PCs from the medium- and long-term landslide inventories respectively. Thus, for each landslide observation, there is a corresponding prediction of landslide probability based on the short-term dataset (i.e. whether a landslide occur). Here, a distinction between lithological groups was not made for the medium- and long-term inventories (i.e. all landslide locations identified by Kargel et al. (2016) and Roback et al. (2018) were utilized).

Therefore, the landslide model was deployed on the medium- and long-term inventories regardless of lithological classification.

The overall prediction accuracy and results are summarized in Table 4.3. As shown in Table 4.3, the long-term landslide inventory within the study sector has close to a 7-fold increase in number of landslides identified as compared to the medium-term inventory. As mentioned previously, this is due to the higher spatial resolution of satellite images used by Roback et al. (2018), resulting in numerous smaller landslides which were not present in the short- and medium-term inventories. This is further exemplified in a landslide density map shown in Figure 4.40, where the landslides not captured by the short-term inventory (as circled in red dashed lines) were found to have an average landslide area of approximately 345 m² (i.e. less than 500 m², corresponding to 22.5 m sampling resolution used in the short-term landslide inventory). Consequently, these smaller landslides were not able to be identified using the rapidly available open-source satellite imageries.

Figure 4.40 Long-term landslide locations overlaid on short-term inventory landslide density map; region of landslides not captured by short-term inventory is circled in red dashed lines

From Table 4.3, good overall predictive accuracy was obtained using the short-term probability model, with an accuracy of 95.1% when applied on the medium-term inventory, and 93.0% when applied on the long-term inventory. A further verification was conducted by limiting the long-term landslide inventory only to the larger landslides (i.e. range of landslide areas in the short-term inventory). By only including landslides larger than 500 m², the predictive accuracy was (expectedly) higher at 98.1%.

Table 4.3 Summary of landslide prediction for medium- and long-term inventories using the short-term landslide probability model

Inventory	Total landslides ¹	Predicted landslides	Predicted landslides (incorrect)	Accuracy (%)
Medium-term	2,506	2,383	123	95.1
Long-term	15,186	14,115	1,071	93.0
Long-term (filtered) ²	9,326	9,147	179	98.1

¹ Within the study sector as defined in Figure 4.3

² Long-term landslide inventory filtered to include only landslides larger than the typical landslide resolution of the short-term landslide inventory (~500 m²)

Figure 4.41 and Figure 4.42 further presents the landslide density clusters for the short- (which is also representative of medium-term) and long-term landslide inventories. The zones with greatest number of landslides (circled in red dashed lines) were found to be mostly similar between the short- and long-term datasets.

Thus, these findings ultimately show that, despite the lack in spatial resolution, short-term landslide inventories are extremely useful to assess landslide prone areas in times of emergencies, especially during rescue efforts which are time-critical. As open-source satellite imageries are readily available, the timely nature of these data sources serve as a major tool for decision makers, such as the deployment of relief efforts in earthquake-induced landslides.

Figure 4.41 Landslide density clusters for short-term inventory; medium-term inventory shows similar distribution; red dashed lines show concentrations of landslide clusters

Figure 4.42 Landslide density clusters for long-term inventory; red dashed lines show concentrations of landslide clusters

4.9 Conclusion

The 25th April 2015 Nepal earthquake induced a large number of landslides which caused widespread destruction. In this study, the assessment of three scales of landslide inventory was conducted on the basis of seismic source, terrain and lithology. As strong motion data was severely lacking in this earthquake leading to poorly constrained values for modelled peak ground accelerations and velocities, epicentral distance and surficial soil classifications were used as suitable proxies.

An in-depth examination of landslide trigger was first conducted using the short-term landslide inventory which was assembled on the basis of open-source satellite imagery before and after the earthquake. Landslide concentration and inventory percentage were both employed to account for the respective landslide densities within each parameter. A study area comprising of a 20° sector from the epicentre was defined to encompass the densest landslide clusters. Two lithological groups consisting of weak surficial soils, namely eutric regosols (RGe) and humic cambisols (CMu), accounted for up to 80% of the total landslides and thus these lithologies were selected for the trivariate evaluations (Figure 4.7 and Figure 4.8). *Weighted landslide concentration* (LC_w) was further introduced to avoid misinterpretations when examining landslide concentrations. The trivariate analyses include identifying high LC_w values within each parameter as these correspond to regions of high landslide risk. The LC_w was observed to approximate a normal distribution across epicentral distance which implies effects of topographic amplification. Steeper slope angles between 35° to 45° presented higher occurrences of landslides for both RGe and CMu with a more compelling relation for the RGe lithological group (Figure 4.31). There is also evidence of a greater tendency for landslides to be located on slopes facing the

same direction as rupture propagation (i.e. southeast) and significantly lesser for those in the perpendicular direction (Figure 4.14 and Figure 4.15). The LC_w were highest at elevations between 1600 to 2400 m, which comprised of high clay content soils amplifying ground motion (Figure 4.17 and Figure 4.18). Curvature analyses revealed that articulated slopes (i.e. concave or convex) were more likely to fail than uniform-surface slopes (Figure 4.20 and Figure 4.21). The results of topographic openness showed that positive (above ground) and negative (below ground) openness were largely similar, with most landslides occurring on terrain classified with positive openness values of 50° to 60° (Figure 4.23 and Figure 4.24). These regions of low openness correspond to valleys and canyons which were further reflected in the topographic position analyses. Landslides on valleys, followed by ridges, were most prone to failure due to the presence of weathered material and anthropogenic influences (Figure 4.26 and Figure 4.27).

To assess the relative importance of the landslide predisposing factors, a multivariate analysis was conducted using principal component analysis (PCA). In the selection criteria of the number of principal components, an approach involving parallel analysis was used. Five principal components were eventually retained, with major loadings from slope angle, aspect, elevation, curvature, openness, position, and lithology as well as epicentral and fault distances. A stepwise binomial logistic regression was used to obtain a landslide probability model described by the principal components. Based on this model, a true positive prediction rate of 95.4% for landslide occurrences within the short-term inventory was achieved. Furthermore, the area under the receiver-operator-characteristic (ROC) curve presented a high overall

model accuracy of 98.3% (i.e. capable of distinguishing between false positives) (Figure 4.39).

An assessment of two other landslide inventories published within months to years due to the same earthquake event was also conducted. These are based on the works of Kargel et al. (2016) (i.e. medium-term, within few months after the earthquake) and Roback et al. (2018) (i.e. long-term, approximately three years after the earthquake). The main differences are the higher spatial resolution satellite imageries as well as time and resources available with increasing time. The long-term landslide inventory was able to identify many smaller landslides, which would otherwise be undetected by the short- and medium-term landslide inventories. Thus, the unique opportunity of this earthquake event allows for a temporal comparison of landslide inventories. Repeat analyses revealed that the conclusions for the medium- and long-term landslide inventories are generally similar to the short-term inventory obtained by open-source imagery. Additionally, a quantitative examination was made by using the landslide probability model obtained from the short-term landslide inventory to predict against the landslides present in the medium- and long-term inventories. Predictive accuracy of the medium-term landslide inventory was at 95.1%, while the long-term landslide inventory was at 93.0% (Table 4.3). By limiting the long-term landslide inventory only to the larger landslide sizes detectable by open-source imageries (i.e. $\geq \sim 500 \text{ m}^2$), the accuracy was remarkably higher at 98.1%. Moreover, the locations of dense landslide clusters were mostly similar, even though the long-term landslide inventory identified a number of smaller landslides. Based on these results, open-source satellite images, which are freely accessible and allows for rapid processing, are sufficiently representative of landslide susceptibilities which

consequently suggests that the use of high resolution satellite imageries are not necessary in such studies.

CHAPTER 5 IONOSPHERIC PRECURSORS OF EARTHQUAKES

5.1 Addressing the five aspects in using PETA for earthquake prediction

To begin the discussion on seismo-ionospheric precursory phenomena, topics raised earlier in Section 2.2.1 are first revisited (i.e. the five questions raised by Tong (1998)). In this regard, the subjects listed below shall form the basis of discussion in the following sections of CHAPTER 5 :

- 1) Differences between ground- and satellite-based PETA observations.
- 2) Variability of ionospheric total electron content in seismically and non-seismically active regions
- 3) Spatial and temporal confounding effects from adjacent earthquakes have to be accounted for in the analyses.
- 4) Parameters with arbitrarily defined values ought to be objectively justified or standardized. Those identified in this study include ionospheric shell height, elevation angle, detection confidence (i.e. Z-value), N-day and space-related indices.
- 5) Relevancy of the earthquake preparation zone (EPZ) in retrospective and prospective analyses.
- 6) Lack of research to correlate spatial and temporal PETA variations (e.g. IAZ, n_{pre}) with seismic parameters (e.g magnitude, epicentre) which is central to establish time, location and strength for earthquake forewarning.

5.1.1 Nature and reliability of TEC observations

TEC data can be generally classified based on ground-based or space-borne (i.e. satellite) platforms. A vast majority of retrospective PETA studies were conducted

based on the former due to the increase in GPS stations in the last decade (Choosakul et al. 2009; Contadakis et al. 2010; Devi et al. 2008). Various GPS networks have been utilized for this purpose. Examples of these are Continuous Operating Reference Station (CORS) (Plotkin 2003), International GNSS Service (IGS) (Aggarwal 2015; Astafyeva et al. 2014; Cahyadi and Heki 2013; Chen et al. 2014a; Hao et al. 2012; Hasbi et al. 2009; Lin 2011a), Jabatan Ukur dan Pemetaan Malaysia (JUPEM) (Hasbi et al. 2011; Hasbi et al. 2009; Hwa and Zain 2005), Sumatran GPS Array (SuGAR) (Astafyeva et al. 2014; Cahyadi and Heki 2013; Hasbi et al. 2011; Hirooka et al. 2012; Hirooka et al. 2011), Crustal Movement Observation Network of China (CMONC) (Jin et al. 2015), GPS Earth Observation Network (GEONET) (Astafyeva and Heki 2011; Astafyeva et al. 2013; Astafyeva et al. 2014; Galvan et al. 2012; Kakinami et al. 2011; Komjathy et al. 2012), Korean GPS Network (KGN) (Choi and Lee 2016), EUREF Permanent Network (EPN) (Contadakis et al. 2008; Contadakis et al. 2015; Contadakis et al. 2010), Marmara Continuous GPS Network (MAGNET) (Dogan et al. 2011), Argentina Network of Continuous Satellite Monitoring (RAMSAC) (Jiang et al. 2017) and the GPS Ionospheric Scintillation and TEC Monitor (GISTM) (Karia et al. 2013) network. In addition, two-dimensional TEC maps derived from these ground-based observations are also frequently used (Akhoondzadeh and Saradjian 2011; He et al. 2014; Jhuang et al. 2010; Jing et al. 2011; Ke et al. 2016; Kon et al. 2011). Apart from their convenience and global coverage, ionosphere maps (GIMs), such as those produced using long-term TEC data from the Center for Orbit Determination of Europe (CODE), are regarded as the most precise TEC maps available and typically treated as a high-accuracy reference (Mukhtarov et al. 2013; She et al. 2017; Wu et al. 2015). These ionosphere TEC maps from CODE are

generated on an hourly-basis and provide relatively good temporal resolution with hourly intervals.

On the other hand, there are comparatively few studies utilizing space-borne TEC data for PETA studies (Hsiao et al. 2010; Liu et al. 2009). This is possibly due to the lack of satellite platforms carrying relevant instrumentations or performing TEC-related processing (i.e. GPS-derived TEC). In contrast to ground-based GPS stations, satellites provide dynamic observations along their orbit (i.e. location of satellites differs) (Zakharenkova et al. 2016). Compared to ground-based GPS stations which have typical sampling resolutions of 15 seconds to 2 hours, satellites can only measure TEC over a particular location at a lower temporal resolution depending on their orbit characteristics (e.g. polar vs. equatorial revisit rates). As a result, Plotkin (2003) and Galvan et al. (2012) aptly stated that single satellites are often deficient and inadequate for measurement of TEC. However, the recent availability of satellite constellations (e.g. multiple satellites along different orbits) allows for further reduction in sampling time, while simultaneously increasing spatial coverage. Therefore, while ground-based measurements may not provide measurements at locations where earthquakes occur (especially those within oceans where ground stations are unavailable), space-borne systems could overcome such limitation (Aggarwal 2015). In addition to the FORMOSAT-3/COSMIC-1 satellite, the relatively recent launch of Singapore's climate research satellite VELOX-CI, satellite constellation SWARM Alpha, Bravo and Charlie by the European Space Agency (ESA) in 2013 along with the follow-up missions of FORMOSAT-7/COSMIC-2 in 2016 and 2018 provide more sources of TEC data for PETA studies as illustrated in Figure 5.1.

Figure 5.1 Integration of ground-based and space-borne assets for monitoring of PETA and associated effects (adapted from Tsai et al. (2004) and De Santis et al. (2015))

To assess the reliability of the two forms of TEC data, a comparison was conducted for a ‘non-seismically active’ location within Russia (68.6° N 56.9° E) for the year 2016 (Figure 5.2) where the closest earthquake ($M_w \geq 4.5$) during that period was located approximately 2000 km away to examine TEC variations in the absence of earthquake-induced effects.

Figure 5.2 Seismically active (densest earthquake clusters) and non-seismically active (quiet) zones

The GIM-CODE TEC (GIM-TEC) was used as reference, while satellite-derived TEC from the SWARM (S3-TEC) and COSMIC (C6-TEC) constellations were acquired. In the conversion of slant (STEC) to vertical TEC (VTEC) as well as the computation of sub-ionospheric points (SIPs), the ionospheric thin shell height of 1000 km and elevation angle cutoff of 20° were employed. The ionospheric thin shell height was selected to coincide with the altitude of the ionosphere/plasmasphere boundary (thus allowing for maximum probing distance) and to be greater than the satellites' orbit altitudes (Carpenter 2004; Dieminger et al. 2012; Karatay et al. 2010; Mazzella 2009). The direct comparison of ground- and satellite-based TEC is not a straightforward process since the multiple GPS links for the case of satellites would cause noisy TEC measurements (Zakharenkova et al. 2016). To address this concern, the seasonal variability of VTEC, which is primarily characterized by semi-annual and annual components along with weaker transient patterns, is considered (Mukhtarov et al. 2013; Natali and Meza 2011). Thus, for a coherent comparison, the background VTEC values were extracted using the Savitzky-Golay filter accounting

for semi-annual variabilities which preserves low frequency TEC structures (Savitzky and Golay 1964). The VTEC time series is shown in Figure 5.3 where several observations could be made. Firstly, the overall TEC variations for each platform are similar, where the symmetrical semi-annual behaviour is seen from the VTEC peaks between months of April to July 2016. The differences between satellite-based and ground-based TEC values were also most pronounced within this period. Secondly, ground-based TEC values registered the highest values as compared to satellite-based TEC across the year. This is expected as the GPS signals traverse a longer path to reach the ground receivers as compared to satellite receivers, consequently yielding larger STEC values as the signals probe the entire extent of the ionosphere. Thirdly, S3-TEC trend better reflects the semi-annual pattern exhibited by GIM-TEC, whereas C6-TEC variation was relatively flat. The reasons for this occurrence are: (1) SWARM's orbit (approximately 500 km) is at a lower altitude than COSMIC (approximately 800 km), which allows a longer signal path for the dual GPS frequencies, and (2) Since the electron density in the plasmasphere (above 1000 km altitude) is significantly lesser than the contributions in the ionosphere, SWARM's TEC would have likely probed the electron 'richer' part of the ionosphere (Wu et al. 2015). This is further reflected by a strong cross-correlation between daily-averaged GIM-TEC and S3-TEC values with a correlation coefficient of 0.86 against 0.40 for the case of C6-TEC. Therefore, if TEC data is required over land, GIM-TEC derived from ground GPS receivers is the ideal choice for precursory studies. However, if the location of interest is over the ocean where ground-based GPS stations are poorly distributed or if intra-hour measurements are needed to improve

temporal resolution, both S3-TEC and C6-TEC would act as a potential synergistic supplements to GIM-TEC, although the former is preferred (Ping et al. 2004).

Figure 5.3 Background VTEC from three TEC sources over non-seismically active location in Russia (68.6°N 56.9°E) for year 2016

5.1.2 Seismically active vs. non-seismically active zones

The fundamental objective (i.e. alternative hypothesis) of a retrospective PETA analysis is to establish that ionospheric TEC perturbations are due to a specific earthquake. Thus, the influence from spatially and temporally-adjacent earthquakes must be considered. In seismically active regions (especially for countries situated along tectonic plate boundaries), such effects are even more pronounced as earthquakes are not only clustered together, but occur within days (or even, hours) of one another. For example, in the highly seismically affected areas of Japan and South America (primarily Chile) for the year 2016, the average temporal gaps between adjacent $M_w \geq 4.5$ earthquakes were 0.81 and 0.62 days, respectively. Assuming that all earthquakes contribute to TEC changes, the ionosphere above these locations would likely be in a constantly perturbed state. To illustrate this behaviour, an

examination in the statistical dispersion for VTEC (GIM/CODE) in several seismically active and non-seismically active (or quiet) zones (Figure 5.2) was conducted using two years of data (2015 and 2016). The analyses consisted of long-term (annual) as well as short-term (15- and 30-days) VTEC standard deviations. This was based on detrended TEC where standard deviations were calculated through the entire year (long-term) and also using a moving filter corresponding to 15- and 30-days for the short-term periods. The seismically active zones were identified on the basis of a global inventory of earthquakes ($M_w \geq 4.5$) from the United States Geological Survey (USGS), where the densest earthquake clusters were derived from a kernel density analysis. These regions include Chile, Japan, Indonesia and within the Pacific Ocean, while the selected non-seismically active regions are located in Canada and Russia. Table 5.1 summarizes the long-term annual VTEC standard deviations for these regions.

Table 5.1 Long-term (annual) VTEC standard deviations for seismically quiet and active zones¹

Year	Zones					
	Quiet		Active			
	Canada	Russia	Chile	Japan	Indonesia	Pacific Ocean
	68.6° N 93.4° W	68.6° N 56.9° E	21.5° S 68.7° W	37.3° N 141.4° E	4.3° N 126.9° E	19.8° S 175.1 W
2015	6.21 (5.10)	7.13 (5.66)	20.7 (19.1)	9.12 (7.83)	19.8 (19.0)	16.7 (14.0)
2016	3.77 (3.08)	3.96 (2.98)	14.3 (13.3)	5.04 (4.40)	13.6 (13.2)	11.5 (9.71)

¹ Values in parentheses refer to standard deviations for detrended VTEC

The standard deviations for non-seismically active regions were consistently lower than seismically active regions for both raw and detrended VTEC values. Among the four seismically active regions, Chile exhibit the greatest variability, where the annual standard deviation is greater than three times (3.8 for year 2016) that of the non-seismically active region (Canada). Japan VTEC readings showed the least dispersion among the seismically active regions, where its standard deviation was approximately up to an average of 1.4 times that of the non-seismically active region in 2015 and 2016. Table 5.2 shows the results for the short-term. It is observed that the short-term VTEC variations of seismically active regions compared to non-seismically active regions were greater than that of annual variations. For the case of Chile in 2016, the 15-day standard deviation was found to be more than four times that of Canada and Russia. For example, the ratio between Chile and Canada in 2016 for the 15-day and 30-day standard deviations were $11.4/2.82 = 4.04$ and $11.0/2.75 = 4.00$, respectively. As for Chile and Russia, the 15-day and 30-day standard deviations were $11.4/2.65 = 4.30$ and $11.0/2.63 = 4.18$. Additionally, Indonesia demonstrated even larger VTEC variation with its complex geology as several tectonic plates converge at its location. The 15-day standard deviation ratio (year 2016) between Indonesia and Russia could be as high as 4.5 (i.e. $12.0/2.65$), while for daily-averaged detrended VTEC values, the ratio was close to 2 (Figure 5.4).

Table 5.2 Short-term (15- and 30-days) moving average VTEC standard deviations for seismically quiet and active zones^{1, 2}

Year	Zones					
	Quiet		Active			
	Canada	Russia	Chile	Japan	Indonesia	Pacific Ocean
	68.6° N 93.4° W	68.6° N 56.9° E	21.5° S 68.7° W	37.3° N 141.4° E	4.3° N 126.9° E	19.8° S 175.1 W
2015	4.34 (7.60)	4.66 (8.34)	16.0 (25.4)	6.35 (10.9)	16.9 (24.7)	11.8 (20.3)
	4.25 (7.01)	4.65 (7.95)	15.6 (25.1)	6.27 (10.7)	16.5 (24.5)	11.4 (19.6)
2016	2.82 (4.96)	2.65 (5.38)	11.4 (17.3)	4.03 (6.69)	12.0 (16.7)	8.11 (16.6)
	2.75 (4.92)	2.63 (5.04)	11.0 (17.1)	3.95 (6.59)	11.6 (15.9)	7.75 (16.4)

1 Top row refers to 15-day values while bottom row refers to 30-day values

2 Values in parentheses refer to maximum standard deviation values

Figure 5.4 Daily-averaged and detrended GIM-TEC values for Russia and Indonesia for year 2016

In summary, three observations could be deduced: (1) seismically active regions exhibit greater TEC variability as compared to non-seismically active regions, (2) short-term TEC variations were stronger than its long-term annual counterpart, which could be attributed to the temporally localised earthquake preparatory effects on the ionosphere, and (3) smaller earthquakes (i.e. $M_w \sim 4.5$) (not necessarily only large magnitude main shock events) could induce ionospheric perturbations as well. Consequently, for a retrospective PETA analysis, it is necessary to ascertain the state of ionospheric variability (i.e. determining whether the location is in a seismically active region or not) and adjusting anomaly detection methods accordingly to prevent false-positives or negatives (Guo et al. 2016). For example, in areas of high seismic activity, the standard deviations which are used in the statistical envelope method might be too high leading to false-negative cases. Simply testing for the existence of PETA with regards to a large magnitude earthquake within an earthquake swarm (which is typically the case for large seismic events) could be problematic due to influence of adjacent earthquakes and the recurrence times of earthquakes (Liu et al. 2010). The simultaneous exclusion of these two effects were addressed by Le et al. (2011), where a period of 15 days before and after were excluded if an adjacent earthquake occurred within a 5° zone. Nonetheless, studies accounting for adjacent earthquake effects are rare.

