No increase in drug dispensing for acute gastroenteritis after Storm Klaus, France 2009

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ABSTRACT

During the night of 23–24 January 2009, Storm Klaus hit south-western France and caused power outages affecting 1,700,000 homes and stopping numerous pumping and drinking water disinfection systems. In France, medicalized acute gastroenteritis (MAGE) outbreaks are monitored by analysing the daily amount of reimbursements of medical prescriptions, registered in the French National Health Insurance database, at the 'commune' administrative level. As AGE is suspected to be associated with perturbations to water supply systems as well as power outages, Storm Klaus provided an opportunity to test its influence on the incidence of MAGE in the communes of three affected French departments (administrative areas larger than communes). The geographical exposure indicator was built by using the mapping of the water distribution zones, the reported distribution/production stoppages and their duration. Irrespective of exposure class, a relative risk of MAGE of 0.86 (95% confidence 0.84–0.88) was estimated compared with the 'unexposed' reference level. Although these results must be considered with caution because of a potential marked decrease in global medical consultation probably due to impassable roads, they do not suggest a major public health impact of Klaus in terms of increased MAGE incidence.

Key words | drug prescription, gastroenteritis, power outage, syndromic surveillance, water supply systems, windstorm

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INTRODUCTION

During the night of 23–24 January 2009, the severe Storm Klaus hit south-western France. Wind speeds over 130 km/h directly caused the death of seven persons and a great deal of damage, including forest and power-line falls. As an indirect result, the misuse of fuel-powered generators resulted in four fatalities from carbon monoxide poisoning (Coquet *et al.* 2013). The power outage affected 1,700,000 homes. It took over a week to restore power to every household. This blackout also heavily impacted the local drinking water supply systems by preventing pumping as well as drinking water disinfection and leading to production or distribution stopping (Figure 1). Power outage was by far the main cause of disruption. The rainfalls were of 20–30 mm according to location during these 2 days, which is not

exceptional and mentions of water distribution systems with flooded intake points were very rare (Figure 1).

