

D 5.2

Report on projecting the future social, health and economic burden of risk factors, disease and injury in the EU

Report Information

Title:	Validated European Health Policy Model software and documentation
Authors:	Michele CECCHINI, Sebastien CORTAREDONA, Marion DEVAUX, Anissa ELFAKIR, Yevgeniy GORYAKIN, Alienor LEROUGE, Jean-Paul MOATTI, Thierry PELLEGRINI, Franco SASSI, Klaus STEINNOCHER, Bruno VENTELOU
Version:	Version 1
Work Package:	WP5 Modelling and policy simulation
Date of publication:	31/12/2017
Dissemination level:	Public

Project Information

Project Acronym	FRESHER
Project Full Title:	Foresight for health policy development and regulation
Grant Agreement N°:	643576
Starting Date:	01/01/2015
Duration:	36 months
Coordinator:	AMU - Jean Paul Moatti

Table of Contents

1. Background	3
2. Exploration of environmental risk factors influence on the future health	5
2.1. Understanding the distribution of risk factors at the local level.....	5
2.1.1. Importance of the geospatial analysis for environmental risk factors	5
2.1.2. Analysis at the City level – AIT contribution for the FRESHER consortium	5
2.2. What is the evidence on the effects of environmental RFs and NCDs?	22
2.2.1. Air pollution – Ozone (O3) and particulate matter (PM2.5).....	22
2.2.2. Temperature: heat waves.....	23
2.2.3. Green space area	26
2.2.4. Fast food and alcohol outlet density	31
3. Data and Methods: Overview of the Microsimulation model and how Scenarios are modelled.....	34
3.1. General principle	34
3.2. Baseline 2050 projections	36
3.3. Integrating Scenarios.....	37
4. The influence of behavioural RFs on the future health outlook: Results of the microsimulation model	40
4.1. Europeans will live longer, but with more chronic diseases	40
4.2. Quantifying the impacts of alternative scenarios	43
4.3. Health expenditures projections	44
5. Policy actions: what can be achieved?	48
5.1. How policies have succeeded to reduce smoking, alcohol use and obesity?	48
5.2. What could be expected with the traditional public health policy packages?“	48
6. Conclusion and discussion.....	50



1. Background

In the coming decades, European Countries will be facing the major challenge of an increasing burden of chronic diseases (NCDs). This burden will weigh heavily on the European population, with likely impacts on the sustainability of welfare systems. According to the World Health Organization, taken together, the five main chronic conditions (diabetes, cardiovascular diseases, cancer, chronic respiratory diseases and mental disorders) account for an estimated 86% of the deaths and 77% of the disease burden in the Region.

However, the true spread of all these diseases will remain, for the future, strongly dependent on the distribution of risk factors and societal trends that –following several scientific studies- are strong determinants of their epidemiology (WHO (2014) *Global status report on non communicable diseases 2014*. Geneva: World Health Organization). The FRESHER project has evaluated the potential impact of four prospective scenarios at the horizon 2050 based on alternative hypotheses for how major societal trends may fuel, or mitigate, a further spread of chronic diseases, and, using a microsimulation modelling, has produced quantitative forecasts of these trends and the possible impacts policies may have on them.

In economics, microsimulation methods are used to evaluate consequences of alternative policy decisions, both for individuals and for the whole society (Orcutt, 1957, Citro and Hanushek, 1991, Bourguignon and Spadaro, 2003); this methodology has been applied for the ex ante assessment of various reforms in the areas of tax policies and/or social policies (including health, see Abraham 2013). In health sciences, microsimulation refers to a type of simulation modelling which generates individual life histories, generally health-status transitions (see Briggs and Sculpher, 1998, for a review, Cogneau and Grimm, 2008, for HIV application). We propose here a mix between these two approaches in order to evaluate the impact of alternative scenarios and healthcare policies on the future of European population' health and healthcare expenditures: from the medical perspective we borrow the idea that individual life histories can be virtually created (through a probabilistic process) under different scenarios; from economics, we use the idea that aggregated impact of scenarios or policy decisions, for instance on healthcare expenditures, can be captured by a microeconomic modelling of individual behaviors.

This report is made of the five following sections: section 2 discusses the environmental risk factors for NCDs, both at the thin geographic level of the cities and at larger levels; some of these works have been included in the microsim exercise, although we had to make a pragmatic selection among the risk-factors to be finally included in the modeling exercise. Section 3 offers a general overview of the microsimulation model and how projections are made taking into account four alternative scenarios for our future health (see deliverable D4.2). Section 4 presents the main results of the 2050 projections in terms of health outcomes and medical expenditures. Section 5 discusses the effects of



public health policies to tackle unhealthy behavioural risk factors. Section 6 provides elements for conclusion and discussion. As this document D5.2 mainly focuses on results and policy messages, the reader should keep in mind that (s)he can also refer to a complementary document, deliverable D5.3, for more technical details on the model. More generally, this report should be read in connection with a series of reports presenting the work that has been carried out in other FRESHER work packages.



2. Exploration of environmental risk factors influence on the future health

2.1. Understanding the distribution of risk factors at the local level

2.1.1. Importance of the geospatial analysis for environmental risk factors

Researchers and health professionals increasingly recognize that the built environment influences health and health behaviors. A famous study using the American Cancer Society (ACS) cohort has assessed the relation between particulate air pollution and mortality, with conclusive results on the causal relationship (Pope and al, 2003). More recent studies with longer follow up and improved exposure data have all demonstrated air pollution effects on all-cause and cause-specific mortality¹. The city of Los Angeles, in particular, has been observed extensively, with the outcome of alarming results, even more alarming than the first one using the same ACS cohort (Jerret and al, 2005). The ACS studies have also been used by the World Health Organization as a basis for estimating the burden of mortality attributable to air pollution.

Longstanding expositions to air pollution is not the only risk factor that urban life creates. Studies have shown a relation of availability and proximity of certain types of food outlets in a neighborhood to bad dietary behaviors and then nutrition related disease (Morland, Wing & Roux, 2002).

Following all these elements of literature, the geographic distribution of health-related risk factors in cities is now recognized as an important source of better knowledge and understanding of the NCDs epidemiology. The FRESHER project therefore has decided to invest resources in geospatial analysis.

2.1.2. Analysis at the City level – AIT contribution for the FRESHER consortium

The Austrian Institute of Technology (AIT) geospatial model, developed under task WP5.2, aims at analyzing different aspects of health exposure at city-level. Three case study areas were selected, representing one city each in three different European regions (Central-Eastern, Northern, Southern). Those cities are Vienna (Austria), Tallinn (Estonia) and Lisbon (Portugal).

Various environmental and socio-contextual risk factors are considered for health exposure analysis. These include directly measured parameters related to air pollution as well as approximated adverse influencing parameters like access to fast food and nightlife locations as well as green urban space. In a geospatial sense the aforementioned environmental variables refer to continuous fields (i.e. grids interpolated from point station measurement data) that are overlaid with disaggregated population distribution grids in order to directly estimate exposure patterns. The approximated variables refer to modeling exposure in a sense of people's accessibility to discrete spatial features such as fast food restaurants and urban parks.

Results of the geospatial analysis serve as input for the micro-simulation model developed by OECD. While modeled in spatially-explicit manner (raster and vector), output is eventually aggregated and provided in tabular format (e.g. at district or municipality level) to OECD for integration in the micro-simulation modeling framework. For compliant interfacing of the two models, certain compromises need

¹ For example : Pope, C. A., Burnett, R. T., Thurston, G. D., Thun, M. J., Calle, E. E., Krewski, D., & Godleski, J. J. (2004). Cardiovascular mortality and long-term exposure to particulate air pollution. *Circulation*, 109(1), 71-77.



to be taken. Aside the tabular aggregation, the main issue to be addressed thereby is the handling of population and its characteristics. The OECD micro-simulation model handles population as individuals.

The geospatial model, in its initial setup, handles population in absolute terms, illustrating distribution patterns in space and time, without individual characteristics attached. That approach refers to the earlier-developed *DynaPop* model (Aubrecht et al., 2014) which represents dynamic spatio-temporal patterns of human activity (e.g. diurnal, weekly). To facilitate linking the two models, one option (keeping the dynamic setup) is to model population groups, e.g. certain age and activity groups (such as working population, students, retired people etc.). In order to be able to handle these population groups properly the temporal variation of population is limited to day-time and night-time representations.

Comparing the three test cities – Vienna, Tallinn, Lisbon

To compare the results of all three test-cases, one has to consider that the actual modelling-area of the three cities differ quite strong, in size as well as in their statistical and environmental characteristics. Figure 1 and table 1 demonstrate this fact. Especially for the test-case Lisbon one should keep in mind, that only the municipality of Lisbon is considered. Due to its considerably smaller extent compared to the other two cities, evaluations have been carried out on the level of five UIT (*Unidades de Intervenção Territorial*) instead of 24 parishes (*freguesias*). This should guarantee a better comparability of the results.

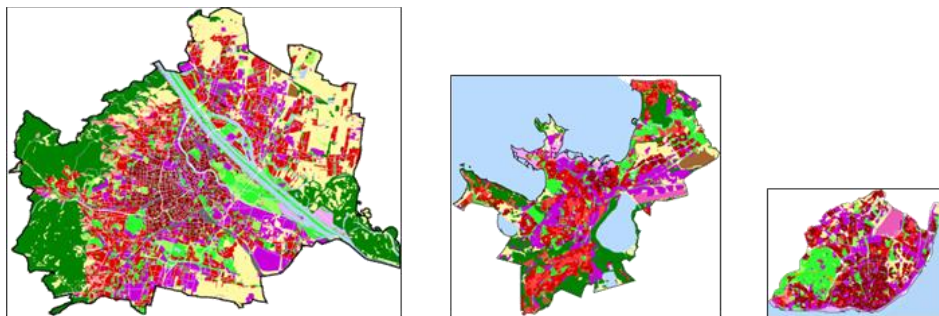


Fig.1: Urban atlas representation of Vienna (left), Tallinn (middle) and Lisbon (right), considering a comparable scale for the three cities

	area [km ²]	# of districts	reference years	population	population density per [km ²]	annual pop-change [%]	share of pop 65yr+ [%]	unemployment rate [%]
Vienna	414.87	23	2006 / 2013	1,741,339	4197	0,74	17.0	13.3
Tallinn	156.31*	8	2006 / 2015	434,426	2779*	0,85	17.5	6.2
Lisbon	86.90**	5***	2006 / 2014	548,163	5904**	-0,28	23.6	17.6

* without island Aegna; ** new admin borders 2012; *** 5 UIT instead of 24 freguesias

Table 1: Comparison of basic indicators for Vienna, Tallinn and Lisbon

For the analysis of exposure to air pollution particulate matter (PM₁₀) and Ozone (O₃) were chosen. The first one contains 50 % of particles with a diameter of 10µm, a higher proportion of smaller particles and a lower proportion of larger particles. Particles of this size can reach beyond the larynx and deep into the lungs. They are therefore particularly harmful to health, especially for very young and elderly people. Higher concentrations of Ozone (O₃) may result in impaired lung function, increased lung disease and possibly premature deaths. At the ground, higher concentrations of ozone are produced by other air pollutants - the ozone precursors, e.g. nitrogen oxides and volatile organic compounds - and sunlight. The higher solar radiation is therefore a main reason for higher concentrations during summer month. Conversely, the rapid reaction between O₃ and NO is responsible for lower concentrations near heavy emission sources such as major roads. Therefore, higher levels remain in less polluted areas. PM_{2.5} - finer particulate matter with 50 % of particles with a diameter of 2.5µm – initially considered for exposure analysis was not taken into consideration due to very few measuring stations in the three cities. Figure 2 below shows interpolated PM₁₀ (left) and O₃ data (right) on a European scale for the year 2012, provided by the European Environment Agency (EEA).

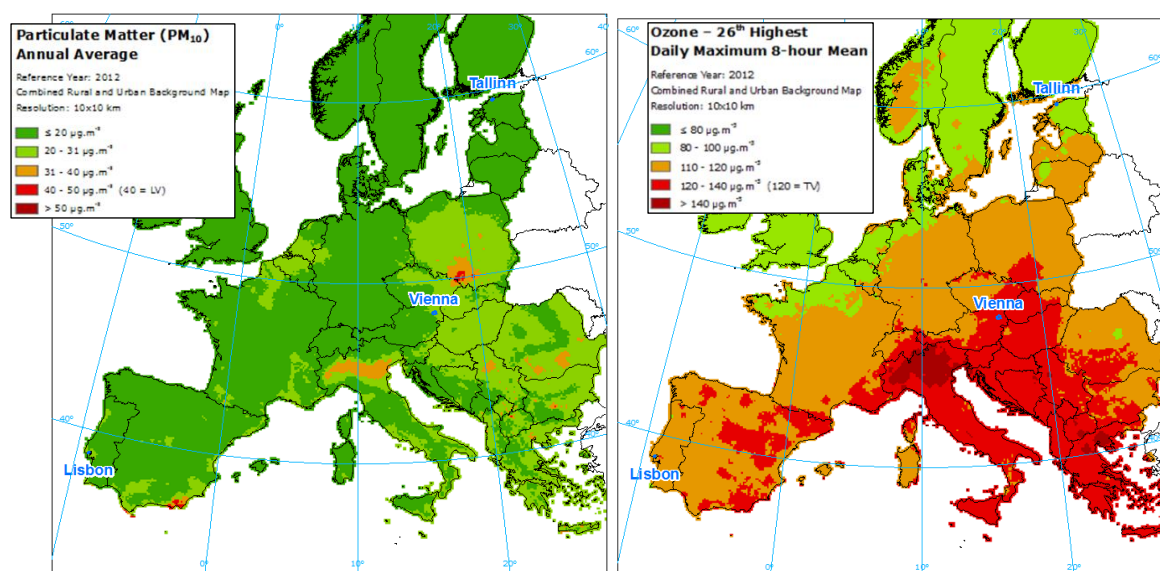


Fig.2: Interpolated air quality data 2012 - PM₁₀ (left) and O₃ (right) (source: 2012_shapefile.zip from EEA-homepage <https://www.eea.europa.eu/data-and-maps/data/interpolated-air-quality-data-2#tab-based-on-data>)

Comparing the three test-sites in a Pan-European context (10x10 km grid, daily 8-hour maximum loads) highlights the general differences: while PM₁₀ seems to be rather low in the three test cities on the coarse European level, Vienna shows high ozone concentrations, mainly because of transport of precursors from eastern neighbor countries. The maps are derived primarily from Airbase background station monitoring data, few EMEP monitoring station data supplemented with altitude, meteorological ECMWF data and EMEP concentration modelling data. Additional information can be found at the EEA homepage, e.g. <https://www.eea.europa.eu/data-and-maps/data/aireporting-2>.

Modelling of population exposure for Vienna case study

The Vienna case study covers the 23 administrative districts of Vienna with a total area of 415 km² and a population of 1.75 Mio. As temporal reference the years 2006 and 2013 were chosen due to data availability. The modelling of night time population is based on census data, including 18 age classes (< 05, 05-09,, 80-84, >85 years), and gender. These population-classes were spatially disaggregated to a 100 x 100m raster representing residential areas and housing densities. For the day time population model, commuting data per district (for working population and pupils) were taken into account, as well as locations of workplaces, schools, kindergartens and retirements homes.

According to the specification given by OECD only population resident in the city of Vienna were considered in the modelling approach. In-commuters from the Viennese suburbs or other places out of Vienna were neglected. Figure 3 shows the input on district level and the dis-aggregated 100m cell population.

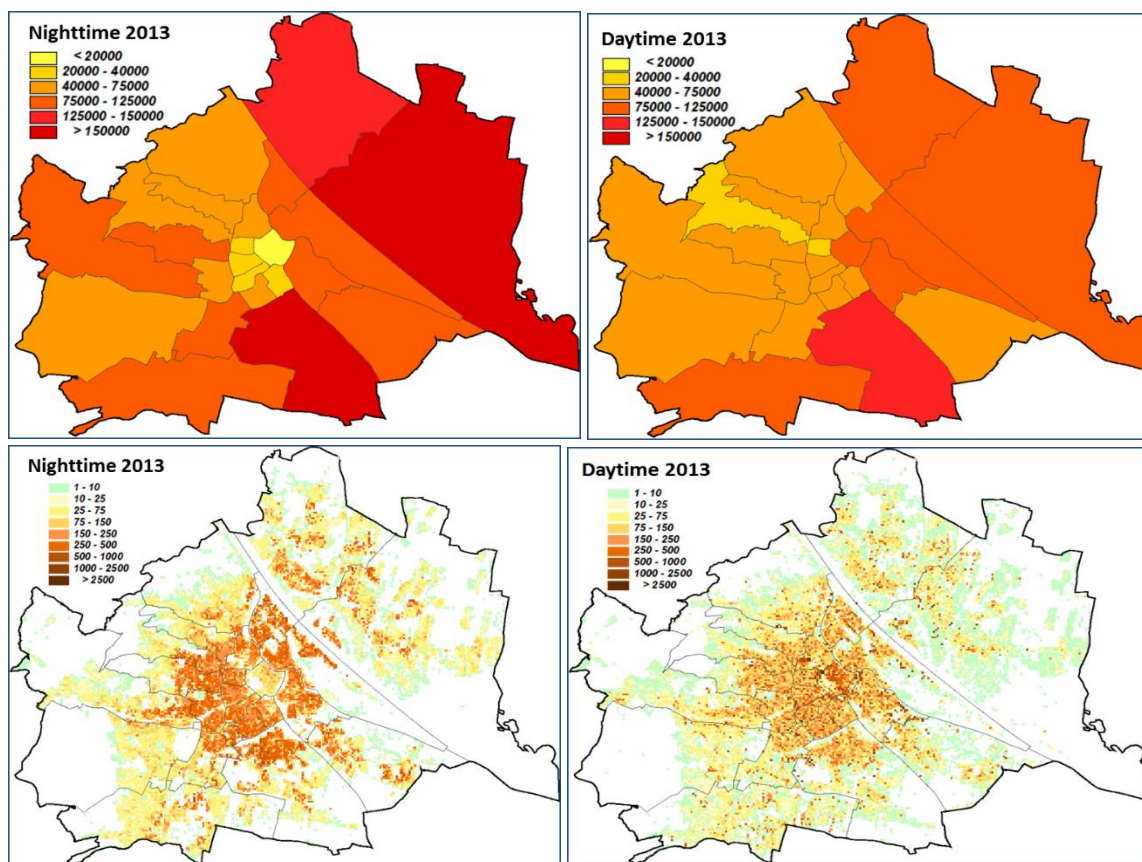


Fig.3: Nighttime (left) and daytime population (right) on district-level (above) and dis-aggregated to 100m (below) of the City of Vienna

For modelling of PM₁₀ and O₃ concentrations, data from the air pollutant measurement network of the City of Vienna were used. For PM₁₀ data from 13, for O₃ from 5 measuring stations were available providing continuous measurements over the last 10 years. Analysis of the data shows the following trends: PM₁₀ has higher concentrations in the winter half year, due to emissions of car traffic and heating, while O₃ has higher concentrations in summer due to stronger solar radiation (required for the formation of O₃). Both long-year trends are shown in the figure 4. The two reference years for the more detailed analysis are highlighted as red bars.



Fig.4: Annual and seasonal means of PM₁₀ (left) and O₃ (right) for the City of Vienna - evaluation years are highlighted

Originally short term average values (1h/8h) were proposed by AIT according to WHO guidelines for Europe (WHO, 2006²), as annual/seasonal/monthly means might not be indicative for modelling local exposures. Days with exceeding loads (according to WHO recommendations) were selected and counted per measurements stations. These counts can then be used for mapping areas with a high risk of exposure to high PM₁₀ and Ozone values.

However, for input to the micro-simulation model of OECD a different approach seemed more appropriate: the proportion of population (split into age classes and gender) exposed to air pollutants over a certain threshold were estimated, based on monthly means and seasonal differentiation. Figures 5 and 6 illustrate the annual variation of both parameters during the two selected evaluation years.

² WHO (2006) WHO Air quality guidelines for particulate matter, ozone, nitrogen dioxide and sulfur dioxide. Global update 2005. Summary of risk assessment. World Health Organization, 2006.

