

1 Full Title: **Predicting drowning from sea and weather**
2 **forecasts: development and validation of a model on surf**
3 **beaches of southwestern France.**

4 Short Title: **Predicting drowning from sea and weather**
5 **forecasts along beaches of southwestern France.**

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21 **Abstract :**

22 **Objective:** To predict the risk of drowning along the surf beaches of Gironde, southwestern
23 France.

24 **Methods:** Data on rescues and drownings were collected from the Medical Emergency Center of
25 Gironde (SAMU 33). Seasonality, holidays, weekends, weather, and sea conditions were
26 considered potentially predictive. Logistic regression models were fitted with data from 2011–
27 2013 and used to predict 2015–2017 events employing weather and ocean forecasts.

28 **Results:** Air temperature, wave parameters, seasonality, and holidays were associated with
29 drownings. Prospective validation was performed on 617 days, covering 232 events (rescues and
30 drownings) reported on 104 different days. The area under the curve (AUC) of the daily risk
31 prediction model (combined with 3-day forecasts) was 0.82 [95% confidence interval (95% CI)
32 0.79–0.86]. The AUC of the 3-hour step model was 0.85 (95% CI 0.81–0.88).

33 **Conclusions:** Drowning events along the Gironde surf coast can be anticipated up to 3 days in
34 advance. Preventative messages and rescue preparations could be increased as the forecast risk
35 increased, especially during the off-peak season, when the number of available rescuers is low.

36 **INTRODUCTION**

37 According to the 2017 Global Burden of Disease study, drowning (294,000 fatalities yearly) is a
38 major cause of non-intentional deaths from injury worldwide¹. In France, the national public
39 health agency (Santé Publique France) performs a national study every 3 years, registering all
40 cases of drowning leading to hospitalization or death between June 1 and September 15. In 2015,
41 there were 1,266 drownings in France, with 637 (50.3%) occurring along the seashore². In a
42 previous study on the surf beaches of Gironde, southwestern France, 576 people required rescue

43 over 6 years; there were 24 fatalities³. In terms of the length of the coastline, the annual mean
44 was 3.3 deaths/100 km, a rate comparable to the highest recorded along the US coastline⁴.

45 The Gironde coast is a 126-km-long stretch of sandy beaches exposed to high-energy waves that
46 drive intense, narrow seaward-flowing jets of water termed “rip currents”; these flow through
47 deep channels in sandbars that parallel the shore. In southwest France, rip-current activity normal
48 to the shore increases with increasing wave height and period, lower tide height, and variability in
49 beach morphology⁵. A previous study showed⁶ that these currents cause 79% of drownings. Rip
50 currents are the leading causes of rescues and drownings off many surf coasts worldwide^{4,7-10}.

51 Drowning is sudden; prevention is key when the aim is to reduce the incidence of drowning¹¹⁻¹³.
52 Primary prevention may modify beachgoer behavior¹⁴. If a drowning appears imminent, a fast
53 response by paramedics (and a medical team if necessary) is essential¹⁵. Lifeguards can impart
54 preventative messages¹⁶, reducing the need for medical attention and cardiopulmonary
55 resuscitation of drowning victims^{17,18}.

56 Drowning prevention on the Gironde beaches features patrolled areas, signs at most beach
57 entrances, and leaflets describing the rip current and shore-break hazards. However, the beaches
58 are not patrolled during the entire bathing season, which extends from April to October. Most
59 lifeguard stations are open only in July and August; the locations most frequented by tourists are
60 patrolled from mid-June to mid-September. On weekends in May and June, some areas are
61 watched, depending on local authorities. The mayor is responsible for beach supervision, which
62 is regionally coordinated by the departmental prefect in collaboration with the pre-hospital care
63 department of Bordeaux University Hospital. During high season, rescue helicopters are on
64 standby. On low-season weekends, one helicopter may be on duty, depending on the regional
65 authority.

