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Multiple Bayesian Models for the Sustainable City. The Case of Urban Sprawl.

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Abstract. Several possible models of urban sprawl are developed as Bayesian networks and evaluated in the light of available evidence, also considering the possibility that further, yet unknown models could offer better explanations. A simple heuristic is proposed in order to attribute a likelihood value for the unknown models. The case study of Grenoble (France) is then used to review beliefs in the different model options. The multiple models framework proves particularly interesting for geographers and planners having little available evidence and heavily relying on prior beliefs. This last condition is very frequent in research on sustainable cities. Further options of multiple models evaluations are finally proposed.

Keywords: Urban Sprawl, Uncertainty, Model Selection, Belief Revision, Bayesian Networks, Grenoble.

1 Introduction

Practitioners and policy-makers assume that attaining sustainable urban development is essentially a question of data monitoring, decision making and policy implementation in a context of well-established scientific theories and positive knowledge of the urban realm. On the contrary, understanding, measuring and managing urban sustainability is a complex task and uncertainty is omnipresent in the kind of knowledge we have on the sustainable city. Urban sustainability is in fact a multi-dimensional issue, involving socioeconomic, environmental, urban design and governance aspects. Cities are complex systems, whose knowledge is always partial, incomplete, if not contradictory (when different points of view are taken into account). Even more, when dealing with sustainable development, researchers and practitioners have to foresee alternative possible futures, whose knowledge is by definition uncertain.

This paper will focus on the case of the possible effects of policies aimed at limiting urban sprawl. Urban sprawl is a central issue for the sustainable city. Letting the city grow through low-density, functionally specialized new suburban developments produces direct consequences (over-consumption of natural and agricultural land) and indirect ones (longer trips, car-dependence, increased greenhouse gas emissions, need of new expensive road infrastructures and/or high level of road congestion) which challenge the goals of sustainable urban development [1,2]. The spatial interaction between the city and its suburbs also plays an important role. Camagni, Capello and Ni-

jkamp [3] highlight that the city/suburbs opposition poses a social dilemma: households want to take advantage of economy of agglomeration offered by the city (in terms of job opportunities, services, etc.) but try individually to avoid the diseconomies of agglomeration of living in the dense city (congestion, poor environmental quality). By moving to the suburbs they obtain better environmental amenities and are still capable of profiting of jobs and services offered by the city thanks to increased car-mobility. By so doing, they increase congestion and pollution in the city, worsening quality of life for city dwellers and pushing more households to opt for a suburban residence. Densification strategies, both in the inner city and in its suburbs have thus been proposed [4-6] in order to limit and eventually revert urban sprawl. These strategies make nevertheless strong assumptions on the impacts and even on the acceptability of densification by resident populations [7]. Conflicting hypothesis can thus be identified in an extremely rich literature on the ability of planning policies to curb urban sprawl, namely through densification strategies [8-11]. In North America, authors like Gordon and Richardson [12, 13] have challenged both the feasibility and the opportunity of sprawl containment, seeing suburbanization as the most efficient market-driven allocation of land respecting consumer preferences. Consensus is wider in Europe on the impossibility of accommodating uncontrolled sprawl in much more constrained geographical settings. Negative consequences on the traditional city centers (often observed in North America) are also seen as a major challenge for European cities, given the economic, heritage and symbolic value of traditional urban cores.

But even within this consensus, different assumptions can lead to different models of the interplay between population growth, congestion, city/suburbs relations, densification policies, resident perceptions and urban sprawl. These underlying assumptions also reflect different beliefs in the most plausible outcomes of observed trends of urban sprawl and of the capacity of densification policies to have a real impact on these trends. We think that modelers accompanying decision-making and policy formulation should integrate and not ignore this multiplicity of possible models. We follow in this the principle of multiple explanations first formulated by the ancient Greek philosopher Epicurus: if several theories are consistent with the observed phenomena, retain them all.

Within this paper we will thus propose in Section 2 two extremely simplified alternative models of the interplay between densification policies and urban sprawl. These models reflect two particularly prominent views in the debate on urban densification that can be found in Europe and, more specifically, in France. We will formalize the models as Bayesian networks (BN) organizing expert knowledge in the form of probabilistic relations. At the same time the two BN should not be considered as the only possible explanatory models. An expert within a decision-making context could be more or less confident in each of the two models, but should also allow some skepticism in the ability of either of them to capture reality. Some plausibility should thus be given to the fact that both models fail to explain urban sprawl and that a third, unknown model or even no model at all links urban sprawl to underlying trends and to densification policies. In Section 3, we will assess how new evidence could be used to review beliefs in models through a Bayesian framework and how beliefs in model and evidences could be combined to calculate beliefs in outcomes of urban sprawl. The fi-

nal section will explore how different theoretical frameworks could be used instead of Bayesian probabilities to integrate uncertainties linked to multiple possible models of urban sprawl.