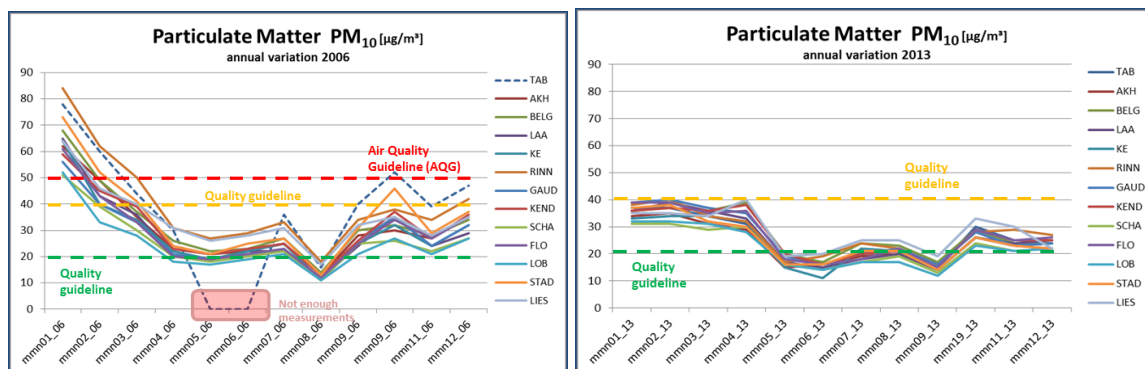


Fig.5: Monthly mean loads for PM₁₀ 2006 (left) and 2013 (right) for the 13 measuring station of Vienna

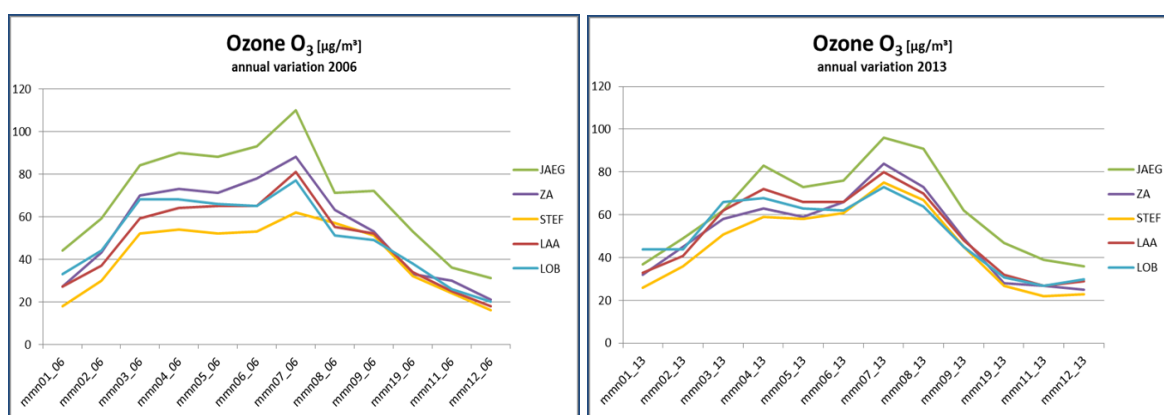


Fig.6: Monthly mean loads for O₃ 2006 (left) and 2013 (right) for the 5 measuring stations of Vienna

In the following the exposure to a certain threshold of an air quality parameter is shown exemplarily. The left map in figure 7 shows the location of 13 stations with continuous PM₁₀ measures in Vienna. Out of the location of these stations, the monthly means of the air-quality measures have been interpolated by using inversed distance weighted (IDW). IDW determines cell values using a linear-weighted combination set of sample points. The weight assigned is a function of the distance of an input point from the output cell location. The greater the distance, the less influence the cell has on the output value. As result a spatial distribution of the interpolated parameter is produced. Intersection with population data allows for estimating the number or percentage of a certain population group exposed to air pollution above a defined threshold.

Figure 7 (right) presents the exposure to a monthly average Pm₁₀ load higher than 35 µg/m³ for April daytime 2013. The exposure is aggregated to district level, with the highest exposure occurring in the south-western districts. Within 11 districts 516,476 persons or 64.5 % of the population were exposed to a Pm₁₀ load higher than 35 µg/m³. In the other 22 districts no exceedance of the threshold occurred during the chosen period.

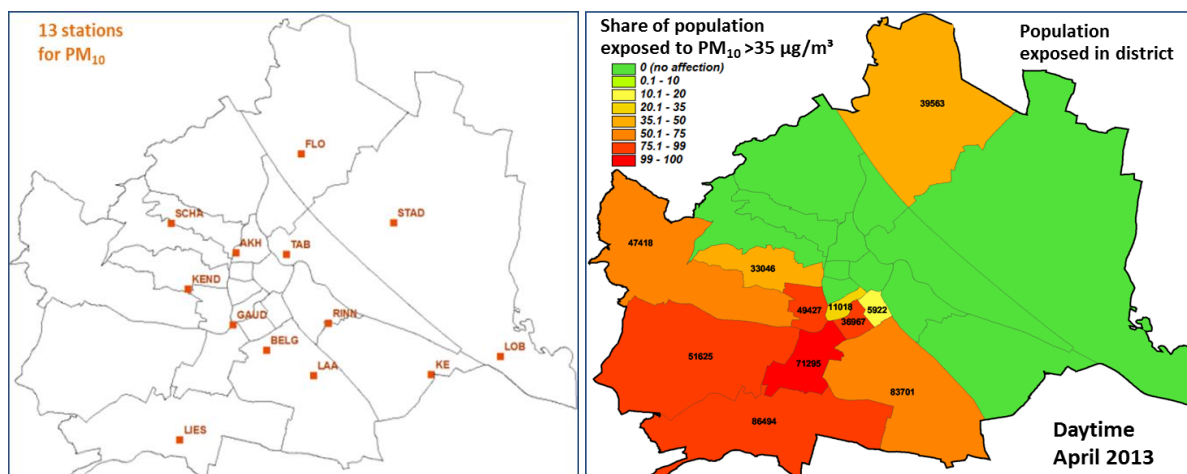


Fig. 7: Distribution of the 13 measuring stations for PM₁₀ (left) and population exposed during daytime to monthly averaged PM₁₀ > 35 µg/m³ in April 2013

Modelling accessibility to certain locations is performed by adding up the population within predefined distances to these locations. In order to do that exercise, the relevant locations have to be represented in a spatial context. For the modelling of accessibility to green urban areas the urban atlas data of Vienna were used (<http://land.copernicus.eu/local/urban-atlas>). The distance to the class “green urban areas” were buffered and intersected with the population age groups resulting in number/percentage of people of a certain age class with access to parks at the given distance. As an example Figure 8 shows the location of green urban areas (left) and the share of elderly people (age 65 or more) per district within 100m to these locations (right). Additionally the total number of this population group is indicated.

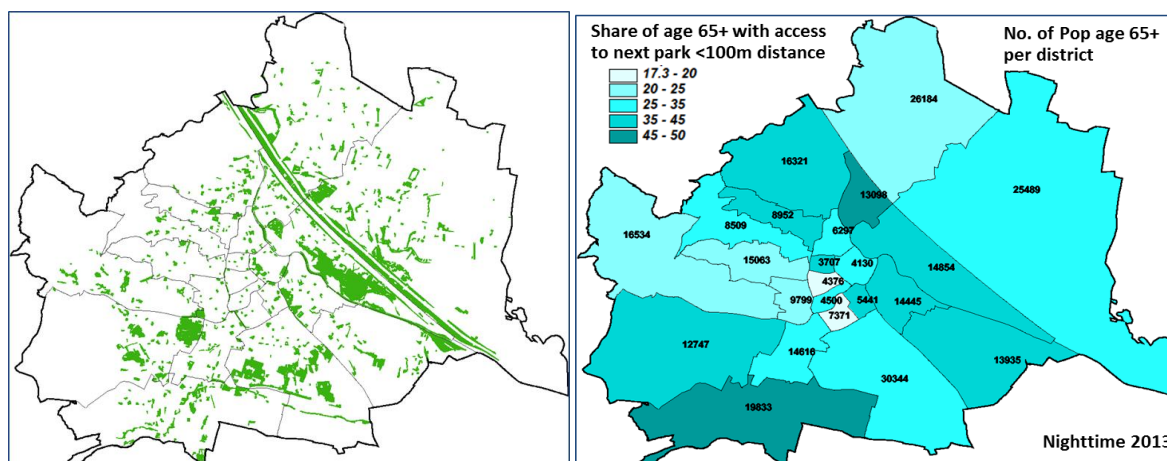


Fig. 8: Green urban areas (left) and access to these areas for population over 65 years within 100m (right)

For the accessibility to fast-food (or alcohol) outlets, data from Foursquare were used (Aubrecht & Steinnocher, 2016). Foursquare (for further information see <https://foursquare.com/about>) is a location-based social network service, providing the location of specified venues, as well as a classification of its type (e.g. restaurant, bar, etc.). Figure 9 (left) shows data points that are interpreted as fast food venues (such as Burger Joints, Hot Dog Joints or Pizza Places). The accessibility is again modeled by using buffers

with defined distances around the locations and adding up the population per age group within the buffer area. Figure 9 (right) shows the share and number of pupils per district within 150m distance of fast food venues. Assuming that the access of pupils to fast food is related to school hours, the daytime distribution is used in this presentation.

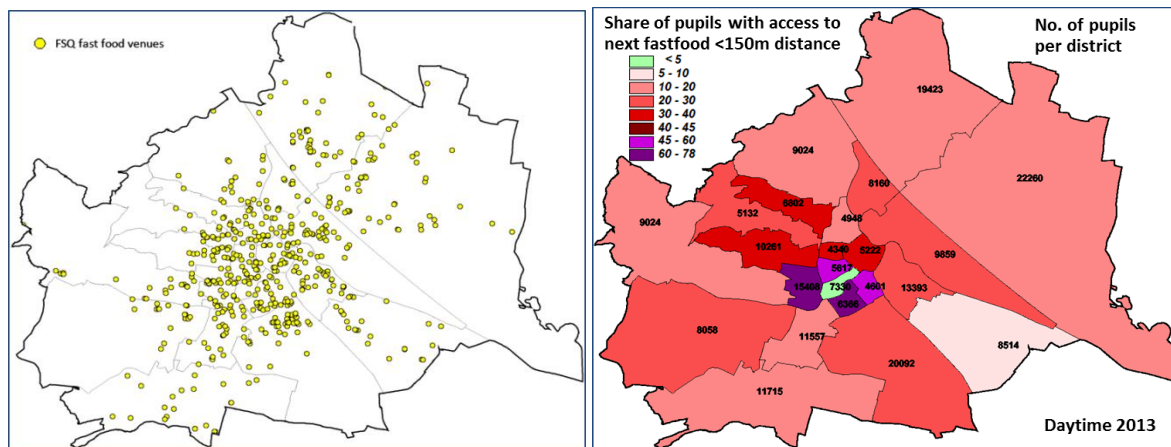


Fig. 9: Distribution of Fast Food venues (left) and access to Fast Food venues for pupils within 150m (right)

Interesting is the very small share in the 6th district compared to the neighboring districts, where extremely high shares occur. The reason seems to lie in the rather small number of school locations (11, but with relatively high school enrollments) leading to higher mean distances to fast food venues. Nevertheless, choosing a larger distance might lead to a different result. During nighttime (not presented here) the shares and numbers are much more balanced (at a lower level), as residential places and fast-food venues - mostly in center-near streets or at traffic junctions – do not necessarily correspond spatially.

Modelling of population exposure for Tallinn case study

In order to keep the analyses comparable we tried to use as much as possible the same statistical and spatial input data for modelling Tallinn as were used for the Vienna test case. The main difference in terms of population data was the limitation on commuting data. Therefore all out-commuters (pupils and work force separately) had to be summed up and distributed proportionally to the districts by using locations (schools and work places).

As we have no information on commuting on district level, the upper right map in figure 10 is rather the sum of the 100m daytime population cells, than an input for dis-aggregation as in the Vienna test-case. This is the reason that results are not as precise as for the Vienna case.

Comparing the disaggregated population at night time in Figure 10 (lower left) one can easily recognize the three “sleeping districts” *Lasnamäe*, *Mustamäe* and partly *Haabersti* with their huge Plattenbauten (prefabricated housing blocks from Soviet times) leading to high densities. Noticeable at daytime are the high concentrations at the campus of the *Tallinn University of Technology*, including eight faculties, the *Tehnopol* science park with around 150 high-tech companies and the *MEKTORY* innovation center.

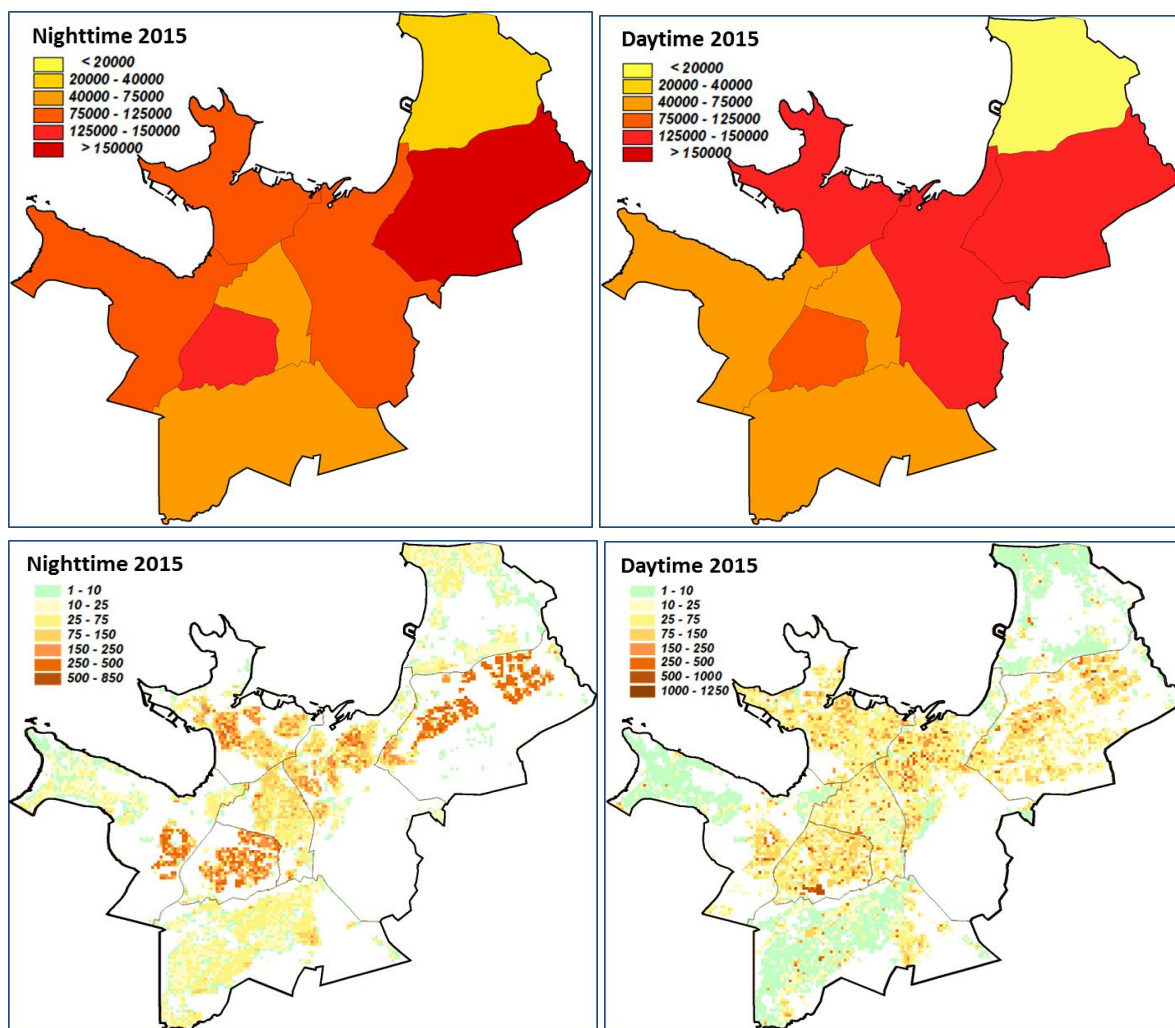


Fig. 10: Nighttime (left) and daytime population (right) on district-level (above) and disaggregated to 100m cells (below) of the City of Tallinn

Another challenge for modelling Tallinn is the small number of measuring stations within (or near) Tallinn. In contrast to Vienna only three stations with measurements of PM_{10} and O_3 are available. Although this is sufficient for analyzing long-term and annual variation of both air-quality parameters, as shown in Figures 11-13, it weakens the spatial interpolation of the point data.

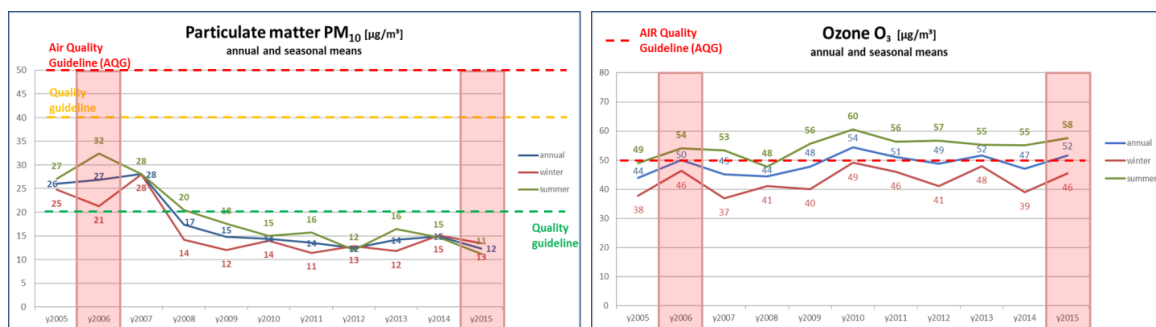


Fig.11: Annual and seasonal means of PM₁₀ (left) and O₃ (right) for the City of Tallinn - evaluation years are highlighted

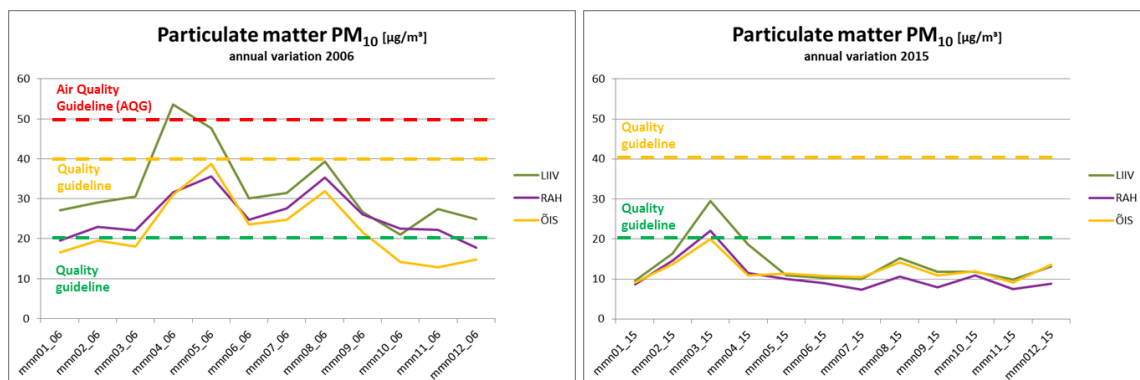


Fig.12: Monthly mean loads for PM₁₀ 2006 (left) and 2015 (right) for the 3 measuring station of Tallinn

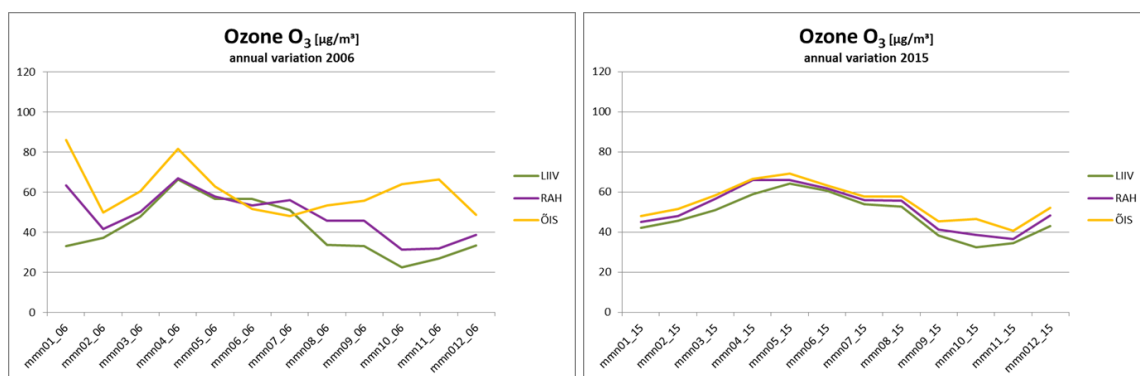


Fig.13: Monthly mean loads for O₃ 2006 (left) and 2015 (right) for the 3 measuring stations of Tallinn

As can be seen in the figures above, PM_{10} has decreased significantly in Tallinn over the past years, while Ozone still reaches loads near the air-quality guideline. Nevertheless, the values are substantially lower than those in Vienna. As an example for spatial representation, March 2015 is chosen. The left map in Figure 14 shows the location of the measuring stations, the right one the population share exposed to $\text{PM}_{10} > 25 \mu\text{g}/\text{m}^3$ during daytime. As one can see, higher loads occur in the north-eastern districts, affecting 191.037 persons or 49.6 % of the population during daytime. As no transgressions occur in the south-western districts, a predominant west wind might cause this spatial pattern.

