12. THE ROLE OF SPACE-TIME ACTIVITY PATTERNS IN THE EXPOSURE ASSESSMENT OF RESIDENTS

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Introduction

Industrial development can generate hazardous situations – in particular, when there is a need to deal with dangerous substances, such as those in chemical or petrochemical plants. Too often, these industries are located in the heart of urbanized areas with high-density populations, as urbanization intrudes on the hazardous sites (originally established outside of cities). Protecting civil populations from these risks – either through precautionary measures or special crisis management plans, if a catastrophe occurs – is a key issue. To better protect citizens, identifying the risks to which they are exposed and also how they perceive the risks in their area can help authorities and stakeholders better understand the risks (Glatron & Beck, 2008). Adequate knowledge of these risks can also dissuade populations from settling in certain zones and thus lower their vulnerability. Finally, authorities need to assess the exposure of populations to hazards – through modelling – to set up appropriate and efficient risk management plans based on land planning.

The present chapter – founded on responses to a questionnaire-based investigation (see the Annex) carried out in the Milazzo–Valle del Mela area of Sicily, in 2008 – explores two main aspects of exposure assessment:

- space-time-pattern methodological challenges; and
- results of individual space-time activity data extracted from the investigation in the Milazzo–Valle del Mela area.

Methods

Since an evaluation of the impact of the petrochemical industry depends on accurate exposure estimates, different procedures have been developed to obtain them. For example, the use of GISs with exposure estimates at the individual level can lead to significant results (Yu et al., 2006). On the other hand, as in the case of the Milazzo–Valle del Mela area, simulation procedures also offer significant results. When trying to assess individual exposure to risk, space-time activity data are of crucial importance, because they allow the description of an individual's activities and mobility at very fine spatial and temporal resolution and in great detail.

Several methods exist to capture such data, their level of technological sophistication depending on budget and feasibility constraints. Some models consider accessibility measures (such as distances between relevant locations or the amount of time available for travel), to emphasize the potential for travel, conditioned by the performance of the transportation system (Wu & Miller, 2001). Other models consider individual decision-making processes and the elementary factors that determine travel activity (Wu & Miller, 2001).

Another research (or modelling) possibility is to adopt an intermediate solution, which proved efficient in other contexts (Banos, 2001). This solution is a survey adapted to *data poor* situations, as in our case study.

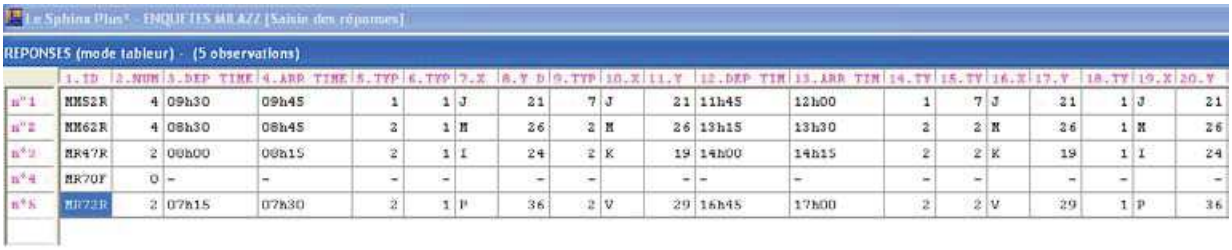
The idea of this intermediate solution is simple: sometimes, more is less. So, by using clear assumptions, a bit of simple information on mobility patterns can provide many insights. If fully disaggregated spatial and temporal information proves to be of great interest, several problems need to be solved. First, even if the data-processing technology progresses quickly, it is still difficult to produce a repetitive method that is not time consuming. Second, most of the time it is difficult to obtain information about people's addresses (this can be a problem in some countries, such as France, although Italy can collect individual data),

because of a general inclination towards mistrust. Finally, such personalized information is very sensitive, for reasons of privacy and confidentiality, so even if we manage to collect it, it is often impossible to use spatial information at that very fine scale, because single individuals can be easily identified.

The question we then have to answer is: do we really need exact spatial information? Most of the time, more accurate information about activities is needed, rather than *exact* spatial information. Therefore, in our case, we adopted methods that took into account the worst case scenario, where it is both difficult to use a global positioning system and to ask for the address of people surveyed. A solution that has proved efficient is to supplement the questionnaire with a map of the city with a superimposed grid. Using grids helps to convert the different places indicated by the people surveyed into geographical coordinates (S. Novak & E. Beck, unpublished observations, 2008).

