

1 **Influences of socioeconomic vulnerability and intra-urban air pollution exposure on**
2 **short-term mortality during extreme dust events**

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1 **Abstract**

2 Air pollution has been shown to be significantly associated with morbidity and
3 mortality in urban areas, but there is a lack of studies focused on studying extreme
4 pollution events such as extreme dust episodes in high-density Asian cities, even
5 though such cities have had extreme climate episodes that could have adverse health
6 implications for downwind areas. More importantly, only a few studies have
7 comprehensively investigated the mortality risks of extreme dust events for
8 socioeconomically vulnerable populations.

9 This paper examined the association between air pollutants and mortality risk in Hong
10 Kong from 2006 to 2010, with a case-crossover analysis, to determine the elevated risk
11 after an extreme dust event in a high-density city. The results indicate that PM_{10-2.5}
12 dominated the all-cause mortality effect at the lag 0 day (OR: 1.074 [1.051, 1.098]).

13 This study also found that people who were aged ≥ 65 , unemployed, or non-married
14 had higher risks of all-cause mortality and cardiorespiratory mortality during days with
15 extreme dust events. In addition, people who were in areas with higher air pollution
16 had significantly higher risk of all-cause mortality.

17 In conclusion, the results of this study can be used to target the vulnerable among a
18 population or an area and the day(s) at risk to assist in health protocol development
19 and emergency planning, as well as to develop early warnings for the general public in

1 order to mitigate potential mortality risk for vulnerable population groups caused by
2 extreme dust events.

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4 **Capsule:** Data-driven methods are established 1) to identify socioeconomically
5 vulnerable populations and high-risk areas across a city, and 2) to evaluate the utility
6 of more general health protocols prior to their adoption.

7

8 **Keywords:** extreme dust events; short-term mortality risk; social vulnerability;
9 socioeconomic vulnerability; spatial analytics

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1 **Introduction**

2 Air pollution has been associated with all-cause, respiratory and cardiovascular
3 morbidity and mortality in urban areas (Garcia et al., 2016; Jerrett et al., 2005; Lu et
4 al., 2015; Pope III & Dockery, 2006), especially in a common urban form in Asian
5 countries, namely a “high-density city” or a “compact city” with high-density living (Ko
6 et al., 2007; Meng et al., 2013; Wong et al., 1999; Wong et al., 2002; Wong et al., 2015).

7 Some studies have also found that extreme pollution events, especially an extreme
8 dust event, can severely increase the health risk within a short period. For example, a
9 39% increase in emergency admissions in Brisbane and a 20% increase in respiratory
10 emergency department visits in Sydney were found during an extreme dust event
11 across Australia in 2009 (Barnett et al., 2012; Merrifield et al., 2013). While the number
12 of extreme dust events across a city may be rare, it is important to analyze their
13 impacts on morbidity or mortality prior to the occurrence of the next extreme event,
14 in order to improve health warnings and emergency plans for disaster risk
15 management. Similar health studies have commonly been conducted for the other
16 types of extreme weather (e.g. heat waves) with an event-based model or a case-
17 crossover model (Ho et al., 2017; Kosatsky et al., 2012). However, there are only a few
18 studies analyzing the adverse effect of extreme dust events on the elevated mortality
19 risk within a very short period (“short-term mortality”). In addition, most pollution

1 studies have not focused on extreme dust events in a high-density Asian city, despite
2 the fact that dust storms across Asia have been recognized as extreme climate
3 episodes with adverse health implications (Zhang et al., 2005; Wong et al., 2010; Wong
4 et al. 2015; Xiao et al., 2015). For example, deserts in Mongolia and northwestern
5 China on average have released 800 tera-grams of dust each year and induced serious
6 air pollution in the northern China and South Korea (Chung and Yoon, 1996; Zhang et
7 al., 1997). Strong easterly and south-easterly winds from the desert and arid surfaces
8 can also bring desert dust to other areas. As a result, Japan (Var et al., 2000), Taiwan
9 (Lin, 2001) and Hong Kong (Wai & Tanner, 2005; Wong et al., 2010) have also observed
10 extreme dust events in the past. In an extreme case, Wong et al. (2010) found a
11 significant increase of PM₁₀ concentration on days with extreme dust events that could
12 be 2 to 6 times higher than the days without dust storms. It is important to evaluate
13 the mortality risk during such storms in order to develop an appropriate mitigation
14 protocol for public health surveillance.