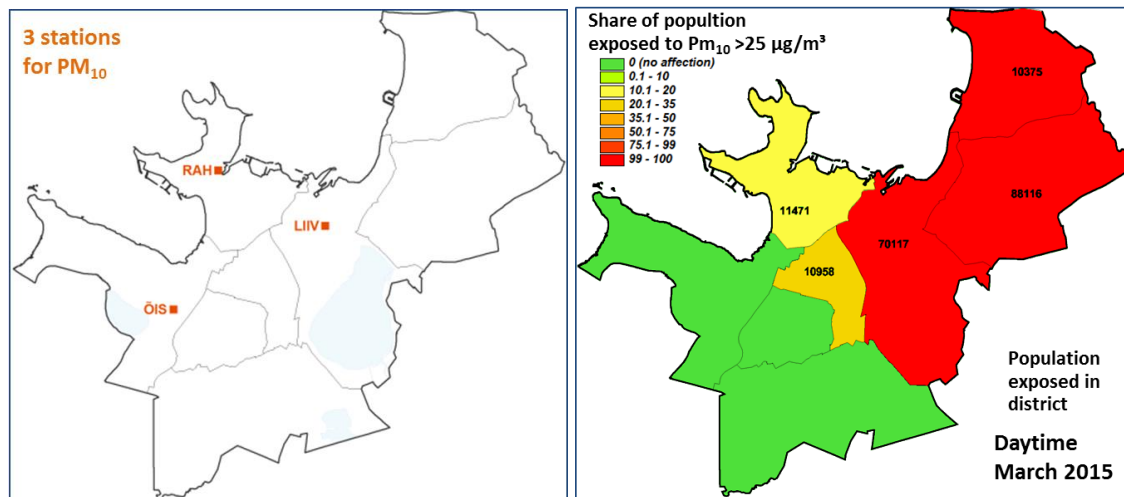


Fig. 14: Distribution of the three measuring stations for PM_{10} (left) and population exposed during daytime to monthly averaged $\text{PM}_{10} > 25 \mu\text{g}/\text{m}^3$ in March 2015

Figure 15 gives an example for the share of elderly people having **accessibility** to green urban areas. The lowest shares occur – not surprisingly – in the rather dense built-up central districts, while in the outer ones the accessibility is much higher. Like in the Viennese example additionally the total number of elderly people is indicated.

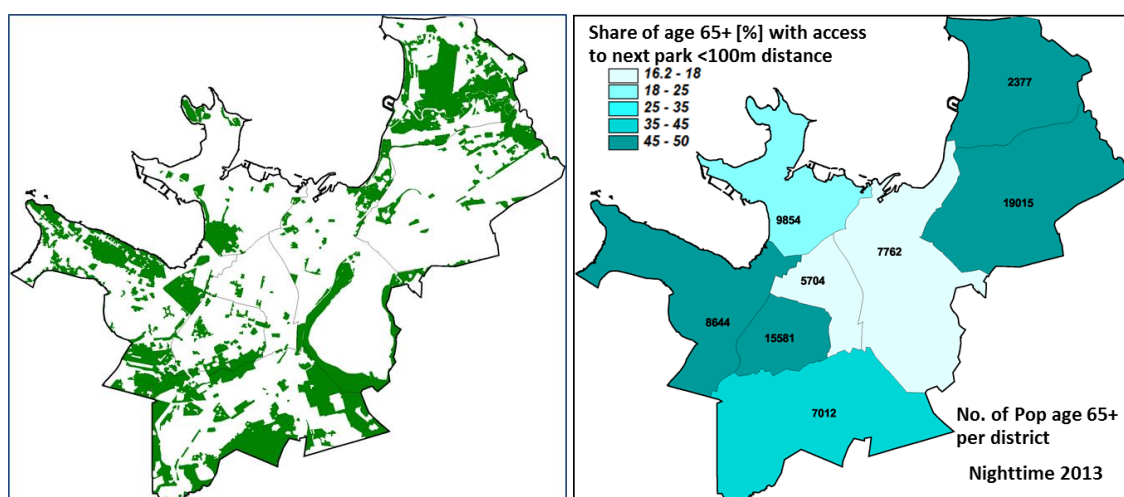


Fig. 15: Green urban areas (left) and access to these areas for population over 65 years within 100m (right)

When analyzing the accessibility of pupils to fast-food venues during daytime, one recognizes the rather small number of such venues compared to the other two test-cases (Figure 16, left). Only in the central *Keskelinn* district (including the old historical town) a higher concentration occurs. This might be the explanation that this district shows only a moderate share of pupils with access to fast food venues. The highest shares occur in the neighboring district *Kristiine* and the southern *Nõmme*, although there the number of schools and enrollments are relatively small. The only reasonable explanation is that in these districts most of the fast food venues are actually located near schools.

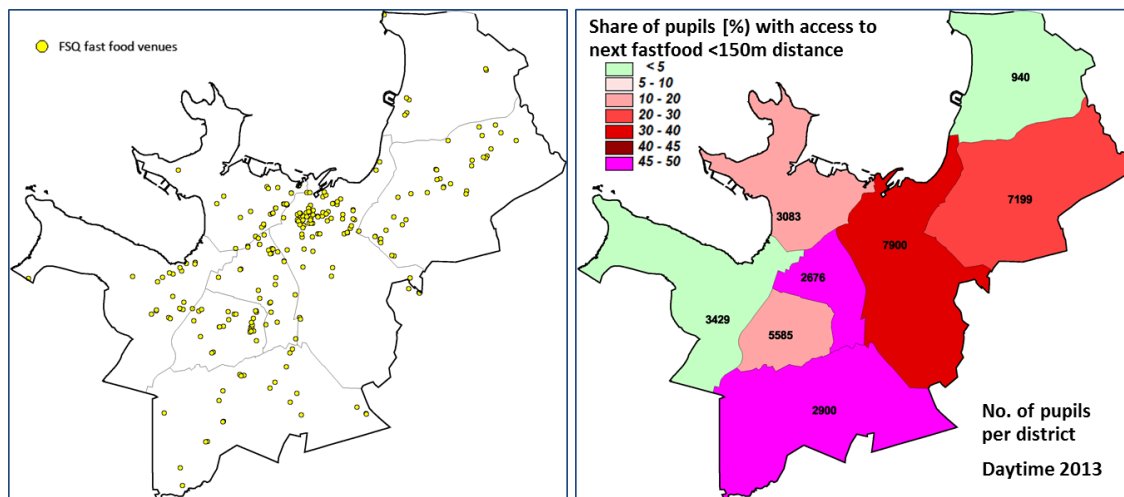


Fig. 16: Distribution of Fast Food venues (left) and access to Fast Food venues for pupils within 150m (right)

Modelling of population exposure for Lisbon case study

As was the situation for Tallinn, also for Lisbon commuting data are only available in limited form, i.e. only total commuting numbers for the entire city could be found. Thus, daytime-population on administrative level is again based on school- and workplace distribution analysis. It is obvious that this reduces the quality of the disaggregation approach. In addition information on the location of institutions such as kindergartens is far from being comprehensive.

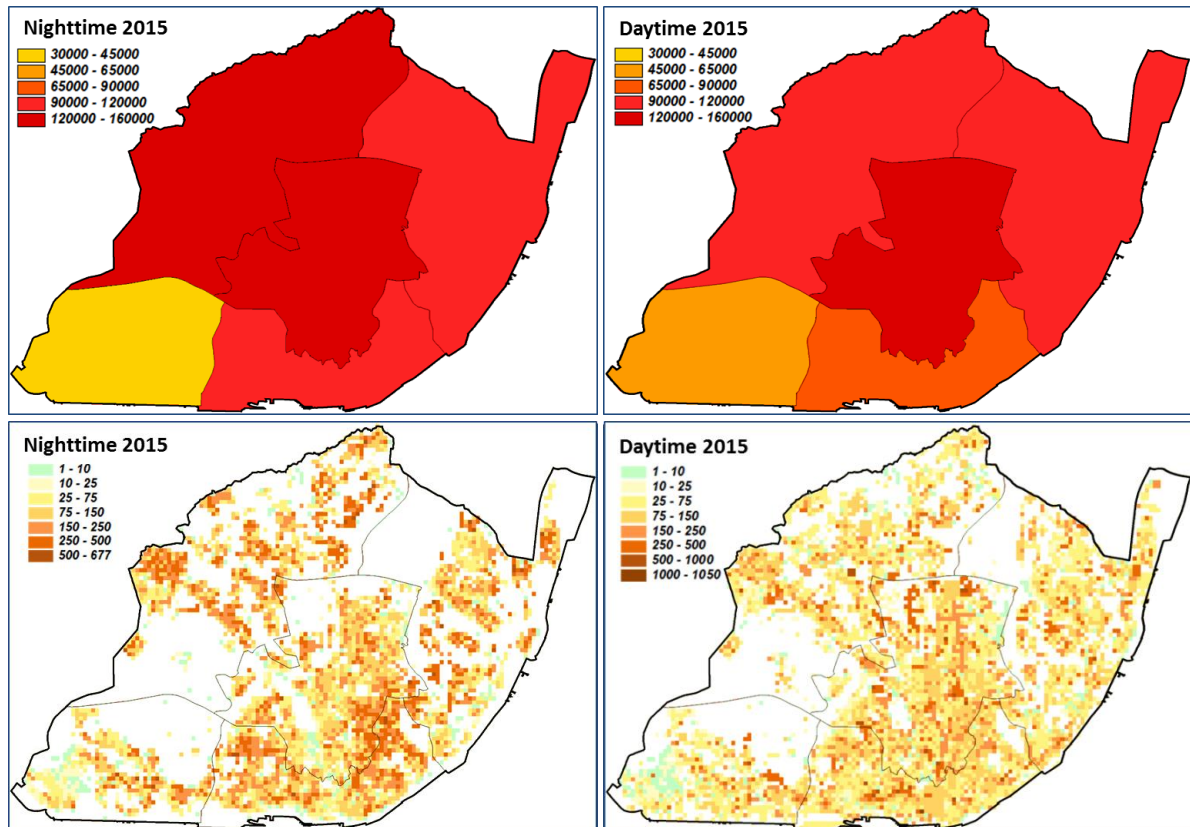


Fig.17: Night-time (left) and daytime population (right) on district-level (above) and disaggregated to 100m cells (below) of the City of Lisbon

The long-term trend of air-quality presented in Figure 18 shows a significant decline of PM₁₀ over the years, while Ozone concentrations stay more or less constant slightly above the air-quality guideline (mainly due to high summer loads).

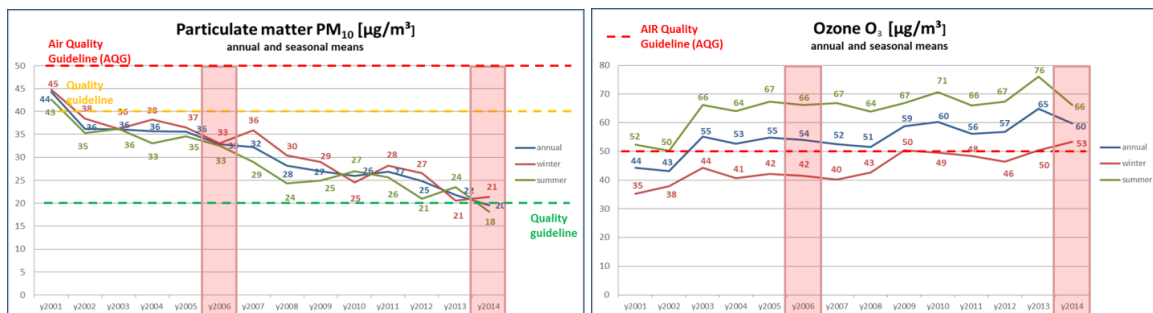


Fig.18: Annual and seasonal means of PM₁₀ (left) and O₃ (right) for the City of Lisbon - evaluation years are highlighted

The number of measuring stations with continuous long-term data (eight for PM₁₀ and seven for O₃) are sufficient for IDW interpolation, considering the rather small extent of Lisbon compared to the other two cities. Figure 19 and 20 show the PM₁₀ and O₃ monthly variations for the two evaluation years 2006 and 2014. Measurement failures occurring at two PM₁₀ stations (RES – station *Restello* in 2006, REB – station *Reboleira* in 2014) were not considered in the analysis.

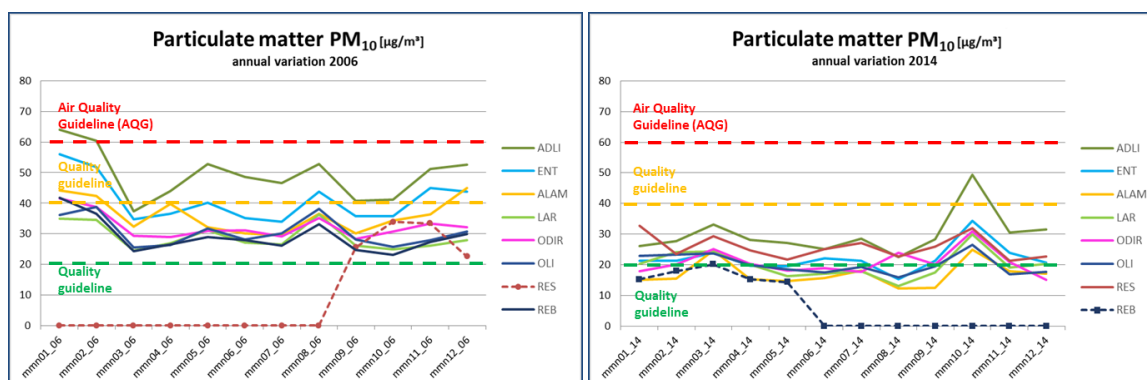


Fig. 19: Monthly mean loads for PM₁₀ 2006 (left) and 2014 (right) for the 8 measuring stations of Lisbon

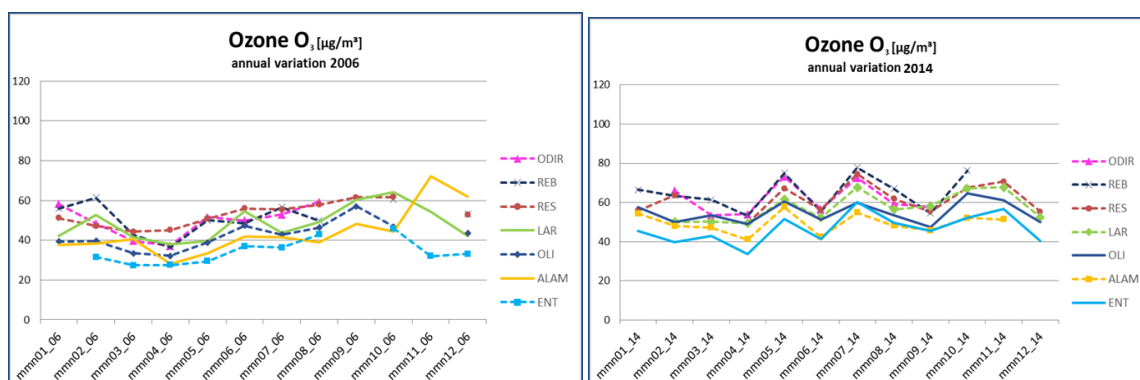


Fig. 20: Monthly mean loads for O₃ 2006 (left) and 2014 (right) for the 7 measuring stations of Lisbon

Figure 21 gives an example for population exposed to PM₁₀ above a certain threshold. The left figure shows the location of the used measuring stations for PM₁₀. The map-extent shows only eight stations, in order to improve the interpolation two additional stations outside the area were used. The right figure

presents the aggregated number of people exposed to Pm_{10} loads higher than $40\mu\text{g}/\text{m}^3$ on average in October 2014. In the two affected UITs *Centro Historico* (along the waterfront) and *Centro* at daytime a total of 116,021 persons or 22.7 % of the population were exposed to concentrations above the threshold.

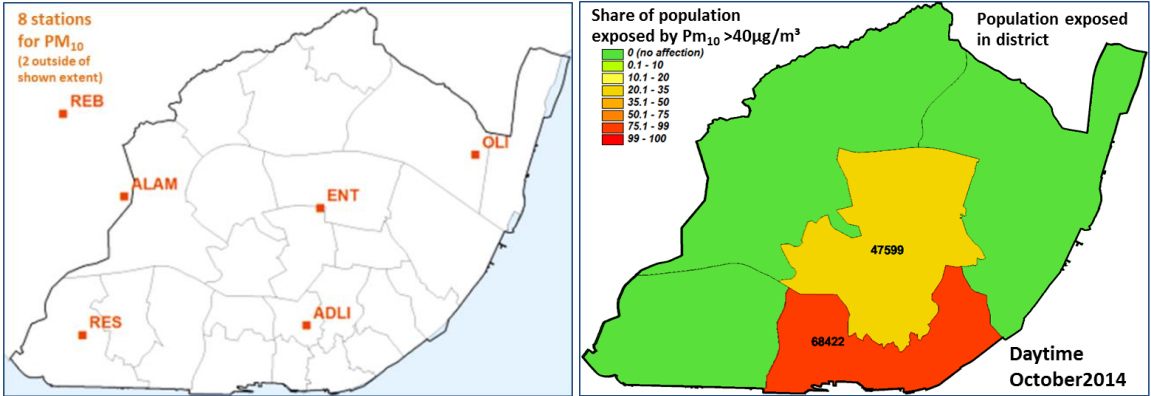


Fig. 21: Distribution of measuring stations for PM₁₀ (left) and population exposed to PM₁₀ > 40 µg/m³ in October 2014

The last two Figures 22-23 show examples of **accessibility** of elderly people to green urban areas and the accessibility of pupils to fast food venues.

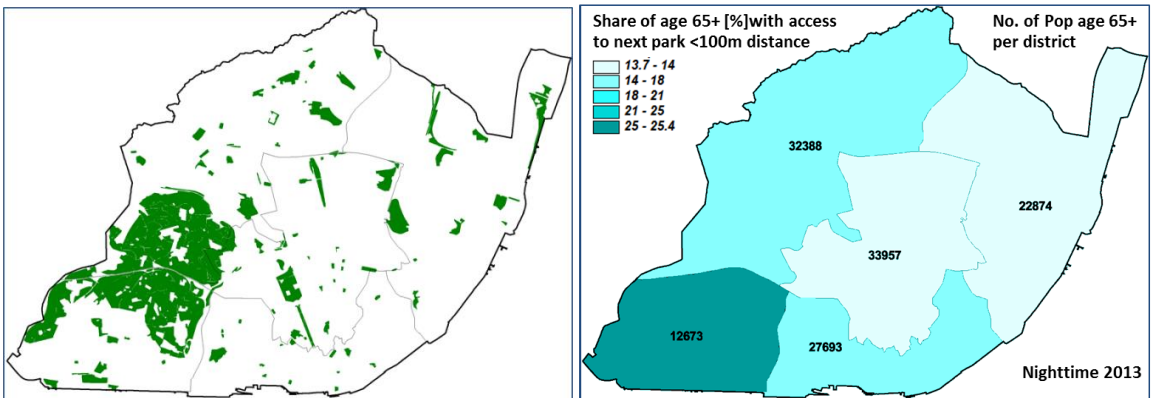


Fig. 22: Green urban areas (left) and access to these areas for population over 65 years within 100m (right)

The small number of green urban areas and their relatively small extents (except the huge park in the western part of the city) limits the accessibility for elderly to green urban areas, especially in the central and eastern UIT. The best accessibility shows the western UIT *Ocidental* with 25.4 %, also having the highest share of elderly people of all 5 UITs.