One of the most significant impacts of windstorms on infrastructure is the loss of electricity (Goldman *et al.* 2014) and storms can contribute strongly to the deterioration of the quality of water (Lee *et al.* 1993). Reduced levels of hygiene and sanitation, due in part to the lack of electricity and water, can result in higher rates of infection (Shultz *et al.* 2005; Goldman *et al.* 2014). Furthermore, acute gastroenteritis (AGE) is associated with perturbations to water supply systems as well as power outages. For example, a diarrhoea outbreak in Milwaukee in 1993, caused by *Cryptosporidium* oocytes, was associated with a decrease in the efficiency of the filtration system (MacKenzie *et al.* 1994;
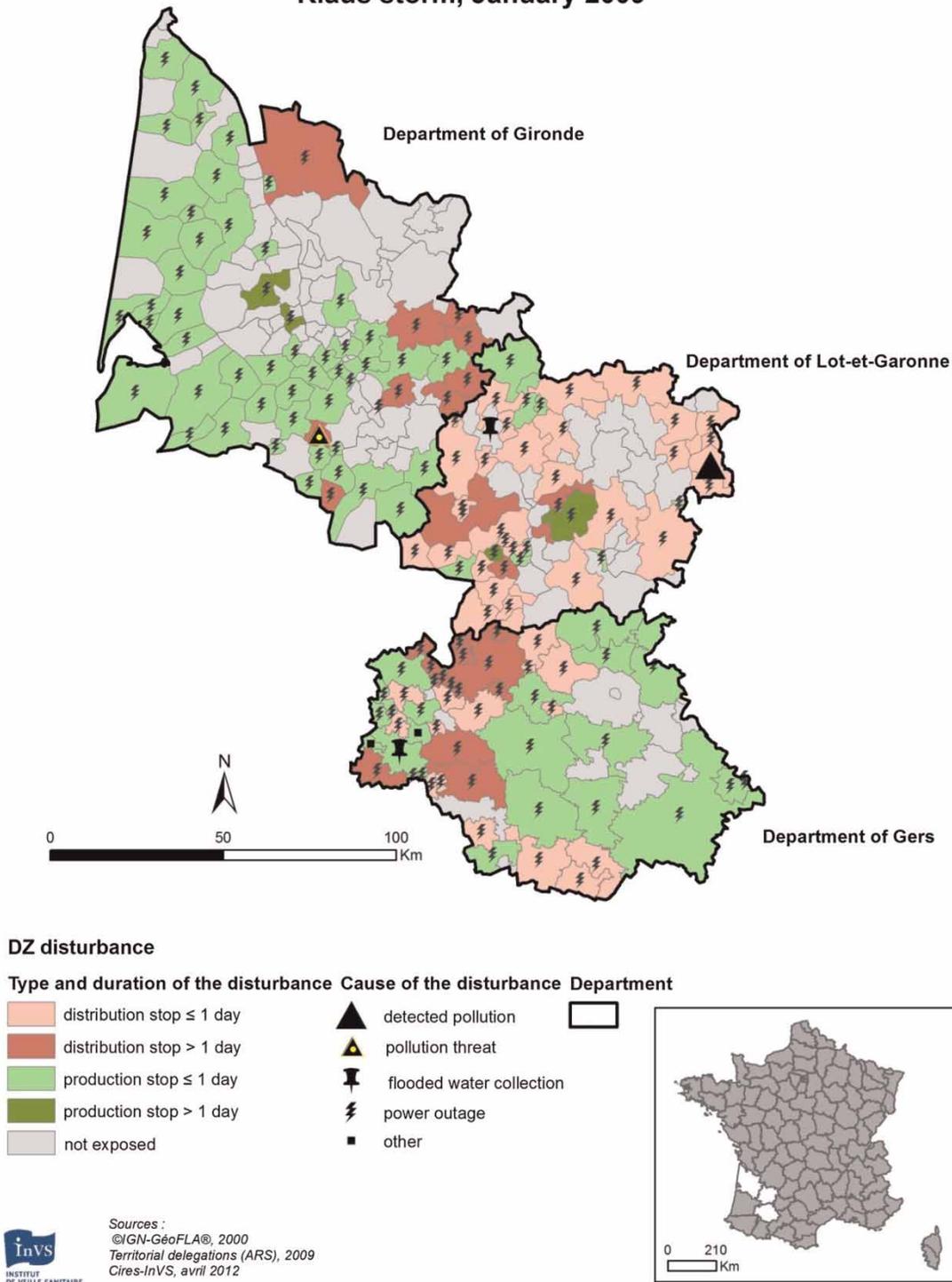
Figure 1 │ Nature and duration of the post-Klaus reported disruptions for water distribution zones (DZs) in the study area.

Hoxie *et al.* 1997). In Taiwan (Huang *et al.* 2011) and in Sweden (Nygard *et al.* 2007), increased AGE incidence was observed in downstream consumers after short-term water outages due to pipe changes and cracks. In August 2003 in New York City, a massive 2-day power outage was linked to an increase of 70% in the number of patient visits for diarrhoeal syndromes in emergency units, and an increase in antidiarrhoeal medication sales the day after the outage (Marx *et al.* 2006).

These examples show that even if the risk of infectious outbreaks in developed countries is considered to be relatively low after natural disasters (Shultz *et al.* 2005; Menne & Murray 2013), it may occur through power outage and water system disturbance. Klaus generated a serious and long power outage which affected numerous local drinking water supplies for 1 to 4 days, preventing pumping as well as drinking water disinfection. More probably, longer power cuts during and after the storm (e.g. >12 h) may have led to the emptying of the drinking water tanks. Subsequent low pressure conditions in the network could then have resulted in backflow of contaminated waters from soil or sewage into the pipes (Hunter *et al.* 2005; Nygard *et al.* 2007). Consequently, delayed exposure of the consumers to pathogens may have occurred when water distribution was finally restarted (Nygard *et al.* 2007).

