☑ **Fact-Checked Science**

PAPER CHECK · SPACE WEATHER AND HEALTH

Cardiac arrests after a 2015 storm: an unconfirmed drop, no shown cause or difference

An abstract for AGU's December 2026 meeting reports that U.S. cardiac arrests fell in the 14 days after the severe geomagnetic storm of March 2015, more in women and in people 65 or older [1 ¶3][1 ¶4], and calls this the causal impact of geomagnetic activity [1 Title][1 ¶3]. The storm was real and severe [3 p. 1], and the abstract's counts add up. But it tests one of 2015's two G4 storms [4 p. 1], reports no check of its causal reading, and on its own numbers the gaps between women and men, and between older and younger people, are within chance.

By Fact-Checked Science · Published November 21, 2026

OUR ANALYSIS marks our own reasoning and calculations, which here include arithmetic on the abstract's printed numbers and a check of national death counts, and the verdicts are our assessment. The abstract [1] is our only view of the work, since the poster hasn't been presented and no paper has appeared; it is cited by paragraph (¶) or Title. Everything else comes from the numbered sources.

A drop worth testing, but neither its cause nor its age and sex differences are shown

OUR ASSESSMENT

1 of 2
G4 storms of 2015 that the abstract tests: NOAA reported severe storm levels on March 17 and again on June 22–23 [3 p. 1][4 p. 1]

p ≈ 0.55
for a difference between the drops in women and in men, on the abstract's own numbers, by our analysis [1 ¶4]

≈ 504
people: the 6.4% drop the abstract builds on, over 14 days at its own 2015 count of 562 cardiac arrests a day, by our analysis [1 ¶1][1 ¶3]

THE ABSTRACT'S CLAIMS

UNCONFIRMED

Arrests fell after the storm

"…this drop in cardiac arrests during periods of intense geomagnetic variation."

The abstract [1 ¶5], after reporting falls over 14 days of 8.3% in females, 5.7% in males, 9.1% in people 65 or older and 4.4% in those under 65 [1 ¶4]

An unreviewed abstract, to be presented on December 7, 2026 [1]. Its numbers hang together: the counts add up, and its p-values imply uncertainties about twice the chance variation of a 14-day count, by our analysis. But it reports one storm, no model details and no counts of the drop, and its data aren't public [2][9 Data Subsets]. National death counts show no drop after the storm; a drop of the abstract's size would sit inside, or at most just past, the edge of what that check can detect [15]. See section 5 and section 7.

OVERSTATED

Geomagnetic activity caused it

"Causal Impact of Geomagnetic Ap on Cardiac Arrest Incidence"

The abstract's title [1 Title]. Run together, "Causal Impact" is also the name of the R package CausalImpact, whose method the abstract appears to use [13 Manual], but the abstract also says "Ap has a stronger impact" on cases in some groups [1 ¶4], with results "obtained using a very large dataset and applying causal machine learning methods" [1 ¶5]

The method reads the gap between what happened and a model's forecast as an effect, if its assumptions hold [12 p. 253][13 Vignette]. The abstract reports no test of them: no placebo date, no control beyond temperature, and one storm when 2015 had two; June's went untested [4 p. 1]. In a description of ours made after the national check had run, U.S. heart-disease deaths dropped back from a winter excess in the same fortnight of 2015, and by as much in 2018, a spring with no storm [15]. See section 4 and section 6.

UNSUPPORTED

Stronger in women than in men

"Ap has a stronger impact on cardiac arrest cases in females (-8.3%, p=0.006) than in males (-5.7%, p=0.025)"

The abstract [1 ¶4]

The abstract gives no test of the difference. On its own numbers, the 2.6-point gap has p ≈ 0.55: well within chance, by our analysis. A significant result beside a less significant one doesn't make a difference between them [14]. See section 5.

OVERSTATED

An age difference in the drop

"…has a significant impact on older persons (-9.1%, p<0.001). Younger persons showed no significant effect (-4.4%, p=0.077)."

The abstract [1 ¶4], under a title that announces "Age and Sex Differences" [1 Title]

Each sentence is right at the usual 0.05 line. But the 4.7-point gap between the age groups has p ≈ 0.08–0.27 on the abstract's numbers (0.13–0.27 if the two estimates are independent), by our analysis; it could fall below 0.05 only on readings beyond ours, such as two-sided p-values, which the package's are not, with correlated errors. So the difference the title announces isn't shown: one group's result is significant and the other's isn't, which is not the same thing [14]. See section 5 and section 11.

UNVERIFIED

Confirms a 6.4% earlier drop

"Previous research showed a causal relationship … amounting to a drop in incidence of 6.4% (p=0.009)."