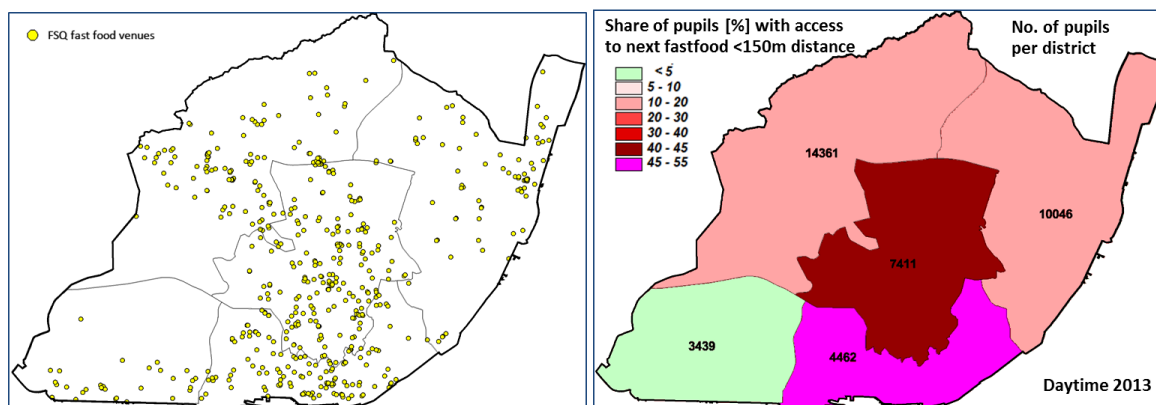


Fig. 23: Distribution of Fast Food venues (left) and access to Fast Food venues for pupils within 150m (right)

The highest concentration of fast food venues occurs in the two central UIT (Figure 23, left), as these two units are the economic heart of the city. In Portugal separated school campuses are much more common than in Austria and Estonia, thus distances to fast food venues are generally larger. Nevertheless, applying a 150m distance still leads to relatively high accessibility rates due to the high enrollments of the single campuses (Figure 23, right).

Indicators for micro-simulation model

The data sets collected and modelled for the three cities have a huge potential for estimating indicators on exposure and accessibility, as were shown exemplarily in the chapters above. For input to the FRESHER micro-simulation model only selected data sets were chosen. Table 2 lists the indicators that were delivered to FRESHER-group for further use.

Indicators	Description
Demography	18 age-classes (age 00-04, 05-09, ...80-84, 85+): total, male & female day- & nighttime population
Exposure to PM ₁₀ and O ₃	for day- & nighttime share of population within 4 defined classes of annual & seasonal means; for PM ₁₀ : < 20 µg/m ³ , 20-30 µg/m ³ , 30-40 µg/m ³ and > 40 µg/m ³ ; for O ₃ : < 40 µg/m ³ , 40-50 µg/m ³ , 50-60 µg/m ³ and > 60 µg/m ³
SES (socio-economic status)	share of population per district with mandatory school, secondary education and higher education
Access to green urban areas	share of population within 5 distances: < 100m, 100-300m, 300-500m, 500-1000m and > 1000m (based on nighttime-population)
Access to alcohol- & fast-food outlets	count & density of venues per district
Estimation of future population	year 2034 for Vienna & Lisbon, 2035 for Tallinn; just for Vienna with demographic subdivision, for Lisbon & Tallinn only male & female

Table 2: List of indicators delivered to FRESHER consortium

All indicators were provided for two reference years, one representing the past, the other one representing the current status. Due to data availability the reference years are not identical for the three cities: 2006 and 2013 for Vienna, 2006 and 2015 for Tallinn, 2006 and 2014 for Lisbon. The last indicator refers to population development estimated for next 20 years.

Indicators were provided to OECD as Excel sheets in a standardized format. In total 10 csv-files have been created for each City: *PopulationNightTime*, *PopulationDayTime*, *PopulationNightTimeFuture*, *Pm10NightTime*, *Pm10DayTime*, *OzoneNightTime*, *OzoneDayTime*, *SES*, *DistanceGreenSpace* and *DensityAlcohol/Fast-food*.



2.2. What is the evidence on the effects of environmental RFs and NCDs?

2.2.1. Air pollution – Ozone (O₃) and particulate matter (PM_{2.5})

Air pollution has become a growing concern in the past few years, with an increasing number of acute air pollution episodes in many cities worldwide. As a result, data on air quality is becoming increasingly available and the science underlying the related health impacts is also evolving rapidly (WHO, 2016). Ambient air pollution is the number one environmental risk factor and rank among the leading risk factors in the Global Burden of Disease Study (Forouzanfar et al., 2016). The most dangerous consequences from outdoor air pollution are related to the number of premature deaths. A recent OECD report projects an increase in the number of premature deaths due to outdoor air pollution from approximately 3 million people in 2010 to 6-9 million annually in 2060, in the absence of more stringent policies (OECD 2016).

The mixture of pollutants in the air is complex, epidemiological studies focus on a few pollutants, such as particulate matter (PM) and ozone, which are used as markers/indicators of the air pollution mixture. Particulate matter with a diameter $\leq 10 \mu\text{m}$ (PM₁₀) and particulate matter with a diameter $\leq 2.5 \mu\text{m}$ (PM_{2.5}) include inhalable particles that are small enough to penetrate the thoracic region of the respiratory system. PM_{2.5} has been investigated in many epidemiological studies, and has been shown to be a robust indicator of risk associated with exposure to PM from diverse sources and in different environments.

• *Evidence for short term and long term effects of Ozone and PM_{2.5}*

The relation between exposure to ozone, particulate matter and specific health outcomes is well-documented and supported by the consistency of epidemiological findings across different cities, periods and study designs (Pascal et al., 2013). Several epidemiological studies have reported associations between an increase in daily levels of ozone (O₃) and particulate matter (PM), and an increase in the following days, of the mortality and hospital admissions predominantly related to respiratory and cardiovascular diseases. These short-term effects have been extensively documented in multicentre time-series studies such as (Garrett and Casimiro 2011; Gryparis et al. 2004). Chronic exposure to fine particles (PM_{2.5}) has also been associated with an increase in long-term mortality, and with an increased risk of developing lung cancer and cardio-pulmonary diseases (myocardial infarction, chronic obstructive pulmonary disease, asthma) (for example, Pope et al. 2002, 2004). Jerrett et al. (2009) linked long-term respiratory mortality with exposure to ozone during summer.

Susceptible groups with pre-existing lung or heart disease, as well as elderly people and children, are particularly vulnerable. For example, exposure to PM affects lung development in children, including reversible deficits in lung function as well as chronically reduced lung growth rate and a deficit in long-term lung function (WHO, 2016a).

• *International Exposure Recommendations*

There is no evidence of a safe level of exposure or a threshold below which no adverse health effects occur. The WHO recommends that mean exposure concentrations should not exceed 100 $\mu\text{g}/\text{m}^3$ per 8-hour for ozone and for PM_{2.5} 10 $\mu\text{g}/\text{m}^3$ annually and 25 $\mu\text{g}/\text{m}^3$ daily (WHO, 2006). Only one person in ten lives in a city that complies with the WHO Air quality guidelines (WHO, 2016a).



Results of the APHEKOM project conducted in 25 European cities found that complying with the PM_{2.5} WHO guideline of 10 µg/m³ in annual mean would add up to 22 months of life expectancy at age 30, depending on the city, corresponding to a total of 19,000 deaths delayed (Pascal et al., 2013).

- *Quantitative estimates for health effects of Ozone and PM_{2.5}*

The effects of air pollution on health are assessed with concentration-response functions, which link health impacts to the population-weighted mean concentrations of PM_{2.5} and O₃. Concentration-response functions are typically estimated by gathering data on the occurrence of the health impacts, and running regressions that relate them to population weighted concentrations of air pollutants, controlling for factors such as temperature, relative humidity, wind speed or season.

The Global Burden of Disease Study (GBD) conducted every year by IHME is the most comprehensive worldwide observational epidemiological study to date. It describes mortality and morbidity from major diseases, injuries and risk factors to health at global, national and regional levels. As part of this work, IHME provide risk functions and relative risk estimates, by age-group and sex when relevant, for the associations between major risk factor and health outcome pairs with strong enough evidence. The WHO under the “Health risks of air pollution in Europe” (HRAPIE) study recommended to use the concentration-response functions developed by GBD 2010, at the time of the report (WHO, 2013). At the time of this Fresher project, the most recent concentration-response functions and relative risks estimates for long-term effects of air pollutants (ozone and PM_{2.5}) available were from the GDB 2015 estimates (Forouzanfar et al., 2016). For ozone, the health outcome retained was chronic obstructive pulmonary disease (COPD) and was directly taken from the available literature (Jerrett et al., 2009). For PM_{2.5}, the health outcomes retained were tracheal, bronchus, and lung cancer, Ischaemic heart disease and chronic obstructive pulmonary disease (COPD) and specific extensive modelling work was conducted by IHME to obtain updated concentration-response functions as detailed in their supplementary material.

- *Conversion ratio from PM₁₀ to PM_{2.5}*

As explained on section 2.1, the particulate matter concentrations recorded by the monitoring stations is PM₁₀. Estimates of corresponding PM_{2.5} concentrations could be obtained by applying a conversion factor to PM₁₀ measurements. The WHO recommend to use a conversion ratio (PM_{2.5} / PM₁₀) of 0.5 for developing countries, and usually between 0.5 and 0.8 for developed countries, and local correction value when available (WHO, 2006).

The relation between exposure to ozone, particulate matter and specific health outcomes is now well-documented. For later analyses, the use of the most recent GBD, or equivalent; concentration-response functions for health effects of air pollutants is recommended.

2.2.2. Temperature: heat waves

The interest in this topic has increased after episodes of extreme weather and in response to reports about climate change.

The European Environment Agency (2016) recently published a note on extreme temperatures and health. It stated that temperature affects human well-being and mortality. Both cold and heat have public



health impacts in Europe. The number of heat extremes has substantially increased across Europe in recent decades. Heat waves, hot weather that lasts for several days, can have a significant impact on health, including a rise in mortality and morbidity. Heat waves have caused tens of thousands of premature deaths in Europe since 2000. For example, the record warm summer of 2003 caused an estimated premature mortality of 70 000 people in Europe (Robine et al., 2008) and the heat waves of the summer of 2015 caused more than 3 000 deaths in France alone (CRED, 2016). Future climate change is very likely to increase the frequency, intensity and duration of heat waves. The capacity to adapt to the effects of heat and cold in Europe is high compared with other world regions, but there are important differences in the impacts of heat and cold and in the capacity to respond between and within the European sub-regions.

- *Evidence support the effect of extreme high and low temperatures on health*

Morbidity such as respiratory and heart problems can be exacerbated by heat (Ye et al., 2012). The effects of exposure can be directly related to heat (heat stroke, heat fatigue and dehydration, or heat stress) or can be the result of a worsening of respiratory and cardiovascular diseases, electrolyte disorders and kidney problems. Heat-related problems are greatest in cities; among many interrelated factors, the urban heat island effect plays an important role. The largest effect of heat has been observed among the elderly, but in some cities younger adults have also been affected (Baccini et al., 2011; D'Ippoliti et al., 2010). In addition, those with chronic diseases and persons of lower socio-economic status also have a heightened risk of heat-related mortality (Wolf et al., 2015).

Extreme cold can also significantly affect human health. The physiological and pathological effects of short-term exposure to cold are well known. People with cardiovascular and respiratory diseases and the elderly are potentially more susceptible to the effects of cold spells. Excess winter mortality in Mediterranean countries is higher than in northern European countries, and deaths often occur several days or weeks after the coldest day of a cold period.

As well as extreme temperature events, 'non-extreme' temperatures outside a local comfort temperature range are also linked to increased mortality and other adverse health outcomes. The effects of heat occur mostly on the same day and in the following three days, whereas cold effects were greatest two to three weeks after the event. A multi-country global observational study found that moderate temperatures, rather than extreme temperatures, represented most of the total health burden (Gasparini, 2015). Data were collected from Italy (11 cities, 1987–2010), Spain (51 cities, 1990–2010), Sweden (one county, 1990–2002), the United Kingdom (10 regions, 1993–2006) and other areas outside Europe. The results should be interpreted with caution when applied to other regions that were not included in the database. Risk increases slowly and linearly for cold temperatures below the minimum mortality temperature, although some locations (e.g. London and Madrid) showed a higher increase for extreme cold than others. Risk generally escalated quickly and non-linearly at high temperatures. Deaths attributable to extreme heat are roughly as frequent as those attributable to moderate heat, while those attributable to extreme cold are negligible compared with those caused by moderate cold. The author noted that other studies have estimated that 1.6–2.0 % of total mortality in the warm season is attributable to heat; about 40 % of these deaths occur on isolated hot days in periods that would not be classified as heat waves (Baccini et al. 2011). They warned that comparison of these estimates should be made with caution, as not only the methods used to estimate the excess deaths, but also the exposures were different. The impact of high temperatures later in the summer is sometimes diminished after an



early heat wave. In Europe, heat waves occurring in June result in relatively high mortality compared with those occurring later in the summer (WMO and WHO, 2016).

Epidemiological studies of the topic face important challenges in modelling of the health effects of temperature.

- *There is no standard definition of heat waves*

Temperature thresholds for health impacts differ according to the region and season. There is no standard heat wave definition, although they are commonly defined as a few consecutive days with high temperatures above a certain threshold that can either be physiologically based (absolute threshold) or community based (relative threshold). Heat waves definition differ across studies on several parameters: the indicator being based on daily mean, minimum or maximum temperature, with a duration ranging from 2 to 4 days, the intensity varying from the ≥ 90 th, 92.5th, 95th, and 97.5th percentile of daily mean temperature, or the number of days with maximum temperature above a specific threshold (such as 30, 33 or 35°C).

In a recent multi-country, multi-community study, Guo et al. (2017) defined 12 types of heat waves definitions and showed that heat waves of all definitions had significant cumulative associations with mortality in all countries, but varied by community. The higher the temperature threshold used to define heat waves, the higher heat wave associations on mortality. However, heat wave duration did not modify the impacts. The association between heat waves and mortality appeared acutely and lasted for 3 and 4 d. Heat waves had higher associations with mortality in moderate cold and moderate hot areas than cold and hot areas. There were no added effects of heat waves on mortality in all countries/regions, except for Brazil, Moldova, and Taiwan. Heat waves defined by daily mean and maximum temperatures produced similar heat wave-mortality associations, but not daily minimum temperature. The authors concluded that results indicate that high temperatures create a substantial health burden, and effects of high temperatures over consecutive days are similar to what would be experienced if high temperature days occurred independently. People living in moderate cold and moderate hot areas are more sensitive to heat waves than those living in cold and hot areas. Daily mean and maximum temperatures had similar ability to define heat waves rather than minimum temperature.

- *There is a combined effect of high temperature and air pollution (particulate matter and ozone)*

During hot weather, synergistic effects between high temperature and air pollution (particulate matter with a diameter ≤ 10 micrometres (PM₁₀) and ozone) were observed (Analitis et al., 2014). The authors concluded that heat wave effect on mortality was larger during high ozone or high PM₁₀ days. When assessing the effect of heat waves on mortality, lack of adjustment for ozone and especially PM₁₀ overestimates effect parameters.

Ambient temperature represents an important risk factor and this is clearly a very active research area. Progress on the modelling and a deeper understandings of the specific effects of temperature across different cities/ regions/country and within susceptible populations are likely to be reached in the coming years.



2.2.3. Green space area

Over the last decade, various studies and reports have contributed to evidence and guidance on access to green space in relation to public health benefits. Recent studies have provided evidence of multiple benefits from urban green space, through various mechanisms, and with potentially differential impacts in various populations.

The 2010 WHO report on urban planning, environment and health states that green spaces can positively affect physical activity, social and psychological well-being, improve air quality and reduce exposure to noise; however, they can also be associated with an increased risk of injury due to increased recreational and sport-related use (WHO, 2010). Another WHO report evaluated the effects of green spaces on physical activity and their potential to reduce public health inequalities. It states that access to public open space and green areas with appropriate recreation facilities for all age groups is needed to support active recreation, but recognizes that multidisciplinary and intersectoral interventions may be needed to support disadvantaged groups where physical activity levels are lowest (WHO, 2013). A third WHO report was edited to summarize the available evidence of beneficial effects of urban green spaces, such as improved mental health, reduced cardiovascular morbidity and mortality, obesity and risk of type 2 diabetes, and improved pregnancy outcomes (WHO, 2016)

- *There are various pathways between access to green space and health benefits and some may have synergistic effects*
-

The WHO 2016 report recognised that access to green space may produce health benefits through various pathways, some of which may have a synergistic effect. Mechanisms leading to these health benefits include psychological relaxation and stress alleviation, increased physical activity, reduced exposure to air pollutants, noise and excess heat. Various models have been proposed to explain the observed relationship between green space and health. (Hartig et al., 2014) suggested four principal and interacting pathways through which nature or green space may contribute to health: improved air quality, enhanced physical activity, stress reduction and greater social cohesion. (Lachowycz and Jones, 2013) emphasized physical activity, engagement with nature and relaxation, and social activities and interactions as major pathways to health. (Villanueva et al., 2015) proposed a model that emphasizes respiratory health and resilience to heat-related illness, social capital and cohesion, and physical activity. (Kuo, 2015) suggested a central role for enhanced immune functioning as a pathway between nature and health, recognizing that there may be multiple pathways, some of which may interact and offer both direct and indirect benefits.

In the context of this FRESHER project, the aim was focus on the link between **enhanced physical activity** and **access to urban green spaces**, which is one of the most straightforward and well-documented link.

- *There exist various measures of green space exposure*
-

Epidemiological studies have used a multitude of approaches to measure the effects of urban green space availability and accessibility on the health outcomes of study participants. Currently, there is no



universally used definition of urban green space, with regards to its health and well-being impacts. Urban green spaces may include places with ‘natural surfaces’ or ‘natural settings’, but may also include specific types of urban greenery, such as street trees, and may also include ‘blue space’ which represents water elements ranging from ponds to coastal zones. Typical green spaces in urban areas are public parks; other definitions may also include private gardens, woodlands, children’s play areas, non-amenity areas (such as roadside verges), riverside footpaths, beaches, and so on. The definitions are nuanced and context-specific. The most common definition of urban green space that has been used in studies in Europe is based on the definition from the European Urban Atlas (European Union, 2011). The Green Urban Areas as defined by Urban Atlas code 14100 include public green areas used predominantly for recreation such as gardens, zoos, parks, and suburban natural areas and forests, or green areas bordered by urban areas that are managed or used for recreational purposes.

Greenness and green space access have been quantified in epidemiologic studies predominantly using a vegetation index (typically the Normalized Difference Vegetation Index (NDVI)), land-use databases or the distance from a participant’s residence to the nearest park, major green space, or public open space. Vegetation indices, derived from satellite imagery, measure light reflected from the earth’s surface during photosynthetic activity, from which vegetative density can be estimated. Greenness is often defined as the mean NDVI value within a spatial area (e.g., census tract or radius around a participant’s home). Studies that have employed land-use databases which classify land units according to their predominant use, typically calculated the percent of a spatial area covered by parks, public gardens, sports fields, forests, or other green space types. Some studies conducted environmental queried participants about the perceived greenness of their neighbourhood. Both a European Commission working group and the WHO recommend universal access to a green space defined as living within a 300-m linear distance of a green space ≥ 0.5 ha (European Commission, 2001; WHO, 2016). There is still some question as to the accuracy with which this indicator might characterize a person’s greenness exposure. For example, residential greenness may not fully capture exposure among people who work or recreate away from home.

• *Green space and physical activity*

In a recent review, James et al. (2015) identified 15 cross-sectional studies and 1 prospective study investigating the link between green space access and physical activity: 4 studies in the USA, 6 in the UK, 2 in France, 1 each in Australia, Netherlands, New Zealand, and Spain (**Erreur ! Source du renvoi introuvable.**). One study of physical activity and proximity to green space in Bristol, United Kingdom suggested that people living closer to green spaces were more likely to engage in levels of physical activity that met government recommendations (Coombes et al., 2010). However, the authors used a minimum green space area of 2 ha, which they considered as a minimum to support physical activity. The authors concluded that while individual cross-sectional analyses may limit causal inference, the strong consistency across studies after adjustment for a range of individual and area-level potential confounders (age, gender, individual socioeconomic status (SES), area-level SES, and population density) suggests that greenness may promote physical activity. They also highlighted that some analyses suggested that both green space access and its health benefits differ according to individual and neighbourhood-level characteristics and that it would deserve further exploration.