66 Models predicting the risk of drowning would be useful if they enhanced the preventative
67 measures taken to reduce risk. Predictive models of rip currents have been implemented in
68 Florida, Puerto Rico¹⁹, Mexico²⁰, India⁹, and Great Britain²¹. The models are based on physical
69 hazards, and have been evaluated both retrospectively and in the field. To the best of our
70 knowledge, they have not been prospectively evaluated; forecasts have not been compared to
71 actual drownings.

72 Exposure to a rip hazard increases as the number of swimmers rises. Attendance rises on
73 holidays, weekends, and with increased air temperature and less cloud cover (nebulosity); the
74 number of bathers reflects air and water temperatures and (possibly) wind speed. As the risk of
75 drowning is a combination of the hazard per se and exposure to it, and as the latter is poorly
76 quantified, we created a model including parameters reflecting exposure to rip currents. We
77 assessed whether drownings off Gironde beaches could be anticipated using a risk prediction
78 model based on forecast weather and ocean conditions.

79 **MATERIALS AND METHODS**

80 **Study setting**

81 We performed an observational study along the French Atlantic coastline of Gironde. We first
82 developed a model based on medical emergency calls from beaches, along with weather and sea
83 conditions, in 2011, 2012, and 2013. We evaluated only the bathing season (April to October).
84 We used the model to assess whether weather forecasts accurately predicted events that occurred
85 from April to October in 2015, 2016, and 2017. We used the RiGoR guidelines to address
86 common sources of bias in risk-prediction models,²² and we adhered to the STROBE statement
87 for observational studies²³.

88 **Data sources**

89 Medical emergency calls

90 In Gironde, every medical emergency call from a beachgoer or lifeguard is received by a single
91 medical emergency call center (SAMU, Service d'Aide Médicale d'Urgence). During each call, a
92 physician records all information given by the caller, paramedics, and (when applicable) pre-
93 hospital care teams. All calls dealing with rescue from water or drowning were included in the
94 data for this study; these were the events of interest. "Rescue" refers to a need for evacuation
95 from the water, and "drowning" refers to respiratory impairment caused by submersion or
96 immersion, as defined by the World Health Organization²⁴. We excluded calls lacking victims,
97 training calls, and duplicates. As every instance of a need for medical advice or a pre-hospital
98 care team triggered a call, we considered that all events of importance would be identified.
99 Information on every call was carefully read to avoid errors. Intentional drownings and
100 drownings associated with known diseases were excluded.

101 Environmental conditions

102 Hourly tidal data were modeled by the "Service Hydrographique et Océanographique de la
103 Marine" (SHOM, authorization no. 296/2014) using the Lacanau shore as the reference. Lacanau
104 is located in the approximate center of the study area; according to the SHOM, the maximum tide
105 phase lag over the entire study area is approximately 15 min. Wave conditions were measured
106 every 30 min by the CANDHIS buoy²⁵ located at 044°39.150'N and 001°26.800'W. The wave
107 propagation time from the buoy to the coast is about 1 h. Observed and forecast meteorological
108 and wave conditions were provided by Météo-France, the French national meteorological service.
109 We used data from Cap Ferret; Météo-France claims that these well-represent the weather along
110 the entire Gironde coast. Forecast data were available for up to 3 days and at 3-h steps (7:00 am

111 UTC, 10:00 am, etc.). We recorded sea height, the wave factor (the product of wave height and
112 period), and the wave incidence factor (as defined in Appendix 1). We also recorded wind speed
113 and direction, air and water temperatures, and nebulosity. Other factors influencing beach
114 attendance were the season and type of day. High season was defined as the period from June 15
115 to September 15, when most lifeguard stations are open. We distinguished between weekdays,
116 weekends, and holidays.

117 Statistical methods

118 We fitted two logistic regression models: a “daily model” predicting the overall risk of at least
119 one drowning on a given day, and a “3-h-step model” predicting the risks at different times of the
120 day (9:30 am–12:29 pm, 12:30–3:29 pm, 3:30–6:29 pm, and 6:30–9:30 pm; all local times).
121 Given differences in the data collection modes between the training and validation periods, we
122 checked data coherence both visually and using the Wilcoxon–Mann–Whitney and Student’s t-
123 tests.