Based on these results, it further illustrates the fact that ionospheric conditions at varying latitudes can be markedly different (Sun et al. 2019). This becomes a significant problem especially when trying to prescribe a standardized value for indices such as f10.7, Dst or Kp, in identifying space weather influences. Since it consequently leads to the subjectivity in PETA detections, an objective way of

accounting for space weather activity is required which is further discussed in Sections 5.1.4 and 5.2.

5.1.3 Anomaly detection by statistical envelope methods

Depending on the nature of TEC data used, there are several techniques to determine if a particular TEC data point is anomalous. For example, when two-dimensional TEC maps are used, novel algorithms involving parametric (i.e. pattern recognition) analyses (e.g. neural network, wavelet transform, support vector machine) were recently explored (Akhoondzadeh 2013a, b, 2015; Sompotan et al. 2015). While the general conclusion of these analyses showed the existence of PETA owing to a particular earthquake, such analyses require more justification in the definition of the ‘normal’ TEC behaviour.

Since earthquakes possess statistical natures (e.g. Gutenberg-Richter law), statistics-based approaches have also been used in the detection of PETA (Chen et al. 2004; De Santis et al. 2015). These approaches include relative deviation (Kouris and Fotiadis 2002, Kouris et al. 2006), time derivative analysis (Ciraolo and Spalla 1999), correlation analysis (Leyva-Contreras et al. 2005; Pulinets 2004; Pulinets et al. 2004; Pulinets et al. 2007), TEC difference analysis (Plotkin 2003) and ionospheric correction (Trigunait et al. 2004). Besides the statistics-based approaches, statistical envelope methods (e.g. N-day moving mean and median-based techniques) to detect PETA are becoming more common and have become popular (Akhoondzadeh 2013c; Astafyeva and Heki 2011; Dai et al. 2015; He et al. 2012; Oikonomou et al. 2016; Pundhir et al. 2014).

In the mean statistical envelope method (Chauhan et al. 2009; Contadakis et al. 2015; Hasbi et al. 2009; Jhuang et al. 2010; Jing et al. 2011), TEC of a particular point in time ($TEC_{CURRENT}$) is compared against the previous N-day mean TEC values ($TEC_{MEAN,N}$) with upper and lower bound constructed using the associated standard deviation (s). Anomaly therefore occurs when $TEC_{CURRENT}$ exceeds the bounds defined by Z-value and s (i.e. Eq. (5.1)). Eq. (5.2) which is similar in form as Eq. (5.1), is the median method, which gives greater PETA detectability (Astafyeva and Heki 2011; Chen et al. 2014a; Dogan et al. 2011; Liu et al. 2010; Ulukavak and Yalcinkaya 2016) on the basis of upper (UQ) and lower (LQ) quartiles (typically with $k = 1.5$). Under the assumption of normal distribution and since the TEC data spans over 10 days, UQ and LQ could in fact be approximated by Zs (with $Z = 1.34$) (Aggarwal 2015; Klotz and Johnson 1983; Zhu et al. 2018).

$$PETA : |TEC_{CURRENT}| > TEC_{MEAN,N} + Zs \quad (5.1)$$

$$\begin{aligned} & TEC_{CURRENT} > TEC_{MEDIAN,N} + k(UQ - TEC_{MEDIAN,N}) \\ PETA : & \quad \quad \quad or \quad \quad \quad (5.2) \\ & TEC_{CURRENT} < TEC_{MEDIAN,N} - k(TEC_{MEDIAN,N} - LQ) \end{aligned}$$

As such, there are two major parameters when using the statistical envelope method: 1) N-day value, and 2) Z-value. The N-day value is the number of days before the earthquake event used for anomaly detection. Ideally, the N-day value should be as large as possible to provide better statistical characterization and yet small enough to capture local variability (Karatay et al. 2010). There is a need to prescribe a N-day value corresponding to systematic background TEC fluctuations such as the diurnal TEC variability caused by sunrise and sunset (i.e. magnetic local times) (Nenovski et al. 2015). However, currently there is no clear justification for the selection of the N-

day value used in previous PETA studies. The N-day values that have been used are 5 (Nenovski et al. 2015), 10 (Fuying and Yun 2011; Jing et al. 2011; Xu et al. 2013b; Yiyan et al. 2009), 15 (Aggarwal 2015; Astafyeva and Heki 2011; Chauhan et al. 2009; Chen et al. 2004; Hasbi et al. 2011; He et al. 2014; Hirooka et al. 2012; Hirooka et al. 2011; Karatay et al. 2010; Ke et al. 2016; Kon et al. 2011; Le et al. 2011; Liu et al. 2010; Thomas et al. 2017; Ulukavak and Yalcinkaya 2016), 27 (Guo et al. 2015), 30 (Guo et al. 2016; Jhuang et al. 2010; Oikonomou et al. 2016) or even 60 (Xu et al. 2013b). Consequently, statistical envelope methods face the challenging task of accounting for ionospheric variability (owing to different phenomena such as space weather and possible seismic effects) within a single N-day value.

Currently, the implication of the N-day value on the number of days leading up to the earthquake event (n_{pre}) is inadequately quantified (i.e. approximation of the time of earthquake, should an anomaly be detected). For example, Karatay et al. (2010) defined a 30-days earthquake-days period (EDP) consisting of 15 days prior and after an earthquake when the ionosphere is presumed to be under a state of seismically-induced perturbation. Thus, PETA detected within a 15 days window would suggest a likelihood of earthquake occurring within 15 days. However, from previous studies, n_{pre} after an anomaly has been detected differs. Plotkin (2003) reported n_{pre} was 2 days for an M_w 6.6 event while Liu and Xu (2017) as well as Chauhan et al. (2009) reported n_{pre} as 0 to 6 days for M_w 7.0 and M_w 4.5 to 5.1 earthquakes, respectively. Singh et al. (2009) concluded that for 43 events of $M_w \geq 5$ (i.e. average $M_w = 5.6$), n_{pre} was between 0 to 9 days and similarly, Yiyan et al. (2009) found n_{pre} to be up to 9 days. More recently, Guo et al. (2015) established that n_{pre} could be as long as 11 days from two events which occurred in 2012 (M_w 8.6 in Sumatra and M_w 6.7 in

Mexico). Figure 5.5 expresses the frequency of n_{pre} (based on statistical envelope methods) from the literature and shows that n_{pre} may be up to 2 weeks before an earthquake, while $n_{\text{pre}} = 3$ days was most frequently observed. Figure 5.6 illustrates the variations of average n_{pre} with earthquake magnitude where n_{pre} exhibited greater variability at larger earthquake magnitudes, with the exception of $M_w \geq 9.0$ (perhaps due to lesser occurrences of such events). These results thus show that large magnitude earthquakes exemplify greater variability regarding the manifestation time of PETA. Nonetheless, it should be noted that both Figure 5.5 and Figure 5.6 do not differentiate between finer details such as earthquake nature and sign of PETA anomaly (e.g. positive vs. negative).

Figure 5.5 Frequency of n_{pre} reported in literature for statistical envelope methods

Figure 5.6 Variations of average n_{pre} and associated standard deviations with earthquake magnitude for statistical envelope methods

As shown in Eqs. (5.1 and (5.2), the detection of PETA based on statistical envelope methods is associated with a confidence level (i.e. Z-value) which defines the envelope of normal ionospheric variations. Previous studies suggested Z-values of 1 (Karatay et al. 2010, Contadakis et al. 2015), 1.34 (Astafyeva and Heki 2011, Hasbi et al. 2011, Aggarwal 2015, Nenovski et al. 2015), 1.5 (Liu et al. 2010, Akhoondzadeh 2013b), 1.96 (Dogan et al. 2011), 2 (Molchanov and Hayakawa 1998, Chauhan et al. 2009, Hasbi et al. 2009, Yiyan et al. 2009 Jhuang et al. 2010, Fuying et al. 2011, Hirooka et al. 2011, Jing et al. 2011, Kon et al. 2011, Contadakis et al. 2015), 2.5 (Jhuang et al. 2010), 2.9 (Jhuang et al. 2010) and 3 (Contadakis et al. 2015, Thomas et al. 2017). Figure 5.7 shows the variations of Z-value with confidence level (according to probability theory) plotted over the ranges of Z-values used in the literature. The Z-value governs the detection of PETA and is more critical for distinguishing false positives (Chen et al. 2004). The Z-value and earthquake

magnitude have been shown to be related (Krankowski et al. 2006, Yiyan et al. 2009, Kon et al. 2011). Large magnitude earthquakes tend to induce greater degree of PETA (Astafyeva et al. 2014; Jin et al. 2015; Le et al. 2011; Perevalova et al. 2014; Šlégr and Váňová 2017). These results consequently imply that smaller magnitude earthquakes could only be detected with lower Z-value, since the effect on the ionosphere due to these earthquakes would similarly be lower (Lin 2011a). Recently, Ke et al. (2016) and Guo et al. (2015) challenged this notion and concluded that a greater degree of PETA was not observed in larger magnitude earthquakes. Since the prescription of a Z-value restricts the magnitude of earthquake (i.e. lower bound) that can be detected, more work is needed to ascertain the appropriate Z-value to be used.

Figure 5.7 Variation of Z-values with confidence levels

5.1.4 Exclusion of space weather effects and other sources of ionospheric TEC perturbations

In order to attribute earthquakes as the sole cause of ionospheric perturbations, other sources (e.g. space weather effects such as solar flares, magnetic storms) which may

affect ionospheric TEC have to be excluded (Davies 1980; Leonard and Barnes 1965; Liu et al. 2006). Such checks are made when PETA is detected to exclude space weather effects using geomagnetic indices such as Kp, Disturbance Storm Time (Dst) and solar flux index F10.7 (Devi et al. 2014; Saba et al. 1997). However, the straightforward use of these indices is problematic and made worse by the highly variable state of the ionosphere before and after earthquake (He et al. 2014; Heki and Enomoto 2013). For instance, Kon et al. (2011) showed that positive PETA was induced by 52 earthquakes of $M_w \geq 6$ in Japan. However, their study was challenged by Masci (2012) on the basis of misinterpretations in the normal levels of geomagnetic activity.

Figure 5.8 shows the variations in the number of space-related indices used previously to exclude space weather effects from a sample of 50 PETA case studies in the literature. Verifications relying on either one or two indices were the most common. A closer examination of the specific indices in Figure 5.9 reveals that the most frequently used indices were in the order Dst, Kp and F10.7.

Figure 5.8 Number of space-related indices used in literature

Figure 5.9 Frequency of individual space-related index used in literature

At present, there is no consensus on the values of the indices. For example, acceptable (i.e. either quiet or low) geomagnetic activity may be identified on the basis of Kp

with value less than 2 (Klimenko et al. 2011), 2.5 (Mayaud 1980, Parrot 1995, Hayakawa and Molchanov 2002, Liu et al. 2004, Pulinets and Boyarchuk 2004, Akhoondzadeh and Saradjian 2011), 3 (Rostoker 1972, Chauhan et al. 2009, Singh et al. 2009), 4 (Hasbi et al. 2011), 5 (Dogan et al. 2011; Lin 2011a) and 6 (Karatay et al. 2010). Karia et al. (2012) used cumulative values of Kp below 20 over eight days and Ke et al. (2016) used Kp value below 30 within one day. When the parameter of Dst (units of nanotesla) is used to indicate geomagnetic levels, threshold values of 10 (Klimenko et al. 2011), 15 (Hasbi et al. 2011), 20 (Mayaud 1980, Parrot 1995, Hayakawa and Molchanov 2002, Liu et al. 2004, Pulinets and Boyarchuk 2004, Akhoondzadeh and Saradjian 2011, Dogan et al. 2011), 40 (Jiang et al. 2017), 50 (Ke et al. 2016) and 60 (Kon et al. 2011) have been used. To account for solar-related effects, the F10.7 index was used as a proxy for the solar extreme ultraviolet (EUV) flux which ionizes the neutral atmosphere into the ionosphere (Bruevich and Yakunina 2014; Liu et al. 2011). Similar to Kp and Dst, many values of F10.7 have been used to indicate low solar activity levels. Values of F10.7 (solar flux units) lower than 70 (Guo et al. 2015), 100 (Akhoondzadeh 2013d), 120 (Mayaud 1980, Parrot 1995, Hayakawa and Molchanov 2002, Liu et al. 2004, Pulinets and Boyarchuk 2004), 130 (Akhoondzadeh 2013a) and 150 (Jiang et al. 2017) have been used.

The choice of suitable indices could be justified based on location, depending on data availability and stations coverage (e.g. Dst for equatorial regions while Kp for global/polar latitudes) (Jhuang et al. 2010; Mayaud 1980). However, the values of these indices used for defining space weather activity levels (e.g. quiet, low, moderate, high) may eventually lead to incorrect identifications of PETA, resulting in both false-positive and false-negative cases. Ideally, all relevant space weather indices

should be verified for quiet or low activity levels in order to confidently demonstrate the lack of space-related influences on ionospheric perturbations. As some of the indices are not independent, a judicious selection could reduce the number of indices considered. For example, the geomagnetic indices of Kp and Ap differ in terms of scale used (Saba et al. 1997). While Kp is represented on a quasi-log scale, Ap is based on the linear scale and the choice of either one may suffice. To circumvent the subjectivity of activity levels, statistically-derived methods could also be applied on space weather indices. For example, Jhuang et al. (2010) employed standard deviations (similar to the PETA detection process) to objectively analyse the significance of space weather variations. The use of such procedures could provide better justification of the values of the indices. However, there is no consensus on the procedures.

Furthermore, the likelihood remains that TEC anomalies may be due to other sources besides space weather or seismic preparation effects (Komjathy et al. 2012). For example, geophysical processes such as volcanic eruptions (Lin 2013), tsunami (Galvan et al. 2012) as well as man-made events such as nuclear tests (Kakinami et al. 2011), launch of rockets/missiles (Ding et al. 2014; Kakinami et al. 2013) and even scientific experiments such as HAARP have been shown to cause ionospheric perturbations (Karia et al. 2012). The simultaneous occurrence of these processes with seismic preparation effects are likely to be rare compared to space weather phenomena. Nonetheless, possibilities for non-seismic related TEC anomalies have to be accounted for in detection of PETA.

5.1.5 Extent of ionospheric perturbations

To spatially associate TEC measurements (whether from ground or space-based platforms) to a particular earthquake, TEC samples falling within the ‘earthquake preparation zone’ (EPZ) are conventionally assumed to be spatially collocated (i.e. attributed to that earthquake). From Liu et al. (2001) and Pulinets et al. (2003), Akhoondzadeh and Saradjian (2011), He et al. (2014), Akhoondzadeh (2015), Guo et al. (2015), PETA was most significant at a location away from the epicentre (Zhao et al. 2008). The EPZ may not be circular at the epicentre (Bowman et al. 1998). However, most PETA in retrospective case studies determine PETA at the epicentre (Liu and Xu 2017). Various EPZ equations have been proposed, the most frequently used equation (i.e. Eq. (2.3)) was suggested by Dobrovolsky et al. (1979).

According to Eq. (2.3), large magnitude earthquake events (e.g. M_w 7.0 and above) typically result in EPZ spanning over large areas (e.g. EPZ radius for an M_w 7.0 earthquake is approximately 1023 km). Other equations for estimating the EPZ were previously summarized in Table 2.3 and illustrated in Figure 2.5.

It can be observed from Figure 2.5 that the EPZ determined from Dobrovolsky et al. (1979) differs from Rikitake (1969) and Rikitake (1975) by two orders or more across the entire range of EQ magnitudes. The EPZ equations proposed by Rikitake (1969) and Rikitake (1975) were based on anomalous crustal deformations while Dobrovolsky et al. (1979) (i.e. Eq. (2.3)) was founded on mostly geochemical precursory phenomena (e.g. radon, helium, carbon dioxide, hydrogen, fluorine and chlorine). When comparing pre-seismic crustal deformations (occurring on earth’s surface) and geochemical emanations above earth’s surface (in the air near ground), the dimensions of affected area were clearly larger for the latter as indicated in Figure

2.5. Although the data used in Dobrovolsky et al. (1979) was limited to 24 events and did not account for ionospheric anomalies, the authors concluded that Eq. (2.3) could be used to estimate the ‘effective precursor manifestation zone’ (i.e. EPZ) which is independent of the precursor’s physical nature. Subsequently, Eq. (2.3) has been used by many researchers for investigating PETA (e.g., Chauhan et al. 2009, Liu et al. 2010, Hasbi et al. 2011, Lin 2011b, Pulinets and Ouzounov 2011, Choi et al. 2012, Aggarwal 2015, De Santis et al. 2015, Choi and Lee 2016). In addition, the EPZ radius computed in this form is also typically prescribed as an upper limit, beyond which PETA was assumed not to occur (Devi et al. 2010, Akhoondzadeh and Saradjian 2011, Astafyeva and Heki 2011, Akhoondzadeh 2015). While the use of Eq. (2.3) is straightforward to collocate TEC data, assumptions made in its formulation may result in erroneous interpretations. Bowman et al. (1998) provided some justification of Eq. (2.3) on the basis that the critical region of an earthquake is equal to or less than the thickness of the seismogenic crust. However, such an assumption was only valid for $M_w \leq 6.0$ earthquakes and suggested that the exponential scaling relationship should be increased, for $M_w \geq 6.0$ earthquakes. In addition, PETA-related studies yielded conflicting results – while most researchers agree that PETA is most significant within the close proximity of the epicentre (i.e. centre of EPZ) (e.g. Jiang et al. 2017), other studies reported that PETA is greatest at the edge of the EPZ (Liu et al. 2001, Lin 2011b). Šlégr and Váňová (2017) examined the D-layer region of the ionosphere using very low frequency (VLF) reflected waves and discovered no ionospheric anomaly was induced by shallow earthquakes beyond the EPZ, thus apparently supporting its validity. However, it should be noted that altitude of the ionospheric D-layer (approximately below 80 km) is lower than the F-

layer (approximately 350 to 400 km) which is conventionally probed by the TEC technique and dimensions of the EPZ at F-layer heights would likely be different. Notably, a study involving a large catalogue of strong ($M_w \geq 7.0$) earthquakes conducted by Liu and Xu (2017) revealed that the ionospheric regions which were most perturbed tend to be located south of the epicentre, regardless of the epicentre's geographic positions. In this case, Liu and Xu (2017) studied strong earthquakes and the extents of EPZ were greater than 1000 km (i.e. $\geq M_w 7.0$). Consequently, arguments have been put forth where effects of earthquake preparation on the ionosphere could have a larger radius and thus any ionospheric perturbations would have been observed even if ground-based stations were located far from the EPZ (Karia and Pathak 2011; Pulinets et al. 1994; Singh et al. 2009).

Figure 5.10 exemplifies the implication of the EPZ if PETA is present within the EPZ using the distributions of earthquakes along the western section of 'Pacific Rim of Fire' between the periods of 1st January to 31st March 2015. Hence, determining PETA at one location may not mean that the earthquake effects can be felt at that location given the very large EPZ for a large magnitude earthquake. Therefore, the question arises: does the spatial region confined by EPZ truly mark the limits of PETA affected area?

Figure 5.10 Distributions of $M_w \geq 5.0$ earthquakes (between 1 Jan – 31 Mar 2015) illustrating spatial adjacency effects using EPZ; epicentre symbol is scaled according to magnitude; dashed lines represents tectonic plate boundaries

The above observations unanimously point toward the fact that, while convenient, the arbitrary use of EPZ to spatially identify the existence of PETA appear only to be a proxy parameter for the actual seismic-induced perturbed region in the ionosphere. Here, the term ‘ionosphere affected zone’ (IAZ) is more appropriate to refer to this region in the ionosphere. A schematic of the IAZ with respect to EPZ as well as receiver (i.e. LEO and ground station) to GPS links is depicted in Figure 5.11. Two related parameters are introduced to define the IAZ, where u_{IAZ} essentially accounts for the projection of EPZ onto the ionosphere while R_{IAZ} is the radius of the IAZ itself. When EPZ is used as a proxy for IAZ, the roles of IPP (i.e. latitude, longitude and altitude) and SIP (i.e. latitude and longitude) could be used interchangeably to locate TEC sampling points per receiver-GPS link. However, such a presumption would not be valid with the introduction of IAZ. As mentioned previously, PETA is theoretically detected when TEC samples (i.e. IPP) are within the IAZ. From Figure

5.11, the location of IPP within the IAZ does not guarantee the same for SIP within the EPZ.