MATERIALS AND METHODS

Health data

Health data were collected from the French National Health Insurance System's database. This system was developed in the early 2000s to facilitate patient reimbursement for the payment of drugs prescribed by health practitioners in private clinics. These data represent an important source for syndromic surveillance because of their extensive population coverage (99% of the resident population) (Tuppin *et al.* 2010) and their continuous collection. Drug reimbursement data (all drug codes and the number of items sold) are electronically linked to the commune name and code (=post/zip code) of the patient's place of residence, to his/her gender and age, to the date of the prescription, to the commune code of the health practitioner's workplace and to the date when the pharmacy dispensed the drugs.

Drugs prescribed for AGE are not specific to this pathology and are widely used in the treatment of other illnesses. Therefore a specific algorithm was implemented to discriminate AGE-related prescriptions from prescriptions related to other causes (Bounoure *et al.* 2011). Tested on patients in five pharmacies with at least one targeted drug included in their prescriptions, the most recent version of the algorithm identified AGE with a sensitivity of 89% and a specificity of 89% compared with clinically certified diagnosis (Bounoure *et al.* 2011). This algorithm allowed us to improve the surveillance indicator of medical treatment for AGE or 'medicalized acute gastroenteritis' (MAGE) in the French Health Insurance database (Beaudeau *et al.* 1999; Beaudeau & Bounoure 2006). Furthermore, the discrimination algorithm and the patient's postcode allowed us to identify the number of cases of MAGE per day per commune. The analysis of the evolution of this number in communes where AGE epidemics were followed by field cohort studies allowed French epidemiologists to cross-validate MAGE as a detector and an estimator of AGE outbreaks (Beaudeau & Bounoure 2006).

In the present study, all prescriptions written between 1 September 2008 and 31 December 2010 including at least one targeted drug (i.e. a drug possibly prescribed for AGE) to patients living in the communes of the departments Lot-et-Garonne, Gironde and Gers, were extracted from the database.

Exposure data

For this study, the geographical exposure indicator was built by using the mapping of the water distribution zones (DZs) by the regional health authorities. Immediately after Klaus, local services of the health ministry in charge of water quality monitoring were contacted and asked to report any disruption to water systems. They were also asked to record the name of the DZ, any water distribution and water production stops, the duration of such stops, the notification of any flooded and polluted catchment areas, as well as any pollution of distributed water. Any corrective actions undertaken also had to be reported. Structural information about DZs was drawn from the SISE-eau national database: DZ name, location (communes covered) and the size of the serviced population. The

regional health agency database was used as it contains the geographical coordinates of all DZs.

Definition of exposure and AGE health indicators

AGE epidemics associated with water consumption may be caused by numerous pathogens. The incubation periods vary from 1 day (norovirus) to 10 days and more (*Cryptosporidium* sp.). Disruptions of the water distribution systems lasted from 1 day to 4 days following Storm Klaus. We therefore considered that a 14-day period after Klaus (hereafter 'Klaus days') took adequate account of the onset of AGE symptoms due to exposure to waterborne faecal pathogens which could result in general practitioner (GP) prescriptions and visits to pharmacies. A proxy of exposure to possible deterioration of water quality was defined using the data on reported disruptions to the water supply systems. This indicator was chosen because of the good availability of this data throughout the targeted territory.

Five classes of decreasing exposure were defined, according to the potential health impact they may have had: water distribution stopped for more than 1 day, water distribution stopped for 1 day or less, water production stopped for more than 1 day, water production stopped for 1 day or less, water distribution not reported as exposed.

The discrimination algorithm and the patient's postcode allowed us to identify the number of cases of MAGE per day per commune. Exposure data were available at the DZ level. We reassigned all communal populations and MAGE cases to the DZs.

In France, population distribution at the commune level is available in geocoded areas of 40,000 m^2. Overlapping the surface of those squares with the surface of the corresponding DZs allowed us to estimate the proportion of the population of a commune supplied by different DZs. Most of the communes were completely included in a single DZ and so the populations of these communes were assigned to this DZ. A few communes were supplied by more than one DZ. In this case, if the DZs concerned shared the same class of exposure (=level) they were combined to create a new virtual DZ (mega-DZ = aggregated DZ) covering that commune. For DZs which had different exposure levels, the DZ that supplied water to the largest proportion of its population was assigned for the whole commune.