15 In regard to previous health studies, some have reported a significant association
16 between mortality and dust events (Chan & Ng, 2011; Lee et al., 2013; Johnston et al.,
17 2011; Perez et al., 2008; Perez et al., 2012), while some others found an insignificant
18 increase in mortality after dust events (Al-Taiar & Thalib, 2014; Chen et al., 2004;
19 Hashizume et al., 2010; Kwon et al., 2002). It is, therefore, believed that the adverse

1 health effects of dust are varied because of the geographical location and
2 environmental setting of cities.

3 Compared to traditional cities in developed countries, a high-density city has a
4 completely different urban climatic system due to its urban morphology that can highly
5 influence wind ventilation and can affect air pollution risk (Steward & Oke, 2012). For
6 example, Hong Kong is a typical high-density city, with urban areas occupied by high-
7 rise buildings and narrow streets (Chen et al., 2012). This urban morphology forms
8 “urban canyons” that can control wind speed and wind direction (Wong et al., 2011).
9 On a day with an extreme dust event, urban canyons can trap the dust pollutants, and
10 as a result increase urban mortality. Thus, it is necessary to develop a comprehensive
11 assessment mechanism to evaluate the implications of extreme dust events for daily
12 mortality across a high-density city.

13 More importantly, previous studies mainly focused on adverse effects of dust
14 events based on the mortality of the general population (Chen et al., 2004; Johnston
15 et al., 2011). Only a few studies have sketchily described the difference in mortality
16 risk between sub-groups of the population at the individual level after dust events (Lee
17 et al., 2013; Al-Taiar & Thalib, 2014), but this missing part is essential for understanding
18 the influence of socioeconomic vulnerability on mortality. Referring to the guideline of
19 the United Nations Office for Disaster Risk Reduction

1 (<https://www.unisdr.org/we/inform/terminology>), the relationship between
2 subgroups of a population and mortality is related to the “socioeconomic vulnerability”
3 for disaster risk management, that can determine the socioeconomic conditions or
4 processes increasing the susceptibility of an individual to the impacts of a natural
5 hazard. Among these dust mortality studies, age and gender are the only
6 socioeconomic vulnerability factors that have been examined, while others that should
7 have adverse effects on mortality (e.g. social isolation and socioeconomic deprivation)
8 have not been discussed (Clougherty & Kubzansky, 2009; Makri & Stilianakis, 2008;
9 Martins et al., 2004; Medina-Ramón & Schwartz, 2008). There has also been no study
10 identifying the difference in mortality risk between areas with higher and lower air
11 pollution exposure during an extreme dust event. Failure to consider the influences of
12 spatial pollution exposure and individual-level socioeconomic vulnerability may
13 reduce the ability to identify populations at risk during extreme dust events
14 appropriately.

15 In order to investigate the influences of spatial pollution exposure and
16 socioeconomic vulnerability on mortality during a dust storm comprehensively, we
17 applied a time-stratified case-crossover study to estimate the mortality risk of air
18 pollution during extreme dust events between 2006 and 2010 in Hong Kong. Our
19 objectives are 1) to evaluate the contribution of air pollution to dust mortality, 2) to

1 identify the vulnerable population(s) during an extreme dust event, and 3) to evaluate
2 whether areas with higher air pollution are the locations with higher mortality risk
3 (“high-risk areas”) for the general population and vulnerable sub-population(s) during
4 an extreme dust event. The results of our study can further be used to develop
5 environmental health protocols and emergency response systems for extreme dust
6 events across a high-density Asian city in the future.