The questionnaire on risk perception assessment also contained a table for the people surveyed to indicate their movements of the previous day, the types of activities they performed, their mode of transportation, and the time of departure and arrival of each movement (in intervals of 15 minutes) (see the questionnaire in the Annex). Fig. 23 provides an example of the time activity details of five different people surveyed, who are identified by an alphanumeric code under the heading *ID*.

Fig. 23. Time activity data constructed during the survey



REPONSES (mode tableur) - (5 observations)

	1.ID	2.NUM	3.DEP TIME	4.ARR TIME	5.TYP	6.TYP	7.X	8.Y	9.TYP	10.X	11.Y	12.DEP TIM	13.ARR TIM	14.TY	15.TY	16.X	17.Y	18.TY	19.X	20.Y
n°1	MMS2R	4	09h30	09h45	1	1	J	21	7	J	21	11h45	12h00	1	7	J	21	1	J	21
n°2	MM62R	4	08h30	08h45	2	1	H	26	2	H	26	13h15	13h30	2	2	H	26	1	H	26
n°3	MR47R	2	08h00	08h15	2	1	I	24	2	K	19	14h00	14h15	2	2	K	19	1	I	24
n°4	MR70F	0	-	-	-	-		-	-		-	-	-	-	-		-	-		-
n°5	MR72R	2	07h15	07h30	2	1	P	36	2	V	29	16h45	17h00	2	2	V	29	1	P	36

Note. Each individual in the survey has an identification number (1.ID) and a number of activities (2.NUM), plus a vector of data: departure time (3. DEP TIME), arrival time (4. ARR TIME), transport mode (5. TYP), type of departure activity (6. TYP), cell location of departure activity (*x* coordinate: 7. X), cell location of departure activity (*y* coordinate: 8. Y), type of arrival activity (9. TYP), cell location of arrival activity (*x* coordinate: 10. X) and cell location of arrival activity (*y* coordinate: 11. Y). Then information is collected for the following trip: departure time (12. DEP TIME), arrival time (13. ARR TIM), and so on.

As can be seen, the approach is clearly event-based, and even if a temporal unit of 5 minutes is fixed, experience suggests people often approximate time by events. Since we did not want to introduce artificial precision in the questionnaire by asking people for *exact* times, each individual in the survey is assigned a linear matrix – that is, an alphanumeric vector of data. The dimension of this vector is *n* by 9, with *n* being the number of activity changes during the period surveyed (one day here) and 9 being the number of variables collected for each activity – that is:

1. departure time (3. DEP TIME)
2. arrival time (4. ARR TIME)
3. transport mode (5. TYP), such as car, motorcycle, bus or bicycle
4. type of departure activity (6. TYP)
5. cell location of departure activity (*x* coordinate: 7. X)
6. cell location of departure activity (*y* coordinate: 8. Y)
7. type of arrival activity (9. TYP)
8. cell location of arrival activity (*x* coordinate: 10. X)
9. cell location of arrival activity (*y* coordinate: 11. Y).

With the aid of the questionnaire on risk perception, sociodemographic data were also collected, describing each individual's responses, in terms of gender, age, marital status and education level. More than 400 individuals (454) were questioned, although only 390 questionnaires turned out to be exploitable for the individual exposure assessment.