The abstract [1 ¶1], which concludes: "These results confirm previous research" [1 ¶5]

The abstract cites no source, and we found none in seven indexes or in AGU's 2025 and 2026 meeting programmes. The new results for women and men, or for the two age groups, average a 6.7–6.8% drop, close to 6.4%, by our analysis: if the earlier figure came from the same 2015 data, they restate it rather than confirm it. See section 9.

1 · THE ABSTRACT

A poster abstract about one storm, one fortnight and four groups of people

Michael Marschollek, of Hannover Medical School and the Lower Saxony Center for Artificial Intelligence and Causal Methods in Medicine, will present it as a poster at AGU's annual meeting on December 7, 2026 [1]. It is a conference abstract, not peer reviewed, and no poster or paper has been published. S0 News linked it on November 20 [35].

What we could read: the abstract, in full

AGU's meeting site loads the text by script, so we read it in a browser and quote it from that reading; the page our tools receive holds only the title and the first 80 characters [1]. The abstract names no software, gives no counts or intervals for its results, and cites no sources. The author deposited the Ap, solar-flux and temperature series on Zenodo under CC BY 4.0; the record is public but its files are restricted, so we couldn't compare its Ap with GFZ's [2].

In the abstract's words Its aim, its data and its method, verbatim; ¶ numbers count its paragraphs.

> *"The aim of this study is to use advanced causal machine learning to investigate and report on sex and age differences concerning the incidence of cardiac arrests in the entire U.S. during the G4 solar storm in 2015."*
>
> Marschollek (2026) [1 ¶2]

> *"Cardiac arrest events for the year 2015 were extracted from the U.S. NEMSIS database, amounting to 205,212 cases, with 124,279 males and 78,358 females (2,575 unknown), and 99,692 persons aged below 65 and 102,336 65 years or above (3,184 missing)."*
>
> Marschollek (2026) [1 ¶3]

> *"Time series of Ap as 'intervention' and census-based-weighted temperature as a potential confounder were used in a causal impact study using a Bayesian structural model for counterfactual prediction of arrest events in the 14-day period of time following the March 15, 2015 coronal mass ejection and subsequent G4 geomagnetic storm."*
>
> Marschollek (2026) [1 ¶3]

The design, as far as the abstract says

One storm, one year of data and one 14-day stretch after it. Ap is a daily index of how disturbed Earth's magnetic field is [6]; temperature is the only other series named; a "Bayesian structural model" forecasts what the 14 days would have held without the storm, and the gap between forecast and count is read as the storm's effect [1 ¶3]. The abstract doesn't say whether the 14 days start on March 15, the day of the eruption, or later, when the storm arrived.

What it concludes, and how cautiously

The author reads the results as confirming earlier research, "yet" obtained with "a very large dataset" and "causal machine learning methods", and asks for more research into the causes of the age and sex differences and the "pathophysiologic relations leading to this drop" [1 ¶5]. It reports a drop, not a harm, and proposes no mechanism.

2 · THE STORM

A severe storm on March 17, 2015, and another in June

The coronal mass ejection of March 15 reached Earth early on March 17 [8 p. 4] and drove the deepest storm of 2015 by the Dst index [7]; NOAA reported severe, G4, storm levels that day [3 p. 1]. The abstract has the storm right; it wasn't the only one.

PEAK KP, MARCH 17
8−
GFZ's definitive index, in three three-hour intervals from 12:00 UT; NOAA counts 8− as G4 [6][5]

DAILY AP, MARCH 17
108
the highest day of 2015, a year that averaged 12.2 [6]

LOWEST DST
−234 nT
Kyoto's final value, 22:00–23:00 UT on March 17, the lowest hour of 2015 [7]