7

8 **Methods**

9 *Data Collection*

10 We retrieved mortality data of 2006 through 2010 from the Hong Kong Census and
11 Statistics Department. This mortality dataset includes the following variables for each
12 decedent: 1) cause of death according to the 10th revision of the International
13 Classification of Diseases (ICD-10), 2) date of death, 3) age, 4) gender, 5) marital status,
14 6) occupation and 7) location of residence. Location of residence is based on the finest
15 district level for regional planning in Hong Kong, namely the “Tertiary Planning Unit”
16 (TPU).

17 Hourly air pollution data (PM_{2.5}, NO₂, O₃, PM₁₀, and SO₂) were retrieved from all
18 monitoring stations of the Hong Kong Environmental Protection Department, and
19 were recalculated to a daily average. In this study, data from three roadside stations

1 (Mong Kok, Causeway Bay, and Central) were excluded from calculation, in order to
2 minimize the bias from traffic-related pollution. This pollution dataset was co-matched
3 with the mortality dataset based on the date of death of each decedent.

4 We also retrieved the spatial pollution exposure data from the Aerosol Optical
5 Thickness (AOT) based on satellite images. The AOT can indicate particulate matters at
6 ground level in a spatial context, with the appropriate combination of land use
7 information and other meteorological factors, such as wind speed (Bilal et al., 2016;
8 Wong et al., 2015). The spatial distribution of AOT can influence the health risk during
9 typical air pollution events (Lai et al., 2014). In our study, AOT data were derived from
10 the average of four cloud-free MODIS images retrieved on Apr 17, 2006, Apr 28, 2009
11 and Mar 26, 2010 to represent a specific scenario during extreme dust events in Hong
12 Kong. Average AOT values of each TPU were calculated based on the AOT images
13 derived from the simplified high resolution Moderate Resolution Imaging
14 Spectroradiometer (MODIS) Aerosol Retrieval Algorithm (Bilal et al., 2013; Bilal &
15 Nichol, 2015) using MODIS images at 500m resolution. The average AOT of each TPU
16 was co-matched with the mortality dataset based on locations of residence.

17

18 *Case-crossover design*

19 We applied a time-stratified case-crossover design to estimate the excess mortality

1 during an extreme dust event. The time-stratified case-crossover approach is a
2 common epidemiological design that can directly estimate the exposure-mortality
3 relationship based on a small sample size of cases, and with less bias due to the
4 number of control samples. Unlike time-series analysis, which needs to be controlled
5 or adjusted by the weekday/weekend effect, seasonality and long-term trends, a case-
6 crossover approach is independent of such effects based on its “cases as their own
7 self-matched controls” structure (Maclure, 1991). The ability of this design to estimate
8 adverse health effects of an extreme weather event has also been amply
9 demonstrated (Bell et al., 2008; Ho et al., 2017; Johnston et al., 2011; Perez et al., 2012;
10 Tobías et al., 2011). In this case-crossover study, days with extreme dust events were
11 identified based on a previous study (Wong et al., 2010) using the NASA Aerosol
12 Robotic Network’s (AERONET) sunphotometer size distribution inversion data, the
13 backward trajectories model of Hybrid Single Particle Lagrangian Integrated Trajectory
14 (HYSPLIT), and meteorological reports. For each death on a day with extreme dust
15 events (case days), exposure on the case days was compared with the exposure on the
16 same weekday each week within the same calendar month (control days), in order to
17 prevent bias introduced by alternative control selection methods (Chan & Ng, 2011;
18 Bell et al., 2008; Ho et al., 2017; Janes et al., 2005; Johnson et al., 2011; Perez et al.,
19 2008; Perez et al., 2012). This set of cases and controls was used to estimate the