2 Two Alternative Models of Urban Sprawl

2.1 Bayesian Networks to Model Uncertain Relations Behind Urban Sprawl

Two alternative models for the relation between densification policies and urban sprawl have thus been formalized as Bayesian Networks [14, 15]. Bayesian Networks (BN) are systems of probabilistic relations implemented on a directed acyclical graph which can be used to model uncertain causal knowledge among stochastic variables. BN have already been proposed as models of spatial systems [16, 17] once appropriate expert knowledge is elicited in terms of probabilities. Marcot et al. [18] give guidelines for BN development and update/revision, combining expert knowledge and empirical evidence, in the field of ecological modelling and conservation.

Figure 1 shows the causal graph of the two models that we developed. Both models include the same fifteen variables, seven of which correspond to the city sub-model and seven to the suburbia sub-model while the last variable, the demographic growth of the whole study area, is considered external to the system. To simplify domain knowledge, variables are either binary (yes/no, stable/increase, preserved/endangered, etc.) or ternary (stable/decrease/increase, stopped/limited /accelerated, etc.). Within each sub-system, decision variables are identified. Densification is a policy applicable both to the city and to the suburbs. Within the city, it can correspond to urban infill, to brownfield development or to replacement of smaller buildings with bigger ones. In the suburbs soft densification (infill of single-family houses) is often opposed to hard densification (where bigger buildings are mixed to single-family houses). A common urban policy in France is also city renovation, which includes the development of modern transit (usually light-rail transit), requalification of public space and public-funded renovation of old buildings. A contested policy is the development of employment in suburbs: some see it as a way of containing daily mobility of suburbanites, other see it as an encouragement to further urban sprawl. Many internal variables are perceptions by resident households: perception of city quality of life, perception of suburban amenities (mainly environmental amenities linked to low-density urbanization) and perception of suburban quality of life (combining environmental amenities with presence of jobs and services). These are often non-observable variables, unless expensive ad hoc surveys are carried out. The four decision variables and the external one are the independent variables of the model.

Even by adhering to a given set of theoretical assumptions, BN are particularly well-suited tools to model the kind of knowledge experts have on the phenomena under study. Cause-to-effect relations between geographic and sociodemographic variables are relatively “dirty”, uncertain: the same causes can produce different effects and several additional variables are missing in the model. Causal probabilistic relations are thus a good option to model uncertain causal knowledge. But even with bi-

nary and ternary variables, the number of probabilistic parameters in the BN is daunting.