What NOAA reported at the time

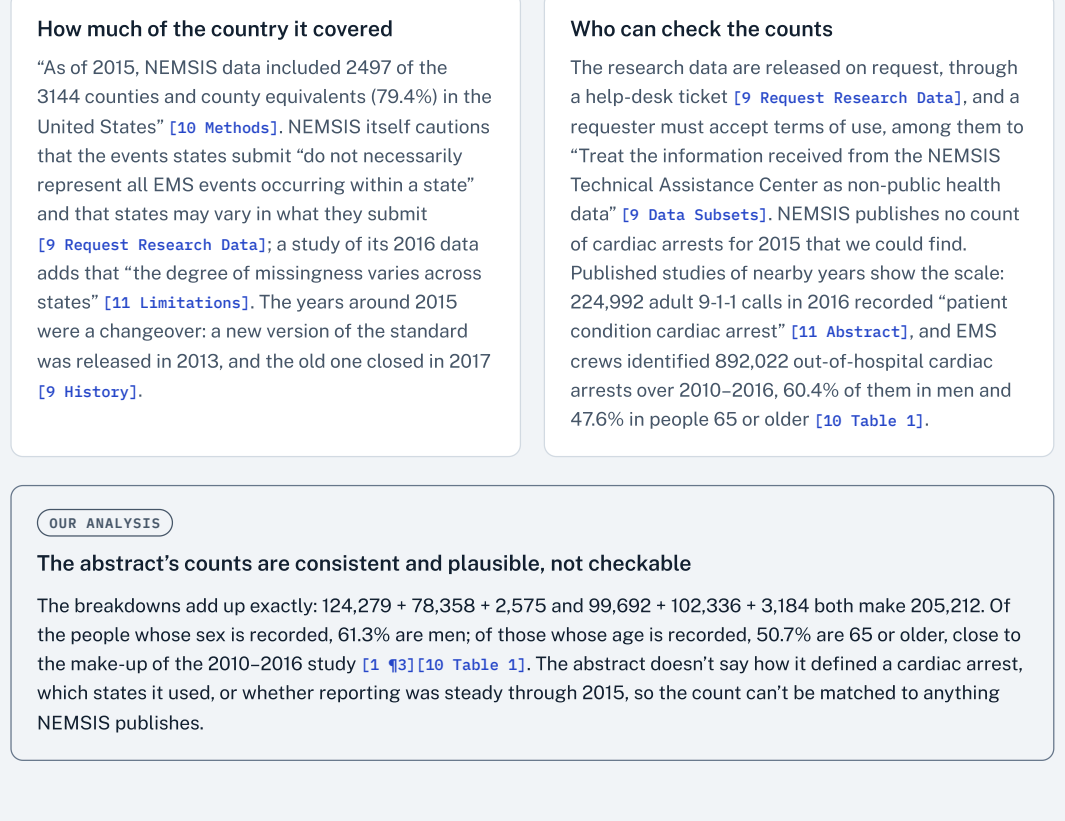
NOAA's weekly report: "Quiet to severe storm levels were observed on 17 Mar followed by minor to major storm levels on 18 Mar due to effects from the 15 Mar CME." [3 p. 1] It lists alerts for K = 8 at 13:58, 17:54 and 23:24 UT [3 pp. 4–5], and an estimated planetary K of 8 in three intervals [3 p. 3]. On NOAA's scale, G4 "Severe" is "Kp = 8, including a 9-", which happens about "100 per cycle (60 days per cycle)" [5].

The eruption came with a long C9 flare that peaked at 02:13 UT on March 15 [3 p. 1][8 p. 3]. Liu and colleagues trace the storm to two interacting eruptions, and date its sudden commencement to a shock that passed the Wind spacecraft at 04:01 UT on March 17 [8 p. 3][8 p. 4].

A second G4 storm, June 22–23

NOAA's report for that week: "The geomagnetic field responded with minor to major storm levels with severe storm periods observed between 22/1800-2100 UTC and 23/0000-0600 UTC." [4 p. 1] GFZ's Kp reached 8+ from 18:00 UT on June 22, the year's highest, with daily Ap of 57 and 72 [6], and Kyoto's final Dst fell to −198 nT [7].

Liu and colleagues call the two "the largest geomagnetic storms of solar cycle 24 so far" [8 p. 1].


Daily Ap in 2015, with the abstract's 14 days

OUR ANALYSIS

GFZ's definitive daily Ap [6]; G4 days by NOAA's Kp scale [5]. Chart data by our analysis.

OUR ANALYSIS

How disturbed were the 14 days?

Over March 16–29, Ap averaged 23.4, twice the rest of 2015 and the second most active fortnight of the year. Most of that is March 17 and 18 (108 and 47); the 14 days from March 18 average 15.8, a moderately active fortnight (rank 89 of 352). March 15 and 16 were quiet (6 and 12). The year's most active fortnight, September 7–20 (24.9), had no G4 storm, and the abstract doesn't say what followed it [6]. So "periods of intense geomagnetic variation" means, here, about two days [1 ¶5].

Over the whole year, by our count in Kyoto's final Dst, 2015 had eight storms that reached −100 nT or lower; March's was the deepest and June's the second [7].

3 · THE DATA

NEMSIS: a large national database of ambulance calls, not a full count

NEMSIS is the national system that collects emergency medical services (EMS) records from states and territories, a program of the National Highway Traffic Safety Administration's Office of EMS, hosted by the University of Utah; the records are "voluntarily submitted" by state and territory officials [9 What is NEMSIS].

How much of the country it covered

"As of 2015, NEMSIS data included 2497 of the 3144 counties and county equivalents (79.4%) in the United States" [10 Methods]. NEMSIS itself cautions that the events states submit "do not necessarily represent all EMS events occurring within a state" and that states may vary in what they submit [9 Request Research Data]; a study of its 2016 data adds that "the degree of missingness varies across states" [11 Limitations]. The years around 2015 were a changeover: a new version of the standard was released in 2013, and the old one closed in 2017 [9 History].