124 Days for which data were lacking were removed from the analysis. Prospective cohort data
125 (including variable selection) were not used during model development. We transformed the
126 wave parameters (Appendix 1). We categorized non-log-linear quantitative variables; these were
127 first divided into quantiles and then reduced using the Akaike Information Criterion (AIC) in a
128 multivariate context²⁶. Model selection used the AIC to perform interaction checks; we tested all
129 possible models²⁷. Odds ratios (ORs) with 95% confidence intervals (CIs) were computed as
130 bootstrap estimates. We checked that residual autocorrelation was absent. Goodness of fit was
131 assessed using the Le Cessie-Van Houwelingen test²⁸. Calibration was assessed graphically
132 employing a locally weighted, least-square regression smoother²⁹ and the Spiegelhalter Z-test.
133 Discriminatory power was assessed using receiver operator characteristic (ROC) curves based in

134 data from each cohort. Fit and validation accuracies were assessed via Brier scoring. The relative
135 importance of the selected predictors was assessed by deriving the associated chi-squared
136 proportions. The outcomes derived using 1-, 2-, and 3-day forecasts were compared by drawing
137 ROC curves using the Delong and Venkatraman method for paired data;^{30–32} we applied Holm–
138 Bonferroni corrections. We created a five-level risk scale using the quintiles of the fitted
139 probabilities. All analyses employed R software³³ running the RMS²⁹ and pROC packages³².

140 Ethics

141 Data collection was approved by the French national committee protecting data privacy
142 (Commission Nationale de l’Informatique et des Libertés, CNIL), provided that only compiled
143 (anonymized) data would be published. French law states that a retrospective observational study
144 does not require ethics committee authorization.

145 RESULTS

146 Retrospective data were lacking for 77 days because of a buoy failure, and for 26 prospective
147 days (21 because of data-link loss and 5 because of server unavailability). We analyzed 563 days
148 during 2011–2013; 242 rescues and drownings were reported on 108 different days. In 2015–
149 2017, data were available for 612 days; there were 232 events on 104 different days (Table 1).
150 All retrospective and prospective cohort data were consistent, except for wind speed, which
151 differed significantly between prospective and retrospective data, and nebulosity, which was
152 measured by different means over the retrospective and prospective periods. Both were excluded
153 from prospective analyses.

Table 1. Description of days without and with rescues and/or drownings. Meteorological and wave conditions (medians and quartiles) and the characteristics of days on which rescues and/or drownings occurred along the Gironde coast of southwestern France.

154

	2011–2013				2015–2017			
	Days without events ^a (n = 455)		Days with events (n = 108)		Days without events (n = 513)		Days with events (n = 104)	
Wave factor ^b , m × s	11.3	5.6–14.6	10.3	6.5–12.9	11.3	5.4–14.4	14.5	8.0–18.0
Wave angle factor ^c	0.80	0.69–0.99	0.89	0.85–0.99	0.80	0.74–0.97	0.88	0.83–0.97
Nebulosity (0–4) ^d	2.8	2.0–3.7	2.4	1.5–3.0	–	–	–	–
Air temperature, °C	21.6	19.2–23.9	25.2	23.3–26.6	21.5	19.0–24.0	25.5	23.0–27.0
Water temperature, °C	19.0	17.6–20.9	21.3	20.3–22.5	18.0	16.0–20.0	20.3	20.0–21.0
Wind speed ^e , m/s	7.0	5.3–8.2	6.6	5.3–7.3	4.9	2.7–5.5	4.2	2.7–5.5
Season ^f , n (%)								
High	187 (41.1)		90 (83.3)		199 (38.8)		79 (76.0)	
Low	268 (58.9)		18 (16.7)		314 (61.2)		25 (24.0)	
Type of day, n (%)								
Weekday	213 (46.8)		18 (16.7)		233 (45.4)		24 (23.1)	
Weekend	82 (18.0)		12 (11.1)		88 (17.2)		17 (16.3)	
Vacation	160 (35.1)		78 (72.2)		192 (37.4)		63 (60.6)	

^a Events include rescues and drownings.