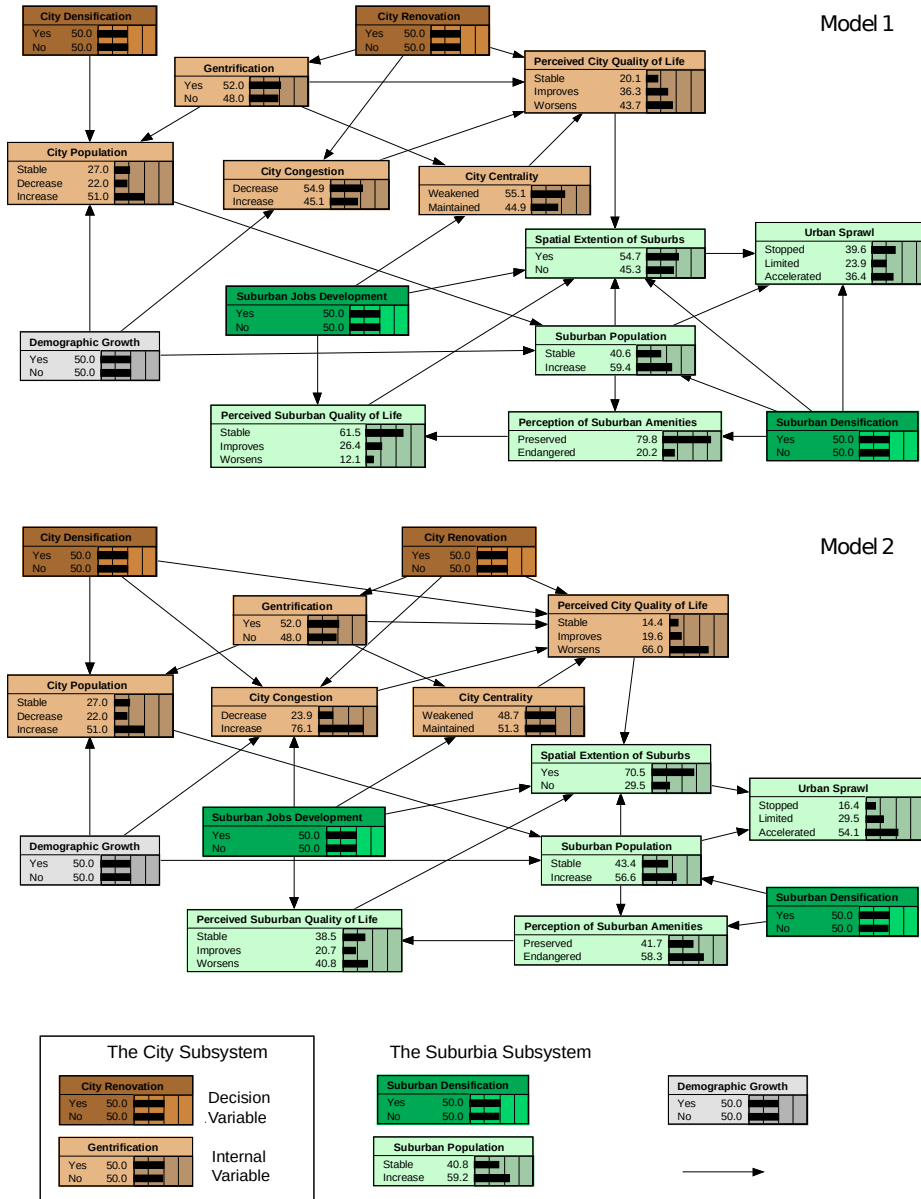


Fig. 1. Two Bayesian Network Models for Urban Sprawl.

The ten dependent variables are governed by almost 300 probabilistic parameters in Model 2 (almost 250 in Model 1), which are clearly impossible to elicit from experts. Noisy logical gates NoisyOr, NoisyAnd and NoisyMax [19, 20] have thus been used to model in a simplified way, under the assumption of independence of causal impact, the sufficient/necessary causal links among the variables. Leak parameters can also be used to take into the account the effect of additional variables which are missing in the models. Model 1 thus required the elicitation of only 38 non-null parameters, Model 2 required 42. These parameters are judgments on the probabilistic force of the relations within a limited number of possible values (0.4, 0.5, 0.6, 0.7, 0.8 and 0.9, the value 1 being reserved to deterministic relations). Two possible leak parameters were also considered: 0.1 for relations, which the expert considers knowing with relatively little uncertainty (there is a 0.1 probability that the phenomena are produced by variables omitted in the model), and 0.2 for relations with higher uncertainty due to missing variables. For every model, we thus had to produce around forty numerical assessments within a very limited number of possible values. This is a realistic effort requested on domain experts. Discrete probabilistic functions associated to the noisy logical gates can then be used to derive the complete conditional probability table for each dependent variable of the models.

2.2 Analogies and Differences between the two Models

Models 1 and 2 are not based on completely different theoretical assumptions and formalize expert knowledge on the possible impacts of densification policies in European cities on a time span of 10-20 years. They share several common points, justifying the use of the same fifteen variables even if, sometimes, with slightly different probabilistic parameters. Both models consider that urban sprawl is the combination of increased suburban population and spatial extension of the suburbs in natural and agricultural land. Both give an important role to perceived quality of life from urban and suburban dwellers. For both models, for examples, perceived quality of life in the city tends to improve with city renovation, with maintained city centrality and with city gentrification (bringing more affluent dwellers to the urban core) as well as with a reduction of city congestion (conversely, perception of quality of life worsens when city congestion increases). For both models, perceived suburban quality of life combines the perception of suburban amenities with the practical aspects related to the presence of jobs and services. Both models finally agree on the demographic connections between city and suburbs. Demographic growth of the whole urban area fuels both city population and suburban population. Gentrification (which is often catalyzed by city renovation) tends nevertheless to diminish city population (wealthier dwellers normally occupy more space than poorer ones), whereas densification increases the ability of the city to absorb its share of demographic growth. Households which are not retained by the city (because of gentrification or because of a desire to leave the city due to a worsened perception of its quality of life) increase the demographic pressure on suburbs. When perceived quality of life in the suburbs worsens, households tend to migrate further away and this produces a spatial extension of suburbs and fi-

nally contributes to the acceleration of urban sprawl. But the two models make opposite assumptions on the role and the impacts of densification policies.

On the whole, Model 1 is relatively neutral on the direct impact of densification policies on household perceptions, considering that the majority of people are not necessarily hostile to densification, though recognizing an important role to city renovation on city congestion and on the perceived quality of life of its inhabitants. On the contrary, it assumes that densification can produce positive indirect effects: it allows the city and the suburbs to accommodate demographic growth within the present urban boundaries and, above all, it limits the risks that population growth in the suburbs endangers the perceived quality of their residents (densification policies aim at controlling the quality of urban and suburban infills). For Model 1, suburban jobs development weakens the traditional city-center and both directly and indirectly (by diminishing the perceived quality of life in the city), it favors further suburbanization, spatial extent of suburbs and ultimately accelerates urban sprawl. Model 1 corresponds to the majority view of European urban planners and to the recommendations of official documents from the French ministry and the EU Commission [4].

Model 2 assumes a positive role of suburban jobs development in reducing city congestion, an assumption that was traditionally underlying many urban plans by local authorities in France and in Europe, even if it has been later put in question by authors like Wiel [21]. Above all, Model 2 assumes that densification policies, both in the city and in the suburbs, will be negatively perceived by a majority of households and will have negative effects on city congestion, even more if they are not accompanied by city renovation policies. On the whole, even without accepting the extreme positions found in the American literature [12, 13], the assumptions behind this model are more pessimistic on the ability of urban planning to stop urban sprawl and suggest more limited goals of sprawl containment.