Table 1. Details of Studies investigating green spaces and physical activity (Derived from James et al., 2015)



Study Population	Study Design	Exposure	Outcome	Main Finding
Chaix et al. (2014) 7,290 adults, France, 2007-2008	Cross-sectional	Self-reported presence and quality of green/open spaces	Self-reported walking time in past week	Those in neighborhoods with most as opposed to least green/open space had increased odds of higher walking time (OR 1.43 95% CI 1.21, 1.70).
Sugiyama et al. (2013) 1,036 adults, Australia, 2003-2004 and 2007-2008	Prospective cohort study	-Perception of green space quality and proximity -Total area, largest, and number of green spaces in 1.6 km buffer around neighborhood center	Self-reported walking time over four years	Subjective and objective measures of green space significantly associated with higher likelihood of walking maintenance over 4 years: positive perceptions of presence of green space (OR for unit increase in perceived score 1.84 95% CI 1.13, 2.99) and positive perceptions of proximity to green space (OR for unit increase in perceived score 1.67 95% CI 1.12, 2.49); total green space within 1.6 km buffer (OR for 10 ha increase in green space 1.03 95% CI 1.00, 1.06) and largest green space within 1.6 km buffer (OR for 10 ha increase in green space 1.10 95% CI 1.02, 1.20).
Richardson et al. (2006) 8,157 adults, New Zealand, 2006-2007	Cross-sectional	Proportion of Census Area Unit composed of green space calculated from three land-use datasets	-Self-reported weekly walking and physical activity -BMI -General and mental health from Short Form 36 -Self-reported diagnosis of cardiovascular disease (CVD)	-Those in greenest areas were likelier to meet physical activity recommendations (OR 1.44 95% CI 1.19, 1.74) but physical activity did not fully explain better mental health and reduced CVD there. -Green space was not related to overweight or poor general health.
Ord et al. (2013) 3,679 adults, Scotland, 2008	Cross-sectional	Proportion of Census Area Statistics Ward composed of green space calculated from land use datasets	Self-reported overall physical activity, walking, green physical activity	Neighborhood green space was not significantly associated with meeting physical activity recommendations (OR 0.77 95% CI 0.59, 1.02) nor participation in green physical activity (OR 1.20 95% CI 0.83, 1.74), comparing those in the greenest to least green areas.
Almanza et al. (2012) 208 children, US, 2009-2010	Cross-sectional	Momentary NDVI based on GPS-derived location	Contemporaneous physical activity measured by accelerometer	-Momentary greenness associated with higher odds of moderate-to-vigorous physical activity comparing those in 90th to 10th percentile of greenness (OR 1.34 95% CI 1.30, 1.38). -Children with >20 min. daily green space exposure had nearly 5 times the daily rate of moderate-to-vigorous physical activity compared to those with near 0 daily exposure.



Karusisi et al. (2012) 7,290 adults, France, 2007-2008	Cross-sectional	Proportion of 1000 m radius around home composed of green space	Self-reported frequency and duration of jogging over past week	Presence and quality of green and open space associated with likelihood of jogging (RR 1.22 95% CI 1.03, 1.44), comparing first and fourth quartiles.
Mytton et al. (2012). 17,345 adults, UK, 2002-2004	Cross-sectional	Proportion of middle super-output area composed of green space (MSOA) from Generalised Land Use Database	Days/week participants achieved physical activity recommendations, derived from survey responses	People in greenest compared to least green areas were likelier to achieve recommended daily physical activity (OR 1.27 95% CI 1.13, 1.44).
Grigsby-Toussaint et al. (2011) 365 children, US, 2009	Cross-sectional	Neighborhood NDVI	Parent-reported average daily total outdoor playing time	A one-unit increase in neighborhood NDVI was associated with an increase in children's outdoor play time of approximately 3 minutes (p=0.034).
Maas et al. (2008) 4,899 adults, Netherlands, 2001	Cross-sectional	Proportion of green space within 1 km and 3 km radius of home address	Self-reported commuting and leisure-time physical activity	-A negative association was observed between greenness and walking/cycling during leisure, and cycling for commuting. -No association was found between greenness and walking for commuting.
Li et al. (2008) 1,221 adults, US, 2006-2007	Cross-sectional	Total neighborhood acreage of green space derived from land use datasets	Self-reported frequency and duration of physical activity	Increased green/open space availability associated with greater likelihood of at least 150 minutes of neighborhood walking/week (OR for 1 standard deviation increase in green/open space availability 1.12 95% CI 1.01, 1.24) and meeting physical activity recommendations, but not walking for transportation or errands.
Hillsdon et al. (2006) 4,732 adults, UK, 1993-1997	Cross-sectional	-Road distance to nearest green space, number of green spaces and area of green space within a 2 km radius of residence calculated in GIS. -Green space quality also assessed using audit tool	Self-reported frequency and duration of physical activity	None of the measures of green space significantly associated with physical activity, and no evidence of a consistent trend across quartiles of green space measures.
Gong et al. (2014) 1,010 adult men, UK, 2004	Cross-sectional	Quantity and variation of green space within 400 m radial buffer of home based on NDVI	Self-reported frequency of physical activity	Greater green space was associated with more participation in physical activity (OR for increase in green space access z-score 1.21 95% CI 1.05, 1.41).



Toftager et al. (2011) 21,832 adults, Denmark, 2005	Cross-sectional	Self-reported shortest distance from participant's home to green space	-Self-reported leisure-time physical activity -BMI calculated from self-reported height and weight	-Living further from green space was associated with lower likelihood of conducting moderate-to-vigorous physical activity (OR 0.88 95% CI 0.79, 0.98) comparing those living 300 m–1 km away from green space to those living less than 300 m away. -Living further from green space was associated with higher likelihood of obesity (OR 1.36 95% CI 1.08, 1.71) comparing those more than 1 km away to those closer than 300 m.
Dadvand et al. (2014) 3,178 children, Spain, 2006	Cross-sectional	-NDVI in buffers of 100 m, 250 m, 500 m, and 1,000 m around each home address -Binary variables indicating whether the child's residential address was located within 300 m separately from a park or forest, based on land use datasets.	-Sedentary behavior as binary (yes/no) variable (hereafter referred to as "excessive screen time") indicating whether the child spent > 1 hr during each working day and > 2 hr during each weekend day on watching television, playing video games, and/or working with computer. -Self reported BMI z-scores	-IQR increase in NDVI was associated with an 11-19% lower prevalence of overweight/obesity and excessive screen time. -Proximity to forests was associated with 39% and 25% lower relative prevalence of excessive screen time and overweight/obesity, respectively.
Tilt et al. (2007) 529 adults, US, 2002	Cross-sectional	Mean NDVI of the walkable neighborhood	-Self-reported walking trips per month; -BMI from self-reported height and weight	Objective greenness was not related to walking trips per month. In areas with high accessibility, BMI was lower in areas that had high NDVI (p-value for interaction 0.0257).
Lachowycz et al. (2012) 902 children, UK, 2007-2009	Cross-sectional	Momentary green space exposure based on GPS-derived location linked to land use dataset	Contemporaneous physical activity measured by accelerometer	33.6% of outdoor moderate-vigorous physical activity on weekday evenings was within green environments, and 46% of outdoor moderate-vigorous physical activity on weekends was in green environments.
Wheeler et al. (2010) 1,053 children, UK, 2006-2008	Cross-sectional	Momentary green space exposure based on GPS-derived location linked to land use dataset	Contemporaneous physical activity measured by accelerometer	Odds of an epoch being moderate-vigorous physical activity in green space (versus outdoor non-green space) were significantly elevated for boys (OR=1.37 95% CI 1.22, 1.53) but not girls (OR=1.08 95% CI 0.95,1.22).
Coombes et al. (2010) 6,821 adults, UK, 2010	Cross-sectional	Distance between home location by road to nearest of several green space types based on land-use files	-Self-reported frequency of visits to green space -Self-reported frequency of physical activity -Self-reported height and weight used to calculate BMI	-Respondents living closest to "formal" green spaces were significantly more likely to achieve physical activity recommendations (OR comparing furthest to closest residents 0.88 95% CI 0.73, 1.06).



Even though currently, there is no universally used definition of urban green space, with regards to its health and well-being impacts and no standard exposure assessment metric. The growing body of literature, mainly cross-sectional studies, on physical activity and greenness, has exhibited consistent results across a wide variety of study populations, suggesting a robust positive association between enhanced physical activity and greenness. Further exploration is needed to investigate how age, gender, and especially SES may modify the association between greenness and health behaviours and outcomes. There is currently no relative risk estimates directly usable to feed the city-level microsimulation assessment of environmental factors on health outcomes.

2.2.4. Fast food and alcohol outlet density

- *Fast food density*

Despite the increasing interest and efforts made over the last fifteen years, the research on the health effects of fast food density seems to be lacking strong evidence.

Most studies are cross-sectional and use aggregated data. Yet, some links between fast-food density and mortality, diabetes rates, obesity rates, and cardiovascular events such as acute coronary hospitalizations have been reported, as summarized in **Erreur ! Source du renvoi introuvable..**

Table 2. Summary of the reviewed literature on fast food outlet and health outcomes



Study Population	Study Design	Exposure	Outcome	Main Finding
Lamb et al. (2017) Australia, Women only	Longitudinal observational	Number of major chain fast-food outlets within 2, 3 or 5 km	Change in BMI	Change in BMI was not found to differ by residential major chain fast-food outlet availability among Victorian women residing in disadvantaged neighbourhoods. It may be that exposure to fast-food outlets around other locations regularly visited influence change in BMI. Future research needs to consider what environments are the key sources for accessing and consuming fast food and how these relate to BMI and obesity risk.
Ahern et al. (2011) US	Cross-sectional multi-county	Fast food outlets (chains and locally owned, number of outlets per 1000 residents)	Overall mortality, diabetes rates, and obesity rates	Overall, and in metro area, availability of fast food restaurants is associated with higher mortality (, diabetes and obesity rates (the result were statistically significant only in metro areas for obesity). In metro areas, 1 additional fast food restaurant per 1,000 residents is associated with a 87.64% higher mortality rates, a 0.87% higher diabetes rate, and a 2.17% higher obesity rate.
Morland and Evenson (2009) US	Cross-sectional	At least one fast food restaurant in the area Distance to nearest fast food restaurant	Obesity prevalence	The prevalence of obesity was lower in areas that had supermarkets and higher in area with small grocery stores or fast food restaurants.
Alter and Eny (2005) Ontario, Canada	Cross-sectional	Fast food chains supply (Number of outlets per 100,000 people) per region	Total mortality and acute coronary hospitalizations	Mortality and admissions for acute coronary syndromes were higher among regions with greater number of fast-food services after adjustments for risk. Each increase of one fast-food outlet per 100,000 people in a region corresponded to an additional one death per 100,000 persons, after adjusting for baseline sociodemographic differences ($p < 0.001$)
Maddock (2004) US	Cross-sectional	Aggregate state-level means for square miles per fast food restaurant and population per fast food restaurant	State-level Obesity prevalence	Correlation between the density of fast food restaurants and state-level obesity prevalence. Multiple hierarchal regressions revealed that square miles per fast food restaurants and residents per restaurant accounted for 6% of the variance in state obesity rates after controlling for population density, ethnicity, age, gender, physical inactivity, and fruit and vegetable intake. The entire model explained 70% of the total variance in state obesity rates.
Morland and Evenson (2009) US	Cross-sectional	At least one fast food restaurant in the area Distance to nearest fast food restaurant	Obesity prevalence	The prevalence of obesity was lower in areas that had supermarkets and higher in area with small grocery stores or fast food restaurants.

There is an increasing interest in considering not only fast food but the whole food environment. So far, most studies evaluating the impact of the neighborhood food environment on obesity and other health outcomes have summarized the density or proximity of individual food outlets by type. Though



informative, there is a need to consider the role of the entire food environment; however, few measures of whole system attributes have been developed.

In a recent review, Cobb et al. (2015) highlighted the general low quality of available studies and the fact that there is no clear definition of fast food and no consensus on fast food accessibility measurement. The authors concluded that there is limited evidence of an association between fast food availability and higher obesity in adults. They also find evidence of an association between fast food restaurant availability and higher obesity in low income children. The authors stressed that moving forward, there is a need for a new research paradigm. Additional longitudinal studies may be helpful as they have the ability to control for neighborhood self-selection. They also recognised that natural experiments may be one of the most powerful tools in this area of research. However, they noted that both types of studies are subject to key issues such as exposure misclassification. Further, with the proliferation of portable GPS technology, they suggested that future studies could use participants' actual travel patterns to determine food availability rather than just relying on their home address.

Focusing only on fast food might be too restrictive as it appears that the whole food environment is playing a role in the health of the neighborhood. Further research is needed and there is a need to reconsider how the food environment is both define and measure to better assess its potential health impacts, including the health effects of fast food.

- *Alcohol outlet density*

Due to time constraints, the literature review on the health effects of alcohol outlet density was not advanced enough to be included in this report.



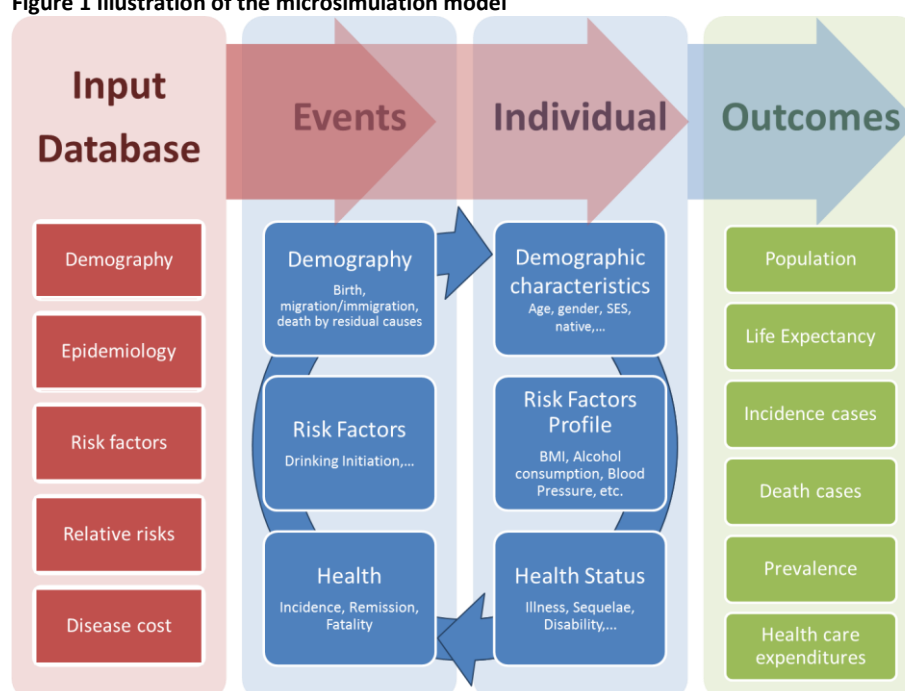
3. Data and Methods: Overview of the Microsimulation model and how Scenarios are modelled

As seen in section 2, environmental risk factors and their geographical distribution may play an important role on health in the future. At the current time of the project, data and evidences available were not sufficient to build a reliable and complete model of projections of health-related impacts taking into account the geospatial distribution of environmental risk factors. The modelling exercise –presented in section 3- exclusively concentrates on individual behavioral risk factors.

3.1. General principle

The projection of the future health outlook relies on a micro-simulation exercise. A microsimulation model is used to project the lives of people representing an entire country or a region of countries. The model simulates lives from birth to death including health events including behavioural risk factors, incidence of NCDs, remission and fatality (see Figure 1). Behavioural risks factors (RF) include: smoking, alcohol use, BMI, physical inactivity, and blood pressure³. The main eight groups of NCDs included in the model are: Diabetes, Ischemic Heart Disease (IHD), Stroke, Cancer, Chronic Obstructive Pulmonary Disease (COPD), mental ill-health, musculoskeletal disorders, and injuries. The matrix below summarizes the existing modelled relative risks that are the relationships between risk factors and diseases (5 behavioural RFs, and 1 physiological RF, and 14 Diseases).

Figure 1 Illustration of the microsimulation model



³ Cholesterol and salt consumption were initially selected as key behavioral risk factors, but they could not be modelled in the microsimulation model due to data issues

Data sources for demography are from the United Nation population projections. Data for the epidemiology of diseases is taken from IHME GBD 2015 (Vos et al., 2016^[1]). Data on risk factors is taken from IHME GBD 2015 (Vos et al., 2016^[1]) and NCD-RisC (NCD Risk Factor Collaboration, 2017). Information on relative risks is collected from IHME GBD 2015 (Vos et al., 2016^[1]) and the DYNAMO-HIA model (Lhachimi et al., 2012^[2]). Medical costs of disease treatment are derived from national health-related expenditure data from Estonia, France and the Netherlands, and generalized to other European countries (see section in Deliverable D5.3). Data sources and model assumptions (e.g., demography, epidemiology, costs) are accessible in the Deliverable D5.3.

The model takes into account the socioeconomic gradient in health, using education as a determinant for behavioral risk factors.

The model is developed for the *2050 time horizon* and for *three zones in Europe*:

- Southern Europe (Croatia, Cyprus, France, Greece, Italy, Malta, Portugal, Slovenia and Spain);
- Central/Eastern Europe (Bulgaria, Poland, Romania, Slovakia, Estonia, Hungary, Latvia and Lithuania);
- Northern Europe (Austria, Belgium, Czech Republic, Denmark, Finland, Germany, Ireland, Luxembourg, the Netherlands, Sweden and United Kingdom).

Model outputs include: measures of effectiveness such as life years and life years in good health (adjusted with DALY weights), and measures of expenditures (health expenditures for treating diseases when they appear). In the case of assessing response/policy scenarios, we compare the response scenario with the business-as-usual (BAU) scenario (and the policy scenario with the BAU scenario).

Table 3 Matrix of risk factors and diseases

Diseases	Behavioural Risk factors					Physiological RFs	
	BMI	Physical activity		Smoking	Alcohol	Diabetes	Blood Pressure
CVDs	X	X		X	X	X	X
Diabetes	X	X		X	X		
COPD				X			
Lung Cancer				X			
Breast Cancer	X	X			X		
Colorectal Cancer	X	X		X	X		
Stomach Cancer				X			
Cirrhosis					X		
Dementia							
Major depressive disorder							
Injuries					X		
Musculoskeletal Disorders	X						

Note: "X" means that the relative risks of developing a disease is included in the model.



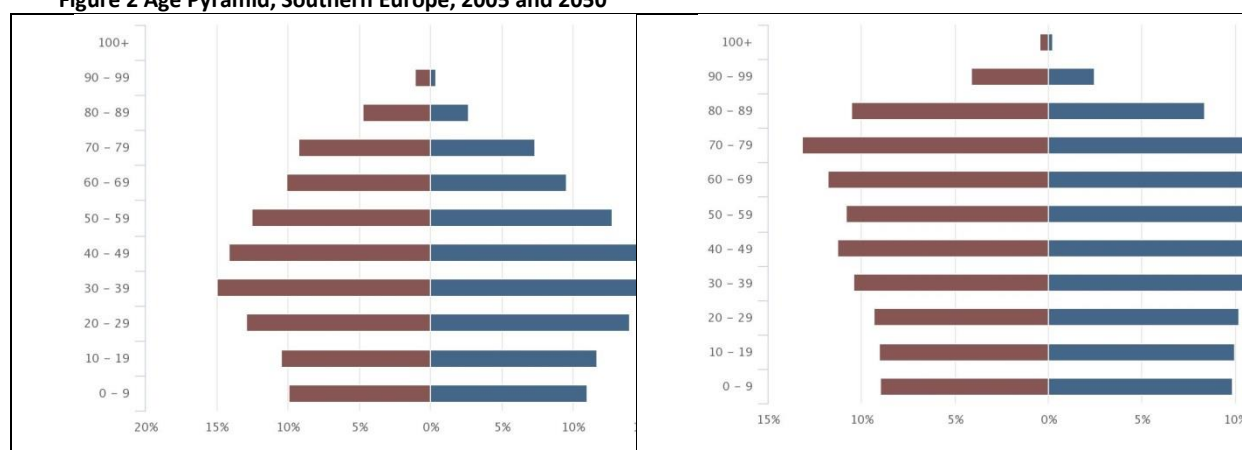
See deliverable 5.3, for more technical details on the way these risk factors are impacting individual risk of disease events.

3.2. Baseline 2050 projections

The baseline of the model uses the United Nation population projections, and all risk factors and relative risks are held constant as observed in 2015 until 2050. Therefore, the change in epidemiology observed in the baseline 2050 projections compared to 2015 are only driven by changes in population structure (more older people who will develop chronic diseases).

Validation of the baseline projections of the model was verified by checking population structure, prevalence and incidence of diseases, as well as prevalence of risk factors for the historical period 1990-2012 (see more details in Deliverable D5.1). The model accurately reproduces the age and sex population structure as can be seen for the year 2005 in Figure 2. Also, the model predicts the evolution of the population structure in line with UN population projections: Population will live older and the age pyramid will evolve (Figure 2).