Who can check the counts

The research data are released on request, through a help-desk ticket [9 Request Research Data], and a requester must accept terms of use, among them to "Treat the information received from the NEMSIS Technical Assistance Center as non-public health data" [9 Data Subsets]. NEMSIS publishes no count of cardiac arrests for 2015 that we could find. Published studies of nearby years show the scale: 224,992 adult 9-1-1 calls in 2016 recorded "patient condition cardiac arrest" [11 Abstract], and EMS crews identified 892,022 out-of-hospital cardiac arrests over 2010–2016, 60.4% of them in men and 47.6% in people 65 or older [10 Table 1].

OUR ANALYSIS

The abstract's counts are consistent and plausible, not checkable

The breakdowns add up exactly: 124,279 + 78,358 + 2,575 and 99,692 + 102,336 + 3,184 both make 205,212. Of the people whose sex is recorded, 61.3% are men; of those whose age is recorded, 50.7% are 65 or older, close to the make-up of the 2010–2016 study [1 ¶3][10 Table 1]. The abstract doesn't say how it defined a cardiac arrest, which states it used, or whether reporting was steady through 2015, so the count can't be matched to anything NEMSIS publishes.

4 · THE METHOD

A forecast of what would have happened, read as the storm's effect

The abstract names no software [1 ¶3], but its description matches a method published by Brodersen and colleagues at Google [12] and their R package, CausalImpact [13 Manual].

STEP 1

Learn

Fit a model to the daily counts before the event, with any "control" series that help predict them; here, temperature [12 p. 249]. With data for 2015 only, that period is at most 73–75 days, January 1 to mid-March, by our arithmetic.

STEP 2

Forecast

Predict the 14 days after the event from the model and the controls' actual values: the counterfactual, what would have happened without the storm [12 p. 249].

STEP 3

Compare

Read the gap between the actual count and the forecast as the effect, with a credible interval from the model [13 Manual].

STEP 4

Report p

The package's p is "the posterior probability that the intervention had any effect, expressed in terms of a one-sided p-value": a Bayesian tail area that depends on the model and its priors [13 Manual][13 Source].

In the method's own words From the paper and the package's guide, verbatim.

> *"This approach assumes that covariates are unaffected by the effects of treatment."*
>
> Brodersen et al. (2015) [12 p. 253]

> *"In the scenarios we consider, advertising is a planned perturbation of the market. This generally makes it easier to obtain plausible causal inferences than in genuinely observational studies in which the experimenter had no control about treatment"*
>
> Brodersen et al. (2015) [12 p. 272]

> *"…it is a good idea to examine how well the outcome data y can be predicted before the beginning of the intervention. This can be done by running CausalImpact() on an imaginary intervention."*
>
> The package's vignette [13 Vignette]

What the method needs to read a gap as a cause

The controls must be untouched by the event, and their relationship to the outcome "as established during the pre-period, remains stable throughout the post-period" [13 Vignette]. Covariates act on the same day unless lagged by hand [12 p. 255]. The package adds no seasonal component unless asked [13 Vignette], and its own report says an effect "can be considered causal if the model assumptions are satisfied" [13 Source].

What "Ap as 'intervention'" can mean

In this method the intervention is a date, not a series [13 Manual]. Most likely the storm, as Ap showed it, set the start of the 14 days. If Ap was instead fed in as a control, that would break the first assumption, since the control would carry the very event being measured. Either way the design is one interrupted time series with one event [1 ¶3].

What the abstract doesn't report

NOT REPORTED	WHY IT MATTERS
When the 14 days start	March 15–16 were quiet; most of the disturbance came on March 17–18 [6]
The model before the storm: its length, trend, seasonality and priors	Together they decide the forecast the count is compared with [12 p. 264], [13 Vignette]
Any placebo date, the June 2015 storm or another year	The package's own suggested check of whether the model predicts well [13 Vignette]
Counts, intervals or an overall effect for 2015	Only percentages and p-values are given [1 ¶4]
How "cardiac arrest" was defined in NEMSIS, and which states took part	Definitions and coverage vary [9 Request Research Data], [11 Abstract]
A test of the differences between groups, or an allowance for four tests	The title's "differences" rest on them (section 5)

5 · THE NUMBERS

On the abstract's own numbers, neither difference is shown

Our arithmetic uses only the numbers the abstract prints [1 ¶3][1 ¶4]. We did it twice, with separately written code and rules fixed first, and the two versions agree where they overlap.