For this study, the health outcome was the daily number of cases of MAGE per retained DZ and mega-DZ of the three departments (remembering that a department is comprised of several communes).

STATISTICAL MODELLING

Spatiotemporal modelling of AGE

We used a spatiotemporal regression model to assess the risk both of MAGE associated with a Klaus day and of residing in an exposed DZ where water distribution or production had stopped.

We used the spatiotemporal model introduced by Bernardinelli *et al.* (Bernardinelli *et al.* 1995; Schrodle *et al.* 2012) to model data. A hierarchical Bayesian model with parametric time trends was fitted. The linear predictor was decomposed into additive components depending on space, time or both (Abellan *et al.* 2008; Fortunato *et al.* 2011). For the spatial component, the standard Besag-York-Mollie specification (Besag *et al.* 1991) was used with a spatially unstructured and a structured component, v and ψ, respectively. Unstructured random effects v were assumed to be independent and mean-zero normally distributed with unknown variance. The spatially structured residual ψ was modelled using an intrinsic conditional autoregressive structure. A main linear time trend and a differential time trend for each DZ were added to the spatial component.

The number of AGE cases O_{ij}, $i = 1, ..., N$ and $j = 1, ..., T$ – where $N = 228$ (the number of DZs studied) and $T = 852$ (the total number of days from 1 September 2008 to 31 December 2010) – was assumed to follow a Poisson distribution with mean $E_{ij}\theta_{ij}$ with E_{ij} and θ_{ij} being, respectively, the expected number of cases and the unknown relative risk (RR) in area i on day j, respectively. The log-RRs can be written as

$$\log(\theta_{ij}) = \gamma_0 + \gamma_1 \times \exp o_{ij} + \gamma_2 \times \text{day of the week}_j$$
$$+ \gamma_3 \times \text{holidays}_j + v_i + \psi_i + \sum_k \alpha_k \times \cos(kwt_j) \beta_k *$$
$$\sin(kwt_j) + (\phi + \varphi_i) \cdot t_j$$

The long-term temporal trend was modelled using a linear function. Seasonality was modelled using trigonometric functions with $w = 2\pi/365$. To take into account periodicities greater than 2 months, k was defined as less than or equal to 6. The parameter ϕ represents an overall linear time trend and φ captures the interaction between the linear time trend and the spatial effects v and φ. The effect φ_i represents the amount by which the time trend of unit i differs from the overall time trend ϕ and is called the 'differential trend' for the ith unit (Bernardinelli *et al.* 1995). Thus $\phi + \varphi_i$ represent the slope of DZ_i and $\gamma_0 + v_i + \psi_i$ its spatial intercept. The differential trend φ was specified as an independent and identically mean-zero normally distributed effect. Weekday and holiday effects were also taken into account. The prior distributions for the unknown variance of the random effects were specified (Bayesian model). Independent gamma priors were assigned to the precision parameters. Data were analysed using Win-BUGS, version 1.4.3 (Lunn *et al.* 2013).

RESULTS

Almost all the disruptions to DZs were caused primarily by the power shutdown. Only two water catchment facilities supplying two DZs were reported flooded while pollution was reported in two other DZs (Figure 1). The three departments studied included 1,897,410 inhabitants and 1,324 communes, which, in the present study, were distributed into 228 real or mega-DZs (=aggregated DZ). Most communes were fully included in the area of one of the 228 DZs (i.e. 1,269 communes and 1,568,391 persons). Bordeaux, the main city in the study area, had 232,260 inhabitants with one aggregated DZ presenting 2 days of production stoppage (60% of Bordeaux's population) and one not reported as exposed DZ (40% of the population). The former was chosen to represent Bordeaux in the analysis. Fifty-four other communes (with 96,759 inhabitants) included two or more DZs with different levels of exposure. They were included among 32 of the selected 228 DZs. In the three departments studied, 143 DZs (63%) were disrupted, and 1,045,414 persons (55% of the study population) exposed.