Figure 5.11 Illustration of ionospheric affected zone (IAZ) in relation to EPZ

While the representation of ionospheric perturbed region by the IAZ is more accurate, its concept is however, not new. Astafyeva et al. (2013) have previously pointed out the possibility of investigating spatial extension of ionospheric perturbations using multiple links from ground-based receivers to GPS satellites. In addition, limited studies have attempted to analyse PETA on the basis of ionospheric tomography with interesting results. For example using two-dimensional principal component analysis (PCA), Lin (2011b) discovered that while anomaly intensity increases, the spatial distribution of PETA reduces with increasing altitude, thereby implying that θ_{IAZ} is greater than 90° (i.e. if $\theta_{IAZ} = 90^\circ$, $IAZ = EPZ$) while Dobrovolsky et al. (1979) stated that the size of the IAZ is of the same order as the EPZ. If $R_{EPZ} < R_{IAZ}$, the EPZ becomes a more stringent parameter set for the detection of PETA. The establishment

of IAZ provides greater insight to PETA spatial manifestations and increases likelihood of its detection due to availability of more collocated data.

A possible complication in earthquake forewarning stemming from the use of IAZ (or EPZ) is the epicentre ambiguity problem arising from TEC observables of a satellite-based GPS receiver. Since the epicentre location of an earthquake is known for retrospective analyses, a single IAZ defines the zone for which PETA is detected (Figure 5.12). The converse is however not true. In prospective analyses, the detection of a single PETA point allows more than one IAZ to be constructed, provided that anomalous TEC data falls within these zones. Consequently, the potential earthquake epicentre could lie anywhere within the IAZs. For the theoretical unbounded case (Figure 5.13), the epicentre could be located anywhere within a circular zone of radius $2R$ from the detected anomaly. This thus poses a significant challenge in ascertaining the location of the seismic event (epicentre) in the absence of supplementary information (e.g. plate boundaries, potential fault zones as well as correlations involving degree of PETA and epicentral distance).

Figure 5.12 Absence of epicentre ambiguity (retrospective case)

Figure 5.13 Unbounded epicentre ambiguity (prospective case)

5.1.6 Challenges on the use of PETA for earthquake forewarning

While many TEC sources are increasingly made available in the coming decade, considerations regarding their intrinsic differences have to be addressed. Several points with regards to the inherent differences between ground and space data sources as well as TEC processing methodology (i.e. shell height, STEC vs. VTEC, elevation angle) in the literature were highlighted. These pertain to the nature of data and potential errors arising from differing assumptions made in processing the parameters. These inconsistencies potentially hinder the application and integration of past experiences and results for the establishment of an earthquake forewarning system using PETA. The availability and temporal resolution of ground-based TEC measurements provide a constant source of measurements. Satellite-derived TEC, on the other hand, may or may not provide timely data (depending on whether constellations are used), but they are valuable in understanding the dynamic characteristics of PETA with respect to the epicentre, without the need for

interpolation (as with two-dimensional TEC maps). As mentioned by Lin (2011b), knowledge of PETA spatial distributions is important as it could point towards the origin of seismic activity. Therefore, the degree of PETA (i.e. how anomalous it is comparing to normal variations) in relation to epicentral distance and time of earthquake occurrence is vital to fix the location and time of an impending earthquake. Certainly, once the three earthquake prediction parameters (i.e. time, location and strength) are deducible from PETA measurements, ingesting data from multiple sources (i.e. virtual constellation) in a robust observation network would be ideal in the real-time observation and detection of TEC anomalies for earthquake forewarning (Ferretti et al. 2015).

Even though ample ionospheric measurements are available, the locations and earthquake events influence the PETA detection procedure. Since seismically active countries exhibit greater degrees of TEC variability, retrospective case studies conducted in such locations would not only need to account for background variability (e.g. space weather), but also contributions from the regular and smaller magnitude earthquake events as well. Non-seismically active regions with spatially and temporally isolated earthquake events thus present a more optimistic opportunity in retrospective analyses. However, for the purpose of earthquake forewarning, this complication could be less important. Earthquakes typically occur closely in time and space with main shocks generally preceded by smaller magnitude foreshocks (Jordan et al. 2011). Therefore, detection of the main shocks is not imperative, but rather, detection of foreshocks is. This is also valid for earthquake swarms defined by the absence of a clear main shock. As a short-term method then, detection of foreshocks-related TEC anomalies, in part, gives ample time to decide if such perturbations are

significant enough to issue an earthquake warning. The establishment of n_{pre} thus becomes a crucial factor in determining the time span of applicability (i.e. interval of alarm window) (Jordan et al. 2011).

In the detection of PETA, disparities between values of N-day and Z are apparent and often unjustified. Furthermore, the obligatory exclusion of space weather effects appears to be subjective in terms of the indices used and the threshold values. As such, it appears that there are three pertinent issues that need to be resolved:

- 1) What should the N-day and Z-values be and how should they be decided?
- 2) How many and which space weather indices should be used?
- 3) What should be the acceptable thresholds for each of these indices be?

In the selection of N-day value, temporally adjacent earthquakes should be considered. The N-day value should ideally not cause an overlap with n_{post} (i.e. period of post-earthquake anomaly) of the previous earthquake to ensure that only normal ionospheric variations are accounted for. While this condition can be fulfilled in non-seismically active regions, it is challenging for locations which are seismically active due to the frequency of seismic events (where the average recurrence interval is d). In an ideal scenario where spatial and temporal confounding effects (i.e. $d \geq 0$) are absent, the range of valid N-day value is thus given in Eq. (5.3), where the maximum value of N (i.e. N_{max}) to capture normal ionospheric variability is d .

$$\{N \mid N \in \mathbb{Z}, N \leq d, d \geq 0\} \quad (5.3)$$

The exponential scaling relationship between EPZ and earthquake magnitude yields unrealistically large EPZ radius for large magnitude earthquakes. While this

consequence would seem less impactful on retrospective studies, a large EPZ radius would imply difficulty in the establishment of a PETA-based earthquake forewarning system. The differing natures of earthquake trigger may also be correlated against PETA. For example, studies with contrasting results by Astafyeva et al. (2014) and Perevalova et al. (2014) have been previously conducted to investigate the link between the degree of TEC anomaly and focal mechanisms (i.e. strike-slip, normal or reverse-faults). Therefore, apart from focal mechanism, studies conducted on different seismic characteristics, such as magnitude, relative plate movement rates, on-land versus submarine events, inter-plate versus intra-plate events, vertical displacements as well as hypocentre in relation to the varying nature of PETA are essential to draw crucial earthquake-associated inferences (Jin et al. 2015).

5.2 Examining deficiencies in retrospective PETA analyses

In this section, examinations are further conducted into understanding problems associated with the detection of PETA in existing case studies. As inconsistent and seemingly subjective methodologies are fundamentally entrenched within a large number of PETA literature, it is necessary to critically scrutinise these approaches in the interest of converting the retrospective analyses into prospective assessments. In general, these matters primarily manifest within topics raised in Sections 5.1.4 (i.e. exclusion of non-earthquake influences in TEC) and 5.1.5 (i.e. relevancy of the EPZ). In the former, this relates to the detectability of abnormal TEC levels due to conditions apart from the solar-magnetic environment. The latter pertains to the location for which TEC anomalies may be associated with a particular earthquake. In the prospective scenario, this has significant implications on the potential location of epicentre once PETA is detected. Thus, the coupling effect between PETA and the earthquake occurrence has to be positively correlated, which has proven to be a significant obstacle in current methodologies.

5.2.1 Detecting anomalous seismo-ionospheric behaviour in the presence of space weather stimuli

It is well known that variations in ionospheric TEC levels arise from the complex and dynamic electromagnetic geophysical interactions such as space weather activity, anthropogenic effects (e.g. missile launches) and meteorological events (e.g. stratospheric sudden warming) (Kakinami et al. 2013; Masci 2012). Among these factors, it has been shown that ionospheric conditions are highly modulated by space weather effects (e.g. solar and geomagnetic activity). For example, Dautermann et al. (2007) found that TEC is dominated by the cyclical nature of

daily solar activity and lunar tides, giving rise to diurnal and semi-diurnal periodicities. Masci et al. (2017) similarly reported the presence of such cycles in what was construed as TEC anomalies in Nenovski et al. (2015). Moreover, Afraimovich et al. (2008) revealed that the global electron content follows a strong 27-day cycle (due to ultraviolet radiation and geomagnetic activity) accounting for large changes to the amplitudes of TEC (i.e. up to 20-30% deviations) (Afraimovich and Astafyeva 2008; Astafyeva et al. 2008). Masci (2013) further scrutinized TEC (i.e. 1999 Hector Mine earthquake) with concurrent geomagnetic indices (i.e. Kp and Dst) and discovered good correlation between them, proving that the TEC fluctuations could be explained by normal solar-terrestrial interactions. Likewise, Rhoades et al. (2015) analysed ionospheric TEC over New Zealand (i.e. 2011 Christchurch earthquake) and discovered that the detected TEC anomaly coincides with a solar coronal mass ejection (CME) event which resulted in post-geomagnetic changes.

In light of these studies, it is challenging to prove a causal link between TEC anomalies and earthquake occurrence as space weather-induced changes are expected to be much stronger than any possible seismic-related contribution. Relying on one statistical envelope test (i.e. Section 5.1.3) to pick up seismo-ionospheric signatures (if any) is problematic since solar-induced effects (whether periodic oscillations or flare events) could potentially overwhelm these signals. For instance, the conclusions by various authors (i.e. Le et al. 2011; Nenovski et al. 2015; Pulinets and Davidenko 2014; Pulinets et al. 2007; Su et al. 2013) supporting the presence of PETA have led to several works (Afraimovich and Astafyeva 2008; Masci 2013; Masci and Thomas 2015; Thomas et al. 2017; Thomas et al. 2012)

denouncing such links as due to space weather influences. To be certain that a TEC anomaly is only caused by earthquake, various space weather indices, such as solar flux index (F10.7), disturbance storm time (Dst) and Kp-index (Devi et al. 2014; Saba et al. 1997) during the TEC anomaly occurrence is examined to check that these space weather indices fall below a certain threshold (i.e. non-influential). The ranges of values for each of these indices are summarised in Table 5.3. Analogous with the issue of N discussed earlier, these thresholds are highly subjective and unintuitive. For instance, Masci (2012) questioned the findings of Kon et al. (2011) on the basis of misinterpretations in the normal levels of geomagnetic activity.

Table 5.3 Threshold levels of space weather indices for low/quiet conditions

Index (units)	Nature	Value	Reference(s)
F10.7 (solar flux units)	Solar	70	Guo et al. (2015)
		100	Akhoondzadeh (2013c)
			Guo et al. (2016)
			Mayaud (1980)
			Parrot (1995)
		120	Hayakawa and Molchanov (2002)
			Liu et al. (2004)
Dst (nanoTesla)	Geomagnetic	130	Pulinets and Boyarchuk (2004)
			Akhoondzadeh (2013a)
		-10	Klimenko et al. (2011)
			Hasbi et al. (2011)
		-15	Mayaud (1980)
			Parrot (1995)
		-20	Hayakawa and Molchanov (2002)

			Liu et al. (2004)
			Pulinets and Boyarchuk (2004)
			Akhoondzadeh and Saradjian (2011)
			Dogan et al. (2011)
		-30	Guo et al. (2016)
		-40 ¹	Thomas et al. (2017)
			Choi et al. (2012)
		-50	Ke et al. (2016)
			Oikonomou et al. (2016)
		-60	Kon et al. (2011)
Kp	Geomagnetic	2	Klimenko et al. (2011)
			Mayaud (1980)
			Parrot (1995)
			Hayakawa and Molchanov (2002)
		2.5	Liu et al. (2004)
			Pulinets and Boyarchuk (2004)
			Akhoondzadeh and Saradjian (2011)
			Rostoker (1972)
			Chauhan et al. (2009)
		3	Singh et al. (2009)
			Guo et al. (2016)
			Ulukavak and Yalcinkaya (2016)
		4	Hasbi et al. (2011)
			Fuying and Yun (2011)
		5	Dogan et al. (2011)
			Lin (2011b)
		6	Karatay et al. (2010)
		20 ²	Karia et al. (2012)

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¹ Also for decrease within a day.

² Cumulative value over a span of 8 days.

³ Daily cumulative value.

Therefore, in order to identify and eliminate non-earthquake related signals from raw measurements of TEC, a proposed approach using the wavelet transform method based on the periodicities of space weather activity is employed. Subsequently, the statistical envelope method is applied on the resulting analytical TEC signal by selecting an appropriate N . The detection of TEC anomaly is then validated using a database of recent earthquake events with inspection of earthquake cases studied previously.

5.2.1.1 Dataset and Methods

A database consisting of 30 recent large earthquakes (i.e. $M_w \geq 7.0$) that occurred between 2011 to 2016 was assembled from the Earthquake Hazards Program database published by the United States Geological Survey (USGS). These include significant events such as the 2011 Japan (Tohoku) and 2015 Nepal and Chile earthquakes. Epicentre coordinates (i.e. latitude and longitude) were utilised as the reference locations for these events. A summary of earthquake occurrence dates, epicentre coordinates, focal depth (i.e. hypocentre) and magnitude is given in Table 5.4.

Table 5.4 Catalogue of large ($M_w \geq 7.0$) earthquakes

ID.	Date	Latitude (°) ¹	Longitude (°) ²	Focal depth (km)	Magnitude (M_w)
1	11/03/2011	38.3	142.4	29	9.0
2	24/06/2011	52.1	-171.8	52	7.3
3	24/08/2011	-7.6	-74.5	147	7.0

4	23/10/2011	38.7	43.5	18	7.1
5	20/08/2011	-18.4	168.1	32	7.2
6	25/03/2012	-35.2	-72.2	41	7.1
7	07/12/2012	37.9	143.9	31	7.3
8	20/03/2012	16.5	-98.2	20	7.4
9	11/04/2012	2.3	93.1	20	8.6
10	02/02/2012	-17.8	167.1	23	7.1
11	06/04/2013	-3.5	138.5	66	7.0
12	16/04/2013	28.0	62.0	80	7.7
13	24/09/2013	27.0	65.5	15	7.7
14	25/09/2013	-15.8	-74.5	40	7.1
15	15/10/2013	9.9	124.1	19	7.1
16	23/06/2014	51.8	178.7	109	7.9
17	01/04/2014	-19.6	-70.8	25	8.2
18	14/10/2014	12.5	-88.1	40	7.3
19	15/11/2014	1.9	126.5	45	7.1
20	18/04/2014	17.4	-101.0	24	7.2
21	26/10/2015	36.5	70.4	213	7.5
22	05/05/2015	-5.5	151.9	55	7.5
23	24/11/2015	-10.5	-70.9	606	7.6
24	07/12/2015	38.3	72.8	26	7.2
25	25/12/2015	-43.4	-73.9	38	7.6
26	25/04/2015	28.1	84.7	15	7.8
27	16/04/2016	0.4	-79.9	21	7.8
28	02/03/2016	-4.9	94.3	24	7.8
29	16/04/2016	32.8	130.7	10	7.0

30	14/11/2016	-42.8	173.1	15	7.8

1 Negative values refer to south

2 Negative values refer to west

There are various sources of TEC measurements available, such as space-borne platforms (e.g. SWARM and COSMIC satellites) as well as ground-based GPS receivers (e.g. stations in the International GNSS Service (IGS) network). Since ground receivers are capable of probing a larger extent of the ionosphere, TEC data is obtained from the Centre for Orbit Determination of Europe (CODE) in the form of global ionospheric maps (GIMs). Furthermore, GIM-TEC has been widely regarded as an accuracy reference (Mannucci et al. 1998; Yue et al. 2012). The GPS signals from IGS stations are used to estimate TEC values using the spherical harmonic (SH) expansion technique up to degree of order 15 (Eq. (5.4)), with GIM-TEC outputs provided at hourly intervals covering $\pm 87.5^\circ$ latitude and $\pm 180^\circ$ longitude at discretized spatial resolutions of 2.5° by 5° .

$$VTEC(\beta_I, s_I) = \sum_{n=0}^{n_{\max}} \sum_{m=0}^n \tilde{P}_{nm}(\sin \beta_I) (a_{nm} \cos ms_I + b_{nm} \sin ms_I) \quad (5.4)$$

where β_I is the latitude of ionospheric pierce point (IPP) in solar-geomagnetic reference frame; s_I is the sun-fixed longitude of IPP, a_{nm} and b_{nm} are SH coefficients of ionospheric model, and $\tilde{P}_{nm} = \Lambda(n, m)P_{nm}$ is the normalized associated Legendre polynomials, where $\Lambda(n, m)$ is the normalization function and P_{nm} is the un-normalized Legendre polynomials.

Since the nodal points for GIM-TEC do not necessarily coincide with epicentre locations, TEC values were obtained via interpolation using a cubic spline function

based on neighbouring values. For the purposes of investigating space weather phenomena, common indices (e.g. F10.7, Kp and Dst) were not used in order to circumvent the need for arbitrary thresholds. Instead, the presence of such effects was identified purely based on the wavelet spectrum which provides frequency, time and amplitude information. The presence of solar flares was characterized using solar x-ray flux measurements in the short (0.05 – 0.4 nm) and long channels (0.1 – 0.8 nm) from the GOES-15 geostationary satellite (Bornmann et al. 1996).

Analysis of the TEC signal constituents and intrinsic variations assume a two-part process comprising of frequency and time domain examinations. As fluctuations in the ionosphere are a result of the dynamic solar-terrestrial interactions, TEC is understandably controlled by solar electromagnetic radiation. In essence, the solar radiation and associated effects (i.e. geomagnetism) serve as a noisy background to the TEC signal, which confounds processing and interpretation. It has been shown that such background solar contributions possess rapid and nonlinear variations (He et al. 2012). In order to remove space weather influences along with short-term (e.g. semi-diurnal and diurnal) oscillations, the wavelet transform method, which is highly effective for nonstationary signals, is used to analyse raw TEC data in the frequency spectrum (Mallat 2008). Compared to Fourier transforms, wavelets have finite energy and thus provide better time-frequency localizations. Using the continuous wavelet transform (CWT), the TEC signal is analysed in a multi-resolution approach (i.e. different frequencies) through scaling and translations of the mother wavelet (ψ). Scaling and translations of the wavelets relate to frequencies and time information, respectively. The mother wavelet serves as a window analogous to the short-time Fourier transform, but has a varying size dependent on the scaling parameter. Among

the various mother wavelets, the Morlet (or sometimes, Gabor) wavelet was selected because of its simplicity and convenience when studying wave-like events, such as those within the atmosphere-ionosphere systems (Liner 2010; Torrence and Compo 1998). Additionally, its non-orthogonality implies that both low and high frequency TEC components can be adequately represented. The values (i.e. coefficients) of CWT implies correlation between the continuous TEC-time signal and ψ . Formulations for CWT and Morlet analysing wavelet are illustrated in Eqs. (5.5) and (5.6), respectively.

$$W_{\psi}^y(a_I, b_I) = \frac{1}{\sqrt{|b_I|}} \int_{-\infty}^{\infty} y(t) \cdot \Psi^* \left(\frac{t - a_I}{b_I} \right) dt \quad (5.5)$$

$$\Psi(t) = e^{-\frac{t^2}{2\sigma_w^2}} e^{i\omega_o t} \quad (5.6)$$

where a_I , b_I refer to the scaling and translational parameters respectively; $y(t)$ refers to the raw and unfiltered TEC signal; $\Psi^*(t)$ refers to the complex conjugate of the analysing wavelet ($\Psi(t)$); t refers to time; ω_o refers to wavelet's frequency; σ_w is a measure of the wavelet's support. Thus, the frequency and temporal variability of ionospheric TEC can be simultaneously assessed over the length of the signal.

Solar and geomagnetic-induced periodicities were systematically identified and removed from the raw TEC data by observing the wavelet spectrum and applying detrending and suitable filters (e.g. bandstop, or bandpass) at frequencies corresponding to the geomagnetic and solar sources. In general, TEC tends to demonstrate strong transiency below 30 days and these sources contributing to potentially large amplitude changes have to be removed from the raw TEC data prior

to PETA statistical analyses (Afraimovich and Astafyeva 2008; Kutiev et al. 2013). For instance, Kutiev et al. (2005) studied TEC behaviour during geomagnetic storms by sequentially removing diurnal, seasonal and solar sources, where the residual TEC signal was subsequently presumed to be geomagnetic in nature. The strong 27-day (i.e. medium-term) solar periodicity observed in their study was accounted for through Fourier wave approximations (Hocke 2008). Geomagnetic variations were also shown to possess significant oscillations at shorter periods of 9 and 13.5 days (Kutiev et al. 2012).

The ensuing statistical envelope method (i.e. Eq. (5.1)) holds a two-fold purpose. Firstly, through an appropriate length of window N , diurnal and seasonal variations are captured in the statistical mean. An incorrect selection of N leads to leakage of periodicities away from the TEC thresholds (Kutiev et al. 2005). The TEC thresholds should ideally contain the background periodicities; thus, N has to be small in order to capture transient ionospheric states. However, a reasonable lower bound of N was not prescribed by Kutiev et al. (2005). Frequencies corresponding to short- (i.e. semi-diurnal and diurnal) and medium-term (i.e. space weather) periodicities can be removed using a combination of wavelet transform and the statistical method. The window size N was selected equal or less than the space weather periodicities identified from a fast-Fourier transform. Consequently, a TEC signal free of space weather influences (i.e. TEC_{β}) is obtained. Using a 95% confidence interval corresponding to a Z-value of 1.96 (i.e., approximately 2s) was used to test TEC_{β} for potential anomalous TEC behaviour. If a TEC_{β} value exceeds the confidence thresholds, the anomaly could not be due to space weather influences and the assumed

null hypothesis (i.e. anomaly is not due to the earthquake) is rejected (Flechner and Tseng 2011). It should also be highlighted that using this approach, PETA may be detected at a greater confidence when employing the mean envelope test, as presented earlier in Eq. (5.1). In summary, a TEC signal free of space weather periodicities (i.e. TEC_{β}) is first obtained through the inverse wavelet transform by reconstructing the signal using wavelet coefficients (Montejo and Suarez 2013; Torrence and Compo 1998). Subsequently, Eq. (5.1) is applied for the detection of PETA using TEC_{β} signal instead of the raw TEC signal, where a suitable N value was employed to account for remaining periodicities (e.g. diurnal). A summary of the proposed method used to identify PETA is illustrated in Figure 5.14.