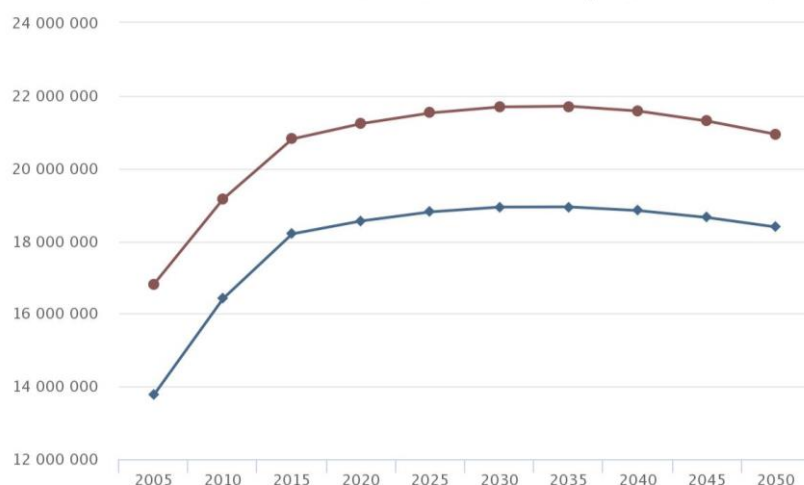
Figure 2 Age Pyramid, Southern Europe, 2005 and 2050



Source: Analysis based on a new model developed by OECD for the FRESHER project, 2017

The age and gender-specific prevalences of risk factors –that follow historical trends for the 1990-2015 period- are kept constant from 2015 in the baseline projections (Figure 3 for obesity prevalence). This means we do not predict any change in the risk factors distribution by age and sex in the baseline projections.

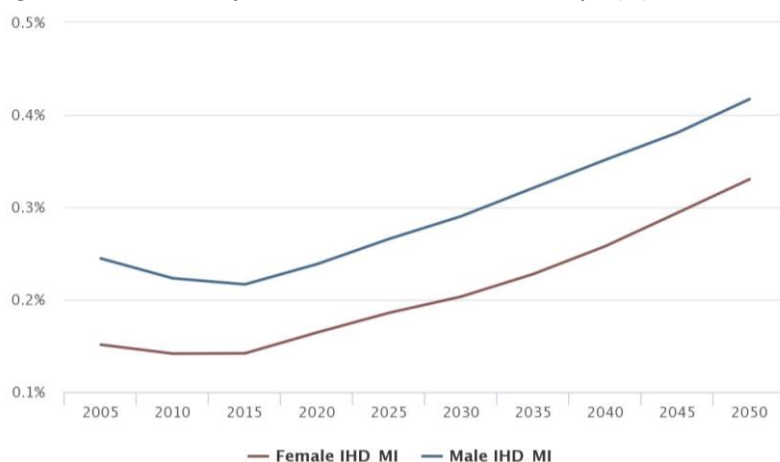
Figure 3 Prevalence of obesity, Southern Europe



Source: Analysis based on a new model developed by OECD for the FRESHER project, 2017

The incidence of diseases is associated with the relative risk of developing a disease attached to risk factors, which are also held constant in the model. As a result of the assumptions of the baseline projections just described, the new cases of diseases increase from 2015 to 2050 in line with the demography changes (Figure 4 for Myocardial Infarction as an example).

Figure 4 Incidence of Myocardial Infarction, Southern Europe, (%)



Source: Analysis based on a new model

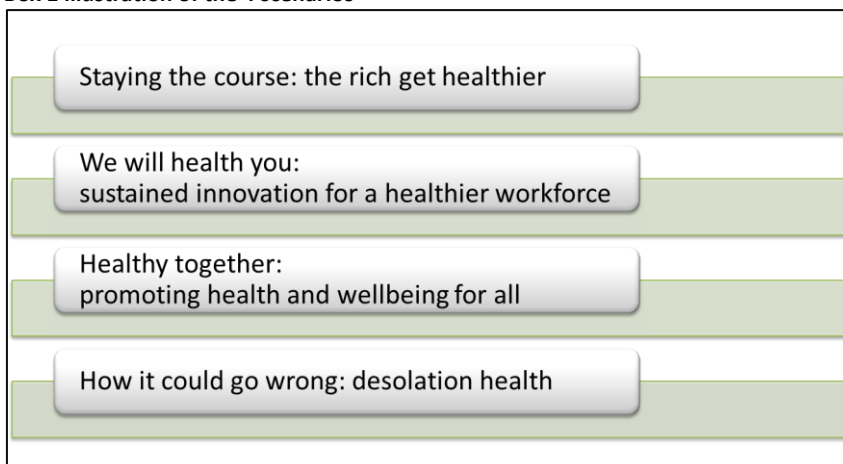
developed by OECD for the FRESHER project, 2017

3.3. Integrating Scenarios

The FRESHER project aims to represent alternative futures health scenarios taking into account structural long-term mega-trends in demographic, gender relations, technological, economic, environmental, and societal factors for European countries at the 2050 horizon. The originality of FRESHER is to combine qualitative and quantitative foresight techniques, merging both mega-trends assessment and microsimulation-based forecasts.



Box 1 illustration of the 4 scenarios



There are 4 foresight scenarios developed by WP4 (see Box 1 and deliverable D4.2) that describe possible future structural mega-trends. These scenarios were incorporated into the microsimulation model through only one entry point: the change in risk factors. To do so, an expert's consultation was carried out in 2017 to survey health experts about the evolution of key behavioural risk factors -at the 2050 horizon- under each of the four foresight scenarios.

Table 4 shows the mean values from the 91 health experts' answers (most of them from academia).

Table 4 Experts' evaluation of future trends in risk factors (mean)

Risk Factors	Average (2015)	Best case (Min in 2015)	Worst case (Max in 2015)	The rich get healthier (2050)	Healthy together (2050)	We will health you (2050)	Desolation health (2050)
Obesity (%)	27	23	32	35.4	24.4	25.4	38.6
Phys inactivity (%)	32	12	55	35.8	28.8	30.4	38.0
Smoking (%)	23	12	35	21.1	15.3	15.5	25.4
Alcohol (g/day)	10.72	4.51	17.52	12.63	9.57	9.54	14.98
High Blood Pressure (% with SBP >140 mmHg)	20	13	30	22.74	16.30	16.63	26.80

Note: Green colour means figures are lower than the 2015 baseline. Blue colour means figures are higher than the 2015 baseline. The levels of alcohol consumption as presented in this table are originally taken from the IHME data, however it has been rescaled in the model to match the OECD average per capita level.

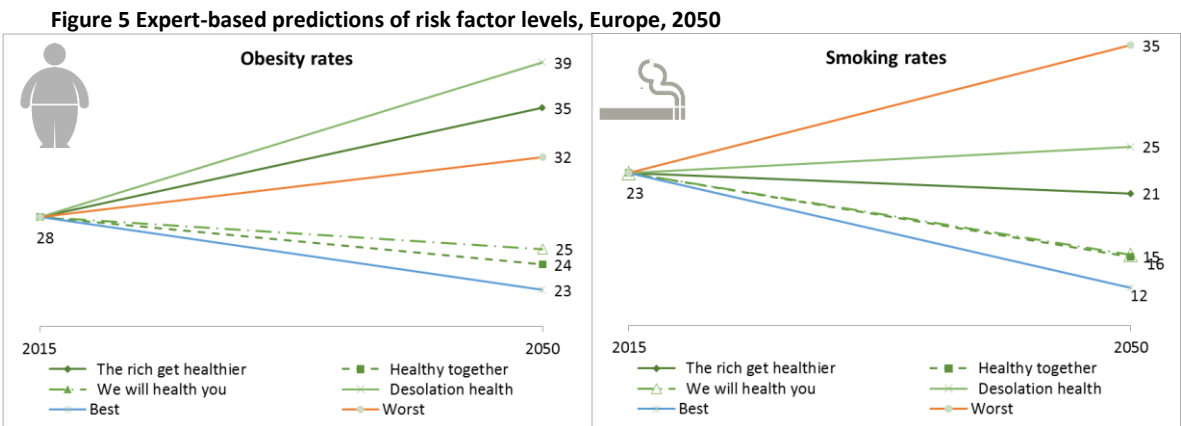
Source: IHME 2015 data in European countries, and Expert's consultation for 2050.

The four scenarios evolve in the expected direction. The 'Rich get healthier' scenario shows a deterioration of most risk factors with the exception of smoking, compared to the 2015 baseline. The 'Desolation health' scenario is associated with deterioration of all risk factors. The 'We will health you' scenario has lowered risks for health compared to the 2015 baseline. The 'Healthy Together' scenario is overall the most positive scenario, with lowered risks for health.

As an example, according to Experts, smoking rates, which have been on the decline over past years, are expected to decrease at the 2050 horizon in three scenarios (from 23% in 2015 to 21% in 'The Rich

Get Healthier’, 15% in ‘Healthy Together’ and 16% in ‘We will health you’) and to rise in the ‘Desolation Health’ scenario (25% in 2050) (Figure 5, right-hand side). Obesity rates are expected to continue to grow in two scenarios (‘The Rich Get Healthier’ and ‘Desolation Health’) and to decrease in two other scenarios (Figure 5, left-hand side).

Expert-based predictions of risk factors are complemented with objective measures of the ‘Best’ and ‘Worst’ case scenarios that assume all countries will converge to the minimum (best) and maximum (worst) values as they are observed in 2015 in European countries. It is interesting to note that experts’ predictions for smoking rates fall between the Best and Worst case scenarios. The picture is different for obesity. Experts predicted that in two scenarios (‘The Rich Get Healthier’ and ‘Desolation Health’), obesity rates will significantly increase, to a higher level than what is observed today in Europe (Figure 5).



Source: FRESHER Experts’ survey, 2017

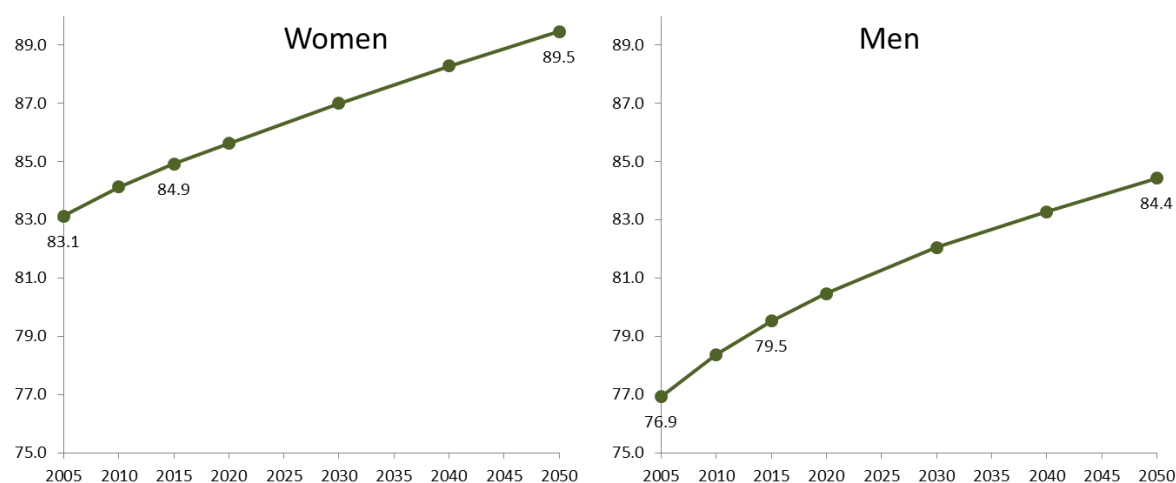


4. The influence of behavioural RFs on the future health outlook: Results of the microsimulation model

4.1. Europeans will live longer, but with more chronic diseases

Europeans will live longer. Life expectancy for women (men) in Europe will rise from 84.9 years old today to 89.5 years old in 2050 (respectively, from 79.5 to 84.4), according to the microsimulation model estimation, under the baseline projections. As a result, the population structure will evolve as shown by the age pyramid in Figure 6. The share of the population aged 65+ will increase from 18% in 2015 to 30% in 2050 in Europe.

Figure 6 Evolution of life expectancy from 2005 to 2050, Europe

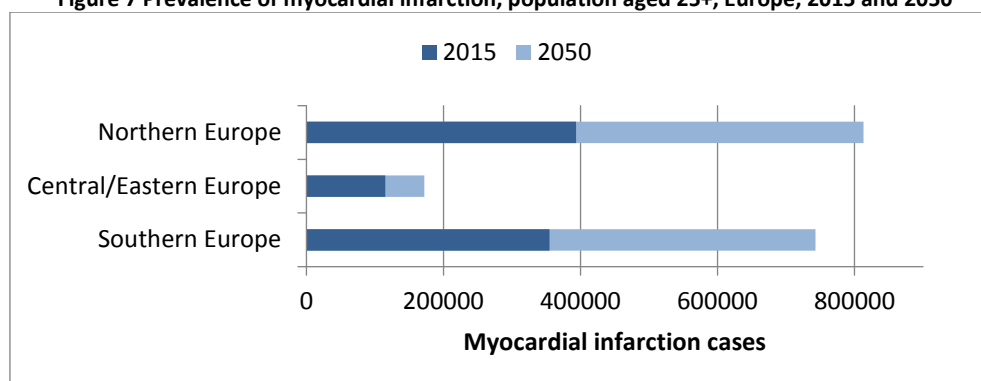


Source: Analysis based on a new model developed by OECD for the FRESHER project, 2017

As people live longer, they also tend to have more chronic diseases such as ischemic heart diseases (IHD), stroke, cancers, chronic obstructive pulmonary diseases (COPD), mental illnesses, and musculo-skeletal disorders. As illustrated in Figure 7, the prevalence of myocardial infarctions in Europe will increase by about 865 000 cases in 2050, assuming no change in risk factors trends and incidences by age and sex (baseline projections). Myocardial infarctions cases will double by 2050 in Southern and Northern Europe and they will increase by half in Central/Eastern Europe.



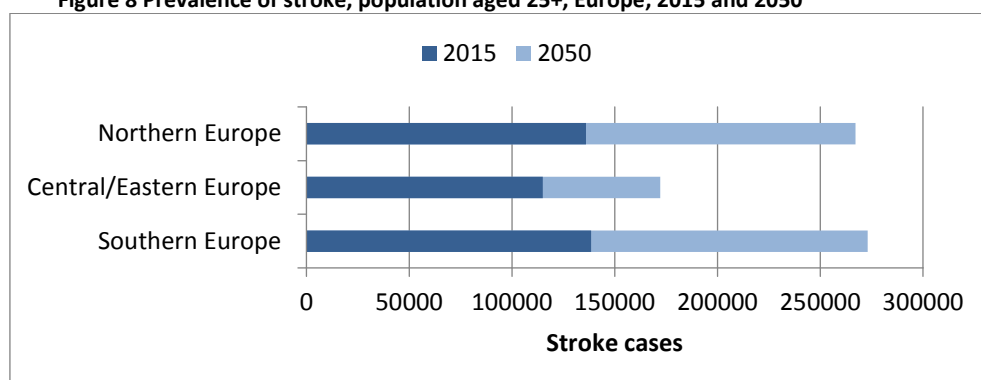
Figure 7 Prevalence of myocardial infarction, population aged 25+, Europe, 2015 and 2050



Source: Analysis based on a new model developed by OECD for the FRESHER project, 2017

As illustrated in Figure 8 Prevalence of stroke, population aged 25+, Europe, 2015 and 2050, the prevalence of people having a stroke in Europe will increase by about 323 000 cases in 2050, assuming no change in risk factors trends and incidences by age and sex (baseline projections). Stroke cases will double by 2050 in Southern and Northern Europe and they will increase by half in Central/Eastern Europe.

Figure 8 Prevalence of stroke, population aged 25+, Europe, 2015 and 2050

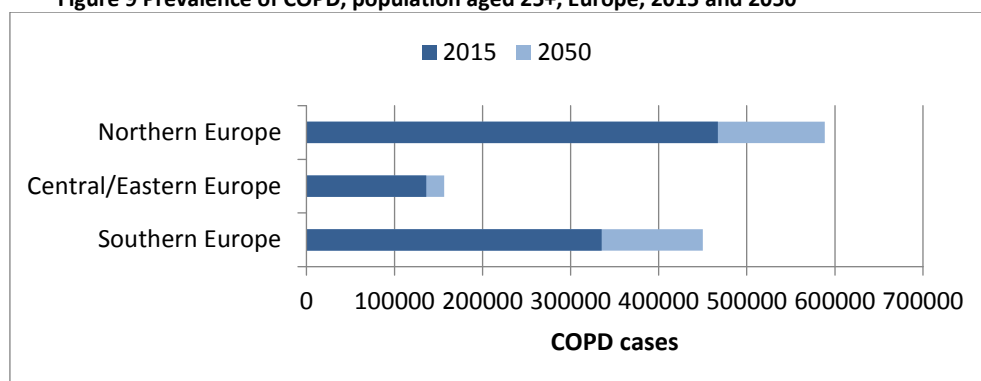


Source: Analysis based on a new model developed by OECD for the FRESHER project, 2017

As illustrated in Figure 9, the prevalence of people having a COPD in Europe will increase by about 257 000 cases in 2050, assuming no change in risk factors trends and incidences by age and sex (baseline projections). COPD cases will increase by 34% in 2050 in Southern Europe, 15% in Central/Eastern Europe, and 26% in Northern Europe. This corresponds to a 25% increase in COPD cases on average in Europe.



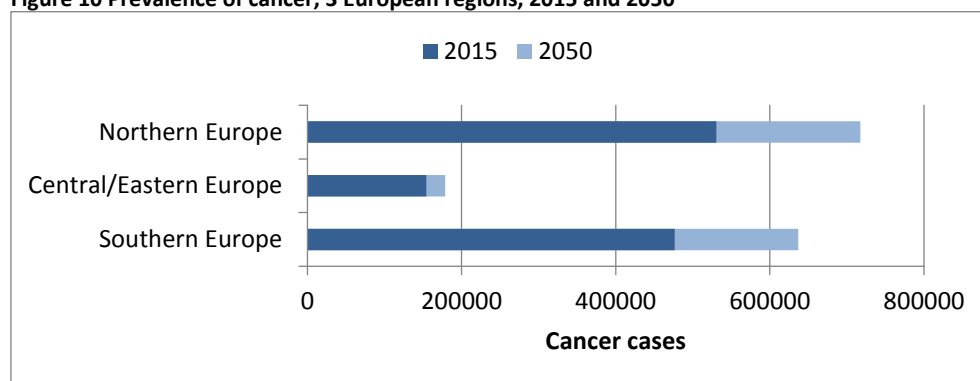
Figure 9 Prevalence of COPD, population aged 25+, Europe, 2015 and 2050



Source: Analysis based on a new model developed by OECD for the FRESHER project, 2017

According to the baseline projections, 372 000 more cases of cancer can be predicted by 2050, in Europe: 160 000 in Southern Europe, 25 000 in Central/Eastern Europe, 187 000 in Northern Europe (Figure 10). This corresponds to a 26% increase in cancer cases on average in Europe.

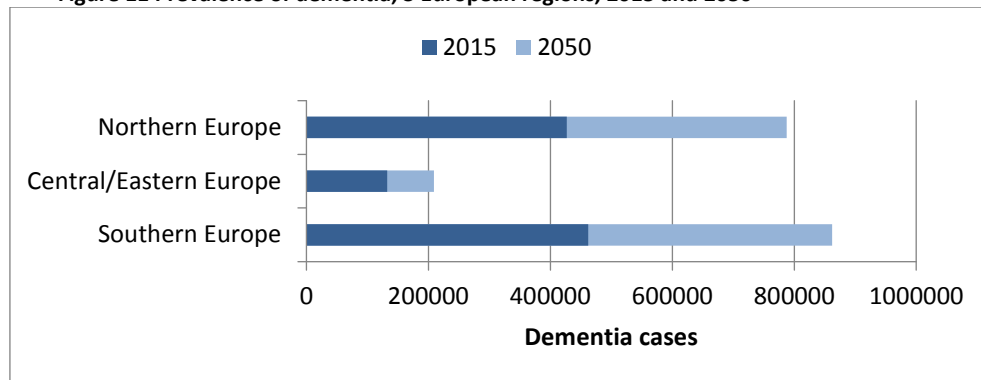
Figure 10 Prevalence of cancer, 3 European regions, 2015 and 2050



Source: Analysis based on a new model developed by OECD for the FRESHER project, 2017

The progress of dementia is even more significant with 837 000 more cases predicted by 2050, in Europe: 400 000 in Southern Europe, 77 000 in Central/Eastern Europe, 360 000 in Northern Europe (Figure 11). This corresponds to a 76% increase in dementia cases on average in Europe.