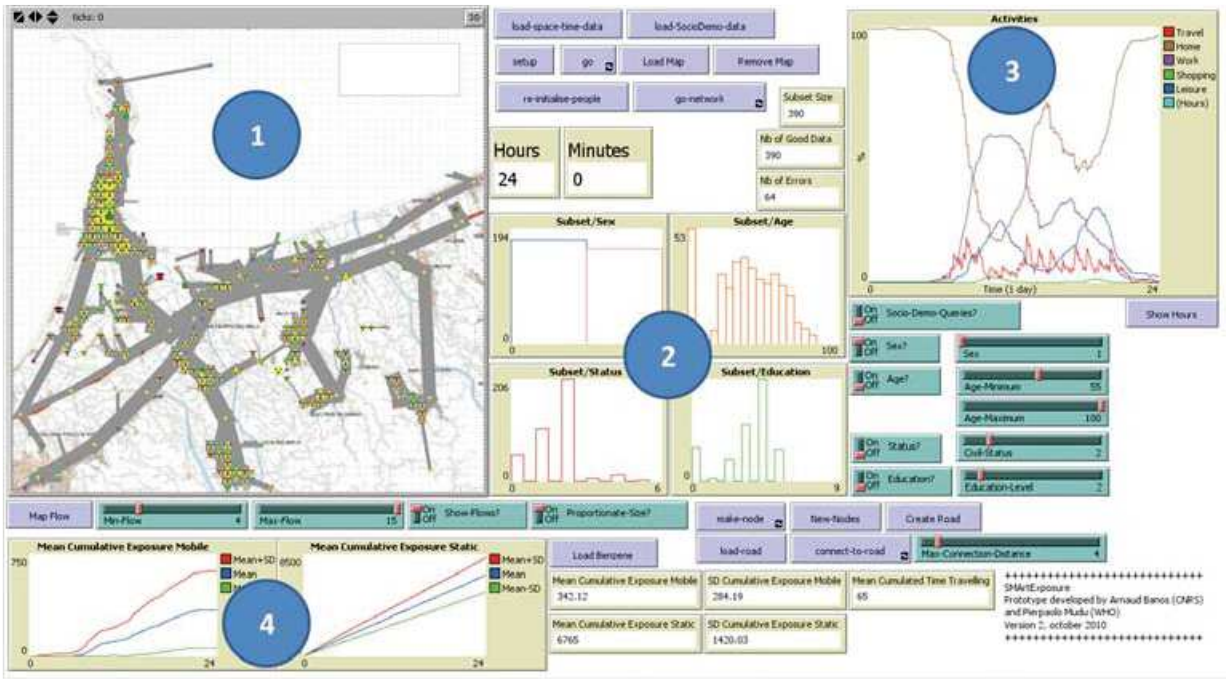
Assessing individual exposure

What can be done with such detailed spatio-temporal information? Three main ideas guide this exposure assessment. First, a lot can be learned from these complex data by properly visualizing them and playing with them. Second, individual exposures to air pollution or to industrial hazards can be estimated, for given scenarios, as long as these data can be linked to those on hazards. Third, the accuracy of the present study can be much greater than that of studies in which populations in the vicinity of industries are expected to receive the largest exposure (Newhook et al., 2003).

Exploring data on space-time activity

To allow precise exploration of these spatio-temporal data, we designed and implemented a specific prototype, called SMArtExposure (Fig. 24).

Fig. 24. SMArtExposure spatio-temporal navigator



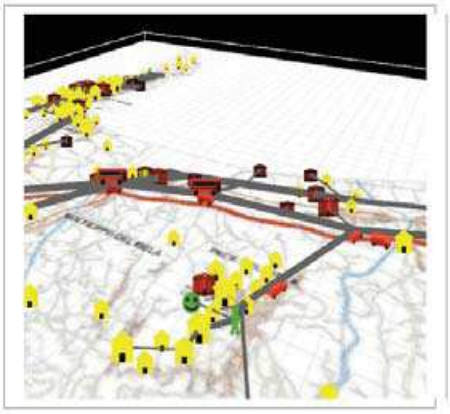
SMArtExposure may be seen as a spatio-temporal navigator, allowing the space-time activity data collected during the survey to be explored, and it is developed in NetLogo (for further details about this agent-based modelling platform, see Wilensky, 1999). SMArtExposure is composed of four graphic components (Fig. 24):

1. a map that displays activity types and locations, as well as transportation modes and movements (the line width is proportional to the amount of traffic);
2. sociodemographic plots, based on the four sociodemographic data subsets (sex, age, status and education) and allowing the definition of specific subsets;
3. a time–activity plot, displaying the proportion of activities (with sums up to 100%) realized by the subset members during the day (24 hours); and
4. plots, displaying mean cumulative exposure to benzene that occurs during the day for the subset defined, with this individual cumulative exposure aggregated for group comparisons and divided into static and mobile components.

The road network was digitized from the map used for the questionnaire, and the most probable routes that correspond to individual trajectories were simulated using a shortest path algorithm (Floyd, 1962).

Each individual surveyed is then displayed on the graphical user interface and their space-time activity trajectory is constructed and produced dynamically in two and three dimensions (Fig. 25). Primarily, activities, transportation modes and routes are displayed, as they convey the main information.