Figure 5.14 PETA-detection methodology proposed in the current study

5.2.1.2 Statistical results

The objective of the wavelet transform analysis is to identify the solar and geomagnetic influences on the raw TEC signal. Annual wavelet spectrum plots at several locations (i.e. listed in Table 5.4) are presented in Figure 5.15. Note that when performing the conversion to period in days, the frequencies were scaled by a factor of $1/24$. From Figure 2, it is apparent that solar influence (along with minor contributions due to lunar phase period of 29 days) dominates the raw TEC signal approximately between the scaled frequencies of 8 to 16 μHz , which is equivalent to a period of 17.4 to 34.7 days. This range is demarcated on the plots as solid red lines and is consistently present throughout the different locations. Additionally, the peak amplitudes due to these solar effects (i.e. red-dashed regions in Figure 5.15) can be narrowed down to within 22.1 and 27.2 days (highest value at 25.4 days). While solar-induced TEC changes are exhibited throughout the year, it is clear that there is a seasonal effect since solar rotation control is considerably affected by seasonal variations. Solar effects appear to be most significant approximately between mid-March to end-May as well as between mid-September to end-November. There are also distinct differences between the peak wavelet amplitudes across locations (likely due to the equatorial ionization anomaly (EIA)). It is known that ionospheric conditions at equatorial and low-latitude regions are temporally and spatially dynamic (Aggarwal 2011; Kumar and Singh 2009). As shown in Figure 5.15, Indonesia possessed large TEC wavelet amplitude changes (i.e. up to 35 times that of non-affected frequencies) as compared to places such as New Zealand, where solar effects were comparatively weaker. Based on these observations, past methods of setting standardized thresholds (i.e. one-size-fits-all approach) for indices such as

F10.7 without appropriate consideration for geographic regions would result in erroneous interpretations of space weather activity. For instance, a threshold based on Indonesia may be unrealistically high for New Zealand and could yield false negative results (Type II errors) in such areas (the converse is also true).

Geomagnetic influences (with minor contribution from semi-monthly lunar tides of 15 days), although more than two times weaker in magnitude than solar sources, are also clearly distinguishable in the wavelet spectrum (i.e. regions defined by yellow lines). These signals exhibit periodicities between 8 to 17 days (mean at 12.5 days), corresponding to scaled frequencies of approximately, 16 to 32 μHz . Since geomagnetic disturbances are invariably the consequence of relative differences in solar plasma velocities, it generally reflects seasonal variations similar to solar rotation control (Kutiev et al. 2012). Consequently, the removal of solar and geomagnetic effects involves rejecting scaled frequencies between 8 to 32 μHz such that the reconstructed signal does not contain space weather influences. Additionally, presence of high frequencies (i.e. beyond the 32 μHz range), which are more pronounced in places such as Japan and Mexico, were excluded to eliminate spurious signal peaks due to diurnal variations. It ought to be noted that if a TEC anomaly of seismic origin does indeed exist, it is presumed to manifest at frequencies outside this range. Such an assumption is reasonable because in the case where the seismic-induced TEC fall within this range (especially within 8 to 32 μHz), it would be dwarfed by the solar rotation fluctuations and is unlikely to be detected by a single statistical test.

Once the filters have been applied, the reconstructed TEC_{β} signals over locations listed in Table 5.4 were used for statistical envelope analysis. To select an appropriate

window length N , TEC spectral densities were utilised to localise periodicities for the space weather signals. Figure 5.16 shows the corresponding spectral density plots for the same locations shown in Figure 5.15. The observed geomagnetic periodicities (i.e. within the grey regions) show that its periods vary between approximately 8.3 and 12.5 days. For the cases of Japan, Peru and Mexico, geomagnetic periods were more significant at 8.3 days as compared to Indonesia. As for locations of Nepal and New Zealand, geomagnetic effects though vaguely present, were clearly much weaker than the solar-induced variations. As geomagnetic (and solar) contributions are inherently a global phenomenon, the value of N was thus selected based on the shortest periodicity observed at 8.3 days to account for short-term fluctuations. Figure 5.17 illustrates the results from the variations of TEC_{β} at various locations listed in Figure 5.15 while the statistical assessments of TEC anomalies for the earthquake database in Table 5.4 are presented in Table 5.5. Here, anomaly directionality refers to the exceedance of TEC_{β} beyond the upper (i.e. positive) or lower (i.e. negative) bounds, while its amplitude indicates the percentage difference between the observed TEC_{β} and its respective bound on the anomalous epoch. In general, the appearances of abnormal TEC_{β} levels were discovered days prior to each large seismic event. For example, the detected PETA between 7 to 9 days (i.e. 2 – 4 Mar 2011) prior to the 2011 M_w 9.0 Japan earthquake (ID. 1) agrees with the findings of Liu et al. (2018b), who was able to detect more PETA occurrences using the median-base method. This also shows that despite the mean method being a more stringent criteria (with higher confidence of at least 95%), the proposed approach was still able to detect PETA. As shown in Figure 5.18, multiple TEC_{β} anomalies can continue to show up at different

number of days prior to the earthquakes. The range of precursory days varies between 1 to 10 days with most earthquakes displaying anomalous TEC_{β} signals occurring at 4 or more days before the earthquake. The earliest TEC_{β} anomalies were observed at approximately 2 weeks (i.e. within short-term periods) before the earthquake with 30% of the cases exhibiting initial TEC_{β} anomalies at 12 and 4 days before the earthquake. Overall, the initial TEC_{β} anomalies were observed around 7.9 days before the earthquake and has a standard deviation of 3.5 days. Various authors have identified possible links between precursor manifestation times and fundamental seismic characteristics such as magnitude and focus (Astafyeva and Heki 2011; Le et al. 2011; Yiyan et al. 2009). Figure 5.19 further explores the relations between the PETA manifestations and the underlying fault mechanisms of each earthquake. Figure 5.19a illustrates the initial appearance of PETA with the three major fault mechanisms – reverse (i.e. compressional), thrust (i.e. extensional) and strike-slip (i.e. translational) and Figure 5.19b shows the number of PETA anomalies occurring in relation to these fault types. Initial PETA appears, on average, about 7 to 8 days before the earthquake and about two days with anomalous TEC_{β} will be detected, irrespective of fault mechanism. Additionally, while both positive and negative TEC_{β} anomalies were present, there was no clear preference for either. The directionality of these TEC_{β} anomalies could likely be influenced by the direction of the anomalous electric field at ground surface and position of the ionospheric regions (Choi et al. 2012; Pulinet et al. 2003). The anomalous amplitudes vary widely, with most cases exhibiting anomalies up to 20% from the usual variations (Figure 5.20). Moreover, there were several events which possessed significant anomalous variations larger than 100%

(especially the 2015 Tajikistan M7.2 earthquake (ID. 24)). Previously, Astafyeva et al. (2014) discovered that small displacement earthquakes of the strike-slip mechanism, similar to the Tajikistan event, are able to generate large ionospheric perturbations comparable to dip-slip earthquakes. In addition, the amplitudes of these ionospheric perturbations can be further emphasized in the detection methodology if data processing and filtering methods (i.e. wavelet-based band filters in this case) are employed. Finally, geographic variations did not appear to influence the TEC anomalies.

Figure 5.15 Typical raw ionospheric TEC wavelet spectrum at various earthquake locations; (dashed) red and yellow lines denote range of frequencies under (strong) solar and geomagnetic influence respectively; white dashed lines denote cone of influence (COI)

Figure 5.16 Spectral density plots (for same locations shown in Figure 5.15) showing differences in dominant geomagnetic periodicities and overall amplitudes; grey regions show periodicities under geomagnetic influence

Figure 5.17 TEC_{β} time series (for locations shown in Figure 5.15); shaded bar indicates PETA

Table 5.5 Assessment of TEC_{β} anomalies for earthquake catalogue

ID.	No. of days before earthquake ¹	Directionality ²	Anomaly amplitude (%) ³	Fault mechanism
1	9, 8, 7	+, +, +	102.9, 3.9, 40.7	reverse
2	8, 4	+, +	4.3, 18.6	normal
3	5, 4	-, -	20.1, 3.2	normal
4	8, 2	+, +	57.3, 5.4	reverse
5	2	-	7.0	reverse
6	13, 10, 6	+, +, -	68.3, 6.8, 3.4	reverse
7	10	+	24.3	reverse
8	11, 2	-, -	101.2, 8.24	reverse
9	6, 4	-, -	169.6, 13.8	strikeslip
10	6	+	6.5	normal
11	12, 5, 3	-, +, +	7.6, 100.3, 12.2	normal
12	12, 8, 2	+, +, -	162.6, 6.5, 61.5	normal
13	5, 3	+, +	159.3, 48.7	strikeslip
14	8, 1	+, +	16.1, 147.5	reverse
15	12, 9, 6	+, -, +	602.7, 5.8, 103.9	reverse
16	11, 10, 4	+, +, -	37.4, 34.4, 71.1	normal
17	4	+	32.6	reverse
18	2, 1	-, -	13.1, 17.0	normal
19	4	-	285.4	reverse
20	5	-	239.8	reverse
21	11, 10, 9, 8	+, +, +, +	18.5, 644.8, 72.8, 35.8	reverse
22	12, 10	+, -	11.7, 183.2	reverse

23	4, 3	-, -	219.1, 136.1	normal
24	12, 7	-, +	31.7, 908.8	strikeslip
25	4	+	539.7	reverse
26	3, 2	+, +, +	2.4, 16.2	reverse
27	10, 3, 2	-, +, +	12.9, 117.0, 8.5	reverse
28	6	-	104.4	strikeslip
29	12, 3, 1	+, +, -	18.6, 85.0, 6.4	strikeslip
30	4	+	50.6	reverse

1 Occurrences of TEC_{β} anomalies

2 Positive and negative anomalies refer to the exceedance of TEC_{β} from the upper and lower bounds, respectively

3 Percentage difference between anomaly and detection bound

Figure 5.18 Occurrences of TEC β anomaly prior to earthquake events

Figure 5.19 Relationships between a) number of days before earthquake (initial PETA) and b) number of PETA occurrences, with seismic fault mechanisms

Figure 5.20 Number of cases at each anomaly amplitude range

5.2.2 Revisiting negative case studies

5.2.2.1 Rhoades et al. (2015)

Rhoades et al. (2015) examined TEC variations over New Zealand for four earthquakes. They concluded that while a short-term TEC anomaly was observed for only one of them (i.e. 2011 M6.3 Christchurch earthquake), it is likely to be a result of a solar flare-induced geomagnetic anomaly. Rhoades et al. (2015) adopted a two-fold approach, where they conducted a statistical envelope test followed by the precursor mask technique, which is essentially a correlation test (Lomonosov et al. 2000; Pulinets et al. 2002). It is noted that even though Rhoades et al. (2015) alluded to the concept of earthquake preparation zone (EPZ), they did not select the external ground station (i.e. presumably free from seismic influence) based on the conventional EPZ formulation proposed by Dobrovolsky et al. (1979) (Pulinets 2004).

For instance, the M6.3 Christchurch earthquake will necessitate an EPZ radius of approximately 511 km, however a distance threshold of 250 km was employed. Hence, it is expected that the ionospheric conditions of the internal and external ground stations are similar. Thus, the degree of correlation between TEC of the two stations is understandably high, mostly implying the absence of anomalous TEC signals.

Using the proposed approach, the Christchurch event, where a solar flare originating on 15 February 2011 was the source of contention for the observed TEC anomaly three days later, was re-examined. Here, the existence of the solar flare was examined based on x-ray flux observations from the GOES-15 platform. The wavelet spectrums for both short and long channels (corresponding to 0.05 to 0.4 nm and 1 to 8 nm, respectively) are illustrated in Figure 5.21. It can be seen that the solar flare occurrence affecting the dates between 15 to 18 February 2011, fall within the scaled frequencies (i.e. 8 to 32 μ Hz) identified to be space weather periodicities. After filtering out these frequencies, the TEC_{β} variation for the Christchurch event is presented in Figure 5.22 (for the same range of analysis dates) which shows anomalous TEC_{β} behaviour around 11 and 7 days prior to the earthquake (i.e. 10 and 14 February 2011, respectively). This was not within the supposed period affected by space weather activity mentioned by Rhoades et al. (2015). This significant enhancement on 14 February 2011 was close to 110% from the normal variation (i.e. upper limit), while the slightly weaker anomaly was around 68.7%. Using the proposed approach, anomalous TEC_{β} was also detected for the remaining three earthquakes reported in Rhoades et al. (2015) as illustrated in Figure 5.23 to Figure

5.25 and summarized in Table 5.6. It is worth noting that where Rhoades et al. (2015) employed a detection confidence of approximately 82%, the anomalies detected here were at least 95% confidence.

Figure 5.21 Wavelet spectrum of solar x-ray flux for February 2011 (left – short channel; right – long channel); red box indicates solar flare associated with M6.3 Christchurch event; black-dashed lines indicate frequencies corresponding to space weather effects

Figure 5.22 TEC_β time series (for 2011 M6.3 Christchurch earthquake); shaded bar indicates PETA

Figure 5.23 TEC_β time series (for 2010 M7.1 Darfield earthquake); shaded bar indicates PETA

Figure 5.24 TEC_{β} time series (for 2013 M6.5 Seddon earthquake); shaded bar indicates PETA

Figure 5.25 TEC_{β} time series (for 2013 M6.6 Lake Grassmere earthquake); shaded bar indicates PETA

Table 5.6 Assessment of TEC_{β} anomalies for New Zealand earthquakes in Rhoades et al. (2015)

ID.	No. of days before earthquake ¹	Directionality	Anomaly amplitude (%) ²
Darfield	6	-	17.5
Christchurch	11, 7	+, +	68.7, 109.9
Seddon	16, 11	+	30.3, 20.3
Lake Grassmere	12, 2, 1	+, +, +	23.6, 81.0, 9.1

¹ Occurrences of TEC_{β} anomalies

² Percentage difference between anomaly and detection bound

5.2.2.2 Thomas et al. (2017)

Thomas et al. (2017) examined the claims of Le et al. (2011) on the observed PETA from a large number of global earthquakes and concluded that the apparent anomalies were not statistically significant. In particular, Thomas et al. (2017) raised the examples of two large magnitude earthquake cases (i.e. 2010 Chile M8.8 and 2011 Japan M9.0) where geomagnetic activity (indicated by the Dst index) could explain the anomalous TEC readings. Following Le et al. (2011), they excluded days which were geomagnetically ‘disturbed’ identified by two criteria (see Table 5.3). While it was not clearly stated by Thomas et al. (2017), the supposedly geomagnetically disturbed periods for the 2011 Japan event were presumed to be 14 to 16 February, 1 to 3 as well as 10 to 11 March 2011 (i.e. day of earthquake). As for the 2010 Chile event, the disturbed period was approximately from 15 to 18 February 2010.

The two earthquake events are re-examined using the proposed approach. To inspect the correlations between the two parameters (i.e. Dst and TEC) near the earthquake times, a wavelet coherence test was conducted using the aforementioned earthquake cases. Figure 5.26 presents the wavelet coherence spectrum between TEC and Dst

index for the two earthquake events. As highlighted by Thomas et al. (2017), strong correlations were indeed observed near both earthquake times, thereby implying a significant geomagnetic stimulus on the ionospheric TEC. Furthermore, the effect of geomagnetic activity on TEC was prominent for an extended period of approximately two weeks (i.e. 13 and 17 days for the 2010 Chile M8.8 and 2011 Japan M9.0, respectively). This suggests that discounting single days at the exceedance of a prescribed threshold is not an effective way (i.e. insufficient) to account for these influences. Filtering in the proposed approach can eliminate these effects, since the correlations were greatest at the identified geomagnetic scaled frequencies (i.e. approximately 16 to 32 μHz shown in Figure 5.26). For the entire month of February 2010 (Chile event), Figure 5.27 illustrates a TEC_{β} depletion (approximately 66.8% decrease from the normal fluctuations) on the day of the earthquake as well as a significant TEC_{β} enhancement (about 17 days earlier) which was more than twice the normal fluctuations ($> 200\%$). Furthermore, it can be observed that these two anomalous days do not reside within the geomagnetically disturbed period previously flagged by Thomas et al. (2017) (note: the 2011 Japan event is shown earlier in Figure 5.17).

Figure 5.26 Wavelet coherence between TEC and Dst index for 2010 Chile M8.8 (top) and 2011 Japan M9.0 (bottom); red regions indicate high coherence (greater than 0.9); black arrow denotes earthquake day

Figure 5.27 TEC_{β} time series (for 2010 M8.8 Chile earthquake); shaded bar indicates PETA

5.2.2.3 Guo et al. (2016)

Guo et al. (2016) investigated the presence of TEC anomalies over the region of south-western China where there is frequent seismic activity. For a database of 18 earthquakes occurring between 2001 and 2013 with magnitudes between M_w 6.0 to 8.0, they found that 72.2% (i.e. 13 cases) of the earthquakes exhibited TEC anomalies mostly within 15 days prior to each seismic event. The authors particularly highlighted the M_w 6.1 event which happened on 11 August 2013 in Tibet, where a TEC anomaly manifested 19 days earlier.

Using the proposed approach, an analysis was conducted on the M_w 6.1 event. Figure 5.28 illustrates the results in the TEC_{β} time series with range of dates similar to Guo et al. (2016), where anomalies were represented by ΔTEC_{β} (i.e. percentage exceedance of TEC_{β} from its normal variation). The main features of the TEC anomaly presented by Guo et al. (2016) were observed here – 1) large positive Δ

TEC_{β} ($\sim 74.8\%$) on 23 July 2013 (i.e. 19 days before earthquake), and 2) minor positive ΔTEC_{β} ($\sim 47.7\%$) on 10 July 2013 (i.e. 1 day before earthquake). Due to a geomagnetic storm, Guo et al. (2016) excluded anomalies which were within 1 to 3 days after 5 August 2013. Without excluding anomalies in this fashion (as in Guo et al. (2016)), the proposed wavelet-based approach yielded no anomalies within this period (i.e. 5 to 8 August 2013, although both Dst and Kp indices showed mostly normal geomagnetic behaviour on the 8th). This was due to rejection of geomagnetic frequencies when the frequency filters were applied to obtain TEC_{β} . Finally, the earthquake cases (i.e. ID. 1, 6, 10, 12, 13) which were identified by Guo et al. (2016) as having no anomalies were re-examined using the proposed approach and were found to all exhibit TEC_{β} anomalies up to 13 days before the earthquake, as shown in Figure 5.29 to Figure 5.33. The findings are further summarized in Table 5.7.

Figure 5.28 TEC_{β} time series (for 2013 M6.1 Tibet); shaded bar indicates PETA

Figure 5.29 TEC_β time series (for earthquake ID 1); shaded bar indicates PETA

Figure 5.30 TEC_β time series (for earthquake ID 6); shaded bar indicates PETA

Figure 5.31 TEC $_{\beta}$ time series (for earthquake ID 10); shaded bar indicates PETA

Figure 5.32 TEC $_{\beta}$ time series (for earthquake ID 12); shaded bar indicates PETA

Figure 5.33 TEC_{β} time series (for earthquake ID 13); shaded bar indicates PETA

Table 5.7 Other earthquake cases¹ studied by Guo et al. (2016)

ID.	No. of days before earthquake ²	Directionality	Anomaly amplitude (%) ³
1	13	+	33.4
6	12, 11, 10	+, +, +	22.1, 64.5, 36.0
10	8, 2	-, -	6.6, 17.1
12	12, 11, 7, 1	-, -, -, +	15.9, 13.7, 12.4, 555.1
13	7, 6	-, -	199.3, 85.4

¹ These cases were found to possess no anomalies previously

² Occurrences of TEC_{β} anomalies

³ Percentage difference between anomaly and detection bound

5.2.3 Discussions on the detection of PETA

While there is vast literature highlighting the enhancement or depletion in ionospheric total electron content (TEC) prior to earthquakes, many of the existing methodologies become problematic when space weather effects are present. In Section 5.2.1, various definitions of ‘normal’ space weather indices were examined to emphasize the disparities between these thresholds. In order to circumvent these subjectivities, the

continuous wavelet transform method was utilized to localize frequencies corresponding to solar and geomagnetic periodicities. Contributions from solar-induced origins could be removed by filtering and to construct a TEC signal free from background noise (TEC_β). Secondly, the window length N , which is vital for anomaly detection in the statistical envelope method was examined. In order to account for short-term fluctuations and to transfer periodicities to statistical means, an N value corresponding to the shortest geomagnetic period of 8.3 days was utilized to construct the envelope in order to identify anomalous TEC_β . Using the proposed approach described in Section 5.2.1.1, a database of 30 large seismic events was analysed to show that TEC_β anomalies (whether positive or negative enhancements) were detected for all the earthquakes and multiple occurrences of PETA could be detected days prior to the earthquakes. Majority of the cases registered anomalies at approximately 4 days before the seismic event, although the range of precursory days vary between 1 to 13 days. Overall, the initial TEC anomalies were mostly found at 12 and 4 days before the earthquake. An examination of precursory days in relation to seismic fault mechanisms revealed that the initial PETA will be detected, on average, 7 to 8 days before the earthquake with 2 days possessing anomalous TEC activity, irrespective of fault mechanism. Further research is needed to quantify the nature of these observations in relation to seismic characteristics. For majority of the cases, anomalous TEC_β was found to be within 20% of its normal variation, defined by a 95% confidence interval. The TEC_β of several seismic events also showed large degree of anomalous TEC_β behaviour (greater than 100% of its normal variation), likely related to their fault mechanisms. In addition, re-visiting several previous negative case studies showed that TEC_β anomalies could be detected in all the

negative cases using the proposed approach. In a recent review of future perspectives in earthquake forewarning, Hayakawa (2018) highlighted several technical challenges when it comes to the detection of reliable ionospheric perturbations among noisy data, such as the necessity of incorporating novel signal processing techniques. Thus, the proposed method of utilizing the continuous wavelet transform presents a potential step in this direction.