The number of MAGE cases observed during the period from September 2008 to December 2010 was 471,429. The distribution of daily MAGE cases showed marked but irregular seasonal variations, peaking in January 2009 and 2010 (Figure 2). These peaks corresponded to common viral winter outbreaks. No other outbreak patterns were observed. Klaus occurred during the 2009 winter outbreak.
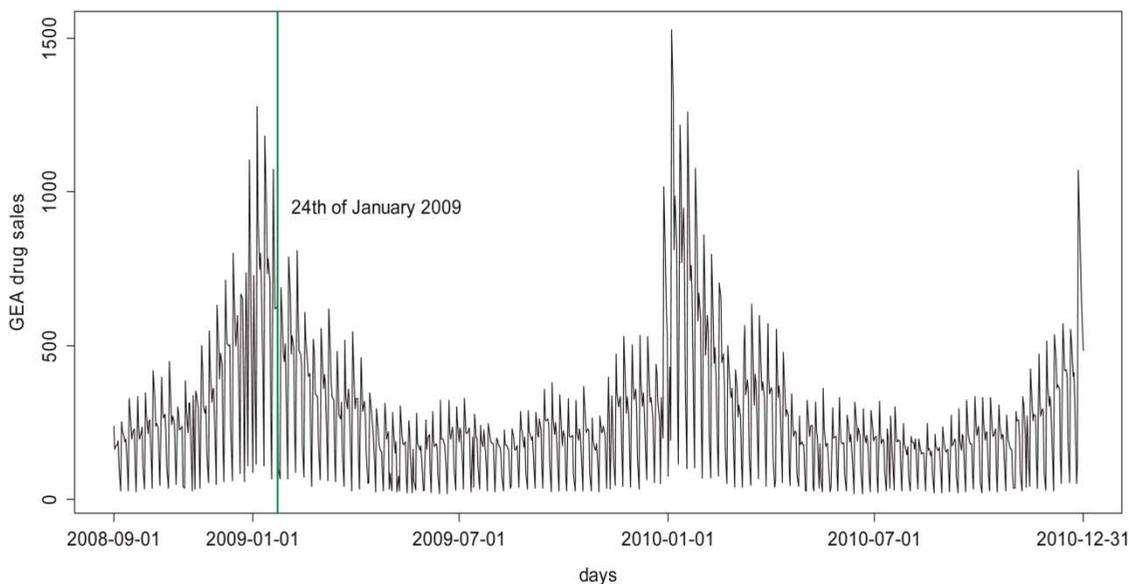
Figure 2 │ Daily number of MAGE cases from 1 September 2008 to 31 December 2010.

The spatiotemporal model

We observed 224,751 AGE cases during the study period in the 85 DZs not exposed to Klaus and 246,678 in the 143 exposed DZs. The number of DZs and the number of observed MAGE cases by exposure class are presented in Table 1.

The results of the statistical analysis are provided in Table 2. Irrespective of exposure class, a RR of MAGE of approximately 0.86 was estimated compared with the 'unexposed' reference level (i.e. the risk of MAGE for people resident in unexposed DZs and for days other than Klaus days).

DISCUSSION

During the 14 days after Klaus, the daily number of MAGE cases did not increase. This is not surprising. Klaus was characterized by very strong winds, and despite rainfall being heavy during the event the overall amount was not exceptional and flood phenomena were very localized. In developed countries, some reports describe gastrointestinal episodes after windstorms (Ahern & Kovats 2013; Goldman et al. 2014) and show that these episodes are linked to floods (CDC 1993b, 2000, 2002; Ahern & Kovats 2013). More typically no increase in gastrointestinal disease is found (CDC 1993a; Lee et al. 1993; Aavitsland et al. 1996; Shultz et al. 2005; Bayleyegn et al. 2006; Meusel & Kirch 2013).

Distribution stoppage is linked to higher risk of exposure through low-pressure events and possible backflows of sewage waters into drinking water pipes (Hunter et al. 2005; Nygard et al. 2007). The risk of water contamination is thus proportional to the stoppage duration (Nygard et al. 2007). In our study, reported perturbations to the water supply systems following Klaus were associated with a 15% decrease in the risk of MAGE during the 14 days following the storm. Furthermore neither the type of disruption nor its duration modified the risk of MAGE among people provided with a water-supply service. This does not support an effect of DZ disruptions on the risk of MAGE.