Fig. 25. Three-dimensional (3D) view of SMArtExposure[a]



(a) Three-dimensional view of the area



(b) Individual's identification card (updated during the simulation)

Transportation mode	Symbol
Pedestrian	Green person
Car	Red car
Motocycle	Red bike
Bus	Red bus
Taxi	Yellow car
Train	Red train
Bicycle	Green bike
Others	Red star
Activity	**Symbol**
Home	Yellow house
Work	Red building
Shopping	Blue store
Sport	Green smiley
Market/Supermarket	Green store
Leisure	Green smiley

(c) Symbols for activities and transportation modes

[a] Each individual moves along the road network between successive activities, using various transportation modes.

Based on the representative sample of those surveyed, group comparisons can be conducted.

Assessing exposure

While exposure assessment methods work mainly for aggregated populations, individual exposure assessments provide complementary results that shine a different light on this complex issue. In practice, the general exposure model by Duan (1982), which follows, holds for individuals, groups and larger populations:

$$E_i = \sum_{j=1}^{m} T_j C_j$$

where the cumulative exposure E_i of any individual i, during a given time period, may be seen as the sum of the product of the local concentration C_j (for example of a pollutant) in various micro-environments j and the time (T) spent in j. Therefore, a static component of exposure, ES_i, can be distinguished from a mobile component of exposure, EM_i, the latter focusing on individual exposure during travel (see results of the case study in the next section).

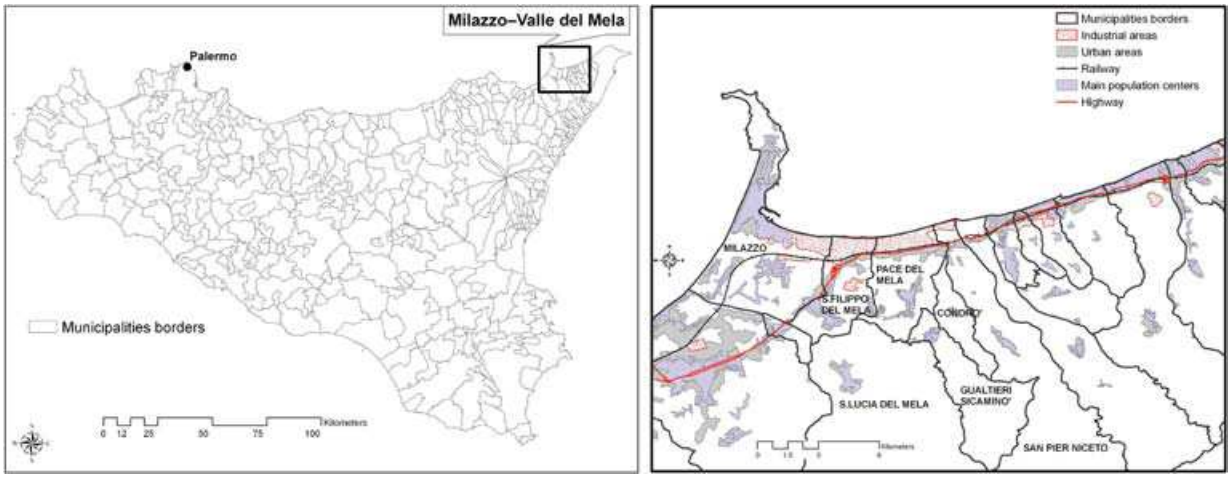
The first thing to do is to introduce a risk distribution in the model. As we are in a data poor situation, we cannot expect detailed and accurate data on pollutant concentrations. To perform a case study, it is necessary to have data of some kind on targeted pollutant dispersion or on a number of different pollutants. In our case, we had data on only a single pollutant – benzene. The reader, however, must consider that, in some cases investigated in the literature, exposure is estimated for a mixture of pollutants (Nadal et al., 2006).

The Milazzo–Valle del Mela case study

Sicily is an appropriate place to study both exposure to risk and risk perception, because the eastern part of the island includes many zones that accumulate natural and industrial risks (seismic, volcanic, and industrial – with petrochemical plants and power stations). Because Sicilians are constantly exposed to these risks, it is important to assess exposure and to estimate whether or not (and the manner in which) the population is conscious of these risks (see Chapter 15).