1 potential increase in health risk immediately after an extreme dust event. A
2 conditional logistics regression model from the *survival* package of R statistical
3 software was used to estimate the odds ratios (OR) for mortality associated with
4 extreme dust events (Therneau, 2015). Following previous studies using a case-
5 crossover approach for dust mortality estimation (Chan & Ng, 2011; Johnson et al.,
6 2011; Tobías et al., 2011), the daily average of air pollutants (PM_{10-2.5}, PM_{2.5}, NO₂, O₃,
7 and SO₂), average temperature and relative humidity for case days and control days
8 were included in the model, while concentrations of PM_{10-2.5} were retrieved by
9 subtracting PM_{2.5} from PM₁₀. In addition, a non-linearity test of additional squared
10 terms for both PM_{10-2.5} and PM_{2.5} were added to the regression models (Basu et al.,
11 2015). This case-crossover analysis was repeated for deaths on the three days after
12 extreme dust events (lag 1 to lag 3), in order to evaluate whether there was a
13 prolonged effect on mortality due to trapping of massive amounts of dust in urban
14 canyons. All-cause mortality and cardiorespiratory mortality (ICD-10 codes I00-I99 and
15 ICD-10 codes J00-J99) were examined in this study.

16

17 *Effect modification of mortality risk*

18 We examined the effect modification of individual-level socioeconomic
19 vulnerability by creating a dummy interactive variable for vulnerable and high-

1 exposure groups. Four vulnerable groups were selected: 1) age ≥ 65 , 2) female, 3)
2 economically inactive, 4) non-married. In detail, the categories are: 1) represents
3 seniors who have been recognized as a vulnerable group in past research (Cutter et al.,
4 2003; Medina-Ramón & Schwartz, 2008); 2) indicates the difference in vulnerability by
5 gender (Cutter et al., 2003); 3) represents socioeconomic vulnerability due to
6 unemployment or retirement (Bell et al., 2012; Cutter et al., 2003; Ho et al., 2015; Ho
7 et al., 2017; Makri & Stilianakis, 2008); and 4) represents a group with potential social
8 isolation (Wong et al., 2016). These vulnerability and exposure factors were compared
9 with the control groups (age < 65 , male, employed, and married) in order to evaluate
10 the statistical significance of each variable.

11 For the vulnerable populations identified above, we have further evaluated the
12 effect modification of spatial pollution exposure on all vulnerable groups, in order to
13 investigate whether areas with higher air pollution can further contribute to higher
14 mortality risk. Similar to the analyses above, each vulnerable population group was
15 evaluated by creating a dummy interactive variable for high-exposure groups. In this
16 study, the high-exposure groups are the decedents in areas with higher AOT ($\geq 33^{\text{th}}$
17 percentile), in which these areas represent regions with higher air pollution potentially
18 contributed by particulate matters. We repeated the analyses for decedents in the
19 general population and decedents in each vulnerable population group, by comparing

1 these case groups with the control groups (decedents in AOT <33th percentile), in order
2 to evaluate whether there is a difference in risk with statistically significant between
3 areas with higher and lower air pollution.

4

5 **Results**

6 *Data summary*

7 There were ten identified days with extreme dust events between 2006 and 2010
8 (Apr. 16-17, 2006; Apr. 27-30, 2009; and Mar. 23-26, 2010). Average PM_{10-2.5}
9 concentration of these 10 days was 44.47 µg/m³, and 964 decedents were reported
10 within these days in Hong Kong. Comparing all decedents on case days and control
11 days, PM_{10-2.5} concentrations on case days were on average 147.6% higher than on the
12 control days, while other air pollutants were generally lower except O₃. These findings
13 were consistent with other Asian dust studies indicating exponential increases of PM₁₀
14 and O₃ during extreme dust events (Chen et al., 2004).

15

16 *Mortality risk of air pollution during an extreme dust event*

17 We estimated the ORs of PM_{10-2.5}, and PM_{2.5} on the days with extreme dust events
18 (Table 2). PM_{10-2.5} significantly increased both all-cause and cardiorespiratory mortality.
19 On a day with an extreme dust event (lag 0), a 7.4% increase in all-cause mortality and

1 7.0% increase in cardiorespiratory mortality are expected with a 10 $\mu\text{g}/\text{m}^3$ increase of
2 $\text{PM}_{10-2.5}$. It can be concluded that $\text{PM}_{10-2.5}$, the major component of a dust storm, was
3 the key factor contributing to adverse health effect across this high-density city. In
4 contrast, although some studies have found that $\text{PM}_{2.5}$ may increase mortality during
5 an extreme dust event, this was not the case for Hong Kong.