ARRESTS A DAY
OUR ANALYSIS
562
NEMSIS's 2015 count averaged over the year: 7,871 in 14 days [1 ¶3]

THE DROPS IN PEOPLE
OUR ANALYSIS
≈ 168–357
over 14 days in each group; the 6.4% drop the abstract builds on would be about 504 people [1 ¶1][1 ¶4]

IMPLIED UNCERTAINTY
OUR ANALYSIS
≈ 2×
chance variation: the p-values imply errors of 2.9–3.3 points, about twice the noise of a 14-day count, alike in all four groups

The four results, in people and in uncertainty

OUR ANALYSIS

GROUP	CHANGE	P	EXPECTED IN 14 DAYS	DROP IN PEOPLE	IMPLIED ERROR	CHANCE NOISE ALONE
Females	−8.3%	0.006	3,006	249	3.3 points	1.8 points
Males	−5.7%	0.025	4,767	272	2.9 points	1.5 points
65 or older	−9.1%	<0.001	3,925	357	2.9 points or less	1.6 points
Under 65	−4.4%	0.077	3,824	168	3.1 points	1.6 points

Changes and p-values from the abstract [1 ¶4]; counts at its 2015 averages [1 ¶3]. Implied error: the change divided by the z-score of its p, read as the package's one-sided tail area [13 Manual]; chance noise: the Poisson spread of a 14-day count. Our analysis; the model's own forecast isn't published, so the people are approximate.

OUR ANALYSIS

Women against men, older against younger

The gap between women (−8.3%) and men (−5.7%) is 2.6 points, with an uncertainty of about 4.4: p ≈ 0.55, and 0.41 if the two estimates tend to move together. The gap between people 65 or older (−9.1%) and under 65 (−4.4%) is 4.7 points: p ≈ 0.08–0.27 (0.13–0.27 if the two estimates are independent), a range set by "p<0.001" being only a bound and by how closely the two estimates move together, up to a correlation of 0.5. Neither is a difference anyone could call shown. Calling one result significant and the other not doesn't make them differ [14].

OUR ANALYSIS

Four tests at once, and one result broken four ways

Allowing for four tests, with 0.05 shared over the four (0.0125 each), the results for men and for people under 65 fail; Holm's step-down method keeps the men's result exactly at its threshold. The four are two splits of the same cases, so this allowance is conservative. Weighting the four results by their groups' sizes gives an overall drop of 6.7% (by sex) or 6.8% (by age), close to the 6.4% of the "previous research" [1 ¶1].

6 · OTHER EXPLANATIONS

Mid-March brings changes a forecast must handle

The method holds only if the model fitted before the event, with its trend and its controls, still describes the counts after it, apart from the event [12 p. 264]. Several things change in mid-March. We name them, test what public data allow, and assert none of them as the answer.

The season

Out-of-hospital cardiac arrests peak in winter: in a U.S. registry of 18,588, the "highest incidence" was in December [16 Abstract]. Among adults who reached U.S. emergency departments after such an arrest in 2014, a weighted national sample counted about 396 a day in January, 359 in February, 330 in March and 339 in April, by our arithmetic on the study's monthly counts [17 Methods][17 Table 1]. A model fitted on January to mid-March learns the steep part of that fall; whether that pushes its forecast too high or too low depends on choices the abstract doesn't report.

OUR ANALYSIS

A winter excess that faded, with or without a storm

Post hoc, and descriptive only: U.S. deaths from heart disease ran 4.4% above the other years' level in weeks 1–10 of 2015, and 0.2% above it in March 15–28, a step of 4.2 points. The same step came in 2018, a spring with no storm [15].

YEAR	WEEKS 1–10	WEEKS 11–12	STEP
2015	+4.4%	+0.2%	−4.2
2018	+3.8%	−0.7%	−4.5

In 2014, 2016, 2017 and 2019 the step ran the other way, from +0.6 to +3.8 points. This shows national deaths only; it can't show what the abstract's series or model did [15].

A second description, also made after the check, looked at influenza: U.S. deaths from influenza and pneumonia peaked in the week to January 10 and were back near the other years' level by early February; in March 15–28 they were 12% below it [15].

Influenza

The 2014–15 season was severe and fell hardest on older people, whose hospitalization rate was the highest since that surveillance began in 2005; the share of deaths attributed to pneumonia and influenza was above the epidemic threshold from January 3 to February 21 [18]. In Japan, extreme influenza epidemics were followed by more out-of-hospital cardiac arrests, at lags of up to 21 days [19 Abstract].

But influenza-and-pneumonia deaths were back near the usual level by early February, as our description in the box on the winter excess shows, so they don't explain a fall that starts in mid-March [15]. Whether a severe winter left fewer people at risk by March can't be judged from these numbers.