However, Sicily may also be characterized as being data poor: only a few data are available; and, basically, most of the relevant data have to be gathered without reference to previous work that normally helps to carry on exposure and risk-perception studies. Milazzo–Valle del Mela is located in the north-eastern part of Sicily (Fig. 26). The main municipality in this area is Milazzo, but it is not the only municipality of concern in this study. Many other small villages (such as Gualtieri Sicaminò, Santa Lucia del Mela, San Filippo del Mela, Condrò, Pace del Mela and San Pier Niceto) are also involved in the study (Fig. 27). With the major economic activities of the island being agriculture, fishing and tourism, the area of Milazzo–Valle del Mela prospers principally from the presence of heavy industries. Abundant oilfields and methane fields were discovered on the island 60 years ago, and a large petrochemical complex was built in this part of Sicily to produce and refine hydrocarbons.

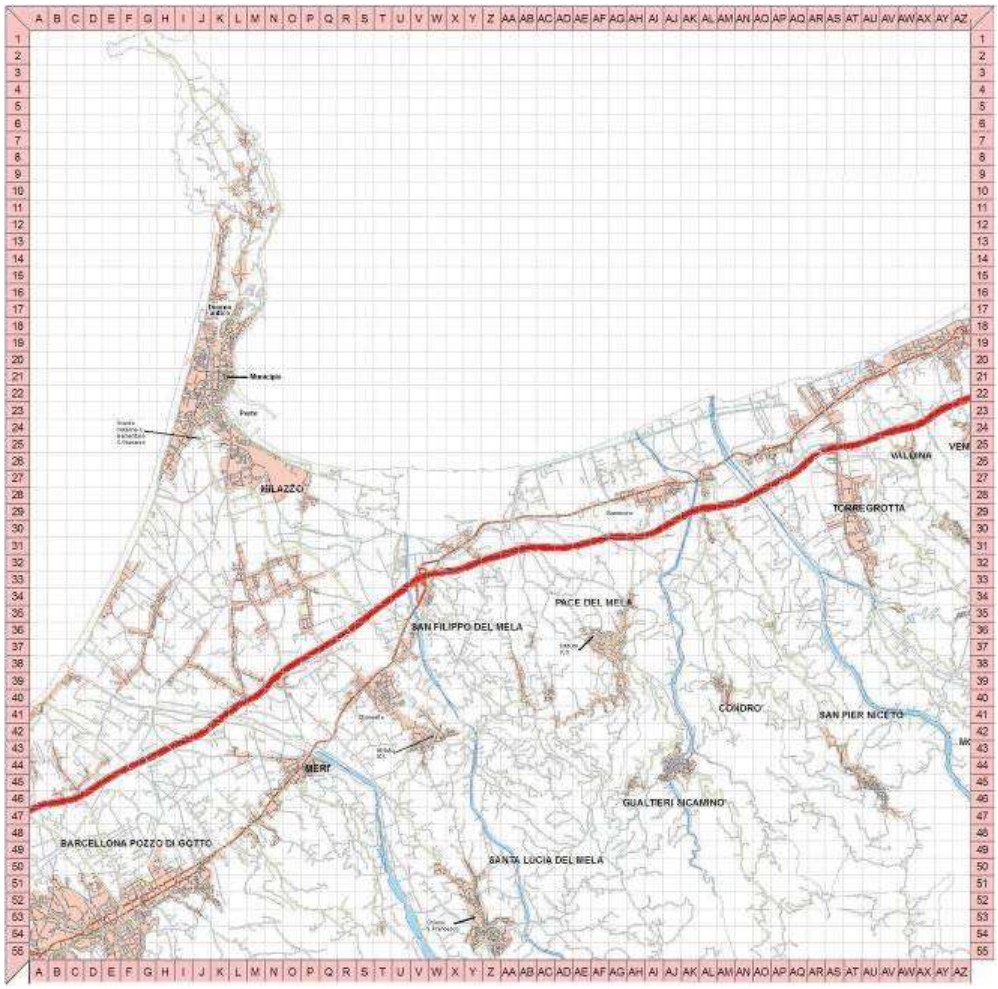
Fig. 26. Location of Milazzo–Valle del Mela



From a couple of different perspectives, the huge petrochemical plants in the Milazzo–Valle del Mela area constitute a hazard to the population. First, the pollution generated by the plants leads to health problems for the population exposed to it (Cernigliaro et al., 2008). Second, the industrial process can create such major accidents as fires and explosions. In this context, it is important to know the space-time patterns adopted by the population. Knowing when, where and which activities are carried out can offer (at least) relevant information for potential differential exposure patterns and for potential accidents.