2.3 Using BN models to Revise Beliefs

Once elements of evidence are entered in the models, the BN can propagate this information and revise the beliefs on non-observed variables. Bayesian belief revision, based on Bayes' theorem (1) and on its generalization given by Jeffrey's rule (2), can thus be used to propagate both elements of certain and uncertain evidence [22, 23].

$$p(H_i \vee E) = \frac{p(E|H_i)p(H_i)}{\sum_i p(E \vee H_i)p(H_i)} \quad (1)$$

Where H_i are the different hypotheses for which beliefs have to be revised given evidence E .

$$q(H_i \vee E) = \sum_j q_j p(H_i \vee E_j) \quad (2)$$

Where beliefs q_j are distributed over several possible outcomes for E and each $p(H_i|E_j)$ is calculated according to (1).

To be more precise, Bayesian belief revision within a BN is done by considering the probabilities of a child variable for a given configuration of the values of its parent variables as a multinomial distribution (binomial distribution for binary variables). The distributions are defined *a priori* by expert elicited parameters and can be used to revise beliefs on the marginal probabilities of variables of interest once elements of evidence are entered in the model. Following a thorough Bayesian approach, the probabilistic parameters can also be updated through the use of the corresponding conjugate prior distributions (Dirichlet and Beta distributions) if an incremental learning of model parameters is sought for, like in [24]. Within our research, we are not interested in parameter updating (see discussion further).

We can thus suppose we implement a given set of policies and calculate the new beliefs on the variable “urban sprawl” given by the two models (Figure 2). Model 1 suggests that the densification of city and suburbs, together with city renovation and a policy aiming at hindering job developments in the suburbs will very probably stop urban sprawl ($p=0.78$) or possibly limit it ($p=0.14$). These beliefs are particularly insensitive to the demographic growth scenario.

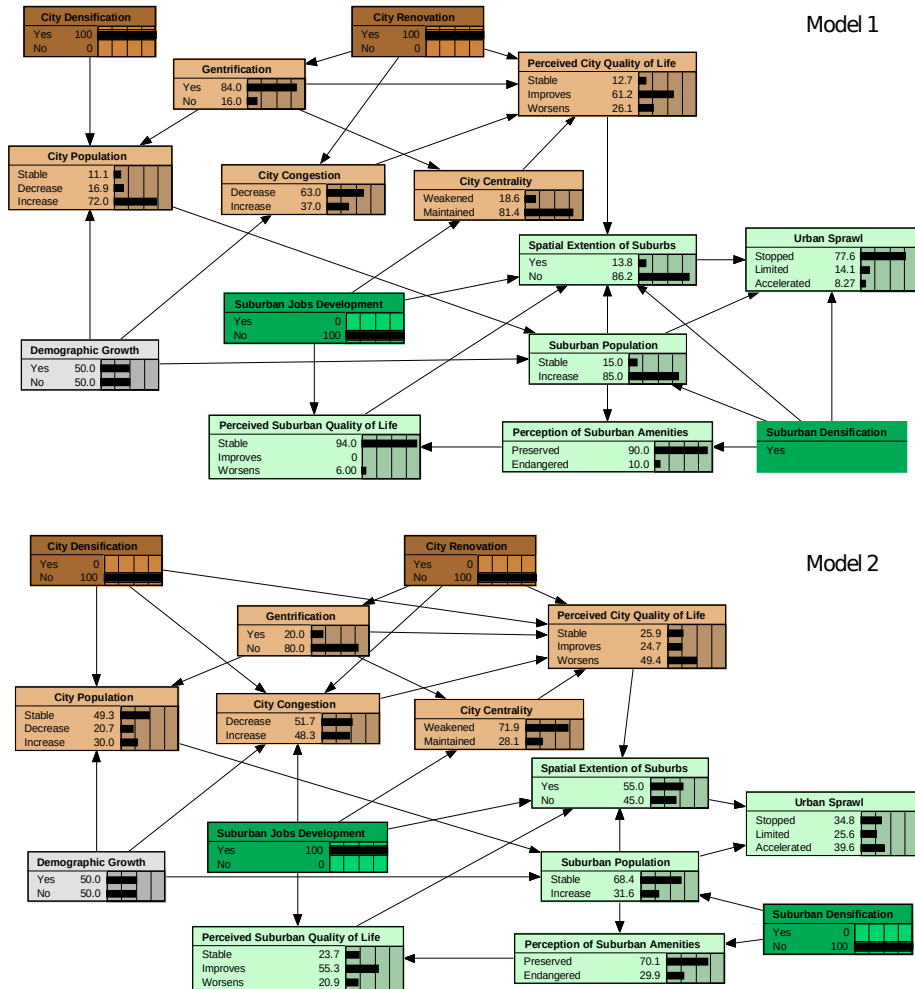


Fig. 2. Implementing Different Policies on the two Models.