Cold that acts later

February 2015 was 2.65 °F colder than the 1991–2020 average across the contiguous U.S., and March 1.83 °F warmer, by our arithmetic on NOAA's figures [21]. The effects of cold on deaths "have been reported to last up to 3 or 4 weeks" [20 Introduction], while the method treats a control series as acting on the same day unless it is lagged [12 p. 255]. A same-day temperature series would miss a cold February's delayed effects fading in a warm March; the abstract doesn't say whether its temperature was lagged.

The clock and the calendar

Daylight saving time began on March 8, 2015, the second Sunday of March [22], a week before the 14 days. Heart attacks rise briefly after the spring change: in Michigan, those treated with angioplasty rose 24% on the Monday, with no change in the weekly total [23 Abstract], and a meta-analysis found an odds ratio of 1.05 after the spring shift [24 Abstract]. That is too small and too early to matter much here. Easter fell on April 5, after the window, and any 14 days hold two of each weekday, so the weekly cycle cancels, by our arithmetic.

Reporting, and one storm

States moved between versions of the NEMSIS standard in these years [9 History]; an agency or a state joining or leaving at the wrong moment would look like an effect, and only the data, or a control series such as other EMS calls, could rule it out. And one storm is one event: June 2015's storm, which reached a higher Kp, is the obvious second test, and the abstract doesn't report it [4 p. 1][6].

7 · NATIONAL DEATHS

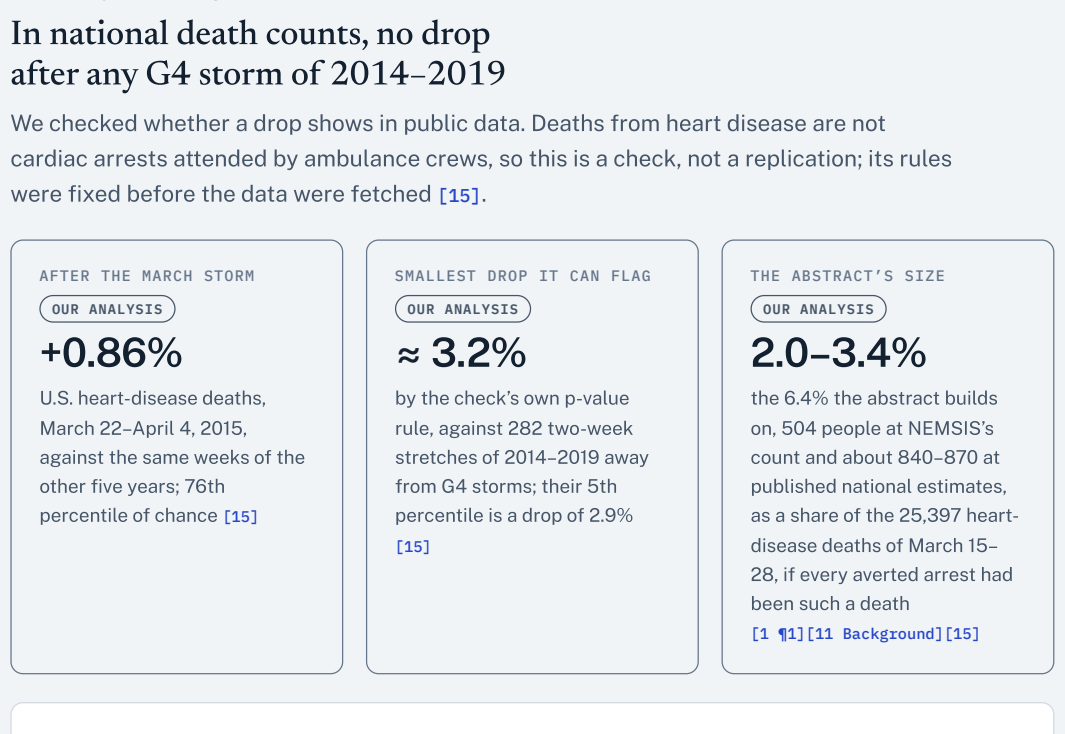
In national death counts, no drop after any G4 storm of 2014–2019

We checked whether a drop shows in public data. Deaths from heart disease are not cardiac arrests attended by ambulance crews, so this is a check, not a replication; its rules were fixed before the data were fetched [15].