Till now, ionospheric TEC and PETA for the various seismic events were examined at the epicentres' location, with the assumption that any TEC enhancement or depletion are likely to be greatest within its vicinity. However, there have been several case studies demonstrating that such an assumption may not be true (i.e. greatest TEC anomaly occurs at some distance away from the epicentre) even though a TEC anomaly is still registered at the epicentre itself. In the next section, an investigation is conducted to ascertain if there is a systematic link between an earthquake's epicentre (or hypocentre) and manifestation of the TEC anomaly in order to employ this precursor for earthquake forewarning. It should be noted that besides space weather effects, other geophysical processes such as volcanic eruptions (e.g. Lin 2013), tsunami (e.g. Galvan et al. 2012) as well as anthropogenic events such as nuclear explosions (e.g. Kakinami et al. 2011) and rocket launches (Ding et al. 2014; Kakinami et al. 2013) have been shown to perturbate the ionosphere. However, the simultaneous occurrence of these processes with earthquakes are rare compared to space weather phenomena. Nonetheless, the possibility for such non-earthquake related TEC anomalies have to be accounted for in using the proposed approach for earthquake forewarning.

5.3 Spatial variabilities in the manifestation of PETA

In order to examine the spatial variations of seismic-induced ionospheric anomalies (i.e. EPZ vs. IAZ), a database of 20 significant global earthquakes ($M_w \geq 5.5$) which occurred from 2008 to 2018 was compiled. These earthquakes were located within the major continental fault boundaries with frequent seismic activity, such as the San Andreas Fault in North America, Nazca Plate Region in South America, Great Sumatran Fault and Japan Trench in Asia, as well as the North Island Fault System in New Zealand. As shown in Table 5.8, the earthquake magnitudes range from M_w 5.5 to 9.1 and are classified as moderate- to large-scale earthquake events (Jimenez et al. 1989; Sato and Mori 2006). Focal depth and fault mechanism are also indicated to determine their relations to EPZ. In addition, several large magnitude earthquake events (e.g. ID 5, 10, 12) examined in previous studies allow for a comparative assessment.

Table 5.8 Catalogue of global earthquake events used in this study

ID	Location	Epicentre coordinates		Focal depth (km)	Magnitude M_w	Year	Fault mechanism ¹
		Lat (°)	Lon (°)				
1	Afghanistan	36.5	70.4	213	7.5	2015	reverse
2	Alaska	51.8	178.7	109	7.9	2014	normal
3	Algeria	36.9	3.2	10	5.5	2014	reverse
4	Australia	-25.6	129.9	10	6.0	2016	reverse
5	Chile	-35.9	-72.7	35	8.8	2010	reverse
6	Chile	-19.6	-70.8	25	8.2	2014	reverse
7	China	31.0	103.4	19	7.9	2008	reverse
8	Indonesia	-4.9	94.3	24	7.8	2016	strike-slip

9	Iran	28.0	62.0	80	7.7	2013	normal
10	Japan	38.3	142.4	29	9.1	2011	reverse
11	Mexico	17.4	-101.0	24	7.4	2012	reverse
12	Nepal	28.2	84.7	15	7.8	2015	reverse
13	Mid-Atlantic Ridge	52.6	-31.9	17	7.1	2015	strike-slip
14	New Zealand	-42.8	173.1	15	7.8	2016	complex ²
15	Pakistan	27.0	65.5	15	7.7	2013	strike-slip
16	Taiwan	24.1	121.6	17	6.4	2018	strike-slip
17	Tibet	30.0	97.9	15	6.1	2013	strike-slip
18	Turkey	38.7	43.5	18	7.1	2011	reverse
19	USA	40.8	-125.1	16	6.8	2014	strike-slip
20	Vanuatu	-18.4	168.1	32	7.2	2011	reverse

Following the methodology outlined in Section 5.2.1, Once TEC_{β} anomaly at the epicentre is detected, the spatial distribution of TEC_{β} anomalies is subsequently determined over a square area circumscribed by the extent of the EPZ from the epicentre. The square area consists of 10 by 10 grid points. Thus, the distance δ between adjacent grid points is dependent on the EPZ, which is pegged to the magnitude of the earthquake. A Cartesian approximation of δ is given in Eq. (5.7). Thereafter, the anomaly detection procedure is performed at each grid point to determine the magnitude of TEC_{β} anomalies. In order to characterize the IAZ, PETA is contoured at 20% of its range of values to circumscribe a well-constrained ellipse (i.e. smaller than the IAZ itself), which is fitted based on least-squares for each earthquake (Fitzgibbon et al. 1999). Ellipse geometrical parameters used to describe the PETA distributions include the semi-major (a) and semi-minor axes lengths (b) as well as its tilt (i.e. rotation, u).

$$\delta = \frac{2(EPZ\_radius)}{nodes_{x,y} - 1} \quad (5.7)$$

5.3.1 Comparing the spatial distributions of PETA from several earthquake cases

On the basis of TEC_{β} , an examination of the spatial distributions for the two smaller events (i.e. below M_w 6.0) in Table 5.8 is first conducted as shown in Figure 5.34, where the anomalies are expressed as the percentage exceedance from the upper bound (i.e. $TEC_{UB} = TEC_{MEAN, N} + Zs$) or lower bound (i.e. $TEC_{LB} = TEC_{MEAN, N} - Zs$) of the statistical envelopes (i.e. Eq. (5.8)).

$$TEC\_anomaly(\%) = \left(\frac{TEC_{\beta} - TEC_{UB/LB}}{TEC_{UB/LB}} \right) \times 100\% \quad (5.8)$$

From Figure 5.34, it is apparent that the EPZ defined by Eq. (2.3) does not provide sufficient characterization of the state of ionospheric TEC since a localized PETA distribution is not observed. At these smaller magnitudes, even though PETA is detected at the epicentre, development of the IAZ is not discernible as the EPZ coverage is simply too small. Given that the EPZ extends approximately only up to 380 km from the epicentre for an M_w 6.0 event, one is unable to ascertain if the maximum PETA found outside of the EPZ could be collocated to the earthquake event. Thus, in cases of smaller earthquake magnitudes, the EPZ does not adequately capture ionospheric variability as shapes of these IAZs are not well-constrained.

Figure 5.34 Spatial distribution of anomalous TEC (IAZs) for earthquakes $M_w \leq 6.0$; left – Algeria M_w 5.5 2014; right – Australia M_w 6.0 2016

Figure 5.35 shows the IAZs for earthquakes M_w between 6.0 and 7.0, which corresponds to EPZ radius of approximately 400 to 1000 km. As the EPZ radius begins to widen exponentially at these earthquake magnitudes, the structure of PETA becomes increasingly distinguishable since the elliptic-shaped IAZ within the EPZ can be sufficiently approximated using the least-squares fitting method. Conversely with smaller magnitude earthquakes, PETA is beyond the EPZ, thus the EPZ is unable to envelope the IAZ (even though they occupy only a smaller region within the EPZ).

Figure 5.35 Spatial distribution of anomalous TEC (IAZs) for earthquakes $6.0 \leq M_w \leq 7.0$; left – Taiwan M_w 6.4 2018; right – Tibet M_w 6.1 2013

Next, an examination of the IAZs for large magnitude earthquakes (i.e. $M_w \geq 7.0$) is conducted based on past studies. At these earthquake magnitudes, EPZ radius is beyond 1000 km and in general, the elliptical shapes for IAZ are well-defined within the EPZ. However, extents of the IAZ spread beyond the EPZ. To illustrate these observations, emphasis is placed on three large magnitude events, namely the 2011 M_w 9.1 Japan (Tohoku), 2015 M_w 7.8 Nepal (Gorkha) and 2010 M_w 8.8 Chile (Maule) earthquakes. A detailed analysis of these anomalies is reported within the context of their respective EPZs.

Firstly, ionospheric anomalies due to the Japan M_w 9.1 earthquake which occurred off the Pacific coast of Tohoku on 11 March 2011 have been widely documented. Using a principal component analysis (PCA) method, Chang et al. (2017) studied the manifestations of TEC anomalies over Japan area prior to the earthquake and found that a significant anomaly occurred three days earlier on 8 March 2011. This was associated with an IAZ appearing towards the south-west of the epicentre starting at 0800 UTC. These observations were reported in earlier studies by Fuying and Yun (2011) and Jian et al. (2012).

Based on the proposed PETA detection technique, an investigation was conducted on the PETA distributions during 8 March 2011 and is illustrated in Figure 5.36. Figure 5.36 shows the distinctively localized IAZ south-west of the epicentre (approximately 1350 km with a bearing of 223° from the epicentre) as well as a minor IAZ towards the north. The more significant IAZ which exceeded 100% of their usual variations is represented by a tilted ellipse towards the south-west direction. Chang et al. (2017) set arbitrary activity thresholds on three space weather indices (i.e. F10.7, Dst and Kp) and highlighted the observation where the solar F10.7 index appeared to be at a

heightened state beyond 100 solar flux units (s.f.u.). In their study, the authors argue that even though F10.7 could have influenced ionospheric TEC (i.e. increased), the occurrence of IAZ close to the epicentre (i.e. a local effect) demonstrates causality due to the seismic preparation process. From Figure 5.36, it is shown that by objectively rejecting the space weather frequencies in the wavelet analysis and subsequently reconstructing the TEC for PETA detection, the IAZ remains and is not affected by solar or geomagnetic activity. As highlighted earlier, several inferences can be made regarding EPZ and the epicentre: (1) it is possible for the IAZ to extend outside the EPZ (i.e. beyond its western edge in this case), (2) the location with the largest anomaly do not coincide with the epicentre, and (3) the IAZ is an elongated ellipse instead of being circular (i.e. Eq. (2.3)). Since the preparatory mechanism causing ionospheric perturbations likely originate from the ground (e.g. LAIC), propagation of this ‘driver’ to ionospheric heights would consequently lead to a different size and (perhaps) shape of the IAZ, as depicted in Figure 5.37. Here, θ_{IAZ} accounts for the projection of EPZ onto the ionosphere while R_{IAZ} is the radius of the IAZ itself (i.e. if $\theta_{IAZ} \leq 90^\circ$, $R_{IAZ} > R_{EPZ}$, where R_{EPZ} is the radius of the EPZ). As such, the occurrence of IAZ outside of the EPZ becomes plausible in this scenario since the sub-ionospheric points (SIP) fall outside of the EPZ. Even if the ionospheric pierce points (IPP) are within the IAZ, location of SIPs within the EPZ is not guaranteed. Thus, it can be deduced that even though the EPZ seems to be a lower bound for which PETA can be detected, the actual IAZ occupies a small section within the EPZ itself (Liu et al. 2010).

Figure 5.36 Spatial distribution of anomalous TEC (IAZ) over Japan region three days before the M_w 9.1 event on 11 March 2011; red star denotes epicentre

Figure 5.37 Interaction between the earthquake preparation zone (EPZ) and proposed ionosphere anomalous zone (IAZ)

Next, anomalous TEC_{β} variations in relation to the 25 April 2015 M_w 7.8 Nepal earthquake (also known as the Gorkha earthquake, largest since 1934) were

investigated (Chum et al. 2016). Similar to Japan which is highly seismically active, Nepal is situated along the Himalayan front which is prone to high seismic hazard (Bilham et al. 2001; Wesnousky et al. 1999). However, based on the levels of seismic activity in Nepal during the period preceding the large M_w 7.8 earthquake, the epicentre's geographic location offers an interesting analysis perspective. Namely, this stems from the fact that the number of moderate and large ($\geq M_w$ 4.5) earthquakes were minimal within the vicinity of the main shock's epicentre (Figure 5.38). Prior to the large event, an M_w 4.8 earthquake occurred in central Nepal (Pokhara city) about 80 km away from the 25 April's M_w 7.8 epicentre (28.230° N 84.731° E), however it happened more than three months before, on 31 January 2015. Hence, should this event result in ionospheric disturbance, it would not carry over to the M_w 7.8 event due to the large temporal gap. In addition, there was an M_w 5.0 event on 21 April 2015 (i.e. 4 days prior to the main shock date), but it was located at the mid-western section of Nepal and was more than 220 km away. Thus, considering the circumstances of minimal seismic activity leading up to 25 April 2015, it can be considered that the M_w 7.8 event was essentially spatially- and temporally-isolated from other earthquakes and likely not to suffer from any potential confounding (i.e. adjacency) effects (Chauhan et al. 2009; Kon et al. 2011; Liu et al. 2010).

Figure 5.38 Occurrences of earthquakes ($\geq M_w 4.5$) in Nepal before 25 April 2015; red line indicates date of $M_w 7.8$ event

There are several works investigating anomalies (e.g. perturbations to F2-region, Rayleigh and acoustic wave analyses, Doppler sounding, radiation and air temperature) pertaining to the Nepal $M_w 7.8$ earthquake (Chang et al. 2017; Chum et al. 2016; Reddy and Seemala 2015). Works involving PETA found that TEC anomalies were mostly observed towards the east/south-eastern direction of the epicentre (Catherine et al. 2017; Oikonomou et al. 2016; Zhou et al. 2017). Here, the TEC_{β} anomalies were found to be most significant two days before the earthquake, i.e., on 23 April 2015 and the solar-terrestrial environment was generally quiet after 21 April 2015, further yielding favorable conditions for analysis (Zhou et al. 2017).

Figure 5.39 illustrates the observations of localized TEC anomalies for the Nepal earthquake on 23 April 2015. Peak of the anomaly was approximately 33.3% from its usual fluctuations and located at an azimuth of 102° from the epicentre's north (i.e. south/south-eastern direction). As with the Japan event, the IAZ was found to be

towards the southern part of the epicentre with its elliptical structure clearly observable. Reddy and Seemala (2015) previously discovered that Rayleigh surface waves were induced by the Nepal earthquake in the south/south-eastern direction with minimal impacts on the western and northern regions, which coincides with the PETA observations. Since the structure of ionosphere is highly organized in accordance to earth's geomagnetic field, the locations of these IAZs are likely affected by the flow of such horizontally stratified phenomena over time. Based on this, a geographic-to-magnetic coordinate conversion using the formulation of Emmert et al. (2010) was conducted. It is revealed that since the geomagnetic (quasi-dipole) latitudinal coordinates (i.e. 22.6° N for Nepal and 31.2° for Japan) are both within the mid-latitudes, there would likely be similarities in the spatiotemporal manifestations of PETA for these two regions.

Figure 5.39 Spatial distribution of anomalous TEC (IAZ) over Nepal two days before the M_w 7.8 event on 25 April 2015; red star denotes epicentre

A large M_w 8.8 Chile earthquake occurred on 27 February 2010 with its epicentre located at 35.9° S, 72.7° W and a hypocentre depth at 35 km. Solar and geomagnetic conditions were found to be quiet for up to 30 days before the earthquake and is ideal to examine ionospheric perturbations due to the event (similar to the Nepal event) (Ho et al. 2013; Píša et al. 2011). Using a combination of ground-based TEC and French micro-satellite DEMETER, Ho et al. (2013) and Píša et al. (2011) previously revealed the presence of TEC anomalies about 11 to 15 days (i.e. 12 to 16 February 2010) and electron density anomalies 17 days (i.e. 10 February 2010) before the earthquake. Note that the ionospheric quantities of TEC and electron density are inter-related, since the integration of electron density along a 1 m^2 column yields TEC. The

IAZs in these studies were found to be within the epicentre region while electron density anomalies were located west of the epicentre.

Based on the proposed technique, PETA for the M_w 8.8 event was detected on 10 February 2010, which coincides with the reported anomalies by Ho et al (2013) and Piša et al. (2011). On that day, $TEC\beta$ enhancement at the epicentre location was slightly over 200% and the corresponding IAZ is illustrated in Figure 5.40. A highly localized PETA anomaly was clearly observed at a bearing of 138° (i.e. south-east) of the epicentre's north and 835 km away, which is within the EPZ boundaries (note: the EPZ radius for an M_w 8.8 event is over 6000 km according to Eq. (2.3)). Remarkably, the IAZ is circular with a radius of approximately 730 km, instead of a tilted ellipse (i.e. more latitudinal-oriented) seen in the 2010 Japan and 2015 Nepal earthquakes. Furthermore, anomaly percentage at the center of the IAZ was found to be greatly enhanced beyond 2000% of the normal variation. Since the solar-terrestrial conditions were quiet during this period, the occurrence of this high amplitude and concentrated anomaly would have been triggered by a significant event and is most likely a precursor to the M_w 8.8 earthquake on 27 February 2010.

Figure 5.40 Spatial distribution of anomalous TEC (IAZ) over Chile on 10 February 2010 (17 days before M_w 8.8 earthquake); red star denotes epicentre

Figure 5.41 and Table 5.9 summarize the IAZs elliptical distributions and properties for the list of earthquakes cases. In general, there appears to be no clear evidence to suggest that EPZ serves as the boundary for the manifestations of PETA. Earthquakes with magnitudes below 6.0 typically do not have their IAZs fully develop within the EPZ. Furthermore, maximum PETA that could be detected for the cases which have their anomalous zone within the EPZ (i.e. $M_w \geq 6.0$), do not occur right above the epicentres. Among those cases where their IAZ is within the EPZ, the majority (~75%) cases exhibit the greatest anomalies at large distances away from the epicentre (i.e. further than 500 km). Also, there is an absence of systematic links between the spatial variations of PETA and fundamental earthquake characteristics (e.g. hypocentre depth, mechanism). From these results, relying on the EPZ alone may

lead to erroneous/inadequate identification of PETA, especially since the EPZ scales exponentially with earthquake magnitude (M_w) according to Eq. (2.3). The observations of PETA occurring away from the epicentre results in collocation issues since it becomes challenging to pinpoint the epicentre given the detected anomalies. Furthermore, PETA is only found within a small subset region (IAZ) of the EPZ. These effects are further discussed in the next section.

Figure 5.41 Distribution of IAZ elliptical envelopes for earthquake database; red star denotes epicentre

Table 5.9 IAZ geometrical properties for earthquakes cases

ID	Location	Max PETA (%) ¹	PETA ellipse properties			
			Semi-major axis, a (km)	Semi-minor axis, b (km)	Axis ratio (b/a)	Tilt (°) ²
1	Afghanistan	-277.8	175.1	51.7	0.29	159.5
2	Alaska	105.3	234.0	48.7	0.21	176.0
3	Algeria	41.3	-	-	-	-
4	Australia	32.8	-	-	-	-
5	Chile	2307.4	83.2	76.7	0.92	7.1
6	Chile	73.7	80.2	39.0	0.49	0.2
7	China	51.1	96.9	27.4	0.31	178.1
8	Indonesia	158.8	229.1	38.8	0.17	177.9
9	Iran	-292.5	167.9	53.6	0.32	3.3
10	Japan	114.0	397.4	98.1	0.25	167.2
11	Mexico	245.5	320.7	51.6	0.16	175.5
12	Nepal	33.3	240.8	52.1	0.22	179.2
13	Mid-Atlantic Ridge	74.2	157.1	34.7	0.22	2.0
14	New Zealand	3203.3	51.5	32.2	0.62	1.5
15	Pakistan	-650	183.2	67.9	0.34	1.9
16	Taiwan	53.8	62.7	18.6	0.30	171.7
17	Tibet	77.5	96.9	22.4	0.23	178.1
18	Turkey	51.2	113.3	48.3	0.43	7.0
19	USA	-64.1	133.6	52.5	0.40	166.7
20	Vanuatu	108.2	92.1	36.5	0.49	163.4

5.3.2 Implications of the earthquake preparation zone (EPZ) and ionosphere affected zone (IAZ)

The above observations suggest that EPZ may be convenient to spatially identify the existence of PETA but it covers a large region that is not affected. As illustrated in Figure 5.37, the IAZ could describe the PETA region more accurately. In order to examine the relationship between EPZ and the theoretical IAZ, a comparison between the IAZ elliptical dimensions and EPZ was made with respect to the earthquake magnitude. While a link between the ellipse major axis and earthquake magnitude was not found, the radius of the ellipse minor axis was found to scale exponentially with earthquake magnitude (Figure 5.42). Remarkably, this scaling relationship (when presented in the natural logarithmic form) adopts a multiplicative exponent of 0.43 which is similar to the equation proposed by Dobrovolsky et al. (1979) (i.e. Eq. (2.3)).