6 In addition, there were no prolonged influences of extreme dust events in Hong
7 Kong. The day after an extreme dust event (lag 1) had 3.1% lower all-cause mortality
8 and 1.9% lower cardiorespiratory mortality than the lag 0 day. Results for two and
9 three days after a storm (lag 2 and lag 3) were very insignificant, with extreme values
10 of the 95th confidence intervals. This implies that extreme dust events do not result in
11 a prolonged pollution event in the post-storm period in a high-density city, and the
12 increase in pollutants on the day of extreme dust events is the only factor contributing
13 to fatal effects in Hong Kong.

14

15 *Effects of socioeconomic vulnerability on mortality risk*

16 Among all socioeconomic vulnerability variables based on individual-level data,
17 economic inactivity had the highest influence on mortality risk (Table 3). People who
18 were economically inactive had approximately 5.5% higher all-cause mortality risk and
19 5.6% higher cardiorespiratory mortality risk from a 10 $\mu\text{g}/\text{m}^3$ increase in $\text{PM}_{10-2.5}$ than

1 those who were employed during a day with an extreme dust event. Seniors and non-
2 married persons also had higher mortality risk. A person aged ≥ 65 had 4.4% higher
3 risk of all-cause mortality and 5.3% higher cardiorespiratory mortality than who were
4 under the age of 65. A person who was not married had 4.1% higher risk of all-cause
5 mortality and 4.7% higher cardiorespiratory mortality. Table 3 also showed that
6 females had insignificantly higher risk of all-cause mortality and cardiorespiratory
7 mortality on a day with an extreme dust event.

8

9 *Effects of intra-urban air pollution on mortality risk*

10 Based on the results above, we further evaluate the influence of intra-urban air
11 pollution on mortality risk of the general population and specific vulnerable
12 populations (seniors, the economically inactive, and non-married). The results
13 indicated that the spatial distribution of pollution exposure influenced dust-related
14 mortality. Grouped by all decedents, there were higher all-cause and cardiorespiratory
15 mortality risks in areas with AOT \geq 33th percentile (ORs: 1.045 [1.020, 1.070] and
16 1.044 [1.004, 1.086]). There were also higher all-cause and cardiorespiratory mortality
17 risks in areas with higher intra-urban air pollution for the senior population (OR: 1.043
18 [1.019, 1.067] and 1.047 [1.002, 1.095]). In addition, for people who were
19 economically inactive, all-cause mortality risk was found to be higher in areas with

1 higher pollution (OR: 1.049 [1.018, 1.080]); and people who were not married were
2 expected to have higher cardiorespiratory mortality risk during an extreme dust event
3 (OR: 1.038 [1.004, 1.073]).

4

5 **Discussion**

6

7 *Comparison with other studies*

8 In this study, a time-stratified case-crossover approach was applied to estimate the
9 mortality risk of air pollution after an extreme dust event. Our results indicate that
10 PM_{10-2.5} is the dominant factor in the air pollution risk of an extreme dust event,
11 contributing to a 7.4% increase in all-cause mortality and 7% increase in
12 cardiorespiratory mortality on the day of an extreme dust event. There was a weak
13 prolonged effect of extreme dust events in Hong Kong, such that the significant
14 influence on mortality from PM_{10-2.5} continued on the day after an extreme dust event,
15 after which there was no further effect on mortality. At lag 0, the mortality risks are
16 1.9-3.1% higher than at lag 1. We also evaluated four socioeconomic vulnerability
17 factors and found that persons who were economically inactive or non-married or
18 seniors had higher mortality risk after an extreme dust event. In addition, both the
19 general population and vulnerable populations had higher mortality risk in areas with
20 higher pollution exposure (AOT \geq 33th percentile) than the other regions in Hong Kong.