AFTER THE MARCH STORM
OUR ANALYSIS
+0.86%
U.S. heart-disease deaths, March 22–April 4, 2015, against the same weeks of the other five years; 76th percentile of chance [15]

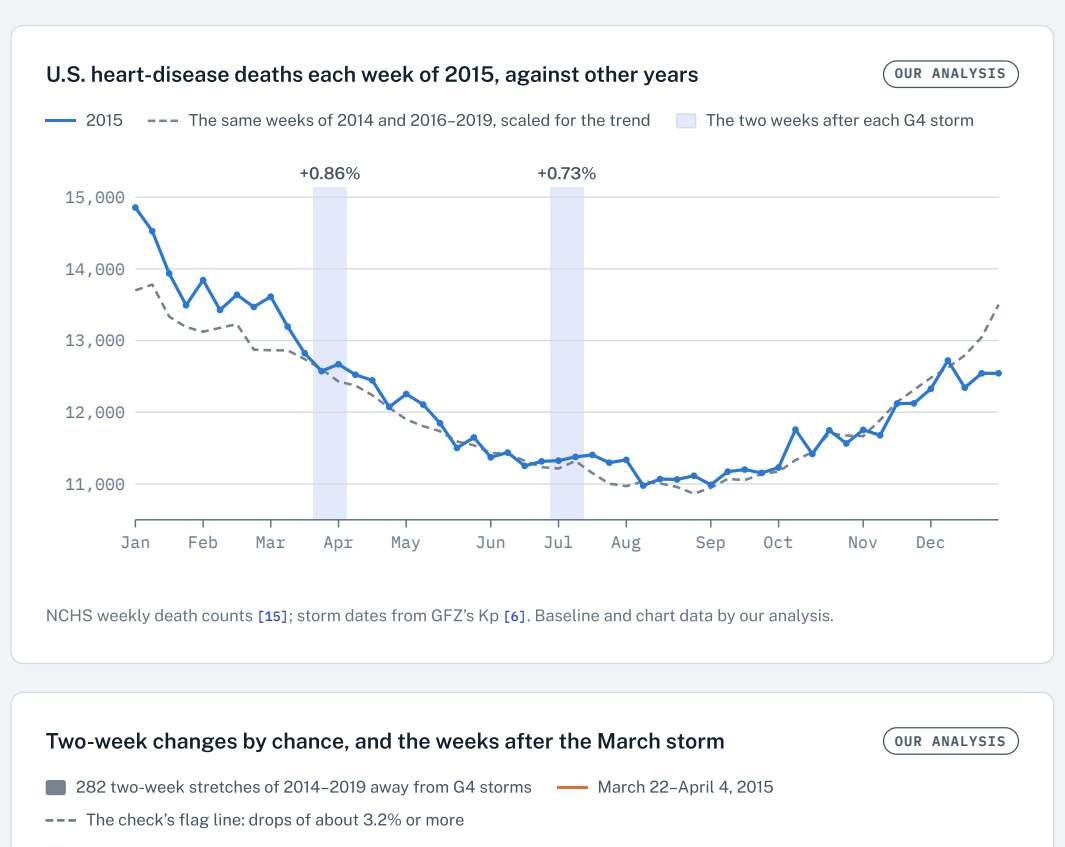
SMALLEST DROP IT CAN FLAG
OUR ANALYSIS
≈ 3.2%
by the check's own p-value rule, against 282 two-week stretches of 2014–2019 away from G4 storms; their 5th percentile is a drop of 2.9% [15]

THE ABSTRACT'S SIZE
OUR ANALYSIS
2.0–3.4%
the 6.4% the abstract builds on, 504 people at NEMSIS's count and about 840–870 at published national estimates, as a share of the 25,397 heart-disease deaths of March 15–28, if every averted arrest had been such a death [1 ¶1][11 Background][15]


U.S. heart-disease deaths each week of 2015, against other years

OUR ANALYSIS

NCHS weekly death counts [15]; storm dates from GFZ's Kp [6]. Baseline and chart data by our analysis.


Two-week changes by chance, and the weeks after the March storm

OUR ANALYSIS

Change in U.S. heart-disease deaths against the same weeks of the other years, in percent; changes beyond ±12% are counted in the end bars [15]. Our analysis.

OUR ANALYSIS

What the check shows, and what it can't

In March 15–28, the two weeks closest to the abstract's 14 days, heart-disease deaths were 0.2% above the other years' level, at the 60th percentile of chance. After the June 2015 storm they were 0.7% above it, and after September 2017's, 2.1% above, in weeks that included Hurricane Irma's landfall and Hurricane Harvey's aftermath, as our rules noted beforehand; deaths from all causes rose too, so there was no drop after any G4 storm of 2014–2019 [15].

A drop the size of the abstract's would be 2.0% of these deaths at NEMSIS's count. But NEMSIS held only part of the country's arrests: at published estimates of 341,397–353,246 adult out-of-hospital cardiac arrests a year in the U.S., figures that a study of NEMSIS data says "have important limitations" [11 Background], it would be about 3.3–3.4%. That is just past the smallest drop the check can flag, about 3.2%, and only if every averted arrest had been a heart-disease death. So the check could not reliably detect a drop of the abstract's size, and it isn't a test of cardiac arrests: it can't refute the abstract, and it adds no support to it.