Figure 5.42 Variations of IAZ ellipse semi-minor axis radius and EPZ with magnitude

The lack of correlation between the major axis and magnitude is further explored in Figure 5.43, where it is observed that the orientation of IAZ typically adopts a latitudinal spatial distribution as indicated by the ellipse tilt angles, regardless of earthquake magnitude. The appearance of such IAZ has been briefly discussed by Pulinets and Boyarchuk (2004), where the plasma drift process could lead to elongation in the zonal direction. Such an elongated structure along the longitudinal direction may also be due to the ionosphere's co-rotation with the earth (Kelley 2009). For example, differential rotational velocities between the ionosphere (about 1.3 times faster) and earth's surface could lead to the 'stretched' IAZ (King-Hele and Allan 1966). According to Figure 5.43 and Table 5.9, it is found that the dimension of the major axis is mostly about three times of the dimension of the minor axis (i.e. ellipse axis ratio ≈ 0.3).

Figure 5.43 Variations of ellipse angular tilt with magnitude; shaded regions indicate the general east-west orientation ($\pm 30^\circ$)

Limited studies have attempted to analyze the IAZs based on ionospheric tomography (Farzaneh and Forootan 2018; Pryse 2003). (Lin 2011c) discovered that while TEC anomaly increases, the spatial distribution of PETA reduces with increasing altitude (i.e. $R_{IAZ} < R_{EPZ}$), thereby implying that θ_{IAZ} is greater than 90° (i.e. if $\theta_{IAZ} = 90^\circ$, $R_{IAZ} = R_{EPZ}$), while Dobrovolsky et al. (1979) suggested that the size of the IAZ is of the same order as the EPZ. Conversely, since atmospheric density decreases with altitude, the propagation of seismic waves (e.g. acoustic and acoustic-gravity waves) into the ionosphere are potentially amplified and could affect broader regions of the ionosphere, even comparable to sources such as solar wind (Van Dam et al. 2009; Zhou et al. 2017). For such case, if $R_{EPZ} < R_{IAZ}$, the EPZ then becomes a more stringent parameter set for the detection of PETA. Additionally, Karia and Pathak (2011) studied the variations in atmospheric refractivity (i.e. related to the troposphere's pressure and temperature gradients) as well as ionospheric TEC over the region of India using the GPS Ionospheric Scintillation and TEC Monitoring (GISTM) network. They found that ionospheric perturbations could be observed even if the instruments are located far from the EPZ zone, thus supporting observations from the results presented in this study.

Inadequacy of the EPZ could stem from the electron $E \times B$ drift along electric and magnetic field lines which are geography-dependent. The bulk movement of perturbed electrons spread over a wide area, potentially departing from the extents described by EPZ. In fact, differences in the spatial distributions of PETA could also stem from the unavailability and/or limitations of spatial and temporal sampling. For example, a sparse network of GPS receivers might not be able to capture localized ionospheric TEC variations which occur in a smaller region (centered on the epicentre)

within the spatial convex hull and over the oceans. Temporal issues which mainly pertain to ionospheric maps derived by ensembling global TEC data similarly suffer from the problem of not being able to capture finer dynamic movements of the perturbed regions. This may lead to the apparent deviation of the anomalous region from the epicentre and a possibility that the anomaly presents itself outside the EPZ. Even with satellite-based observations such as GPS radio occultation, spatial and temporal issues remain pertinent as data coverage at present is simply inadequate and deficient (Plotkin 2003). With the advent of the next generation satellite constellations however, such as the FORMOSAT-7/COSMIC-2, it could perhaps pave a way to shed further light on the origin and dynamic movements of these ionospheric anomalies as well as to establish a basis to derive a better approximation of the IAZ. Recently, ionospheric plasma physics using ion/electron parameters such as densities, temperatures and velocities, have been used to explore the causal mechanisms of seismo-generated ionospheric electric fields, which could be further employed to determine the actual extents of IAZ around the epicentre (Liu and Chao 2017).

As highlighted earlier, the exponential scaling relationship between EPZ and earthquake magnitude yields unrealistically large EPZ radius from large magnitude earthquakes. While this consequence would seem less impactful on retrospective studies, a large EPZ radius would imply exponentially increasing difficulty in the establishment of a PETA-based earthquake forewarning system. For example, in the forewarning scenario, the detection of PETA (for simplicity, assume a single point) implies that the epicentre could be anywhere within the EPZ (or ideally, IAZ). For the worst-case, the PETA point would lie on the edge of the EPZ. This means that for

a hypothetical M_w 8.0 earthquake with an EPZ radius close to 3000 km, the region for which an earthquake might occur is within an area of $2.8 \times 10^7 \text{ km}^2$. The size of such an EPZ effectively spans the entire South-American or African continents with South-East Asia and is therefore, impractical to forewarn against an earthquake.

5.3.3 Conclusion

In many studies examining the existence of ionospheric total electron content (TEC) anomalies as precursors to seismic events, earthquake preparation zones (EPZ) is used to spatially collocate ionospheric observations for a particular earthquake. While convenient to use, the concept of EPZ was originally derived based on geological and tectonic stresses and might not necessarily translate into an actual circular region for which the ionosphere is perturbed. Furthermore, the exponential scaling nature of EPZ with seismic magnitude yields unrealistically large EPZ areas, especially for earthquakes with M_w 8.0 onwards. In this study, the spatial distributions of ionospheric TEC anomalies were examined with respect to the earthquakes' epicentres as well as the EPZ using a database of 20 global earthquakes. As a database consisting of 20 global earthquakes is used, simple arbitrarily-defined space weather thresholds used in anomaly interpretation would not suffice since the solar and geomagnetic activity differs according to geography. Instead, a wavelet-based method is proposed which identifies the contributions of these solar-terrestrial processes and subsequently removed. From each earthquake epicentre, the TECs were reconstructed (i.e. TEC_β) over a 10×10 grid where the grid point spacing depends on the earthquake magnitude. By contouring the TEC_β anomalies, an ionosphere anomalous zone (IAZ) can be identified. In general, analysis of the spatial distributions for TEC_β anomalies for the 20 earthquakes reveals several observations:

(1) IAZ may extend beyond the EPZ region, (2) peak of TEC anomaly may not be found at location of the epicentre, 3) EPZ and its circular shape is a proxy of the IAZ, and 4) IAZs tend to be more zonal-oriented. Using least-squares defined ellipses to describe the IAZs, an exponential correlation is found between the ellipse minor axis and earthquake magnitude, which has a similar form as the EPZ relation widely used in literature. Furthermore, for earthquakes with reverse faulting mechanism, distance between epicentre to location of maximum PETA was observed to correlate well with the number of precursory days (i.e. days in advance of the earthquake). In order to further ascertain the correlations of IAZ with seismic parameters, issues such as limited instrumental coverage in terms of spatial and temporal sampling could be better addressed with complementary satellite missions providing such measurements. From these findings, the EPZ appears to be a spatial proxy to the actual IAZ. Consequently, this leads to difficulties in a prospective scenario (i.e. earthquake forewarning) where it becomes difficult to infer an earthquake's epicentre based on detected TEC anomalies. More work is thus required to associate manifestations of TEC_{β} anomalies to fundamental earthquake characteristics.

5.3.4 Deploying the proposed method in an earthquake prediction system (EPS)

As cities around the world become increasingly urbanized, the looming threat of seismic activity causing disruption and damages in built-up areas is receiving much attention from the scientific community (Benessia and De Marchi 2017). For example, buildings situated in highly urbanized country of Singapore (SG), which lies close to the Sumatran fault zone, has been reported to experience tremors which could render them vulnerable to structural damage (Balendra et al. 2007; Balendra et al. 2004; Lai et al. 2015; Pan et al. 2011; Shao and Tiong 2015). In fact, majority of the country's

residential apartments are high-rise buildings developed by the Housing Development Board (HDB) of Singapore and such tall structures are susceptible to seismic shaking (Brownjohn and Pan 2001; Fesselmeyer and Seah 2018; Goh et al. 2012). Furthermore, several studies have revealed that Singapore is subjected to strong ground motions from the Sumatran strike-slip fault due to short source-to-site distances (Megawati and Pan 2010; Megawati et al. 2003). Thus, an EPS is useful to Singapore as it can help to allay public anxiety and enhance authority preparedness in response to buildings experiencing tremors. To develop the EPS, a primary catalogue, consisting close to 2000 $M_w \geq 5$ earthquakes from January 2000 to July 2017 located within the Sumatran fault zone (Figure 5.44), was first assembled from the United States Geological Survey (USGS) Earthquakes Hazards Program database (Murray and Svarc 2017). Thus, the selection of the Sumatran fault zone for the proposal of an EPS was due to two factors – 1) high frequency of earthquakes with varying magnitudes, and 2) proximity to Singapore.

Figure 5.44 Singapore and earthquakes ($M_w \geq 5$) located in the Sumatran (Indonesia) fault zone from 2000 to 2017 (primary catalogue)

An examination was made to understand the variations of epicentral distance with reported tremors in Singapore. Forty historical earthquakes (i.e. not within the primary catalogue) from the Sumatran fault zone resulting in local earth tremors were documented by various sources, including media reports, archived newspapers from the National Library Board (NLB) of Singapore as well as journal publications (Board 2014; NewsAsia 2016; Pan and Sun 1996; Prawirodirdjo et al. 2000). These historical earthquakes occurred as early as 1833 till 2016, with magnitudes ranging between 5.3 to 9.1. Figure 5.45 illustrates the variations of epicentral distance for earthquakes in the primary catalogue as well as for the 40 historical earthquakes. Brownjohn and Pan (2001) previously stated that Singapore's tall buildings could experience tremors from earthquakes (i.e. $6 \leq M_w \leq 8$) which are located at least 350

km away. From Figure 5.45, a general agreement with Brownjohn and Pan (2001) observations may be made, as the lowest epicentral distance (d_{epi}) was about 377 km as shown by the dotted vertical line (even though there were 3 cases which were below M_w 6.0). As the epicentral distance increases, the magnitude of an earthquake likely to cause tremors in Singapore seemingly necessitates the exceedance of a threshold $M_{w,lower}$ shown as a sloping line in Figure 5.45. The threshold $M_{w,lower}$ as a function of epicentral distance from Singapore is given in Eq. (5.9). Therefore, since epicentral distance and magnitude both serve as proxies to the likelihood of tremors in Singapore in the event of a seismic event in the Sumatran fault zone, these two parameters, along with azimuth from Singapore (to geolocate the epicentre), were adopted as prediction targets to formulate the primary machine learning model. PETA detections at three PETA pseudo-observation stations (PPOS) (i.e. Thailand, Singapore, Indonesia) were used as inputs to the model. As mentioned in a recent study conducted by Liu et al. (2018a), the choice of monitoring stations is important in the detection of PETA and for earthquake monitoring – here, the three PPOS locations were selected for the trilateration technique in determining the epicentre location as well as their proximity to the Sumatran Fault Zone.

Figure 5.45 Variations of earthquake magnitude with earthquake epicentral distance for i) primary earthquake catalogue, and ii) historical earthquakes with reported tremors in Singapore (SG); boundaries of data points corresponding to the historical earthquakes are demarcated in dotted lines

$$M_{w,lower} = 2 \ln(d_{epi}) - 6.82 \quad (5.9)$$

5.3.5 Machine Learning Architecture

Since a direct coupling effect remains the subject of active research, the primary objective of machine learning is to account for the underlying non-linear complexities which are associated between seismic preparation and ionospheric TEC. The approach in addressing this problem was cast as a supervised non-linear regression procedure where epicentral distance, magnitude, azimuth and time-to-earthquake (TTE) were approximated using PETA through continuous adjustments made within hidden layers of an artificial neural network (ANN) during the optimization process. Even though the use of machine learning for such a task is not a new notion, to the candidate's knowledge, this is the first time where PETA processed in a systematic

manner as described above which accounts for the effects of space weather phenomena was utilized to assemble a large database (approximately 2000 earthquake events) for machine learning. During the development of the ANN, several assumptions were made. These include – 1) detection of PETA indicates the occurrence of an imminent earthquake, 2) the earthquake occurs within 14 days once PETA is first detected, 3) PETA is present in at least one PPOS, 4) PETA may still be detected in the days leading to and after the earthquake, following first detection, and 5) TTE is counted from first detection.

A typical ANN consists of three types of layers, the input, hidden and output layers, each containing nodes (i.e. neuron) which are interconnected by weighted links (Figure 5.46). These weights are optimized during each epoch, where the training data is sequentially (e.g. batches) fed into the ANN. Each node is further associated with an activation function (e.g. hyperbolic tangent (tanh), sigmoid (sig), rectifier linear units (ReLU)) which permits the non-linear modelling capabilities of ANNs (Fausett 2006; Zurada 1992).

Figure 5.46 Model of typical ANN architecture

Lately, deep architectures of ANNs have been receiving more attention (as compared to shallow ANNs) due to their capabilities in representing numerous levels of non-linearities, especially if the underlying associations between processes are unclear. Generally, deep ANNs provide increased efficiency and predictive accuracy by adopting more neurons per layer (i.e. wider) and/or increasing the number of hidden layers (i.e. deeper). To avoid underfitting or overfitting during training leading to a poor degree of generalizability, there are several schemes available (e.g. implementing dropout layers and early stopping) to ensure validation and/or testing errors remain close to training errors (Murugan and Durairaj 2017; Srivastava et al. 2014).

Traditionally, the identification of ANN hyperparameters (e.g. number of layers, number of neurons, activation functions, epochs, optimizers, learning rate, dropout rate) are based either on trial-and-error or rules-of-thumb (Panchal and Panchal 2014; Stathakis 2009). However, since ANNs may contain more than ten hyperparameters, manual tuning is well-known to be an arduous task exacerbated by the fact that the solutions obtained are usually suboptimal and unequally distributed in the objective space (Bengio 2012; Malitsky et al. 2013; Qolomany et al. 2017). Typically, parsimonious models possessing good generalization capabilities adopt the smallest number of parameters (Karsoliya 2012). Unfortunately, the ideal ANN architecture is usually not obvious and is problem-dependent, where rules-of-thumb approaches (though easy to implement) may be inadequate, especially if the underlying complexities are unknown (e.g. when the preference of deep rather than shallow networks arises). Consequently, Karsoliya (2012) labelled these ‘guidelines’ as myths due to the complex intra-relationships within parameters of each network,

where one should avoid arbitrarily choosing network architectures (Narejo and Pasero 2018). Another approach involves pruning, where an oversized network is trimmed gradually to remove redundant parameters while maintaining its accuracy. This is also challenging since it is tough to identify manually the appropriate parameters to remove without causing erroneous results (Babaeizadeh et al. 2016). Conversely, two of the most common automated techniques for hyperparameters optimization are the exhaustive grid search or the random search (Bergstra and Bengio 2012b). Yet, the number of possible combinations increases exponentially (for the case of grid search) and hence, these regimes are not only computationally demanding but has no mechanism to narrow the scope of search during the optimization process (Kinnison et al. 2018).

Therefore, in order to minimize the arbitrary selection of ANN parameters for use in this study, a guided approach involving Bayesian optimization, which builds a continuously updated probability model to select the best configuration of hyperparameters, is employed. Here, Hyperopt and the Hyperas wrapper package was used to implement Bayesian optimization of the ANN hyperparameters in the Python programming language, yielding an optimally configured ANN from the pre-defined range of values shown in Table 5.10 (Cosma et al. 2017). Thus, this approach effectively avoids the requirement to assess manually different network topologies in the selection of an ‘ideal’ model based on the typical ANN construct (Figure 5.46) (Narejo and Pasero 2018).

Table 5.10 Ranges of hyperparameters used for network optimization

Parameter	Values
Number of hidden layers	$2^1 - 2^2$
Number of neurons	$2^1 - 2^3$
Activation functions	hyperbolic tangent (tanh), sigmoid, rectified linear units (relu)
Dropout rate per layer	0 - 1
Optimizers	adam, rmsprop, adadelta
Learning rates	$10^{-3} - 10^{-1}$
Batch sizes	$2^4 - 2^7$

Since seismic processes involve complex fault geometry and constructions, machine-learning schemes are built usually upon as many parameters (i.e. input features depicted in Figure 4) as possible to avoid deficient models. For example, Klahcı et al. (2009) employed a total of eight variables, such as geographical coordinates, radon concentration, focal depths and soil temperatures, to predict earthquake magnitude. Likewise, Alarifi et al. (2012) extracted features from various seismic event parameters consisting of year, month, day, time, geographical coordinates and focal depths for magnitude prediction.

In contrast to Klahcı et al. (2009) and Alarifi et al. (2012), the current investigation aims to assess the accuracies of PETA as a singular ionospheric parameter for estimating earthquake location (i.e. epicentral distance and azimuth), magnitude and TTE at the Sumatran fault zone. Hence, only the TEC anomaly percentages at three pseudo-observation stations (PPOS) (i.e., Singapore: PPOS_{SG} - 1.35° N, 103.8° E; Indonesia West Kalimantan: PPOS_{WK}- 0.28° S, 111.5° E; Thailand Bangkok:

PPOS_{BK}- 13.7° N, 100.5° E) were considered. As shown in Figure 5.44, the three PPOS were selected to represent spatial TEC variations due to earthquakes within the Sumatran fault zone. The three PETA inputs were standardized to zero mean and unit variance to ensure a normal distribution for training stability. Model outputs are epicentral distance from PPOS_{SG}, earthquake magnitude, azimuth and TTE based on PPOS_{SG}. Here, two combinations of outputs were evaluated – the first is the primary model consisting of epicentral distance, magnitude, azimuth and TTE. The secondary model is similar to the first, but with the exclusion of TTE. The secondary model excludes TTE because TTE is constrained by the fact that the earthquake occurs within 14 days on first detection of PETA. Prior to the training and validation of the primary catalogue of close to 2000 earthquakes using the K-fold (i.e. K = 10) cross-validation procedure with 80/20 randomized split (i.e. training and testing sets), model parameters were normalized (i.e. min-max scaling) to ensure that the backpropagation routine will not be influenced by the relative differences in value ranges between them. Thus, for each model run, around 1600 cases were used for training while the remaining cases (i.e. approximately 400 cases) were used for validation purposes. The validation procedure was repeated for K = 10 times to yield the model's validation error. The time taken for training of ANNs is significantly influenced by computer hardware (Singaravel et al. 2018). For this study, the ANNs were trained using the commonly used *least mean squares* (LMS) cost function (i.e. Eq. (5.10)) and on a CPU with clock speed of 2.4 GHz (Fessant et al. 1996).

$$J_{LMS} = \sum_{i \in I} \sum_{j \in O} \left(y_{i,j} - \hat{y}_{i,j} \right)^2 \quad (5.10)$$

where J is the minimizing cost function; I and O refer to the entire set of input (i.e. training) and output (i.e. prediction) data, respectively; $y_{i,j}$ and $\hat{y}_{i,j}$ are the values of input data and their corresponding predictions, respectively.

The selected ANN primary (i.e. four outputs) and secondary (i.e. three outputs) models comprised of network architectures and hyperparameters which gave the highest accuracy with similar training and validation errors. This ensures that the effects of over-/under-training were minimized.

5.3.6 Assessment of ANN predictive models

Table 5.11 illustrates the optimized ANN for the primary and secondary models (i.e. with lowest validation errors) using PETA from the catalogue of close to 2000 earthquakes. In Table 5.11, PETA% refers to the percentages of TEC anomalies detected at the three PPOS locations, Singapore (PPOS_{SG}), Bangkok (PPOS_{BK}) and West Kalimantan (PPOS_{WK}). The range of values for PETA_{%SG}, PETA_{%BK} and PETA_{%WK} is listed in Table 5.11 and further detailed in Figure 5.47, where PETA% were mostly concentrated between 5% and 50%. After a total of 100 ANN evaluation runs (i.e. equivalent to the number of different ANN structures considered) which took approximately 40 minutes, the Bayesian-optimization yielded a network topology consisting of a three-layered deep ANN structure, using a 8-4-2 hidden layer configuration (i.e. number of neurons), for both the primary and secondary model. Utilizing the respective activation function for each hidden layer indicated in Table 2 and the *adam* optimization technique (Kingma and Ba 2014), Figure 5.48 shows that the model was able to converge to an optimal solution quickly for both models, where

the number of epochs required for stable convergence is typically below 100. Batch size (i.e. number of samples propagated through the network) was determined to be 16, while dropout rates were 0.234, 0.106, 0.121 for the three hidden layers, respectively, to enhance the model generalization capabilities by randomly dropping sets of neurons. Additionally, the addition of one extra hidden layer (i.e. four-layered ANN) was found to provide negligible reduction in prediction errors.

Table 5.11 Bayesian-optimized ANN architecture for primary and secondary models

Input Features ¹	Hidden layers ²	Output Features ³	
		Model name ⁴	Output features
PETA%, SG [-419.6 %, 597.8 %]		Primary	1) Epicentral distance (d_{epi} ; km) 2) Earthquake magnitude (M_w) 3) Epicentral azimuth (θ ; °) 4) Time-till-earthquake (days)
PETA%, BK [-556.9 %, 491.8 %]			
PETA%, WK [-483.6 %, 555.0 %]		Secondary	1) Epicentral distance (d_{epi} ; km) 2) Earthquake magnitude (M_w) 3) Epicentral azimuth (θ ; °)

¹ Minimum and maximum values for PETA% at corresponding PPOS is shown in brackets (i.e. [min, max]).