^b Wave factor: wave height (m) times wave period (s).

^c The wave angle factor ranges from 0 to 1; see Appendix 1 for details.

^d Forecast values not shown because of differences in the modes of data measurement.

^e Significant differences between observed and forecast data.

^f High season: June 15 to September 15.

155 The final, predictive, daily risk model included wave and wave angle factors, air temperature,
 156 type of day, and season (Table 2). The model predicting risk at 3-h steps featured sea height,
 157 wave parameters, air temperature, time of day, type of day, and season (Table 3). Variation in the
 158 daily model was attributable principally to air temperature (proportion of the overall chi-squared
 159 value, 40.9%), wave factors (21.7%), and time of day (16.2%). The principal 3-h-step model
 160 predictors were air temperature (28.9%), the time of day (17.8%), and wave factors (12.6%).

Table 2: Factors associated with daily rescues and drownings along the Gironde coast. Univariate and multivariate analyses performed with the aid of logistic regression models using retrospective data from 2011–2013.

	Crude OR	(95% CI)	Adj. OR	(95% CI)	χ^2
Wave factor ^a , m × s					22.8
<5.2	Ref.		Ref.		
5.2–9.2	3.89	(2.03, 9.81)	6.41	(2.93, 18.3)	
>9.2	1.96	(1.01, 4.50)	7.10	(3.09, 22.7)	
Wave angle factor ^a	1.83	(1.40, 2.62)	2.27	(1.58, 3.70)	13.2
Nebulosity ^{b,c}	0.52	(0.37, 0.74)	—		
Air temperature ^a , °C					43.0
≤21	Ref.		Ref.		
21–23.5	6.58	(3.03, 19.2)	4.79	(1.93, 16.6)	
>23.5	19.10	(9.62, 61.8)	12.20	(4.69, 52.3)	
Water temperature ^a , °C					
≤19.5	Ref.		—		
19.5–21.3	3.95	(2.13, 9.14)			
>21.3	13.18	(7.60, 27.0)			
Wind speed ^b , m/s					
≤4.3	Ref.		—		
4.3–6.3	1.71	(1.00, 3.14)			
>6.3	0.84	(0.45, 1.66)			
Season					10.4
Low	Ref.		Ref.		
High	7.17	(4.38, 13.5)	3.98	(1.44, 6.11)	
Type of day					17.1
Weekday	Ref.		Ref.		
Weekend	1.73	(0.71, 3.62)	2.96	(1.06, 7.98)	
Holidays	5.77	(3.49, 10.8)	4.25	(2.19, 9.75)	

Note. OR = odds ratio, CI = confidence interval

^a Daily maximal value.

^b Daily mean value.

^c Not incorporated into multivariate analyses because of differences in measurement modes.

161 **Table 3: Factors associated with rescues and drownings during 3-h periods.** Univariate and
 162 multivariate analyses performed with the aid of logistic regression models for risk of drowning
 163 along the Gironde coast during 3-h periods using retrospective data from 2011–2013.

	Crude OR (95% CI)	Adj. OR (95% CI)	χ^2
Sea height, m			8.8
≥ 1.5	Ref.	Ref.	
< 1.5	1.66 (1.12, 2.43)	2.18 (1.33, 3.72)	
Wave factor, m \times s			22.1
≤ 4.7	Ref.	Ref.	
4.7–8	3.12 (1.78, 6.13)	3.71 (2.00, 8.67)	
> 8	2.14 (1.25, 4.31)	5.44 (2.74, 14.3)	
Wave angle factor	1.98 (1.56, 2.66)	2.18 (1.56, 3.21)	15.9
Air temperature, °C			50.7
≤ 20.5	Ref.	Ref.	
20.5–23	7.48 (3.67, 20.6)	5.04 (2.35, 15.1)	
> 23	24.99 (13.9, 66.7)	15.11 (7.76, 48.0)	
Water temperature, °C			
≤ 19	Ref.		
> 19	0.15 (0.08, 0.25)		
Interval (local time)			31.3
9:30 am–12:29 pm	Ref.	Ref.	
12:30 pm–3:29 pm	3.9 (2.10, 8.64)	2.87 (1.60, 6.69)	
3:30 am–6:29 pm	5.10 (2.94, 11.8)	5.48 (2.95, 14.0)	
6:30 am–9:30 pm	1.06 (0.44, 2.58)	1.45 (0.62, 3.95)	
Wind speed, m/ s			
≤ 4.3	Ref.		
4.3–6.3	1.30 (0.87, 2.00)		
> 6.3	0.97 (0.60, 1.54)		
Season			16.6
Low	Ref.	Ref.	