Model 2, on the contrary, favors the implementation of a completely opposite set of policies: no densification, whether in the city or in the suburbs, no city renovation but development of jobs in the suburbs. The final impact on urban sprawl is relatively uncertain (even if it is clearly better than any other set of policies implementing densification): sprawl could be stopped ($p=0.35$), limited ($p=0.26$) but also accelerate ($p=0.39$). These beliefs are very sensitive to the demographic growth scenarios, though remaining relatively uncertain: by increasing population, urban sprawl should probably accelerate ($p=0.47$, with probability of stop falling to 0.25); in the absence of population growth, urban sprawl should be probably stopped ($p=0.45$, with probability of acceleration falling to 0.32). Uncertain evidence could also be propagated, as for example if we consider population growth very probable ($p=0.8$) but not certain.

3 Belief Revision between Alternative Models

3.1 Problem statement

The central point in our paper is not belief propagation within a BN. A much more crucial goal is to make the best use of available evidence from case studies (which are always relatively rare) in order to reassess our beliefs in models. Subsequently, revised beliefs in models and belief propagation within each model could be combined to derive new beliefs on a few variables of interest, given the available evidence.

The main characteristic of our epistemic framework is considering Models 1 and 2 as two alternative plausible explanations of urban sprawl, together with a more uncertain option considering urban sprawl as the consequence of an unknown third model (which could also be a model of stochastic independence from any other domain variable). Raftery [25, 26] has already proposed Bayesian frameworks for model selection in the social sciences, an indication subsequently made by Withers [27] within the geographical science. The core of model selection lies in the identification of the best model between Model 1 (M1) and Model 2 (M2), knowing some empirical evidence E and revising some prior belief on model plausibility ($p(M1)$, $p(M2)$). Using Bayes' theorem (1), one can evaluate the posterior odds of the two models, given the evidence:

$$p(M1|E) \frac{p(E|M1)}{p(E|M2)} = p(M1) \frac{p(E|M1)}{p(E|M2)} \frac{p(M1)}{p(M2)} \quad (3)$$

The first term of the right side of the equation is known as Bayes factor, defined as the ratio of the likelihoods of the evidence given each model. When the parameter space of each model is considered, likelihoods must be calculated as a complete integral on all parameter space, which is often intractable. Bayesian Information Criterion (BIC) is then used as an approximation of Bayes factor. If, as we will do here, we consider model parameters as fixed, Bayes factor can be directly calculated through belief propagation in the two Bayesian networks.

At the same time, as already anticipated, our frame of discernment of possible models is significantly richer:

$$\Theta_{\text{Models}} = \{M1, M2, \dots, \text{Other}\}$$

Where M_i are the possible models considered and *Other* stands for any other possible model not yet formulated. The modeler can have prior beliefs on these possible options (including the option *Other*) and can calculate likelihoods from available models. It cannot however calculate the likelihood $p(E|\text{Other})$, which is necessary in order to apply Bayes theorem for revising the beliefs on the possible models. We thus propose an approach to estimate the likelihood of the option *Other* given the evidence E respecting the following principles:

1. $p(E|\text{Other}) = 0$ if at least one of the formulated explanatory models M_i is completely plausible (for at least one i , likelihood $M_i = 1$);

2. $p(E|\text{Other}) = 1$ if no other formulated explanatory models is minimally plausible (for all i , likelihood $M_i = 0$).
3. $p(E|\text{Other})$ should grow as the likelihood of the formulated explanatory models diminishes.

These principles correspond to the human quest of explanation for observed phenomena, considering the current accepted explanatory knowledge and its ability to explain the new phenomena. If, among several currently accepted models, at least one of them is a plausible explanation of newly observed phenomena, no push for new models is felt, and the newly acquired empirical evidence is used to arbitrate between available models. The plausibility of new, yet to be formulated models is high when newly observed phenomena cannot plausibly be accounted for by any of the available models. History of science often witnessed this course of events. We could then write:

$$p(E|\text{Other}) = 1 - f(\text{Max}(p(E|M_i))) \quad (4)$$

Where f is a suitable monotonic decreasing function varying between 0 (when $\text{Max}(p(E|M_i))=0$) and 1 (when $\text{Max}(p(E|M_i))=1$). One possible operationalization of (4) is:

$$p(E|\text{Other}) = 1 - \text{Max}(p(E|M_i))^\alpha \quad (5)$$

if $\alpha < 1$ the push to look for new models is sublinear with the lack of plausibility of the best available model, if $\alpha > 1$ it is super-linear. Once an appropriate α is chosen, reflecting the attitude to lack of plausibility of the best available model, we can calculate thanks to (5) likelihoods for all model options given observed evidence E and, through Bayes' theorem (1), we can revise our beliefs in the different model options. If, instead of certain evidence E , we have uncertain evidence $p(E_i)$, Jeffrey's rule (2) can be used to revise beliefs.