21 These results are consistent with previous findings; e.g. Johnston et al. (2011)

1 found a 16% increase [3%, 30%] in all-cause mortality at a lag of 3 days after a dust
2 event in Sydney, Australia; Chen et al. (2004) indicated there was a 7.66% and 4.92%
3 increase in respiratory deaths on the first and second day after a dust storm in Taipei,
4 Taiwan; Lee et al. (2013) observed a weaker but significant association between dust
5 and mortality in seven cities in South Korea, with a 2.91% increase in cardiovascular
6 mortality found on the day of a dust storm. These results and our study all indicated
7 an increased risk immediately after a dust event, even though all these study areas
8 were relatively far from the deserts. In contrast, one study of areas nearby the Arabian
9 Desert, such as Kuwait, found no significant association between dust events and
10 mortality (Al-Taiar & Thalib, 2014), which implies that extreme dust episodes induce
11 significant health effects in downwind cities, while cities near the desert may have
12 insignificant links between dust and mortality. This is an important finding, since all
13 these studies demonstrate excessive amounts of particulate matters during an
14 extreme dust event, while not all these studies found significant association between
15 dust and mortality. This further implies that differences in amounts of particulate
16 matters between dusty days and regular days may be the key to inducing severe
17 mortality, in which locations closer to a desert are expected to have higher baseline
18 particulate matters that have already contributed to a long-term adverse health
19 impact to the general population, with less discernable short-term impact from dust

1 storms. This phenomenon is also observed with other extreme climatic events; for
2 example, the difference in temperature between days was found in one study to be
3 the major factor behind increasing mortality risk due to an extreme weather event
4 (Zeng et al., 2014).

5

6 *Protocols for Disaster Risk Reduction*

7 In this study, we also evaluated the relationship of mortality and socioeconomic
8 vulnerability. Based on our finding, a person who is economically inactive or not
9 married or older has the highest risk immediately after an extreme dust event. This is
10 important to public community health planning, since socioeconomic deprivation is
11 well documented as a key variable involved in vulnerability in terms of general health
12 (Bell et al., 2012), climatic risk (Aminipouri et al., 2016; Chan et al., 2012; Ho et al.,
13 2017), and air pollution (Clougherty & Kubzansky. 2009; Makri & Stilianakis, 2008;
14 Martins et al., 2004). This vulnerability factor may be associated with poor housing
15 quality, social isolation, and lack of health care, and all these sub-factors may directly
16 or indirectly raise the community health risk on days immediately after an extreme
17 dust event. Failure to consider such socioeconomic vulnerability factors may reduce
18 the possibility of identifying and protecting at-risk population groups during extreme
19 dust events in the future. Previous dust mortality studies have only focused on

1 vulnerability due to advanced age (Lee et al., 2013; Al-Taiar & Thalib, 2014). Our study
2 shows that factors other than age are important for identifying at-risk groups, while
3 potential social isolation (operationalized here as the non-married population) and
4 unemployment in particular were associated with an increase in risk similar to that for
5 advanced age. This supports our conclusion that more socioeconomic vulnerability
6 factors need to be addressed in research and public policy on dust episodes.

7 These results imply that a protocol for disaster risk reduction should develop as
8 follows: a) a target on sustainable planning in areas with higher intra-urban air
9 pollution (e.g. increases in city ventilation paths and vegetation cover for improving
10 air quality), in order to reduce the modifying effect of mortality risk during an extreme
11 dust event from regional pollution; b) arouse the public especially to seniors and
12 people with lower socioeconomic status to increase their awareness for disaster
13 preparation, as they may have less resources and prior education to cope with an
14 outbreak of disaster; and c) developing community network and social awareness
15 systems for disaster risk management, as results have shown that vulnerable
16 population with higher social isolation can have higher risk from natural disasters; and
17 d) implementing a warning system for reporting days with potential higher risk to the
18 public. In conclusions, items a) and d) involve top-down design involving governance
19 and policy-making for disaster management, while b) and c) can be bottom-up

1 strategies involving local non-governmental organizations (NGOs) and charitable
2 organizations.