Figure 11 Prevalence of dementia, 3 European regions, 2015 and 2050

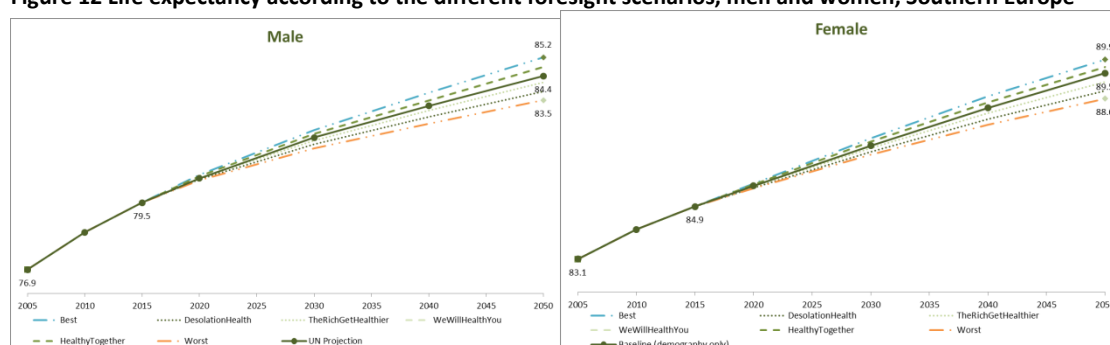


Source: Analysis based on a new model developed by OECD for the FRESHER project, 2017

4.2. Quantifying the impacts of alternative scenarios

Life expectancy is projected to grow, to different extent according to the envisaged scenarios. At the 2050 horizon, women in Southern Europe are expected to live for 89.5 years on average under the baseline demography-driven scenario, this average varying by -10 months to +6 months across scenarios. Respectively, men are expected to live for 84.4 years, this average varying by -11 months to +9 months across scenarios (see Figure 12). In Northern Europe, projected life expectancies are estimated to be 84.3 years for men and 87.2 for women with variations ranging from -11 months to +8 months according to scenarios. In Eastern-Central Europe, projected life expectancies are estimated at 77.7 years old for men and 83.5 for women with variations ranging from -12 months to +8 months according to scenarios. This indicates that the possible improvements –expected by the experts- in the living environment of people can result in sizeable gains in the life expectancy of Europeans.

Figure 12 Life expectancy according to the different foresight scenarios, men and women, Southern Europe



Source: Analysis based on a new model developed by OECD for the FRESHER project, 2017

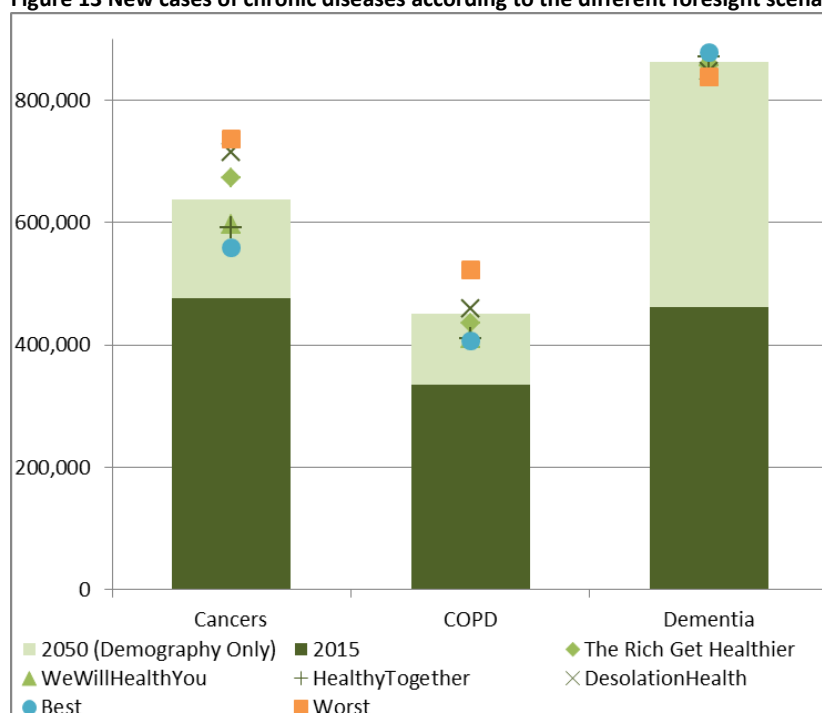
Figure 13 shows the incidence of diseases in different scenarios at the 2050 horizon. 'The Rich Get Healthier' and 'Desolation Health' scenarios lead to increased numbers of new cases of chronic diseases (like diabetes, cancers, COPD, IHD, Stroke), while 'Healthy Together' and 'We will health you' scenarios lead to reduced numbers of diseases. The Best and Worst case scenarios are positioned at the two extremes, as one can expect. Interestingly, the effect on dementia is reversed: as people live older in the



healthier scenarios ('Healthy Together', 'We will health you' and 'Best'), they develop dementia more than in the other scenarios. Results of scenarios should not be viewed as a predictive estimation but rather as a comparative estimation of one scenario to another.

All in all, the effects of scenarios on diseases are consistent –i.e. in the expected direction– although relatively thin compared to the effect of demography. None of the scenarios is projected to counter-balance the effects of the baseline demography-driven scenario. That means the sole effect of population ageing is expected to lead to an increased number of chronic diseases that could not be lessened whatever the future will look like, *if no new policy or breakthrough are considered*.

Figure 13 New cases of chronic diseases according to the different foresight scenarios, Southern Europe



Source: Analysis based on a new model developed by OECD for the FRESHER project, 2017

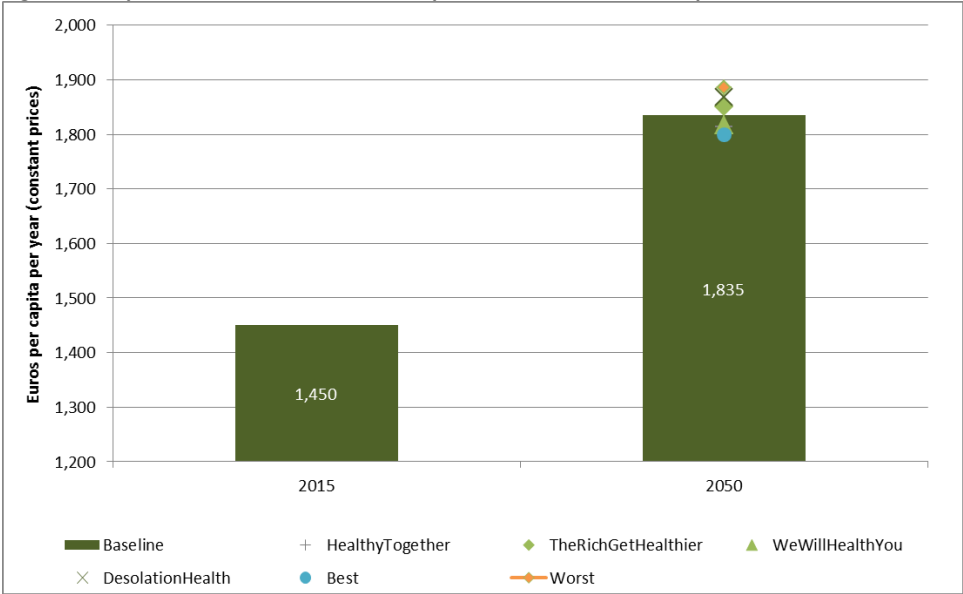
4.3. Health expenditures projections

As the population gets older with more chronic diseases, health expenditure is expected to grow by 26% in constant price in 2050. In Southern Europe, health care costs are estimated to grow roughly from 1450 € per capita in 2015 to 1835 € per capita in 2050. In Northern Europe, health care costs will grow by 21% from roughly 1910 € to 2300€ per capita over the same period. In Eastern-Central Europe, they will grow by 20% from roughly 300 € to 350€ per capita. These figures are calculated for the baseline demography-driven scenario -with no change in risk factors trends nor in the epidemiology of the diseases-. The medical technology/treatment protocols are also assumed to be constant. The four following scenarios try to deal with alternative assumptions on these trends.

As the burden of chronic diseases differs to a small extent from one scenario to another, health care costs will evolve accordingly -with a small magnitude-. The impacts of scenarios are relatively minor compared to the projection of a 25% increase in health expenditure driven by the sole effect of

population ageing. Figure 14 shows that in Southern Europe, health care cost per capita will vary by -2% to +3% across different scenarios. In fact, regarding health care expenditures, two forces counteract when the risk factors trends improve: the incidences of diseases decline, with decreasing effect on expenditures, but, at the same time, the (resulting) gains in life expectancy necessary push up the expenditures with a larger number of elders in the population).

Figure 14 Impacts of scenarios on health expenditures, Southern Europe

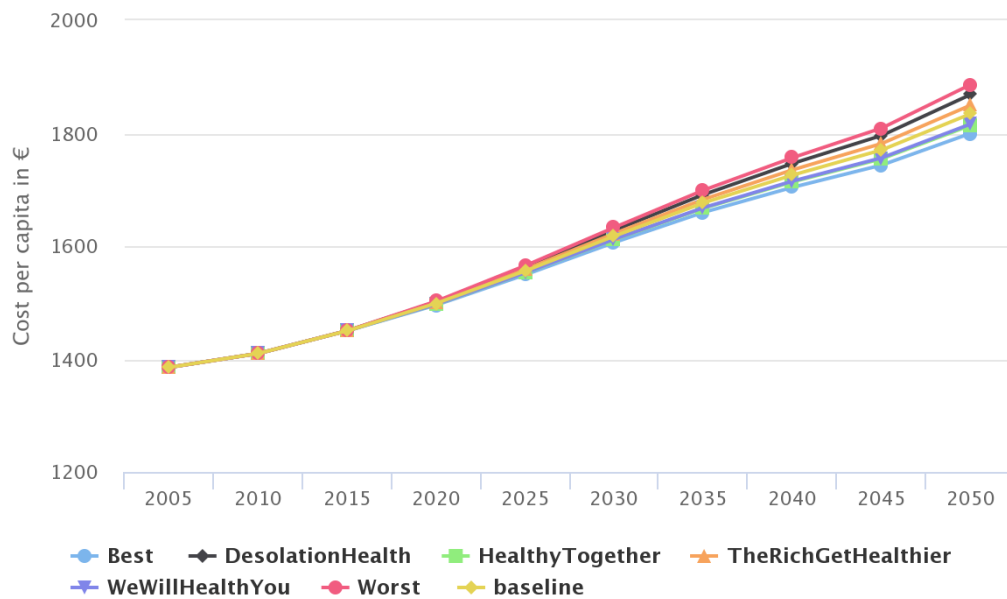


Source: Analysis based on a new model developed by OECD for the FRESHER project, 2017

Health care expenditures are projected to grow gradually from 2015 to 2050, with small degree of variation across scenarios. Figure 15 shows the possible projections of health care expenditures by 2050 for the different foresight scenarios, in Southern Europe.



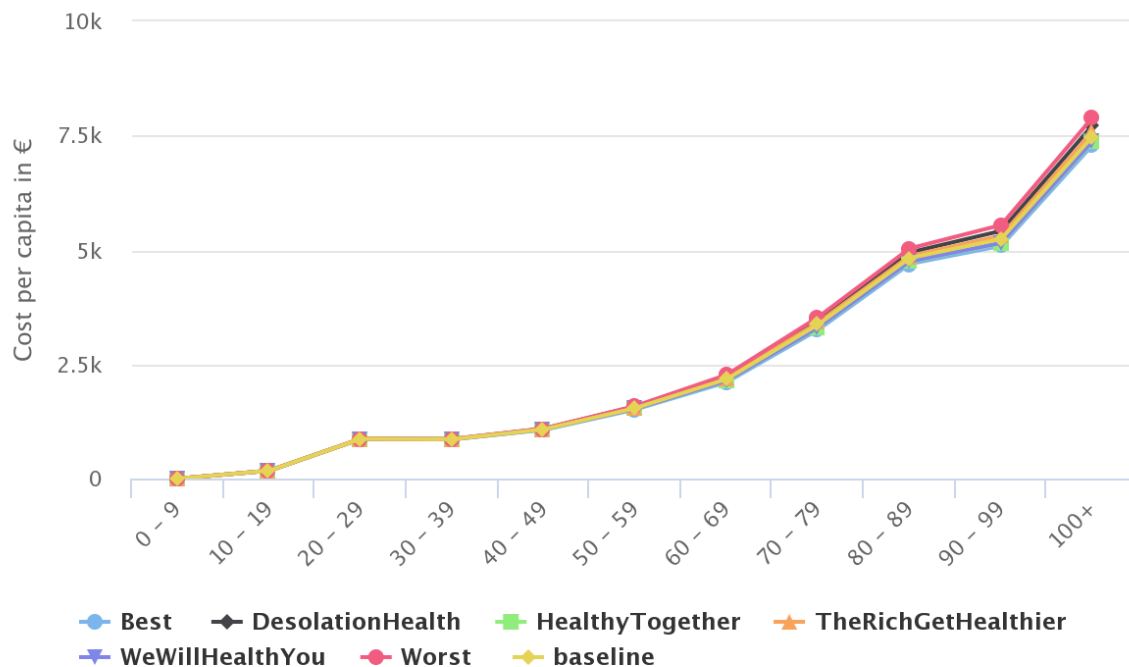
Figure 15 Health expenditure forecast by 2050, baseline projections and 6 scenarios, Southern Europe



Source: Analysis based on a new model developed by OECD for the FRESHER project, 2017

Figure 16 shows the distribution of health care costs by age group as projected in 2050.

Figure 16 Health care expenditure by age group, 2050, baseline projections and 6 scenarios, Southern Europe



Source: Analysis based on a new model developed by OECD for the FRESHER project, 2017

Overall, health care expenditure is projected to grow by 25% in Europe by 2050, with small degree of variations across scenarios. This 25% increase in medical expenditures is solely driven by changes in the demography and the epidemiology. It does not take into account macro-level change (e.g., national income, labor productivity, technological progress). In the line of what has been called by the literature “disease oriented model” (see for ex Thiébaud, Barnay, Ventelou, 2014), the FRESHER project employs a microsimulation model that focusses on changes in epidemiology (taking into account multi morbidity), but does not model macro-level economic factors.

Multi-comorbidity is a key element of the expenditure forecasts. Based on a focus on French data, estimates of health expenditures associated with multi-morbidities suggest, for instance, that treating a respiratory co-morbidity would increase the expenditure required to treat a case of diabetes by circa €670, and a cardiac co-morbidity would increase it by €860, relative to a cost of €1,780 for diabetes patients without comorbidities. (See Cortaredona et Ventelou, 2017.)



5. Policy actions: what can be achieved?

5.1. How policies have succeeded to reduce smoking, alcohol use and obesity?

Several types of public health policies have been used over the past decades aiming at tackling smoking, harmful alcohol use and obesity. One of the objectives of the FRESHER project was to assess the potential effects of public health policies on future health and economic outcomes. Due to time limits, we could not review and assess a comprehensive set of public health policies. Instead, we selected a set of policies which have been shown to be highly effective to reduce smoking, harmful alcohol use and obesity, and we aimed to assess their long-term effects if all countries decided to implement them.

We have identified some of the most effective policies in each of three risk factor domains (tobacco, alcohol, obesity), and quantified their effects (size of the effect, population covered by the policy, and duration of effectiveness). These parameters are key to allow the policy simulation in the microsimulation model. Evidence on policies aimed to tackle harmful use of alcohol relies on the evidence published in the OECD 2015 report (OECD, 2015). Evidence on policies aimed to reduce obesity uses information published in Sassi (2010) complemented by an update of the literature undertaken in the FRESHER project by colleagues from THL, Finland. Evidence of tobacco policies were gathered by colleagues from ISS, Italy.

Table 5 summarizes the four selected policies and their effects. These four policies were modelled together in the microsimulation model. The extent of the incremental policy actions assessed in the simulation reflects policy approaches typically used so far in European countries. In other words, the simulated policy scenario assumes that existing policies are scaled up and spread across all EU countries, but only to an extent that is consistent with previous levels of implementation of these policies in the settings where they have been implemented so far. For instance, increasing levels of tobacco and alcohol taxation so that price hikes can be generated of, respectively, 20% and 10%, is in line with what many EU countries have been doing in recent years. Applying these changes incrementally, and consistently across all EU countries, no doubt would represent a significant public health innovation, but one that remains cautiously designed in line with previous policy actions.

Table 5 Effects of policies modelled

Type of policy	Effect
Tobacco 20% taxation	Effect on smoking prevalence: -7.2% in young and -3.6% in adults
Alcohol 10% taxation	Effect on alcohol consumption from -0.6% to -5.9% (varying by age group and by type of drinkers)
Alcohol advertising regulation	Effect on binge drinker prevalence: -1.6 % of binge drinkers in the whole population
Obesity counselling from GP	Effect on BMI -0.47 kg/m ²

Source: (Hopkins et al., 2001^[3]) Hopkins et al 2001 for tobacco; OECD (2015) for alcohol; (Booth et al., 2014^[4]) Booth et al 2014 for obesity.

Simulations of policies are made in comparison with the ‘The Rich Get Healthier’ scenario which assumes no meaningful policy changes compared with the baseline year in the evaluation. This means that the model simulates the effects of the above policy package over and above the outcomes of ‘The Rich Get Healthier’ scenario. Policy impacts are identified by comparing model outputs for the policy scenario and for ‘The Rich Get Healthier’.

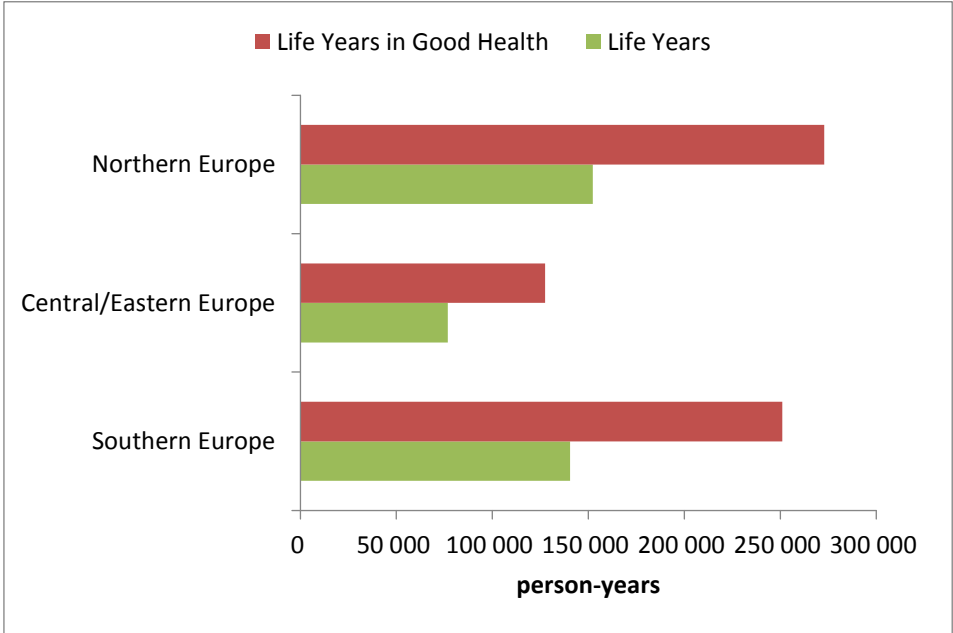
5.2. What could be expected with the traditional public health policy packages?"

A simulation of a scenario involving the scaling up and universal uptake in the EU of effective policies aimed at tackling smoking, harmful alcohol use and obesity, was undertaken to forecast the effects of



those policies on diseases, life expectancy and health care costs. The findings of the simulation show that the incidence of chronic non-communicable diseases would be reduced. Figure 17 shows that the policy package would allow to save a significant amount of life years and life years in good health in the 3 European regions. When considering final outcomes, however, impacts on overall life expectancy in Europe would be small, and certainly much smaller than the effects of switching from one scenario to another of those discussed above in this document

Figure 17 Life years and life years in good health gained with the implementation of a policy package, average per year 2018-2050, 3 European regions

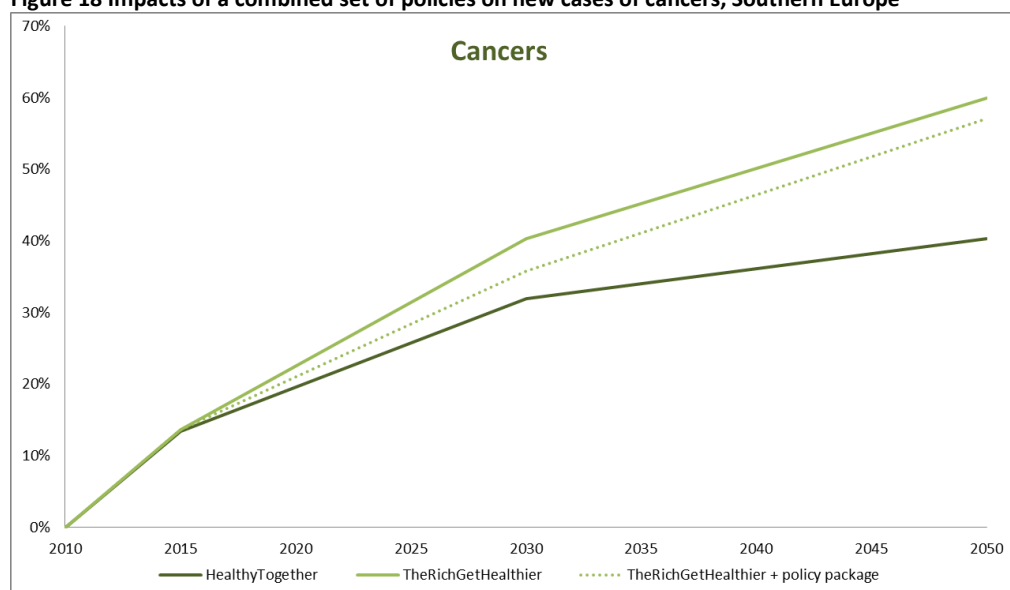


Source: Analysis based on a new model developed by OECD for the FRESHER project, 2017

Figure 18 illustrates the potential effects of a combination of policies on new cases of cancer compared to the ‘The Rich Get Healthier’ scenario taken as the business-as-usual, in Southern Europe. For instance, the implementation of a policy package applied on top of ‘the Rich Get Healthier’ scenario would shift downwards the trend of new cases of cancers. In ‘The Rich Get Healthier’ scenario, the incidence of cancers would increase by 60% from 2010 to 2050 while it would increase by 57% if the policy package were implemented in all countries. For comparison, the ‘Healthy Together’ scenario would see an increase of the incidence of cancers of 40%. This means there is indeed an effect of the combined public health policies, but the size of the effect is rather small since it does not affect the trend.