² Corresponding activation function for each hidden layer are illustrated, respectively; same network architecture is used for both primary and secondary models

³ With respect to PPOS located in Singapore

⁴ Four outputs for primary model; three outputs for secondary model (TTE is pruned)

Figure 5.47 Range of values for PETA% detected at the three PPOS stations (SG, WK, BK) for the primary earthquake catalogue

Figure 5.48 Typical plot showing the rapid convergence of loss (y) versus number of epochs (x) during training; note – losses are calculated based on the three normalized outputs

After the network is fully trained via the 10-fold cross validations, average validation errors of the primary model (i.e. four outputs) were 129.6 km, 0.1, 19.5° and 4 days for d_{epi} , M_w , θ and TTE, respectively. Note that the value ranges for the parameters

are $418.3 \leq d_{\text{epi}} \text{ (km)} \leq 2089.1$, $5.0 \leq M_w \leq 9.1$, $121.3 \leq \theta \text{ (}^\circ\text{)} \leq 304.8$ and $1 \leq \text{TTE (days)} \leq 14$. When TTE is pruned from the primary model, the average validation errors in the case of the secondary model for the remaining three outputs were found to be approximately 66.9 km, 0.1 and 13.8° for d_{epi} , M_w and θ , respectively. Based on the observed validation errors, predictions of location (i.e. d_{epi} and θ) and seismic strength (i.e. M_w) are more accurate without the inclusion of TTE in a single ANN model. The adverse impact of TTE in model accuracies could be due to its general independence from spatial and strength metrics, as implied in Eq. (2.3).

Based on the above results, the secondary model which yielded three outputs (i.e. d_{epi} , M_w and θ) was found to be more accurate than the primary model. In the secondary model, first detection of PETA assumes that the earthquake will occur within a 14-day period. Thus, although the proposed EPS does not provide a precise estimate of TTE, improvements made for location (i.e. d_{epi} and θ) and strength (i.e. M_w) metrics within the secondary model justifies this compromise.

5.3.7 Deploying the proposed EPS on five recent earthquakes

An investigation was separately made to validate the trained ANN when utilized for prospective earthquake cases. From late 2017 to early 2019 (i.e. outside the range of dates used in the catalogue for model generation), there were five significantly large earthquake events in Indonesia. Namely, these earthquakes were from the Sumatran region (i.e. west of Singapore) as well as the Java region (i.e. south of Singapore), with magnitudes between M_w 5.5 to 6.9. Consequently, the EPS (i.e. optimized secondary model) was deployed on the PETA levels observed at the three PPOS during the earthquake periods to simulate the deployment of prospective scenarios.

5.3.7.1 Two earthquakes in Sumatran region, Indonesia

A moderate Indonesian earthquake occurred on 21 July 2018 at approximately 07:58 UTC. The local Meteorological, Climatological and Geophysical Agency (BMKG) of Indonesia initially estimated a magnitude of M_w 5.5 for the relatively shallow (i.e. focal depth of 10 km) event and epicentre located along Southern Sumatra (0.97° S, 100.7° E). However, based on data from nearby seismometer, the German GEOFON (GFZ) network placed this earthquake at M_w 5.2 and at focal depth of 19 km instead. Ensuing tremors could be felt up to Padang city, the capital of West Sumatra located 54 km away. The consequences of this event were reportedly property damages within the epicentre's neighbourhood as well as various injuries with one fatality.

Using the proposed methodology for detecting PETA, Figure 5.49 shows the variations in TEC_β for each of the three PPOS considered along with the corresponding bounds defined according to Eq. (2.3). PETA was detected approximately 6 days (i.e. 15 July 2018) prior to the earthquake occurrence. On 15 July 2018, $PPOS_{SG}$ registered significant PETA at 492.9% while $PPOS_{WK}$ observed PETA at 241.3% and $PPOS_{BK}$ observed PETA at 33.2%. Only PETA at $PPOS_{BK}$ persisted to the following day with an anomaly at 25.5%. Using PETA values detected at the three PPOS on 15 July 2018 (i.e. 492%, 241.3% and 33.2%) as input to the EPS, the predicted outputs for d_{epi} , M_w and θ are 571.4 km (i.e. error = 8.2%), 5.2 (i.e. error = 5.5%) and 228.5° (i.e. error = 1.7%), respectively.

Figure 5.49 (top) $TEC\beta$ time series and first PETA detection (yellow overlay) at 95% confidence ($\pm 1.96\sigma$) for three PPOS (SG, BK, WK) preceding the moderate M_w 5.2 Southern Sumatra earthquake on 21 July 2018; (bottom) PETA levels on 15 July 2018

On 2 February 2019, a strong M_w 6.0 earthquake struck the city of Sungai Penuh which was located on the western coast of the Jambi province in central Sumatra. Although strong shaking was felt by the local population, there were minimal damages to infrastructure as most buildings were designed to be earthquake-resistant. Based on Figure 5.50, significant PETA was registered on 25 January 2019 (i.e. 8 days prior to the earthquake) in $PPOS_{BK}$ (i.e. 185.1%), while relatively lower PETA was found in $PPOS_{SG}$ (i.e. 9.6%) and $PPOS_{WK}$ (i.e. 7.9%). Input of these PETA values

into the EPS yielded predictions of d_{epi} at 640.5 km (i.e. error = 2.9%), M_w at 5.1 (i.e. error = 15.0%), and θ at 215.8° (i.e. error = 2.7%).

Figure 5.50 (top) $\text{TEC}\beta$ time series and first PETA detection (yellow overlay) at 95% confidence ($\pm 1.96\sigma$) for three PPOS (SG, BK, WK) preceding the strong M_w 6.0 earthquake at Sungai Penuh on 2 February 2019; (bottom) PETA levels on 25 January 2019

From Figure 5.50, it can be observed that a minor anomaly of 9.5% for PPOS_{WK} manifested on 23 January 2019 (i.e. two days before the major anomaly). On this day however, PPOS_{SG} and PPOS_{BK} registered no anomaly. To investigate its validity, the EPS was ran with input PETA values of $\{0\%, 9.5\%, 0\%\}$, corresponding to PPOS_{SG} , PPOS_{WK} and PPOS_{BK} , respectively. Consequently, the EPS yielded d_{epi} at

approximately 2000 km, while θ was 125° , which points to a location toward the eastern boundary of the dataset (i.e. eastern edge of Java). Considering no significant earthquake above M_w 5.0 occurred in the region during this period and that the predicted location was beyond the eastern boundary of the earthquake catalogue used in model training, the ANN was considered robust in the treatment of such input data. The sensitivity of the ANN to potential out-of-range values was further examined by defining extreme cases and verifying model output. The four sets of extreme cases were: 1) $\{> \max(\text{PETA}_{\%,SG}), 0\%, 0\%\}$, 2) $\{0\%, >\max(\text{PETA}_{\%,WK}), 0\%\}$, 3) $\{0\%, 0\%, >\max(\text{PETA}_{\%,BK})\}$ and 4) $\{0\%, 0\%, 0\%\}$. For these cases, the EPS generated outputs which were either at, or beyond, the eastern edge (i.e. $\theta \leq 125^\circ$) or the north-western edge (i.e. tip of Sumatra; $\theta \geq 295^\circ$). Thus, predictions would only be valid within these limits.

5.3.7.2 Three earthquakes in Java region, Indonesia

Three significant earthquakes which occurred in the years 2017 and 2018 located in the western and eastern Java region of Indonesia were examined using the same methodology. These earthquakes are – Java M_w 6.5 (15 December 2017), Panyaungan Timur M_w 5.9 (23 January 2018) and Loloan M_w 6.9 (5 August 2018). The time series for these three events are presented in Figure 5.51 to Figure 5.53, where the detected PETA values at the three PPOS were used in the EPS for prediction of d_{epi} , M_w and θ .

Figure 5.51 (top) $TEC\beta$ time series and first PETA detection (yellow overlay) at 95% confidence ($\pm 1.96\sigma$) for three PPOS (SG, BK, WK) preceding the strong M_w 6.5 earthquake at Java on 15 December 2017; (bottom) PETA levels on 12 December 2017

Figure 5.52 (top) $TEC\beta$ time series and first PETA detection (yellow overlay) at 95% confidence ($\pm 1.96\sigma$) for three PPOS (SG, BK, WK) preceding the M_w 5.9 earthquake at Java on 23 January 2018; (bottom) PETA levels on 14 January 2018

Figure 5.53 (top) $TEC\beta$ time series and first PETA detection (yellow overlay) at 95% confidence ($\pm 1.96\sigma$) for three PPOS (SG, BK, WK) preceding the strong M_w 6.9 earthquake at Loloan on 5 August 2018; (bottom) PETA detected on 23 July 2018

The predictions and prediction errors for the three cases together with the earlier two cases are summarized in Table 5.12. Overall, for the five recent case studies, the proposed EPS yielded average errors for $d_{epi} = 3.8\%$, $M_w = 16.4\%$ and $\theta = 2.5\%$. Figure 5.54 illustrates the locations of actual epicentres with their predicted locations for the five cases along with the limits of the ANN's applicability ($125^\circ \leq \theta \leq 295^\circ$). For the event (i.e. M_w 6.5 Java earthquake) shown in Figure 5.51, a minor anomaly

occurring on 11 December 2017 (i.e. 1 day before the major anomaly) at PPOS_{SG} yielded an invalid prediction ($d_{epi} = 1011$ km and $\theta = 296^\circ$) similar to the case shown in Figure 5.50.

Table 5.12 Summary of results for the five recent earthquake cases using the proposed EPS (i.e. optimized secondary model)

Region	Earthquake date	Epicenter		Actual			Predicted			% Error ¹ (individual parameter)			% Error ² (location)	
		Lat (°)	Lon (°)	M _w	d _{epi} (km)	θ (°)	M _w	d _{epi} (km)	θ (°)	M _w (%)	d _{epi} (%)	θ (%)	ΔL (km)	ΔL (%)
Sumatra	21 July 2018	-1.70	99.85	5.5	528.3	232.3	5.2	571.4	228.3	5.5	8.2	1.7	56.7	10.7
	2 February 2019	-2.85	100.07	6.0	622.3	221.5	5.1	640.5	215.5	15.0	2.9	2.7	67.7	10.9
Java	15 December 2017	-7.49	108.17	6.5	1091.8	153.4	5.1	1097.6	156.2	21.5	0.5	1.8	53.7	4.9
	23 January 2018	-7.09	105.96	5.9	963.9	165.4	5.0	933.4	169.6	15.3	3.2	2.5	77.0	8.0
	5 August 2018	-8.26	116.44	6.9	1759.6	127.2	5.2	1830.0	132	24.6	4.0	3.8	163.4	9.3

1 % Error (parameters) is computed with respect to actual value for each parameter

2 % Error (location) is computed using the distance between actual and predicted epicenter (i.e. ΔL). See Figure 14.

A final evaluation of the location error ΔL (i.e. distance between the epicentre and the predicted epicentre) using d_{epi} and θ was conducted using the cartesian formulation as illustrated in Figure 5.55 and Eq. (5.11).

$$\Delta L = \sqrt{\Delta x^2 + \Delta y^2} \quad (5.11)$$

Since d_{epi} and θ are, effectively, polar coordinates, where:

$$\begin{aligned} \Delta x &= \Delta d_{epi} \cos \theta - d_{epi} \sin \theta.(\Delta \theta) \\ \Delta y &= \Delta d_{epi} \sin \theta + d_{epi} \cos \theta.(\Delta \theta) \end{aligned} \quad (5.12)$$

By substituting Eq. (5.12) into Eq. (5.11), Eq. (5.13) can be further obtained:

$$\Delta L = d_{epi} \sqrt{\left(\frac{\Delta d_{epi}}{d_{epi}}\right)^2 + (\Delta \theta)^2} \quad (5.13)$$

Thus, the location error ΔL may be computed once d_{epi} , θ and their associated errors are derived from the EPS. It should be noted that the approximated values and Cartesian nature of Eq. (5.11) does not account for slight differences due to curvature of the earth. However, as distances between the epicentres and predicted epicentres are short, Eq. (5.13) yields a reasonable approximation of the location errors from the EPS. Table 5.12 presents the final location errors ΔL for the five earthquake cases, where the percentage errors is on average, 8.8%. Thus, these results imply that the choice of PPOS location is significant. Since a larger distance between the PPOS to the fault (where earthquakes are most likely to occur) will imply a larger location error and vice-versa, PPOS locations can be further optimized to potentially reduce the error.

Figure 5.54 Locations of the five earthquakes examined; actual epicentres and their corresponding predicted epicentres using the primary model are color-coded

Figure 5.55 Illustration of location error (i.e. ΔL) between epicentre and prediction; Δd_{epi} refers to the epicentral distance error as computed from the EPS prediction

5.3.8 Discussion on proposed EPS

In the current study, only PETA at three PPOS was used as the input in predicting d_{epi} , M_w , θ and TTE. From the analyses conducted on the earthquakes, predictions of d_{epi} , M_w and θ yielded more reliable results than TTE. It is expected that more earthquake features as well as temporal and spatial metrics of PETA (such as PETA occurrence dates, times and seasons and distance from fault boundaries) could be useful to further improve the predictive accuracy of the ANNs. It should be noted that while there are other forms of phenomena which may induce dynamic ionospheric behaviour, such as nuclear explosions and volcanic eruptions, they are relatively less frequent than seismic activity and hence this study does not account for these sources. Nevertheless, the current work demonstrates that it is possible to develop an EPS system based on PETA and ANN, thus yielding information about likely earthquake

location and strength within a 14-day period after first PETA detections at the three PPOS locations. On the basis of five recent earthquake cases, results show that the average percentage errors corresponding to d_{epi} , M_w and θ are 3.8%, 16.4% and 2.5%, respectively.

5.4 Conclusion

The topic of earthquake prediction remains contentious with rare historical success. Till now, the notion that an earthquake may be predicted seems improbable. Current research focuses on earthquake forecasting and mitigating the damage due to earthquake. Earthquake forecasting relies on earthquake precursors. For the past two decades, there have been numerous evidences of seismo-ionospheric anomalies manifesting days up to weeks before an earthquake. The observations of these short-term ionospheric precursors may provide a mean of developing an earthquake prediction system (EPS). In this paper, a proposed method utilizing the continuous wavelet transform was applied on ionospheric TEC data, where periodicities corresponding to solar and geomagnetic influences could be clearly observed and filtered. The reconstructed TEC can subsequently be used to detect TEC anomalies based on the statistical envelope method and is free from space weather influences. Employing this technique, a catalogue of close to 2000 earthquakes of $M_w \geq 5.0$ between January 2000 and July 2017 in the Sumatran fault zone and their associated pre-earthquake TEC anomalies (PETA) was constructed. Knowing that PETA possess a spatial distribution over large areas, PETA at three pseudo-observation stations (Bangkok, Singapore and West Kalimantan) were used to develop an artificial neural network (ANN) to predict the location (i.e. epicentral distance and

azimuth from Singapore pseudo-observation station), magnitude and time-till-earthquake (TTE). Hyperparameters, such as number of neurons, hidden layers and activation functions, were determined automatically from a range of values using guided Bayesian optimization. This removes the need to assess multiple different configurations of ANNs in selecting an ideal network. For the primary model with four output features, error estimates (via a 10-fold cross validation procedure) were 129.6 km, 0.1, 19.5° and 4 days for d_{epi} , M_w , θ and TTE, respectively. As for the secondary model with three output features (i.e. excluding TTE), errors were approximately 66.9 km, 0.1 and 13.8° for d_{epi} , M_w and θ , respectively.

Based on these results, an EPS was proposed on the basis of the secondary model which predicts epicentre location and earthquake magnitude. Instead of predicting TTE directly, the corresponding detection period of up to 14 days served as a proxy to indicate the possible time of earthquake occurrence.

In order to examine the feasibility of deploying the EPS in a prospective scenario, five separate earthquake events which were not part of the primary catalogue used to develop the ANN were employed. Results show average percentage errors for these five cases corresponding to d_{epi} , M_w and θ are 3.8%, 16.4% and 2.5%, respectively. On average, the final location error between epicentres and their corresponding predictions is approximately 8.8%, thus highlighting the importance of a carefully selected PPOS location with respect to fault lines. The outcome of this study shows that it is possible to develop an EPS using PETA at several pseudo-observation stations and ANN, with an alert period up to 14 days. Nonetheless, the EPS developed here needs to be further verified in real time for future earthquakes and the ANN can also be further optimized for greater accuracy.

CHAPTER 6 CONCLUSION AND RECOMMENDATIONS

6.1 Conclusion and research significance

In this thesis, satellite remote sensing was used to uncover characteristics of land-based geohazards, namely, landslides and earthquakes. By evaluating the risks and triggering factors of landslides as well as exploring the use of ionospheric precursors prior to earthquakes, it allows decision makers to prepare for the emergence and occurrences of these natural disasters in order to mitigate their impacts.

The following conclusions may be drawn from the topics discussed in this thesis:

- 1) A geometry-based method was introduced to estimate the volume of a landslide using observations from aerial or satellite imagery. This technique was able to provide the theoretical basis for the observed landslide area-to-volume relationships which have been uncertain till now.
- 2) The geometry modelling approach of landslide failure surface enables the computation of landslide volume from measurements of landslide scar. Validation of this method revealed a volumetric bounding error of $\pm 13.3\%$. This approach is more accurate than simply using the landslide area-to-volume power law, easy to use and less resource intensive than digital elevation models or in-situ work.
- 3) Landslides due to the M_w 7.8 Gorkha (Nepal) 2015 earthquake were rapidly mapped using open-source satellite imagery which is freely accessible but at low resolution. The landslide susceptibility model from the short-term inventory gave a high accuracy of 98.3%.

- 4) Results show that while long-term landslide inventories using commercial satellite images are able to map more landslides at finer resolution, high risk areas remain similar to the short-term landslide inventory. Thus, open-source images are sufficiently representative of landslide prone areas and can provide timely information for rescue and recovery operations long before expensive and high resolution satellite images are available.
- 5) Pre-earthquake total electron content anomalies (PETA) were examined in detail in order to identify short-comings with existing analytical methods. The proposed method using wavelet transform is an innovative and objective way of eliminating space weather influences on ionospheric total electron content, enabling higher detection confidence in correlation with the earthquake.
- 6) Several case studies in the literature were revisited using the proposed method in order to detect PETA. The findings show that PETA may be detected up to two weeks prior to an earthquake and is considered as a medium-term earthquake precursor.
- 7) The implementation of an earthquake prediction system was explored using PETA. A deep learning approach was utilized predict the location and strength of earthquakes within a 14-day window. Based on a regional earthquake database due to the Sumatran fault zone, the proposed earthquake prediction system shows great potential for a real-time deployment.

6.3 Recommendations

Due to the limited period of this candidature, there remains several topics relevant to the thesis which are worth exploring in future. These are:

- 1) Examine a log-spiral décollement plane for landslides in order to have a more realistic approximation of failure surface. Check how well it estimates landslide volume as compared to the current ellipsoidal approximation.
- 2) Expand the landslide database using more precise volume calculations. As the availability of digital elevation models increase, more sources of data would be able to further ascertain the relationship between landslide area and volume.
- 3) Explore more complex machine learning architecture to calibrate h/c to landslide area. Also, supplementary inputs such as landslide aspect ratio could be added.
- 4) Apply the proposed method to analyze landslide spatial distributions on other earthquake events, such as the M_w 7.9 Wenchuan (China) 2008 earthquake. Check if the differences between temporal landslide inventories are consistent with the findings of the current research.
- 5) Examine if the locations recognized as landslide high risk areas in this study due to the M_w 7.8 Gorkha (Nepal) earthquake are correctly identified for a future earthquake within the same region. This will ascertain if the associated landslide triggers still remain the same.

- 6) Examine the occurrences of PETA in the proposed method using the median-base analysis in order to improve the detectability, especially for earthquakes of smaller magnitudes. The IAZ can also be further explored by plotting PETA at a global scale.
- 7) Develop the proposed earthquake prediction system using data from another seismically active region, such as Japan or New Zealand. The accuracies of the predictions at these other locations can then be compared to the results in the present study and to further understand the source(s) of any possible differences.
- 8) Deployment of the proposed earthquake prediction system can be supplemented with existing equipment and methods, such as the detection of p- and s-waves which are caused by the propagation of seismic waves. It is beneficial to have an earthquake warning system capable of predicting earthquakes up to 14 days in advance (i.e. proposed method) and within seconds to minutes (i.e. seismic waves) of the earthquake arrival.

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APPENDIX – A

Ionospheric total electron content (TEC)

The region of ionosphere begins approximately 50 km above ground and is situated between the Earth's terrestrial atmosphere and space. Extending till about 1000 km in altitude, it is primarily composed of partially ionized gas (i.e. electrons and free ions) which envelops the planet (Hajj and Romans 1998; Jin and Jin 2011; Kherani et al. 2009; Petrie et al. 2011). Its dynamic composition is a direct result of the solar's photoionization effect (i.e. solar wind), interaction with the earth's magnetic field as well as responses to the Earth's neutral atmosphere (Anderson and Fuller-Rowell 1999; Zossi et al. 2018). As illustrated in Figure A1, the ionospheric structure generally consists of loosely-defined, horizontally stratified layers (i.e. D- (~ 50 to 90 km), E- (~ 90 to 150 km), F1- (~ 140 – 210 km) and F2- (~ 210 to 1000 km) regions) which differs according to geographic location, altitude, time of day, season and solar activity (Jin and Jin 2011; Kelley 2009; Klobuchar 1996). Note that beyond 1000 km lies the plasmasphere (or protonosphere) which reaches to altitudes of GPS satellites at around 20,000 km and is not the focus of this research. Among these layers, the F2-region is the densest (in terms of ionized particles) at approximately 250 to 450 km where it exhibits the greatest variabilities at these altitudes. The F2-region is thus responsible for most of the effects on the propagation of GPS dual-frequency signals (e.g. signal delays). From Figure A1, the topside ionospheric is typically characterised exclusively by low-earth orbiting satellites (with orbits around 450 to 500 km) and hence, it is a subset of the measurements by ground-based GPS, which profiles the entire extent of ionosphere (i.e. approximately 50 km above ground onwards).