3.2 Application to the Possible Models of Urban Sprawl

Let us imagine that an urban geographer is relatively confident in Models 1 and 2 as possible explanations of urban sprawl and its relations to densification policies in French cities. He does not want to commit to any of the two models in particular and he does not want to bar the possibility that other models, not yet formulated, could explain urban sprawl in French cities. He could thus assign prior probabilities 0.45, 0.45 and 0.1 to Model 1, Model 2 and Other within \mathfrak{M} . How should he revise these beliefs with newly acquired knowledge on a case study to which the models could be applied?

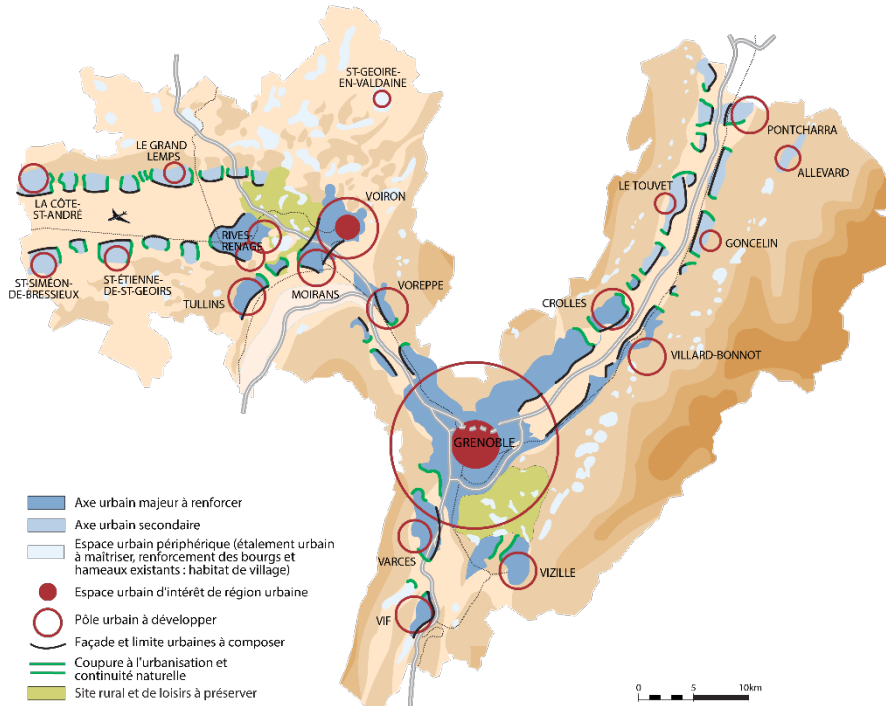


Fig. 3. Densification policies in Grenoble regional master plan of 2000. Source: [27]

The metropolitan area of Grenoble, in the alpine region of southern France, offers a good feedback on densification policies in French cities (Figure 3). At its core lies the city of Grenoble, a mid-sized city of 155 000 inhabitants. Around the central city, a vast peripheral area hosts a population three times more important. The periphery develops along three main axes going south, north-east and north-west and following three main alpine valleys. Most of these peripheral areas are made of residential suburbs, surrounding a few historical villages and industrial or commercial surfaces. We will focus our attention on this study area for a period stretching from 1999 to 2013.

Over this period, Grenoble and its surrounding municipalities have implemented one of the most coherent densification policies in France, both in the central city and in the suburban areas, promoted by the adoption of the development and town planning master plan of 2000 [28, 29] and of several local town plans. The central city has also implemented important policies of city renovation, as the Urban Renovation Program of 2005 [30], the extension of the LRT lines A and B and the opening of two new LRT lines in 2006 and 2007. The same coherence cannot be found in terms of suburban jobs development. The master plan in 2000 foresaw the development of industrial, service and retail jobs in a few key areas of the suburbs. Indeed, jobs have steadily grown between 1999 and 2013 both in the central city (passing from 85 000 to 93 000) and in the rest of the metropolitan area (passing from 136 000 to 207 000 within a much larger geographic perimeter, see further).

We could thus easily assess that, for the Grenoble study area, variables *City Densification*, *Suburban Densification*, *City Renovation* and *Suburban Jobs Development* all have value “yes” over the period 1999-2013. As for the population growth of the study area, it passed from 631 000 inhabitants to 684 000, with an 8.4% increase, which is in line with the general steady demographic growth of France during the same period. We will thus assign value “increase” to variable *Demographic Growth*. These five values define a scenario of policies and demographic growth for our study area, which are independent from the probability relations of our two models.

A few easily measurable variables can also be used to introduce observed evidence in this scenario and evaluate model likelihood given the scenario and the evidence. City population was thus relatively stable over the period, oscillating between 153 000 and 156 000 inhabitants. Suburban population, on the other hand, rose from 478 000 to 528 000, a 10.5% increase over the 15 years. We can thus assign values “stable” and “increase” to variables *City Population* and *Suburban Population*, respectively.

Finally, the spatial extension of the suburbs within the metropolitan area was particularly important. Metropolitan areas are defined in France by the National Institute of Statistics and Economics (INSEE) as functional urban areas where more than 40% of the active population in each municipality commutes to the central city or to other municipalities in the metro area. Thus defined, the metropolitan area of Grenoble included 119 municipalities in 1999 but well 197 in 2013. Even if the newly incorporated municipalities were already well developed in 1999, their population increase strongly depended on household migration from the central city and other central municipalities and they were progressively integrated in the urban functional area. We can thus assign the value “yes” to the variable *Spatial Extension of Suburbs* between 1999 and 2013.