Figure 18 Impacts of a combined set of policies on new cases of cancers, Southern Europe



Source: Analysis based on a new model developed by OECD for the FRESHER project, 2017

Based on its computer simulation analyses, the FRESHER project provides evidence that a consistent implementation and scaling up of established public health policy approaches in tackling major risk factors for chronic diseases would lead to some improvements in the health of the European population. However, those policies alone can, at best, slightly bend the increasing trend of chronic diseases. Those policies will not be sufficient to offset the impacts of current demographic trends, even if supported by favourable societal trends, as encapsulated in the healthier FRESHER scenarios.

6. Conclusion and discussion

European countries will be facing the dual challenge of an increasing burden of chronic diseases, which will likely affect their workforce, productivity and welfare systems, and of an increasing demand for health services, leading to a rise in health and social expenditure. If all this is to be avoided, radical and innovative solutions are required, only some of which may be in sight today. The Sustainable Development Goals agenda for 2030 adopted in September 2015 by the United Nations offers an opportunity to elaborate and promote new inter-sectorial and global policies that would contribute to the control of NCDs.

Treating chronic diseases more and more efficiently, preventing their complications, optimizing medical drug prescriptions, especially in the oldest segment of the population, and coordinating effectively the care required by patients with multiple morbidities are all key steps in containing further growth in health and social care expenditure. However, the most radical, and most difficult, changes required are those that may reduce the number of people with chronic conditions. These changes include focusing public policies for reducing socio-economic and health inequalities, new ways of designing urban environments; new attitudes to the production and consumption of food and nutrition, to physical activity and to the use of technology in everyday life; new and cleaner means of transportation, production and energy generation. New policies and grassroots initiatives must develop around these

objectives, aiming at a much larger impact than the public health measures that have been tried out so far to prevent chronic diseases.

Results presented in this report give a broad indication of the potential future health outlook. Results of projections are to be viewed not as a predictive estimation but rather as a comparative estimation of one scenario to another. Projections in the FRESHER project are based on a microsimulation exercise. It used a software platform that assesses the potential health and economic outcomes at the 2050 horizon. Different prediction scenarios were modelled. These scenarios -developed by WP4 in the FRESHER project- were incorporated into the microsimulation model via the entry point of risk factors. Some other structural factor changes are not part of the model. The scenarios are expected to exhibit changing behavioral risk factors, as predicted by health experts. The future levels of risk factors are assumed to capture all the structural changes observed in the scenarios, which may not be the case. For instance, particular situation described in some scenarios (e.g. Desolation Health) cannot be fully reflected in the experts' assessment of risk factors. This may constitute a limitation of this exercise. Future work may envisage other approaches to integrate scenarios into the microsimulation model.



References

- Abraham, J. M. (2013), Using Microsimulation Models to Inform U.S. Health Policy Making. *Health Services Research*, 48: 686–695.
- Ahern, Melissa, Cheryl Brown, and Stephen Dukas. (2011). "A National Study of the Association Between Food Environments and County-Level Health Outcomes." *Journal of Rural Health* 27(4): 367–79.
- Almanza, Estela et al. (2012). "A Study of Community Design, Greenness, and Physical Activity in Children Using Satellite, GPS and Accelerometer Data." *Health & Place* 18(1): 46–54.
- Alter, David A., and Karen Eny. 2005. "The Relationship between the Supply of Fast-Food Chains and Cardiovascular Outcomes." *Canadian Journal of Public Health* 96(3): 173–77.
- Analitis, Antonis et al. (2014). "Effects of Heat Waves on Mortality: Effect Modification and Confounding by Air Pollutants." *Epidemiology* 25(1): 15–22.
- Aubrecht, C., K. Steinnocher (2016) Volunteered Geo-Dynamic Information for Health Exposure Assessment - a FRESHER Case Study. *GI _Forum Journal for Geographic Information Science*, Vol. 2 (2016), S. 157 - 163.
- Aubrecht, C., K. Steinnocher, H. Huber (2014) DynaPop – Population distribution dynamics as basis for social impact evaluation in crisis management. *ISCRAM 2014, 11th International Conference on Information Systems for Crisis Response and Management* (pp. 319-323). University Park, PA, USA.
- Baccini, M. et al. (2011). "Impact of Heat on Mortality in 15 European Cities: Attributable Deaths under Different Weather Scenarios." *Journal of Epidemiology and Community Health* 65(1): 64–70.
- Booth, H. et al. (2014), "Effectiveness of behavioural weight loss interventions delivered in a primary care setting: a systematic review and meta-analysis", *Family Practice*, Vol. 31/6, pp. 643-653, <http://dx.doi.org/10.1093/fampra/cmu064>.
- Bourguignon, F.J. and Spadaro, A. (2006) 'Microsimulation as a tool for evaluating redistribution policies', *Journal of Economic Inequality* 4(1): 77-106
- Briggs, A. and M. Sculpher (1998) 'An introduction to Markov modelling for economic evaluation', *Pharmacoeconomics* 13 (4): 397-409.
- Chaix, Basile et al. (2014). "The Environmental Correlates of Overall and Neighborhood Based Recreational Walking (a Cross-Sectional Analysis of the RECORD Study)." *International Journal of Behavioral Nutrition and Physical Activity* 11(1).
- Citro, C. and E. Hanushek (1991). "Improving information for social policy decisions: the uses of microsimulation modelling", National Academy Press, Washington.
- Cobb, Laura K. et al. (2015). "The Relationship of the Local Food Environment with Obesity: A Systematic Review of Methods, Study Quality, and Results." *Obesity* 23(7): 1331–44.
- Cogneau, D. and M. Grimm (2008) 'The impact of AIDS mortality on the distribution of income in Côte d'Ivoire', *Journal of African Economies* 17 (5): 688-728.



- Coombes, Emma, Andrew P. Jones, and Melvyn Hillsdon. (2010). "The Relationship of Physical Activity and Overweight to Objectively Measured Green Space Accessibility and Use." *Social Science and Medicine* 70(6): 816–22.
- Cortaredona, S., & Ventelou, B. (2017). The extra cost of comorbidity: multiple illnesses and the economic burden of non-communicable diseases. *BMC medicine*, 15(1), 216.
- CRED, 'Disaster Data: A Balanced Perspective', Cred Crunch Newsletter (Brussels: CRED, 3 March 2016), <http://reliefweb.int/report/world/cred-crunch-newsletter-issue-no-41-february-2016-disaster-data-balanced-perspective> (accessed 18 December 2017).
- D'Ippoliti, Daniela et al. (2010). "The Impact of Heat Waves on Mortality in 9 European Cities: Results from the EuroHEAT Project." *Environmental Health: A Global Access Science Source* 9(1).
- Dadvand, Payam et al. (2014). "Risks and Benefits of Green Spaces for Children: A Cross-Sectional Study of Associations with Sedentary Behavior, Obesity, Asthma, and Allergy." *Environmental health perspectives* 122(12): 1329–35.
- DYNAMO-HIALhachimi SK, Nusselder WJ, Smit HA, van Baal P, Baili P, Bennett K, Fernández E, Kulik MC, Lobstein T, Pomerleau J, Mackenbach JP, Boshuizen HC. DYNAMO-HIA—a Dynamic Modeling tool for generic Health Impact Assessments. *PLoS One*. 2012a;7(5):e33317.
- EEA, Copenhagen, Denmark.
- European Commission. (2001). Appendix 1: Methodology sheets. In: *European Common Indicators. Towards a Local Sustainability Profile*. Pages 174–209. https://www.gdrc.org/uem/footprints/eci_final_report.pdf (accessed 17 November 2017).
- European Environment Agency, (2016). *Extreme temperatures and health*. <http://www.eea.europa.eu/data-and-maps/indicators/heat-and-health-1/assessment-1> (accessed 17 November 2017)
- European Union. (2011). *Mapping Guide for a European Urban Atlas*. European Environment Agency,
- Forouzanfar, M. H. et al. (2016). "Global, Regional, and National Comparative Risk Assessment of 79 Behavioural, Environmental and Occupational, and Metabolic Risks or Clusters of Risks, 1990–2015: A Systematic Analysis for the Global Burden of Disease Study 2015." *The Lancet* 388(10053): 1659–1724.
- Garrett, Pedro, and Elsa Casimiro. (2011). "Short-Term Effect of Fine Particulate Matter (PM2.5) and Ozone on Daily Mortality in Lisbon, Portugal." *Environmental Science and Pollution Research* 18(9): 1585–92.
- Gong, Yi, John Gallacher, Stephen Palmer, and David Fone. (2014). "Neighbourhood Green Space, Physical Function and Participation in Physical Activities among Elderly Men: The Caerphilly Prospective Study." *International Journal of Behavioral Nutrition and Physical Activity* 11(1): 40.
- Grigsby-Toussaint, Diana S., Sang Hyun Chi, and Barbara H. Fiese. 2011. "Where They Live, How They Play: Neighborhood Greenness and Outdoor Physical Activity among Preschoolers." *International Journal of Health Geographics* 10: 66.
- Gryparis, A et al. (2004). "Acute Effects of Ozone on Mortality from The 'air Pollution and Health: A European Approach' project." *Am J Respir Crit Care Med* 170(10): 1080–87.
- Guo, Yuming et al. (2017). "Heat Wave and Mortality: A Multicountry, Multicommunity Study." *Environmental Health Perspectives* 125(8).
- Hartig, Terry, Richard Mitchell, Sjerp de Vries, and Howard Frumkin. (2014). "Nature and Health." *Annual Review of Public Health* 35(1): 207–28.
- Hillsdon, M., J. Panter, C. Foster, and A. Jones. (2006). "The Relationship between Access and Quality of Urban Green Space with Population Physical Activity." *Public Health* 120(12): 1127–32.
- Hopkins, D. et al. (2001), "Reviews of evidence regarding interventions to reduce tobacco use and exposure to environmental tobacco smoke.", *American journal of preventive medicine*, Vol. 20/2



- Suppl, <http://www.ncbi.nlm.nih.gov/pubmed/11173215> (accessed on 05 December 2017), pp. 16-66.
- IHME 2015 available at <http://www.healthdata.org/>
- James, Peter, Rachel F. Banay, Jaime E. Hart, and Francine Laden. (2015). "A Review of the Health Benefits of Greenness." *Current Epidemiology Reports* 2(2): 131-42.
- Jerrett, M., Burnett, R. T., Ma, R., Pope III, C. A., Krewski, D., Newbold, K. B., ... & Thun, M. J. (2005). Spatial analysis of air pollution and mortality in Los Angeles. *Epidemiology*, 16(6), 727-736.
- Jerrett, Michael et al. (2009). "Long-Term Ozone Exposure and Mortality." *New England Journal of Medicine* 360(11): 1085-95.
- Karusisi, Noëlla et al. (2012). "Multiple Dimensions of Residential Environments, Neighborhood Experiences, and Jogging Behavior in the RECORD Study." *Preventive Medicine* 55(1): 50-55.
- Kuo, Ming. (2015). "How Might Contact with Nature Promote Human Health? Promising Mechanisms and a Possible Central Pathway." *Frontiers in Psychology* 6.
- Lachowycz, Kate et al. (2012). "What Can Global Positioning Systems Tell Us about the Contribution of Different Types of Urban Greenspace to Children's Physical Activity?" *Health & Place* 18(3): 586-94.
- Lachowycz, Kate, and Andy P. Jones. (2013). "Towards A Better Understanding Of The Relationship Between Greenspace And Health: Development Of A Theoretical Framework." *Landscape and Urban Planning* 118: 62-69.
- Lamb, Karen E. et al. (2017). "Associations between Major Chain Fast-Food Outlet Availability and Change in Body Mass Index: A Longitudinal Observational Study of Women from Victoria, Australia." *BMJ Open* 7(10).
- Lhachimi, S. et al. (2012), "Dynamo-HIA-a dynamic modeling tool for generic health impact assessments", *PLoS ONE*, <http://dx.doi.org/10.1371/journal.pone.0033317>.
- Li, Fuzhong et al. (2008). "Built Environment, Adiposity, and Physical Activity in Adults Aged 50-75." *American Journal of Preventive Medicine* 35(1): 38-46.
- Maas, Jolanda, Robert A. Verheij, Peter Spreeuwenberg, and Peter P. Groenewegen. (2008). "Physical Activity as a Possible Mechanism behind the Relationship between Green Space and Health: A Multilevel Analysis." *BMC Public Health* 8: 1-13.
- Maddock, J. (2004). "The Relationship between Obesity and the Prevalence of Fast Food Restaurants: State-Level Analysis." *American Journal of Health Promotion* 19(2): 137-43.
- Morland, K., Wing, S., & Roux, A. D. (2002). The contextual effect of the local food environment on residents' diets: the atherosclerosis risk in communities study. *American Journal of Public Health*, 92(11), 1761-1768.
- Morland, Kimberly B., and Kelly R. Evenson. (2009). "Obesity Prevalence and the Local Food Environment." *Health and Place* 15(2): 491-95.
- Mytton, Oliver T, Nick Townsend, Harry Rutter, and Charlie Foster. (2012). "Green Space and Physical Activity: An Observational Study Using Health Survey for England Data." *Health & Place* 18(5): 1034-41.
- NCD RiskC Factor Collaboration, 2017. Available at <http://www.ncdrisc.org/>
- OECD (2015). *Tackling Harmful Alcohol Use: Economics and Public Health Policy*. OECD Publishing Paris.
- OECD. (2016). *Organisation for Economic Cooperation and Development (OECD) The Economic Consequences of Outdoor Air Pollution*.
- Orcutt, G.H. (1957) 'A New Type of Socio-Economic System', *Review of Economics and Statistics* 58: 773-797



- Ord, Katherine, Richard Mitchell, and Jamie Pearce. (2013). "Is Level of Neighbourhood Green Space Associated with Physical Activity in Green Space?" *The International Journal of Behavioral Nutrition and Physical Activity* 10: 127.
- Pascal, M. et al. (2013). "Assessing the Public Health Impacts of Urban Air Pollution in 25 European Cities: Results of the Aphekom Project." *Science of the Total Environment* 449: 390–400.
- Pope, C. Arden et al. (2002). "Lung Cancer, Cardiopulmonary Mortality, and Long-Term Exposure to Fine Particulate Air Pollution." *JAMA* 287(9): 1132.
- Pope, C. Arden et al. (2004). "Cardiovascular Mortality and Long-Term Exposure to Particulate Air Pollution: Epidemiological Evidence of General Pathophysiological Pathways of Disease." *Circulation* 109(1): 71–77.
- Richardson, Sandra, Michael Ardagh, and Philip Hider (2006). "Richardson, S., Ardagh, M., & Hider, P. (2006). The Association between Green Space and Cause-Specific Mortality in Urban New Zealand: An Ecological Analysis of Green Space Utility, 119(1232), 1–14." 119(1232): 1–14.
- Robine, Jean Marie et al. (2008). "Death Toll Exceeded 70,000 in Europe during the Summer of 2003." *Comptes Rendus - Biologies* 331(2): 171–78.
- Sassi (2010). *Obesity and the Economics of Prevention, Fit not Fat*. OECD Publishing Paris.
- Sugiyama, Takemi et al. (2013). "Initiating and Maintaining Recreational Walking: A Longitudinal Study on the Influence of Neighborhood Green Space." *Preventive Medicine* 57(3): 178–82.
- Thiébaud, S. P., Barnay, T., & Ventelou, B. (2013). Ageing, chronic conditions and the evolution of future drugs expenditure: a five-year micro-simulation from 2004 to 2029. *Applied Economics*, 45(13), 1663-1672.
- Tilt, Jenna H., Thomas M. Unfried, and Belen Roca. (2007). "Using Objective and Subjective Measures of Neighborhood Greenness and Accessible Destinations for Understanding Walking Trips and BMI in Seattle, Washington." *American Journal of Health Promotion* 21(4 SUPPL.): 371–79.
- Toftager, Mette et al. (2011). "Distance to Green Space and Physical Activity: A Danish National Representative Survey." *Journal of Physical Activity and Health* 8(6): 741–49.
- Villanueva, Karen et al. (2015). "Developing Indicators of Public Open Space to Promote Health and Wellbeing in Communities." *Applied Geography* 57: 112–19.
- Vos, T. et al. (2012), "Years lived with disability (YLDs) for 1160 sequelae of 289 diseases and injuries 1990–2010: a systematic analysis for the Global Burden of Disease Study 2010", *The Lancet*, Vol. 380/9859, pp. 2163-2196, [http://dx.doi.org/10.1016/S0140-6736\(12\)61729-2](http://dx.doi.org/10.1016/S0140-6736(12)61729-2).
- Vos, T. et al. (2016), "Global, regional, and national incidence, prevalence, and years lived with disability for 310 diseases and injuries, 1990–2015: a systematic analysis for the Global Burden of Disease Study 2015", *The Lancet*, Vol. 388/10053, pp. 1545-1602, [http://dx.doi.org/10.1016/S0140-6736\(16\)31678-6](http://dx.doi.org/10.1016/S0140-6736(16)31678-6).
- Wheeler, Benedict W., Ashley R. Cooper, Angie S. Page, and Russell Jago (2010). "Greenspace and Children's Physical Activity: A GPS/GIS Analysis of the PEACH Project." *Preventive Medicine* 51(2): 148–52.
- WHO (2006) WHO Air quality guidelines for particulate matter, ozone, nitrogen dioxide and sulfur dioxide. Global update 2005. Summary of risk assessment. World Health Organization, 2006.
- WHO. (2010). "Urban Planning, Environment and Health: From Evidence to Policy Action." World health Organization, Regional Office for Europe: 119.
- Wolf, Tanja, Katrina Lyne, Gerardo Martinez, and Vladimir Kendrovski. (2015). "The Health Effects of Climate Change in the WHO European Region." *Climate* 3(4): 901–36.
- World Health Organisation (2013a), Health risks of air pollution in Europe –HRAPIE project. Recommendations for concentration-response functions for cost benefit analysis of particulate



- matter, ozone and nitrogen dioxide, World Health Organization, Regional Office for Europe, Bonn, Germany
- World Health Organisation. 2013b. "Physical Activity Promotion in Socially Disadvantaged Groups: Principles for Action." : 1–86.
- World Health Organization. 2006. "WHO Air Quality Guidelines for Particulate Matter, Ozone, Nitrogen Dioxide and Sulfur Dioxide: Global Update 2005: Summary of Risk Assessment." Geneva: World Health Organization: 1–22.
- World Health Organization. 2016a. "Ambient Air Pollution: A Global Assessment of Exposure and Burden of Disease." World Health Organization: 1–131.
- World Health Organization. 2016b. "Urban Green Spaces and Health - a Review of the Evidence." World Health Organization: 1:92.
- World Meteorological Organization and World Health Organization (2015). "Heatwaves and Health: Guidance on Warning-System Development", ed. Glenn R McGregor et al., WMO-No. 1142 (Geneva: World Meteorological Organization and World Health Organization, 2015), <http://www.who.int/globalchange/publications/heatwaves-health-guidance/en/> (access 17 November 2017).
- Ye, Xiaofang et al. 2012. "Ambient Temperature and Morbidity: A Review of Epidemiological Evidence." *Environmental health perspectives* 120(1): 19–28.