High	8.71 (5.45, 17.2)	3.82 (2.09, 7.47)
Type of day		17.9
Weekday	Ref.	Ref.
Weekend	1.90 (0.85, 3.97)	3.17 (1.35, 7.69)
Vacation	5.74 (3.64, 10.9)	3.62 (2.02, 7.80)

Note. OR = odds ratio, CI = confidence interval

164

165 The daily model had areas under the curves (AUCs) of 0.88 (95% CI 0.84–0.91) for 2011–2013
166 and 0.82 (95% CI 0.78–0.86) for 2015–2017. The 3-h risk model had AUCs of 0.89 (95% CI
167 0.87–0.92) for 2011–2013 and 0.85 (95% CI 0.81–0.88) for 2015–2017. Model outcomes did not
168 differ when forecasts for 1, 2, and 3 days were used ($p > 0.05$). Both models were well calibrated
169 in terms of retrospective data (goodness-of-fit test $p = 0.20$ for the daily model, $p = 0.53$ for the
170 3-h-step model). Both models exhibited significant p -values on Spiegelhalter Z-testing of
171 prospective data, evidencing a lack of calibration: the daily model tended to over-predict days
172 with risks of drowning >0.5 ; the 3-h step model over-predicted risks as low as 0.1.

173 Using prospective data, we found that assessment of the drowning risk using the five-level scale
174 missed 1 of 158 days featuring a rescue at the lowest risk level (0.6%). The missed case was a
175 rescued male who presented without a cough and was discharged on site. The prospective data
176 predicted 45.8% of days with rescue events at the highest risk level (Table 4). The 3-h step model
177 missed 2 of 481 rescues, one at the lowest level (0.4%) and one at the highest (15.7%).

Table 4. Observed rescues vs. predicted drowning risk. Observed rescues and drownings by predicted risk level derived using regression models exploiting 3-day forecasts; Gironde, southwestern France.

Risk Level	2011–2013			2015–2017		
	Events ^a	Total	%	Events	Total	%
	Daily model ^b					
1	3	113	2.7	1	172	0.6
2	1	112	0.9	8	105	7.1
3	11	113	9.7	15	95	15.8
4	23	112	20.5	23	88	26.1
5	70	113	61.9	66	144	45.8
	3-h-step model ^c					
1	0	395	0.0	2	481	0.4
2	3	394	0.8	3	381	0.8
3	6	394	1.5	10	309	3.2
4	19	394	4.8	22	330	6.7
5	103	394	26.1	58	369	15.7

^a Events: Rescues and drownings.

^b Goodness of fit: $p = 0.20$, calibration test $p < 0.001$.

Brier scores: 0.10 for 2011–2013, 0.12 for 2015–2017.

^c Goodness of fit: $p = 0.53$, calibration test $p = 0.10$.

Brier scores: 0.05 for 2011–2013, 0.05 for 2015–2017.

178 The missed case at the lowest risk level in the retrospective cohort occurred during moderate
 179 wave conditions (wave factor $\sim 8 \text{ m} \times \text{s}$) and at low wave incidence (0.47), but the victim required
 180 only rescue, was asymptomatic upon rescue, and was not evacuated. The second missed event
 181 occurred at the tip of the Cap Ferret sandspit, which lacks wave-driven rip currents. The last
 182 missed event occurred at La Salie Nord, adjacent to (south of) the Arcachon inlet, under moderate

183 wave conditions.