When these new findings are entered in the BNs, we can calculate marginal joint probabilities of 0.0636 for Model 1 and of 0.0992 for Model 2. These values correspond to the likelihoods of the two models given the scenario (defined by independent variables) and the observed findings (i.e. the three further empirically determined variables). We can thus revise our beliefs in the different model options using Equation (5).

Table 1 shows the results of the belief revision assuming two different attitudes to lack of plausibility of the best available model: linear ($\alpha=1$) and sublinear ($\alpha=0.25$). The case study of Grenoble is clearly a counter-example for the two acknowledged models of urban sprawl. The most conflicting element of evidence of the case study with the models is the relatively stable city population in spite of overall demographic growth and the city densification policies (for both models city gentrification becomes then the most plausible cause of the observed phenomena). Overall, the likelihood value is relatively low for both models (even if it is higher for Model 2 than for Model 1). Equation (5) thus produces relatively high likelihoods for other possible models, compatible with the observed evidence: 0.4388 in the sublinear case, 0.9008 in the linear case. Bayesian belief revision (Equation 1) thus results in much more uncertainty within our frame of discernment of possible models. In the sublinear case, belief in Model 2 is almost the same as the one in other possible models (0.38 and

0.37, respectively) and slightly higher than for Model 1. In the linear case, the most plausible model is the one yet to be discovered (posterior belief = 0.55), highlighting the weaknesses of available models.

Table 1. Belief revision for model options given the case study of Grenoble.

	Model 1	Model 2	Other
			sublinear ($\alpha=0.25$)
prior belief	0.45	0.45	0.1
likelihood	0.0636	0.0992	0.4388
posterior belief	0.24	0.38	0.37
			linear ($\alpha=1$)
prior belief	0.45	0.45	0.1
likelihood	0.0636	0.0992	0.9008
posterior belief	0.18	0.27	0.55

3.3 Discussion

The interpretation of the Grenoble case study in terms of hard evidence could be challenged. Even if this example was selected for its paradigmatic role and for the ease of interpretation of the available evidence, a soft/virtual evidence approach could be more appropriate [22, 23]. In the absence of an unambiguous protocol allowing the interpretation of available evidence, expert-based interpretation of evidence could be used. This could possibly result in soft or virtual evidence, assigning probabilities or likelihoods (respectively) to the fact that city or suburban densification has really taken place in the study area during the 1999-2013 period. Equation (2) would then be used to propagate evidence in the Bayesian networks. By so doing, the likelihoods of the two models would increase accordingly (reducing as a consequence the likelihood of other models), but the main conclusion would be the same: belief in Model 2 increases slightly compared to belief in Model 1, but belief in other models, which was particularly low a priori, becomes much higher now, increasing considerably uncertainty among model options.

Should Models 1 and 2 be discarded altogether in the analysis of urban sprawl in French metropolitan areas during the last decades? Our Bayesian belief revision doesn't reach this conclusion, as a unique counter-example is not sufficient to invalidate our models, given our prior beliefs. France has around 50 metropolitan areas of more than 200 000 inhabitants, having applied more or less coherent policies of densification to counter sprawl. The proposition to be evaluated is indeed the ability of our two models to cover this domain, and only a more thorough analysis of this set could possibly arrive to such a conclusion. If such analysis were to produce a very low value of posterior belief for one of the two models, this could indeed be disqualified as a pertinent model for our domain. If both models were characterized by very low posterior beliefs, the geographer's conclusion should be the need to look for alternative models, based on different theoretical assumptions and possibly more attentive to specific dynamics observed in French metropolitan areas. As often in the social sciences, we remain within a falsification approach with is much weaker than Popper's

[31]: evidence concurs to make theoretical explanations incrementally more or less plausible, up to the point where the scientific community decides that a given model is no longer acceptable.

From this point of view, we are not interested in Bayesian updating of model parameters. Posterior expected values of parameters could indeed be calculated through conjugate priors of the multivariate distributions in the Bayesian Networks. Parameters in the conditional probability tables would then be allowed to drift considerably from the values derived from the elicited knowledge modelled through the noisy logical gates. Sophisticated parameter updating schemes could also be used, by assigning experience equivalents to the prior knowledge incorporated in the models. Prior knowledge could then be possibly swamped by data, as new case studies are presented to the models. But the resulting models would be less and less linked to precise theoretical assumptions, and finally harder to falsify, given their ability to adaptively incorporate newly acquired evidence.