To assess the exposure of the individuals surveyed – that is, to gather individual daily timetables – people were simply asked to draw a mark in the cells (width 250 m) of the grid that correspond to the different locations of their activities (Fig. 27). In the present study, this map was also used as a support for so-called mental maps – that is, a representation of the perceptions and knowledge a person has of an area (see Chapter 15).

Fig. 27. The map used for the Milazzo–Valle del Mela survey [a]



[a] Cell size: 250 m.

The space-time data for people's displacements were processed, as described in the section on "Methods", and displayed within the SMArtExposure navigator (Fig. 24). The time activity plots were computed to analyse time activity budgets of different sociodemographic groups; the example of men and women is described in Fig. 28.

Evidence of significant differences between men and women can be emphasized (Fig. 28). Time activity budgets present different patterns, in the morning and even more so in the afternoon: the proportion of men working is higher, while the proportion of women at home or shopping is higher. Moreover, while activities present a clear bimodal distribution, the distribution of mobility seems to be more chaotic. The resulting traffic and origin–destination flow also presents differences that deserve attention, since they may lead to differences in individual exposures.

Also, the road assignment algorithm could be improved – for example, by introducing a multimodal network (multigraph) or constraining routes by the times provided by the people surveyed. Such improvements, however, have to fit the objectives of the study and, especially, the nature and accuracy of data obtainable on hazards. As Fig. 29 shows, both the spatial and temporal resolutions of pollution data have a much larger scale. Therefore, one has to find a good balance between algorithmic complexity, phenomenon accuracy and scales of integration. Once precise space-time activity profiles are defined, hazards (such as pollutants) can be introduced, to assess the individual cumulative exposure of the population surveyed.

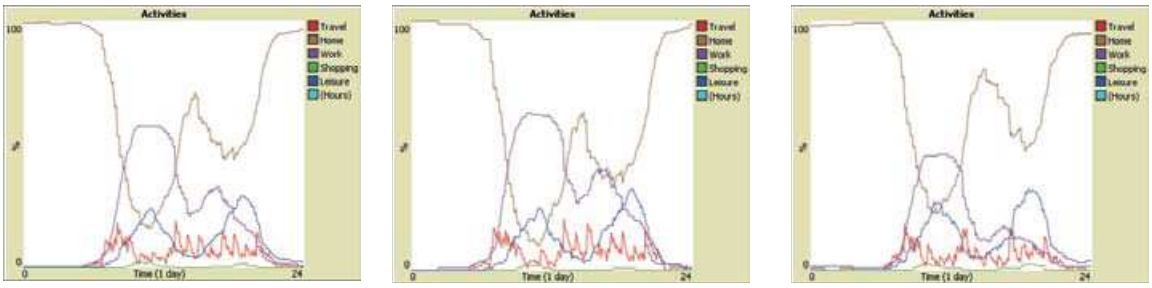
With regard to exposure to a given pollutant, simulations can be carried out – also with rough data (see the case of benzene in Fig. 29). Data on benzene were available from the study discussed in Chapter 11.

Fig. 28. Time activity budgets and traffic for men and women

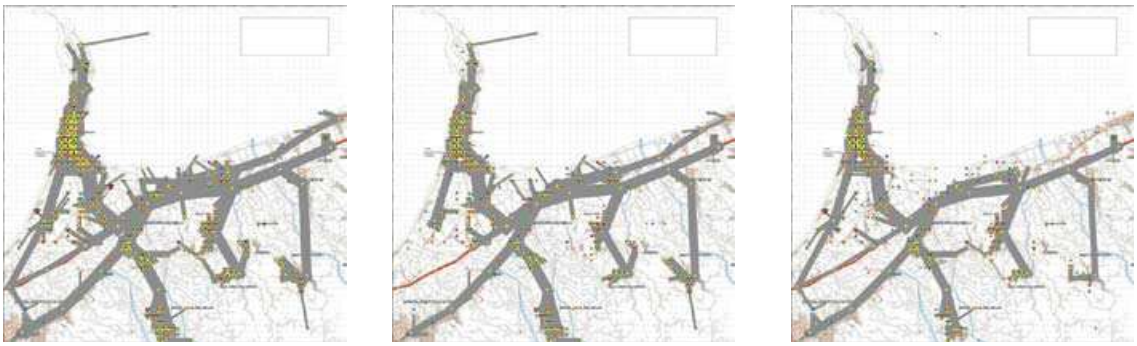
Whole population (n = 390; missing data on gender = 53)