Figure A1 Range of approximate heights for various ionospheric layers; peak of electron density is found at F2-region

The ionosphere TEC is a representative and crucial parameter to understand the state of ionospheric variability as the concentrations of ionized particles in the F2-region vary widely under various geophysical stimuli. Early uses of TEC, aided by its simplicity in measurement, involve the estimation and correction of propagation delays in satellite positioning (Petrie et al. 2011). The ionosphere acts as a dispersive medium which retards the velocity of travelling signals (e.g. GPS), causing a group path delay with an associated timing error, which is in turn directly proportional to the TEC. Thus, these timing errors can be quantified by the frequencies of the transmitted signals and TEC for use in operational navigation systems. With the availability of more platforms (e.g. GPS receivers and satellites) characterizing the ionosphere, TEC was gradually exploited for scientific uses such as space weather

prediction and the understanding of ionospheric disturbances due to periodic solar flares and geomagnetic storms.

TEC refers to the total number of free electrons in a unit column area (e.g. 1 m²) of the ionosphere, where 1 TECu (i.e. TEC unit) = 10¹⁶ electrons/m². To calculate ionospheric TEC, the group (i.e. based on pseudo-ranges) and phase delays (i.e. from carrier waves) experienced by GPS signals propagating through the dispersive ionospheric region are exploited (Farzaneh and Forootan 2018; Petrie et al. 2011). At GPS ground stations, by recording L-band dual frequencies transmitted by the GPS satellite constellation, slant TEC (STEC) values are first derived. During retrieval, since only the first order of ionosphere refraction is considered significant, the ionospheric delay (Δ_d) can be expressed in the form of Eq. (A1) (Seeber 2003).

$$\Delta_d = \frac{k_I}{f^2} STEC \quad (A1)$$

where k_I ($\approx 40.3 \text{ m}^3/\text{s}^2$) (i.e. ionosphere refraction coefficient) and f is frequency.

Owing to the fact that pseudo-range measurements have more noise than carrier phases (which suffers from integer ambiguity), Eq. (A1) can be incorporated into a carrier-smoothed pseudo-range function ($P_{4,sm}$), yielding the STEC, given by Eq. (A2) (Liu et al. 1998).

$$STEC = -\frac{f_1^2 f_2^2}{k_I (f_1^2 - f_2^2)} (P_{4,sm} - c_L DCB_{rcv} - c_L DCB_{sat}) \quad (A2)$$

Here, f_1 and f_2 are the frequencies 1575.42 MHz and 1227.50 MHz, respectively, c_L is the speed of light in vacuum while DCB_{rcv} and DCB_{sat} refers to the differential code biases of the receiver and satellite, respectively.

In order to convert the STEC to the vertical TEC (VTEC; used primarily in this study), (A3) was utilized for its derivation at an assumed shell height (i.e. expected peak electron density) of 450 km (Petrovski 2014; Sekido et al. 2003).

$$VTEC = STEC \sin(Z') \quad (A3)$$

where Z' refers to the zenith angle between satellite, receiver and geocentre.

Therefore, the ionospheric VTEC parameter allows for a convenient collocation with seismic activity (e.g. epicentre) as it specifies the ionosphere TEC at a particular geographic location.

APPENDIX – B

Mathematical justification of observed landslide area-to-volume relationships

For any typical landslide delineated by satellite images, the volume and planar area of the failed soil mass can be represented using Eqs. (3.1) and respectively, following the convention illustrated in Figure 3.1.

$$A_L = \frac{ab(c^2 - h^2)\pi}{c^2} \quad (\text{B1})$$

In a general case utilising an ellipsoidal décollement plane where the aspect ratio of its axes is $k: 1: 1$, the magnitude of its semi-major axis is $a = kr$ while the semi-minor axes, $b = c = r$. When defined in this manner, $k = 1$ for a spherical décollement plane. Since a spherical décollement plane at $h/c = 0.9$ effectively serves as the upper bounds of the area-to-volume power-laws (as shown in Figure 3.2), substitution of the semi-axes parameters in Eq. yields an expression of r ($= a = b = c$) in terms of A_L , as shown in Eq. .

$$r^2 = \frac{A_L}{\pi k \left(1 - \frac{h^2}{r^2} \right)} \quad (\text{B2})$$

Based on the relationship between landslide area and volume shown in the form of Eq. as well as Eqs. (3.1) and , the volume of the failed soil mass V_L can subsequently be expressed in terms of its planar area as follows:

$$V_L = \frac{A_L(c - h)(2c + h)}{3(c + h)} \quad (\text{B3})$$

In the current formulation, the semi-minor axis, $c = r$. Thus, Eq. may be written as Eq. :

$$V_L = \frac{A_L}{3} \cdot \frac{(r-h)(2r+h)}{(r+h)} \quad (\text{B4})$$

By factorizing r from Eq. , V_L can be represented using h/r (instead of c), as shown in Eq. :

$$V_L = \frac{r}{3} A_L \frac{\left(1 - \frac{h}{r}\right) \left(2 + \frac{h}{r}\right)}{1 + \frac{h}{r}} \quad (\text{B5})$$

As presented in Figure 3.2 and discussed in the preceding section, the ratio h/r ($= h/c$) $= 0.9$ demarcates the upper bound of the area-to-volume relationships. Assigning $h/r = 0.9$ in Eqs. and , Eqs. and can be obtained:

$$r = \frac{A_L^{0.5}}{0.773 \cdot \sqrt{k}} \quad (\text{B6})$$

$$V_L = 0.05 r \cdot A_L \quad (\text{B7})$$

Finally, by replacing Eq. into Eq. and since $k = 1$ for spherical décollement plane, the theoretical upper bound area-to-volume relationship could be finally obtained as:

$$V_L = 0.065 A_L^{1.5} \quad (\text{B8})$$

Eq. can be casted into the landslide area-to-volume power-law relationship (Eq. (2.1)), where $\alpha = 0.065$ and exponent $\beta = 1.5$. Following the results acquired by field observations (Guzzetti et al. 2009) and model analysis (Klar et al. 2011), the exponent β value of 1.5 is expected for *self-similar* landslides. In addition, the geometry method is able to provide mathematical justification to the different coefficient values of the

reported empirical area-to-volume relationships. To derive an expression for the coefficient, Klar et al. (2011) introduced arbitrary constants and a ‘reference area’ which depends separately on in-situ soil cohesion and unit weight. In the derivation of Eq. for the case of a spherical décollement plane where $k = 1$, the value of 0.065 stems from the initial assumption where $h/r = 0.9$ to form the upper bound. Further sensitivity analyses show that if h/r decreases to 0.1, the value of 0.065 in Eq. decreases to approximately 0.028, which is within the range of α values observed in literature Table 2.1. Therefore, based on the results from mathematical derivations of the area-to-volume relationship, the proposed geometrical method is able to provide a theoretical basis for the empirical power-law relationships.

APPENDIX – C

Regarding landslide area observed from aerial or satellite images

An additional point to note pertains to the definition of landslide area employed in the currently study. When a satellite image is georeferenced in a typical orthographic projection (i.e. nadir-looking), a landslide observed in the resulting image is in fact a projected view on a horizontal plane (i.e. not the true landslide area). This effect is illustrated in Figure C1, where the semi-major axis (i.e. a^*) observed from a satellite image is located on the horizontal plane (and not the landsliding plane).

Figure C1 Illustration of landslide area observed by orthographic imagery; notice the role of slope angle in the calculation of semi-major axes (a and a^*)

As such, the link between the actual semi-major axis (i.e. a) and a^* is presented in Eq. (C1), where the role of slope angle θ_s governs the transformation between the two parameters.

$$\frac{a^*}{a} = \cos \theta_s \quad (C1)$$

Based on the definition of the geometry modelling method, semi-minor axis (i.e. b) is unaffected by this transformation, which corresponds to the landslide width (i.e. dimension perpendicular to landslide direction). This particular advantage can be utilized to analyze the sensitivity of actual landslide area (i.e. A_L) to the projected landslide area (i.e. A_L^*) according to variations in slope angle θ_s . According to Eq. , the projected landslide area A_L^* may be written in a similar form as shown in Eq. (C2).

$$A_L^* = \frac{a^* b (c^{*,2} - h^{*,2}) \pi}{c^{*,2}} \quad (C2)$$

Eq. (C2) further reduces to Eq. (C3):

$$A_L^* = a^* b \pi \left[1 - \left(\frac{h}{c} \right)^{*,2} \right] \quad (C3)$$

Then, the ratio between A_L^* and A_L is computed according to Eq. (C4):

$$\frac{A_L^*}{A_L} = \frac{a^* b \pi \left[1 - \left(\frac{h}{c} \right)^{*,2} \right]}{a b \pi \left[1 - \left(\frac{h}{c} \right)^2 \right]} \quad (C4)$$

Since $\left(\frac{h}{c} \right)^* = \frac{h}{c}$ as shown in Figure C1, Eq. (C4) effectively reduces to Eq. (C5):

$$\frac{A_L^*}{A_L} = \frac{a^*}{a} = \cos \theta_s \quad (C5)$$

From Eq. (C5), the ratio between the projected landslide area (i.e. A_L^*) and actual landslide area (i.e. A_L) is dependent on $\cos \theta_s$, where $A_L^* \leq A_L$. In general, landslides

(i.e. for both earthquake- and rainfall-induced landslides) tend to occur at slope angles between 20° to 30° , with steeper slope failures (i.e. $\geq 45^\circ$) generally manifesting as rock falls or avalanches (Chen et al. 2016; Donnarumma et al. 2013; Hancox et al. 2002; Huang et al. 2012a; Jeong et al. 2017; Kasai and Yamada 2019; Li et al. 2016). For instance, slope angles in the current inventory include 10° (Corvara), 13° (Maierato landslide), 15° (Ca' Lita), 20° (Ischia, Higashi-Takezawa), 22° (Hope), 25° (Hattian Bala), 30° (Collinabos, Koba, Madison Canyon) and 32° (Oppstadhornet). Based on the typical slope angles, the ratio is 0.94 (i.e. $A_L^* = 0.94 \cdot A_L$) at $u_s = 20^\circ$. At the greater slope angle of 30° , the factor becomes 0.87. The relationship between $\frac{A_L^*}{A_L}$ and u_s is illustrated in Figure C2.

Figure C2 Relationship between $\frac{A_L^*}{A_L}$ and θ_s

From these findings, it appears that the zone of reported landslide area-to-volume relationships (i.e. scatter in the literature) as presented in Figure 3.2 may arise from

the error in estimating landslide area observed via satellite imagery and are generally unaccounted for in the literature. To quantify the resulting error in volume estimation due to the A_L^* , the ratio between V_L^* and V_L as shown in Eq. (C6) is used:

$$\frac{V_L^*}{V_L} = (\cos \theta_s)^\beta \quad (\text{C6})$$

According to Table 2.1, the range of β is between $1.032 \leq \beta \leq 1.95$. With $\theta_s = 20^\circ$ and $\beta = 1.032$, $V_L^* = 0.938 \cdot V_L$. This translates to a volumetric error of approximately 6.2%.

On the other hand, with $\theta_s = 30^\circ$ and $\beta = 1.95$, $V_L^* = 0.762 \cdot V_L$, corresponding to a volumetric error of 23.8%. However, since the source of this volumetric error comes from the projected landslide area A_L^* observed via satellite imagery, it is compensated in the current geometry method by calibrating h/c with A_L^* .

APPENDIX – D

Machine learning for estimating h/c from A_L^*

Apart from the estimation of h/c using the bilinear function shown in Eq. (3.4), a machine learning method incorporating artificial neural network (ANN) was utilized to predict the values of h/c from A_L^* . Since the R^2 from Eq. (3.4) is high at 0.86 (indicating a good degree of fit), only a shallow ANN is employed here. The ANN was implemented using the Keras package in Python with the following range of hyperparameters listed in Table D1. A randomized search within the range of hyperparameters values was then conducted to find the optimum combination to predict h/c from A_L^* (Bergstra and Bengio 2012a). Thereafter, computation of the landslide volume V_L was based on Eq. (3.1).

Table D1 Ranges of hyperparameters used for the shallow ANN

Parameter	Values
Number of hidden layers	1 - 3
Number of neurons	1 - 5
Activation functions	hyperbolic tangent (tanh), sigmoid, rectified linear units (relu)
Dropout rate per layer	0 - 1
Optimizers	adam, rmsprop, adadelta

After 2000 epochs of training the ANN using 48 landslides in the training database, it was found that the *adam* optimizer along with the hyperbolic tangent (*tanh*) activation function was most ideal. The trained ANN shown in Figure D1 was used to predict h/c from A_L^* in the validation dataset. However, the resulting landslide

volume estimation error only performs marginally better as shown in Figure D2. The error was within $\pm 10.4\%$ (as compared to $\pm 13.3\%$ when using the bilinear model).

Figure D1 Optimized shallow ANN architecture to predict h/c from A_L^*

Figure D2 Volume estimation errors for validation dataset based on $h/c - A_L^*$ machine learning model

APPENDIX – E

Background of 25th April 2015 Nepal (Gorkha) Mw 7.8 earthquake

The large magnitude (M7.8) earthquake event in Nepal on 25 April 2015 induced many landslides causing widespread damages. Owing to the main shock of this particular earthquake, the recent availability of landslide inventories across three temporal periods presents a unique opportunity in assessing conditions leading to slope failures. Firstly, to understand the trigger and interactions between landslide predisposing factors, detailed examinations on a factor-by-factor basis were conducted to investigate their spatial distributions and areas of high risk. Secondly, the utility of these factors from the earliest available landslide inventory (termed as short-term inventory) in assessing landslide probabilities for a future event was evaluated using two further revisions of the landslide inventories which were published sometime after the earthquake. Two latest landslide inventories (i.e. Kargel et al. (2016) and Roback et al. (2018)) were developed from higher resolution satellite imageries, much later after the earthquake in April 2015. With more time and resources in identifying the landslide locations, these inventories had greater detail (i.e. higher quantities and smaller landslides). Thus, the two latest landslide inventories (termed as medium- and long-term inventories) provide a unique opportunity to assess the efficacy of landslide probabilities generated from the short-term inventory (i.e. earliest available). A short-term landslide inventory typically suffers from decreased landslide resolution (i.e. only able to identify larger landslides), but it would be helpful, especially to first responders rendering emergency assistance, to have knowledge of areas with significant landslide risk. Thus, the predictive capability of the landslide probability model based on the short-

term inventory and the locations of these landslide prone areas in Nepal are subsequently compared and validated against the medium- and long-term inventories.

The 25th April 2015 earthquake which occurred in central-western Nepal was one of the deadliest in recent times and is currently the worst natural disaster to strike Nepal after an event of similar scale more than 80 years ago (M_w 8.0 Nepal-Bihar earthquake) (Engdahl and Villaseñor 2002). The earthquake, also termed as the Gorkha earthquake with respect to its epicentre (80 km northwest of Kathmandu), had a moment magnitude (M_w) of 7.8 and a shallow hypocentre depth at 15 km which caused widespread damage within the affected region. In addition, the intensity of the earthquake triggered multiple landslides, including the two largest on Mount Everest and in the Langtang valley, which claimed many lives. Close to 9000 deaths in Nepal alone was reported with more than twice as many injured or missing. Regions most adversely affected by this seismic event include Kathmandu, Bhaktapur, Nuwakot, Sindhupalchok, Dhading and Gorkha (i.e. mainly central parts of Nepal) and eventually resulted in economic losses amounting close to \$10 billion (Dhanya et al. 2017).

The cause of the earthquake was attributed to thrust faulting located either on or near the thrust interface between the subducting Indian plate moving at 45 mm/y in the north-northeasterly direction toward the overriding Eurasian plate (USGS 2015). The sudden thrust took place along the fault line (EU-IN) between the two plates at about 06:11 UTC (Galetzka et al. 2015). Various agencies have undertaken damage assessment of the 25th April event (before aftershock events on and after 5th May) using a variety of data sources. These include passive (i.e. optical) and active (i.e. radar) satellite imagery supplemented by GPS motion data as well as ground-based

seismic instruments. For example, the Japan Aerospace Exploration Agency (JAXA) utilized the L-band synthetic aperture radar (PALSAR-2) onboard the Advanced Land Observing Satellite 2 (ALOS-2) to detect post-earthquake surface deformations surrounding the epicentre (28.147°N, 84.708°E) (JAXA 2015). They observed line-of-sight (LOS) displacements up to 48 cm extending to a distance of approximately 170 km in the east-southeasterly direction. Results also indicated that seismic waves propagated towards the east with the largest slip traced to 80 km in the east-southeasterly direction (Kobayashi et al. 2015). However, measurements of strong near-source ground motions were severely lacking. Although various seismic networks such as the Programme for Excellence in Strong Motion Studies (PESMOS), National Seismic Network, Quake-Catcher Network (QCN) were installed in the Nepal Himalayan region, the only strong motion record available for the 25th April event was from the KATNP station under the United States Geological Survey's (USGS) NetQuakes monitoring system (Dixit et al. 2015). For the main shock, peak ground accelerations were observed to be 0.139g in the east-west, 0.144g in the north-south and 0.164g in the vertical directions. While ground motion estimates of neighboring regions could be derived from modelling approaches (e.g. finite element methods and empirical prediction equations), these results are however poorly constrained by the general unavailability of seismic records and might not be fully representative of in-situ conditions (Clark et al. 2016; Dhanya et al. 2017; Goda et al. 2015).

After the 25th April M_w 7.8 main shock and its ensuing aftershocks within the subsequent few hours, several agencies carried out co- and post-seismic landslide mapping to evaluate the aftermath of the earthquake. Within two weeks in the

aftermath on 8th May 2015 (i.e., before the large M_w 7.3 aftershock on 12th May), the British Geological Survey (BGS) partnered Durham University leading the COMET (i.e. Centre for Observation and Modelling of Earthquakes, Volcanoes and Tectonics) consortium, mapping and publishing more than 2500 landslides in the highly affected central and eastern regions. The COMET landslide inventory utilized images with relatively coarse ground sampling distances up to 22.5 m and landslides were only represented as points. An independent landslide mapping was conducted in this study using open-source satellite imagery immediately available after the main shock and prior to the aftershock. The resulting polygonal database with close to 3000 landslides was compared against the COMET landslide inventory and used as a short-term landslide inventory which represented the larger sized landslides with a sampling resolution of 50 m (Williams et al. 2018).

Approximately one year after the earthquake, the University of Arizona (i.e. Kargel et al. 2016) identified a total of 4312 earthquake-induced landslides occurring before 10th June 2015 before the monsoon season in eastern Nepal. Kargel et al. (2016) was able to synergize a more comprehensive landslide inventory, incorporating passive and active commercial satellite imageries (i.e. resolution between 1-15 m) from various platforms such as GeoEye, Pleiades, Worldview, ALOS-2 and Radarsat-2, as well as aerial observations and field reports. Nevertheless, it has been recognized that the quantity of landslides mapped by Kargel et al. (2016) remains lesser than expected considering the magnitude of this earthquake (i.e. M_w 7.8). It was suggested that detailed investigations could reveal further landslides triggered by this event (Collins and Jibson 2015). Similar landslide inventories were also published during this period (i.e. one year after the earthquake), such as Martha et al. (2017) and Xu et al. (2016).

However, since the study conducted by Kargel et al. (2016) was the first inter-agency and multi-national collaboration in producing the extensive landslide inventory since the 2015 earthquake, their findings adequately represents a medium-term landslide inventory. More recently (i.e. three years after the earthquake), Roback et al. (2018) compiled the most comprehensive inventory till date with a total of 24,915 landslides mapped as polygons. They used very high-resolution commercial satellite imagery which was capable in identifying landslides down to a scale of 20-50 cm and was able to discern smaller landslides (i.e. over tens of square meters) absent from earlier datasets. Consequently, Roback et al. (2018)'s database of landslides was utilized in this study as the long-term landslide inventory.

While it is recognized that complete landslide inventories are valuable assets in landslide research and susceptibility assessments, access to the necessary high-resolution satellite imageries is however severely restricted by cost, coverage and data processing times, especially to the general public. Furthermore, a large number of landslides mapped by high resolution images are distinctly smaller in size and seldom pose a hazard. Conversely, while open-source satellite images are generally catered at coarse resolutions, it implies that landslides have to be sufficiently large to be detected on these images. Large landslides are of greater risk to human lives and infrastructure due to the greater amount of material being moved during slope failures. Indeed, for such purposes, open-source satellite imageries are readily available and can be processed at relatively low-cost. Consequently, it is worth investigating the differences in landslide susceptibilities mapped via coarse and high-resolution satellite images. Rapid assessments of landslide susceptibilities using open-source imageries will be immensely useful for timely disaster relief efforts and aid in

identifying critical areas which might be prone to future landslides, such as in the case of aftershock earthquakes. Rescue efforts may then be directed toward these locations.