It is also worth highlighting how our problem differs from more classical robust Bayesian modelling as presented by Bolstad [32]. When modelling binomial or multinomial stochastic processes, Beta and Dirichlet priors are normally linearly combined with a flat prior, to which the modeler assigns a very low prior belief. By doing so, the modeler makes sure that possible miss-specifications of the priors don't result in a wrong posterior distribution: when data contradict the prior, the posterior depends more on the data than on the prior. An important theoretical assumption underpins these operations: the observed phenomena are governed by a simple binomial or multinomial distribution whose parameters can possibly be wrong, but the posterior model will always have the same functional structure. In our problem, the possible models are Bayesian Networks, which are complex combinations of binomial and multinomial distributions. It is impossible to find appropriate conjugate distributions to combine with a flat prior. Moreover, the models have different structures (and not just different parameters) and possible other models are not just the "flat equivalent" of the available ones. They are yet to be developed models with particular structure and parameters, which are presently unknown. Our approach is thus more a belief revision heuristic among available and unavailable models backed by Bayesian calculus, than a precise Bayesian calculus of posterior model parameters within a given model structure.

4 Conclusions: Further Frameworks for Multiple Models of Urban Sprawl

This paper showed how Bayesian belief revision together with a particular framework assigning likelihood to unknown models can be used in order to assess prior beliefs on multiple models. This approach seems particularly interesting whenever the modeler is able to express his beliefs in terms of additive probabilities and when the number of available evidence is relatively small, giving thus great importance to prior probabilities. This last condition is very frequent in research on sustainable cities: a few case studies are the empirical evidence of broadly formulated, alternative models

of sustainable urban development. The case of urban sprawl in the metropolitan area of Grenoble also highlighted issues of knowledge elicitation and domain definition for the models. It was finally shown how a single counter-example is not sufficient to invalidate the two proposed models, given our prior beliefs.

However, Bayesian networks and Bayesian calculi are by no means the only tool that can be employed to reason about alternative hypotheses in the light of the available evidence. Artificial intelligence, in particular, has dedicated much effort to devising formal and computational frameworks for representing and managing uncertainty, on the one hand, of which Bayesian networks are but one offshoot, and belief revision on the other hand.

When it comes to representing and managing uncertainty, it is important to underline that two aspects of uncertainty must be distinguished: (i) stochastic uncertainty, resulting from a system behaving in a random way, and (ii) epistemic uncertainty (or ignorance), resulting from a lack of knowledge about a system.

Dempster-Shafer theory of evidence [33], and Phil Smets' transferable beliefs model [34], which is an interpretation thereof, is a theory of uncertainty whose aim is to give a mathematical account for epistemic uncertainty, besides stochastic uncertainty. The theory of evidence is rooted in probability theory, but it innovates in allowing for the allocation of a probability mass to events, rather than just elementary events or individual sample points.

The basic ingredients of the Dempster-Shafer theory of evidence are:

- a basic belief assignment, in the form of a probability mass distribution m over (sets of elementary) events A included in Ω , such that the mass of the empty set is null and the mass of all events sums up to one.
- a belief function Bel , determined by the basic belief assignment: $Bel(A)$ is the sum of the masses of all events included in A ;
- a plausibility function Pl , also determined by the basic belief assignment and dual to the belief function: $Pl(A)$ is the sum of the masses of all events that have a non-null intersection with A ; thus $Bel(A) = 1 - Pl(\text{complement of } A)$.

The process of changing beliefs when new evidence becomes available is central to the evidence theory. The intuition behind it is that a basic belief assignment m represents an epistemic (or credal state of an agent and, if further evidence becomes available to the agent, in the form of a proposition φ , the agent should change m to reflect this new evidence. In particular, the agent should rule out all worlds where φ does not hold and transfer their previous belief mass to worlds where φ holds. It should be noticed that this is essentially a conditioning process, whereby $m(\cdot)$ is conditioned by φ to yield $m(\cdot | \varphi)$. One possible way to perform such a belief transfer is by means of the so-called Dempster rule of conditioning.

Possibility theory [35] is another mathematical theory of uncertainty based on fuzzy set theory, alternative to probability theory. It differs from this latter by the use of a pair of dual set-functions (possibility and necessity measures) instead of only one. This feature makes it easier to capture partial ignorance. Besides, it is not additive and makes sense on ordinal structures. Possibility theory has a strong relation with the theory of evidence, not only because the two share basically the same objec-

tive, but also because both theories use monotonic (or non-additive) measures to represent beliefs.

The advantage offered by these two theories, with respect to Bayesian probabilities, is their capability of representing epistemic uncertainty in an explicit fashion. The theory of evidence, in addition, may represent stochastic uncertainty as well in a way that is fully compatible with probability theory, while the relationship between possibility theory and probability is subtler; nevertheless, transformations from possibilities to probabilities and *vice versa* have been proposed and studied in the literature [36]. How these two theories might be applied to our problem of model selection is left for future work. The main issue that would have to be addressed to this purpose is a suitable definition of the “sample space” Ω underlying the model selection problem, given which, the uncertainty associated with the models might be represented, respectively, as a probability mass distribution over the power set of Ω or a possibility distribution over Ω . It should finally be assessed how these more sophisticated AI theories of uncertain knowledge could be integrated in decision making in the field of sustainable urban development.

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