Subset: men (n_1 = 176)

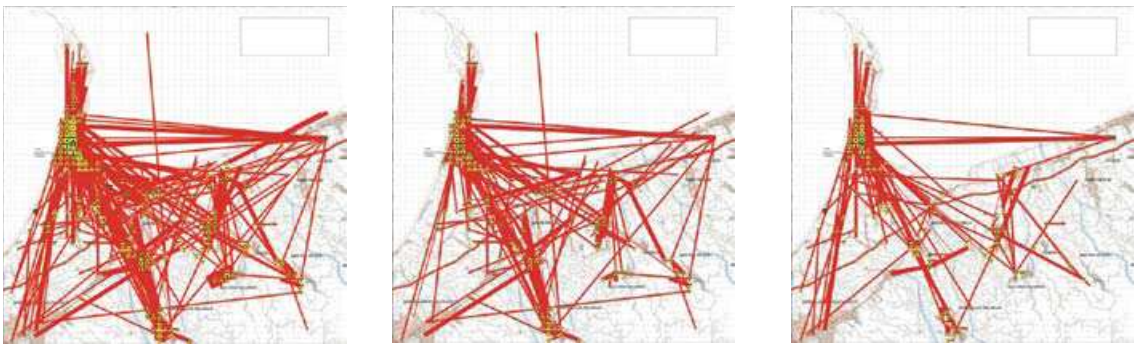
Subset: women (n_2 = 161)



(a) Proportion of individuals occupied by a given activity during the day



(b) Total traffic assigned to the road network during the day (line width proportional to traffic)



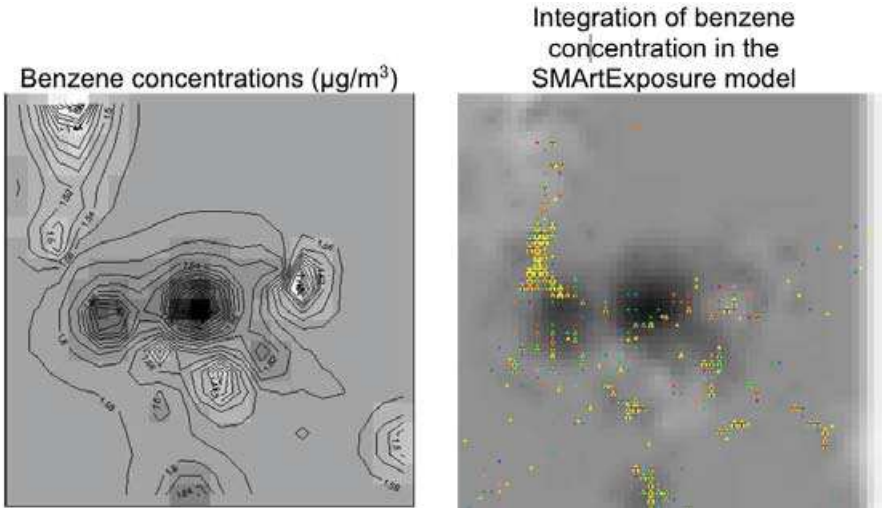
(c) Total origin/destination flows during the day (line width proportional to the number of movements)

Note. In parts (b) and (c) of this figure, the yellow areas indicate the residence of individuals.

The concentration levels were directly incorporated in the time activity model and graphical interface, to estimate individual exposure to benzene, using the formula for exposure that appears in the subsection on "Assessing exposure" (Duan, 1982). Here again, a group comparison between men and women leads to notable results (Fig. 30). On each plot, the horizontal axis displays time (24 hours), while the vertical axis displays the mean cumulative exposure for the mobile and static component.