A contribution of enhanced preventive measures and behaviour to these results cannot be ruled out in a context of low risk of water contamination. But the observed decrease in MAGE may more likely be the result of decreased access to medical help.

An analysis of the information collected about Storm Klaus suggests a low risk of post-event contamination of drinking water. Post-Klaus DZ disruptions were almost exclusively associated with power loss. There were very few reports of flooded DZs (only 2 out of 228). Reports of detected water contamination were very scarce in the data collected by local services (2 reports in 228 DZs). Most of the disrupted DZs were affected by production stoppage. For the latter, safe drinking water stocks were available.

In France, when faced with DZ disruption, local public health officers try to minimize the impact by implementing protective measures such as increasing chlorination. Indeed in the literature, chlorination has been associated with lower AGE risks (Nygard et al. 2007). Enhanced chlorination is known to prevent infection by bacterial waterborne faecal pathogens and even viral pathogens, depending on the dose (Smeets et al. 2011). Systematic chlorination was mentioned

Table 1 | Number of DZs and observed number of AGE by exposure class

| Class of exposure for DZ | DZ (no.) | Population | MAGE cases (no.) | |
			Entire study period	14-day period post-Klaus
DZ not exposed	85	852,096	224,751	6,159
Water production stopped for 1 day	77	368,737	87,316	2,449
Water production stopped for >1 day	5	437,596	106,546	2,939
Water distribution stopped for 1 day	39	145,948	31,412	897
Water distribution stopped for >1 day	22	93,033	21,404	568
Total	228	1,897,410	471,429	13,012

Table 2 | Estimated RRs of MAGE during the 2 weeks following Klaus by exposure class (Klaus days)

	RR	(95% CI)
Unexposed = reference	1	–
Water production stopped for 1 day or less	0.87	(0.83–0.91)
Water production stopped for >1 day	0.86	(0.82–0.89)
Water distribution stopped for 1 day or less	0.89	(0.83–0.95)
Water distribution stopped for >1 day	0.82	(0.75–0.89)

for one department after Klaus. Local public health officers who could be contacted from the other two departments declared that they had recommended chlorination for the disturbed DZs to local operators in charge of the DZ maintenance (mayors of communes, private water distribution companies, etc.). Enhanced chlorination lasted up to 48–72 h after the restarting of the water distribution system; during the time of water distribution stoppage, safe drinking water stocks and mobile drinking water treatment units were dispatched in quarters and villages (personal communications, health officers working in the exposed departments). There are no statistical data on private water supplies in these departments. But the local officers estimate that the use of private water resources for drinking is rare due to the good quality and coverage of the public water networks. Furthermore, they consider the possibility that people used private water resources at times of shortage of public water as very low. At the individual level, many preventative steps are involved from initial DZ disruption to individual exposure to a potential pathogen. The possibility of greater public awareness of potentially contaminated water, together with individuals' own initiatives to implement preventive measures cannot be ruled out. Therefore, one can reasonably hypothesize that the protective measures adopted after Klaus, individually or collectively, were adapted to the risk of AGE linked to DZ disruptions. In addition, no collective evacuations or clustering of people, which could have increased the risk of dissemination of pathogens responsible for AGE, was reported.

However, the marked decrease in medical consultations during this period is most probably the main factor explaining the lower number of MAGE in the 14 days after Klaus, which is something that may even have masked a slight adverse effect in AGE incidence. One of the strengths of using data from the French National Health Insurance information system is that it covers the whole population of the three departments studied and that every purchase of a reimbursed drug is recorded. Outside of storm conditions, the MAGE indicator was sensitive enough to detect local outbreaks of AGE and to link them to DZ disruptions (Beaudeau *et al.* 2008; Rambaud *et al.* 2011). But this indicator only detected AGE that resulted in medical help being sought. In reality, the impact of Klaus was not limited to disruption of drinking water