3

4 *Limitations and future directions*

5 One limitation of this study is that the model has not comprehensively accounted
6 for the spatial effect, as similar to other time-stratified studies. This is partially due to
7 the limitation of weather station data, as stated in other studies (Ho et al., 2017; Thach
8 et al., 2015), in which these stations are sparsely and unevenly distributed. In order to
9 develop a spatiotemporal approach or an ecological study to predict dust mortality,
10 higher quality spatial data are required. Remote sensing satellite imagery may thus be
11 an alternative for developing a spatiotemporal study, but this may be constrained by
12 satellite overpass times and cloud-contamination. Therefore, a combination of both
13 in-situ air quality monitoring data and satellite images may prove most useful for
14 future studies.

15 Another limitation in the present research is the vulnerability variables. Although
16 this study investigated the modifying effect of gender, unemployment, older age and
17 marital status on mortality risk, other factors such as household income, education
18 level, and underlying diseases should also be included in a more comprehensive
19 assessment. However, due to the limitation of the mortality data used in this study,

1 there was no such individual-level information for each decedent in Hong Kong. An
2 alternative method, using census data to represent socioeconomic vulnerability, has
3 been suggested by others (Chan et al., 2012; Ho et al., 2017). However, this method is
4 more appropriate for determining the social environment influencing an individual,
5 but not for defining the personal characteristics of an individual (Kosatsky et al., 2012)
6 who may be more vulnerable and therefore at risk during an extreme event. For the
7 purpose of this study, it is more appropriate to use personal characteristics of each
8 decedent for modelling, while for further study, using census data for estimating
9 community vulnerability may be appropriate for determining intra-city risk (Chan et
10 al., 2012).

11 Results from this study suggest that a combination of pollution data from an air
12 quality monitoring network and a health dataset can be used to develop protocols for
13 future health warning systems. Similar approaches have been applied to determine
14 days with potential disaster risk based on other extreme climatic events, such as heat
15 waves (Chau et al., 2009), with promising results, as significant risk reduction was
16 found after a warning system had been set up (Chau et al., 2009; Tan et al., 2007).
17 Incorporating these ideas, the results from this study can be further used to help set
18 guidelines for public health surveillance, by determining days at risk based on weather
19 forecasting and the hourly reports of PM_{10-2.5} from governmental monitoring stations.

1

2 **Conclusions**

3 In this study, a time-stratified case-crossover approach was developed to evaluate
4 both the risk of PM_{10-2.5} immediately after an extreme dust event, and the difference
5 in risk of vulnerable population groups in a high-density city (Hong Kong). We observed
6 a significant increase in mortality risk on the day of an extreme dust event. The results
7 also show that persons who were economically inactive or elderly or non-married had
8 a higher PM_{10-2.5} risk during a day with an extreme dust event, and areas with higher
9 AOT also had higher mortality risk. Based on these observations, the areas and
10 population groups vulnerable to dust-induced mortality can be pinpointed, while
11 pollution data from an air quality monitoring network can be used to develop a
12 protocol for a health warning system. Combining satellite images and air quality
13 monitoring network data is recommended, in order to provide holistic and synoptic
14 observations over an area, and this can be further developed to estimate community
15 health risks in different neighborhoods and for the purpose of public health
16 surveillance.

17

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- 17

1 Captions of Figures

2 Figure 1 – Total number of deaths in all TPU during extreme dust events between
3 2006 and 2010.

4 Figure 2 – Areas with higher and lower intra-urban air pollution (determined by
5 AOT) in Hong Kong.

6

1

Pollutants	Case (n = 964)	Control (n = 3367)	T-Test (p-value)	% Difference
PM _{10-2.5}	44.47 µg/m ³	17.96 µg/m ³	<0.05	147.6%
O ₃	65.37 µg/m ³	44.02 µg/m ³	<0.05	48.5%
NO ₂	45.1 µg/m ³	55.87 µg/m ³	<0.05	-19.3%
SO ₂	11 µg/m ³	16.95 µg/m ³	<0.05	-35.1%
PM _{2.5}	33.31 µg/m ³	33.64 µg/m ³	0.54	-0.98%

2

3 **Table 1:** Data Summary. This table reports the average values of all pollutants,
4 separated by all cases and all controls. **Bold text** indicates the pollutants with
5 significantly higher values (µg/m³) on the days with dust storms (case days) compared
6 to days without a dust storm. % Difference is the percentage difference between
7 average values of all cases and all controls.