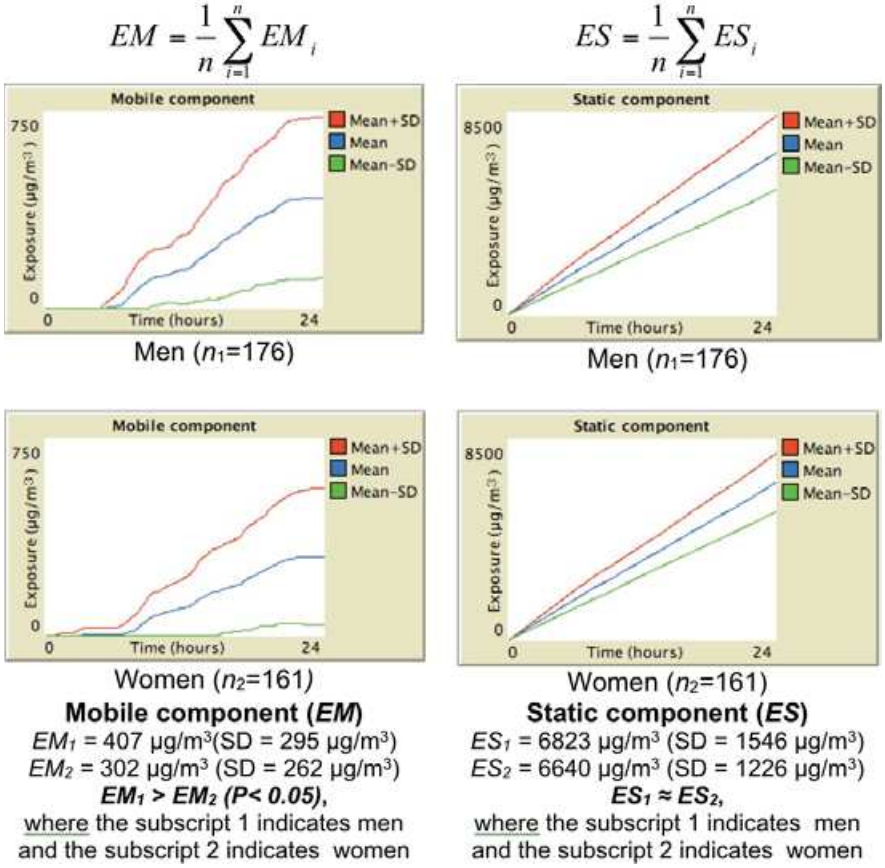
While the static component of exposure (*ES*) presents a linear signature, the mobile component (*EM*) presents a non-linear one, coupled with an inflating variance. Also, while the static component is comparable for the two subsets, the mobile one is significantly higher for men. As exposure is a cumulative during one day (24 hours), this difference may be explained – partly at least – by the different travel budgets: 1 hour on average for women versus 1 hour and 15 minutes on average for men. However, other factors that affect activity location (and therefore routes taken) may also need to be investigated.

Fig. 29. Time activity budgets and traffic for men and women



Note. The yellow areas indicate the residence of individuals.

Fig. 30. Comparison of men and women, for both mobile and static components of mean cumulative exposure to benzene



SD: standard deviation.

Here again, the approach is very generic: even if it was more detailed and dynamic concentration data were used, the process would be exactly the same. Therefore, another important issue concerns the perception people have of their own exposure to risks (see Chapters 15–17).

Conclusions

The integration of different models is an apparent objective when studying the effects of complex risk scenarios (Mudu et al., 2006; Mudu & Beck, 2012). In the case of Sicily's contaminated areas, concentration and exposure are fundamental variables to be combined in a risk assessment (IPCS, 2005). This chapter provides an example of integration of different data and models by using a simulation platform. Also, even in *data poor* situations, disaggregated spatio-temporal information (and mental maps) can be constructed.

The protocol proposed here, based on a cartographical approximation, leads with acceptable accuracy to individual-based exposure estimates and group comparisons. A spatio-temporal navigator, called SMArt-Exposure, was developed, allowing the exploitation of complex data on space-time activity (at both the individual and group level) and its coupling to data on hazards (concentration of a pollutant here).

The results indicate very precise patterns of space-time activity where the population tends to spend its time far from the core of polluting activities. Evidence of significant gender differences should be stressed. Time activity budgets present different patterns, in the morning and even more so in the afternoon: the proportion of men working is higher, while the proportion of women at home or shopping is higher. Moreover, while activities present a clear bimodal distribution, the distribution of mobility seems to be more chaotic. These results represent not only the first step towards building precise exposure profiles of the population, but also represent a dynamic picture of the population that can be used as scenarios and for political discussions and policy planning.

Acknowledgements

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