184 The 3-h step model missed two events in the prospective cohort, both in September 2017, and
185 both occurring under strong wave conditions (wave factor $>15 \text{ m} \times \text{s}$). One was a surfer; the
186 activity pursued by the other victim was not recorded. Both cases were minor and were treated in
187 the local hospital.

188 **DISCUSSION**

189 This study is the first to analyze the association of forecast sea and weather conditions with
190 drowning risk. Air temperature, wave angle, and the wave factor were the primary environmental
191 predictors; the type of day and the season were also significant, but less important, predictors.
192 Given the availability of extensive physical data on rip currents, we were able to build a tool that
193 accurately predicted drowning risk.

194 Warm weather increases sea exposure and therefore the risk of drowning, consistent with other
195 studies^{34,35}. Wave parameters influencing rip current flow velocity were significant predictors of
196 drowning, consistent with the results of physical models²¹. As the wind parameters differed
197 between the retrospective and prospective periods, we could not use these parameters, although
198 they might have further improved the models. Nebulosity was measured differently during the
199 two periods and thus could not be incorporated into the models. Although univariate analysis
200 showed that nebulosity was a significant predictor of drowning, it is strongly correlated with air
201 temperature. Future models should integrate predicted rather than observed measures.

202 Our models tend to overestimate the risk on days associated with moderate to high risks; some
203 variables may thus be unknown. First, the summer beach morphology along the Gironde coast is
204 very variable; beach slopes and channel depths differ markedly, and the rip current hazard
205 changes from one summer to the next. Moreover, drownings are certainly under-reported to the

206 Emergency Call Center; reporting rates may vary over time. We could not directly estimate
207 exposure, as beach attendance is not measured in Gironde.

208 Turning to the missed events, two occurred in sectors adjacent to the Arcachon lagoon inlet,
209 where local, strong tide-driven currents develop at low tide, constituting a major hazard. We
210 hypothesize that the missed events were attributable to these currents. This highlights the need to
211 carefully target preventative messages; the primary hazards vary locally.

212 Use of the 1-, 2-, and 3-day forecasts yielded similar results; this will aid in the efficient
213 deployment of lifeguards and rescue equipment. Accurate local forecasts more than 3 days ahead
214 are not available.

215 How may our findings save lives? The use of a binary scale would trigger many false alarms;
216 thus, we considered that a five-level scale was more appropriate, as such scales are used to
217 predict other risks posed by natural hazards (such as snow avalanches). Our scale should be
218 improved using a risk utility function, which remains to be specifically determined. We concede
219 that our present levels are arbitrary; we must still explore what beachgoers and decision-makers
220 consider to be “low,” “moderate,” or “acceptable” risks.

221 Any message suggested by our models must be consistent with “messages” imparted by beach
222 flags. These flags can be “green” (no or minor hazard, bathing supervised), “yellow” (hazard,
223 bathing supervised) or “red” (major hazard, no bathing allowed). They are determined by
224 lifeguards based on wave conditions, water temperature, and beach attendance, and may vary
225 depending (for example) on lifeguard experience. Unpublished local reports indicate that green
226 and red flags are rarely raised during the high season on the Gironde coast.

227 We are confident that our model can be adapted to similar beaches with rip currents, but complete
228 generalization of our findings is inappropriate in the absence of more data. Lifeguard knowledge
229 and the physical parameters of natural hazards require attention. The next steps are forecast

230 validation by lifeguards and automation of feedback; these will allow the model to be
231 continuously improved. As more data become available, other modeling strategies may be
232 appropriate.

233 **Conclusions**

234 Predicting the need for rescue from water in a hazardous environment is key to reducing the risk
235 of drowning. Our predictive models can be used to efficiently deploy lifeguards and rescue
236 helicopters. An interventional study (performed under real-world conditions) is planned. A utility
237 function reflecting risk perception/acceptance is required. This would allow targeted preventative
238 messages to be broadcast during high-risk periods. The strategy must employ behavioral change
239 theory to reduce the risk to beachgoers. Evaluation requires reliable data from both lifeguard
240 stations and emergency call center files.

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