systems. The storm hit the biggest pine forest in France, which covers the south of the Gironde department (300,000 hectares of forest were affected (Nicolas 2009)). Many roads in the departments studied had fallen trees or other obstacles (e.g. power lines), discouraging non-essential travel (Nicolas 2009). Traffic conditions were declared back to normal only on 29 January (communication of the Ministry of Interior). If symptoms were not too disabling, patients facing the destruction of their private assets may have postponed medical consultation. A population-based study on the burden of AGE and health-care-seeking behaviour in France estimated that 33% (95% confidence interval [CI] 27–40) of AGE cases consult a physician under normal conditions (Van Cauteren *et al.* 2011). The main reported reasons for non-consultation were quick recovery or no serious symptoms (64%) and the feeling that a consultation was not necessary (47%) (Van Cauteren *et al.* 2011). The same study also estimated that 77% (95% CI 70–82) of the AGE cases use medication and that for 42% of them, the source is the family medicine chest (95% CI 35–49). Therefore, there are good reasons, independent of protective behaviours, which may explain why drug sales corresponding to AGE were lower during the first days after the storm than in normal conditions, and why our MAGE indicator may have under-estimated the real health impact. To explore the hypothesis that traffic disruption did indeed play a role, the daily MAGE values of all DZs providing water to the Bordeaux conurbation were modelled, and the effect of the 14 days after the storm was estimated using a generalized additive model (Wood 2006). This conurbation experienced 2 days of water stoppage. In this area where transport connections were preserved, no effect was found (RR = 0.972 [95% CI 0.878–1.075]). This suggests no Klaus-related change in AGE risks.

The indicator of exposure was defined using the DZ cartography. As these data covered all the targeted territory they enabled comparison to be made with daily communal registered MAGE. However, using this type of ecological indicator instead of considering individual exposure to contaminated water can be a source of misclassification. Furthermore, the existence of an ecological bias cannot be ruled out. Such a bias is related to the heterogeneity in the geographical units linked to the existence of one or more

uncontrolled confounding factors which could in turn be related to exposure and/or to health indicators.

The bias due to a lower level of medical consultation must first be addressed if we wish to estimate the post-storm change in AGE incidence through the study of MAGE incidence. To address the dimension of post-storm access to medical care, other indicators measuring medical care activity may be used in possible future investigations. For example the global decrease in medical consultations following Klaus could be assessed by comparing daily numbers of GP consultations inside and outside the impacted area. However, a better indicator could also be the use of drugs indicating consultations for another disease of similar seriousness but whose onset is independent of the consequences of Klaus.

CONCLUSION

This study is the first assay in France to assess a possible risk of AGE in post-extreme climatic event conditions at a regional scale, by using a spatiotemporal ecological methodology based on evaluating daily MAGE cases per area (here DZ).

It helped us identify future methodological improvements. The first is to estimate access to medical facilities, in order to ensure the non-ambiguous interpretation of the results. With respect to exposure, information should be systematically collected: enhanced chlorination and water contamination monitoring after the detection of a disruption, possibility of using private tap water resources and delivery of safe drinking water when public water distribution stops.

As suggested by the literature, an analysis of the incidence of gastroenteritis following other scenarios of storms or natural disasters is also needed, in particular in situations where extreme water-related events such as floods are predominant (Ahern & Kovats 2013; Cann *et al.* 2013).

The results of this work show that Storm Klaus did not lead to increased sales of prescribed drugs for AGE. Although these results must be considered with caution because of potential ecological bias, they do not suggest a major public health impact of Klaus in terms of increasing AGE drug sales. This reinforces the hypothesis that in industrialized countries with generalized sanitation, minimum overcrowding, generalized use of disinfection processes and adequate drinking water

supply the risk of communicable diseases to public health after an extreme weather event appears to be relatively low (CDC 1993b, 2000, 2002; Aavitsland *et al.* 1996; Shultz *et al.* 2005; Bayleyegn *et al.* 2006; Ahern & Kovats 2013; Meusel & Kirch 2013; Menne & Murray 2013) and particularly if there is no flood (CDC 1993a; Lee *et al.* 1993).

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