8

1

Pollutant		OR (all-cause mortality)	OR (cardiorespiratory mortality)
PM _{10-2.5}	Lag 0	1.074 [1.051, 1.098]	1.070 [1.036, 1.105]
	Lag 1	1.043 [1.023, 1.064]	1.051 [1.021, 1.083]
PM _{2.5}	Lag 0	0.899 [0.876, 0.922]	0.919 [0.885, 0.954]
	Lag 1	0.908 [0.888, 0.928]	0.921 [0.891, 0.952]

2

3 **Table 2.** Table of odds ratios (OR) at lag 0 to 1 of all-cause and cardiorespiratory
4 mortality, for 10 µg/m³ increase of PM_{10-2.5} and PM_{2.5}, with the 95th confidence
5 interval. **Bold text** indicates the most significant results

1

Socioeconomic Vulnerability (Individual Level)		OR at lag 0 (all-cause mortality)	OR at lag 0 (cardiorespiratory mortality)
Age	>=65	1.044 [1.029, 1.059]	1.053 [1.029, 1.078]
	<65	1.047 [0.994, 1.103]	1.045 [0.920, 1.186]
Gender	Female	1.057 [1.014, 1.102]	1.062 [0.998, 1.131]
	Male	1.033 [1.018, 1.049]	1.030 [1.009, 1.052]
Socioeconomic Status	Economically Inactive	1.055 [1.039, 1.070]	1.056 [1.030, 1.081]
	Economically Active	1.024 [0.992, 1.057]	1.019 [0.974, 1.066]
Marital Status	Non-married	1.041 [1.018, 1.065]	1.047 [1.004, 1.093]
	Married	1.034 [1.013, 1.056]	1.030 [1.003, 1.056]

2

3 **Table 3.** Tables of the effect modification of socioeconomic vulnerability for 10 $\mu\text{g}/\text{m}^3$
4 increase of $\text{PM}_{10-2.5}$, with 95th confidence interval. **Bold text** indicates results with
5 significant difference between vulnerable and non-vulnerable groups.

6

1

Influence of Intra-urban air pollution		OR at lag 0 (all-cause mortality)	OR at lag 0 (cardiorespiratory mortality)
General Population	Areas with higher AOT ($\geq 33^{\text{th}}$ percentile)	1.045 [1.020, 1.070]	1.044 [1.004, 1.086]
	Areas with lower AOT ($< 33^{\text{th}}$ percentile)	1.031 [1.012, 1.050]	1.029 [1.002, 1.057]
Aged ≥ 65	Areas with higher AOT ($\geq 33^{\text{th}}$ percentile)	1.043 [1.019, 1.067]	1.047 [1.002, 1.095]
	Areas with lower AOT ($< 33^{\text{th}}$ percentile)	1.030 [1.008, 1.053]	1.029 [1.001, 1.057]
Economically inactive	Areas with higher AOT ($\geq 33^{\text{th}}$ percentile)	1.049 [1.018, 1.080]	1.048 [0.999, 1.099]
	Areas with lower AOT ($< 33^{\text{th}}$ percentile)	1.029 [1.011, 1.049]	1.029 [1.001, 1.059]
Non-married	Areas with higher AOT ($\geq 33^{\text{th}}$ percentile)	1.041 [1.014, 1.069]	1.038 [1.004, 1.073]
	Areas with lower AOT ($< 33^{\text{th}}$ percentile)	1.037 [1.000, 1.075]	1.038 [0.982, 1.099]

2 **Table 4.** Tables of the effect modification of intra-urban air pollution on general
3 population and vulnerable populations, for $10 \mu\text{g}/\text{m}^3$ increase of $\text{PM}_{10-2.5}$, with 95^{th}
4 confidence interval. **Bold text** indicates results with significant difference between
5 areas with higher air pollution and lower pollution.

6