8 · OTHER STUDIES

Studies point both ways, and a review calls the evidence inconsistent

The abstract reports fewer arrests after a storm. Some earlier studies found fewer heart-rhythm emergencies on disturbed days; larger studies of deaths and strokes found more; a meta-analysis of six studies found higher risks of heart attack on storm days [27 Abstract], and a scoping review calls the field preliminary [28 Abstract].

More events with geomagnetic activity

In 263 U.S. cities, daily geomagnetic disturbance was associated with more deaths in total, from cardiovascular disease and from heart attacks, though not from stroke [25 Abstract]. Across six studies, stroke risk was 19% higher on days with Ap of 60 or more [26 p. 1639]. A meta-analysis of six studies put the risk of heart attack and acute coronary syndrome on storm days at 1.3–1.5 times normal, while noting its "small number of included studies" [27 Abstract].

Fewer heart-rhythm events on disturbed days

An early study of 480 sudden deaths found them "significantly more frequent on days with the lowest/quiet level of geomagnetic activity" [30 Abstract], and its author later summarised an "inverse relationship" between activity and arrhythmias [32 Abstract]. Among about 59,000 patients a day with implanted defibrillators, shocks were delivered less often on more disturbed days: 1.29 per 1,000 patients on quiet days against 0.94 on storm days [33 Abstract]. This is the closest published support for a drop.

Mixed and null results

Stoupel and colleagues' study of 1,327 sudden cardiac deaths in Kaunas found them more frequent on the more disturbed days overall, with some subgroups trending the other way [31 Abstract]. In northern Sweden, 14 years of data showed "no statistically significant relation" between activity and heart attacks or sudden deaths [34 Abstract].

The newest study of cardiac arrest

A 2026 study of 1,507 resuscitations in Kaunas looked at outcomes, not how many arrests occurred: in patients without a shockable heart rhythm, fewer regained a pulse from a storm's second day to two days after it ended, especially women and those with a presumed cardiac cause [29 Results]; on those days and on more active days, a shockable rhythm made a regained pulse more likely, especially in men [29 Abstract][29 Results]. Its authors call for "larger, multicentre studies" [29 Conclusions].

OUR ANALYSIS

Where the abstract sits

A scoping review of 36 studies found that 28 reported significant correlations and eight found no effect. It found that heart attacks and acute coronary syndromes rose during storms, but also that low geomagnetic activity with high cosmic-ray activity was "consistently associated" with more heart attacks and heart-attack deaths, while "more active solar conditions appeared protective"; and it concluded that the "findings remain inconsistent, and many studies rely on ecological designs with uncontrolled factors that limit interpretation" [28 Abstract]. The abstract's direction has precedents, its sex and age pattern is not established even within its own numbers, and the studies that report subgroups measure different outcomes and don't agree on who is most affected [31 Abstract][29 Results]. One storm can't settle a question that dozens of studies have left open. For the wider evidence on storms and health, see our check of a 2026 review and our check of a preprint on storms and deaths.

9 · THE EARLIER RESULT

The 6.4% the abstract builds on: no source we could find

The abstract's first sentence reports a 6.4% drop (p=0.009) over 14 days after a storm, as a causal relationship, without a citation [1 ¶1].

Where we looked

Crossref, OpenAlex, Europe PMC (with its preprints, medRxiv among them), DataCite (which holds German medical-informatics conference abstracts), Zenodo, arXiv and the author's public ORCID record: nothing on storms and cardiac arrest except the Zenodo data [2]. AGU's meeting site loads by script, so we searched it in a browser, reading only, on November 20 at about 19:56–19:58 UTC: at AGU25, "Marschollek" gave no results and "cardiac" three, none on geomagnetism; at AGU26, "Marschollek" gave only this abstract.

OUR ANALYSIS

A confirmation, or the same result broken down?

Weighted by group size, the new results for women and men average a 6.71% drop, and those for the two age groups 6.78%, within half a point of the earlier 6.4% [1 ¶1][1 ¶4]. That is what one would see if the earlier figure came from all of the same 2015 data. It doesn't show that it did, but if so, the subgroup results restate the earlier one rather than confirm it.

10 · GREAT STORMS

What it would mean for a great storm or a weaker field: nothing yet

Our reading, through the lens of catastrophic space weather: what the abstract would imply if it held, and what it can't.

OUR ANALYSIS

One severe storm, measured in a way that can't be scaled up

If the drop held, a severe storm would have come with fewer cardiac arrests, not more; nothing in the abstract supports fears that storms harm hearts. But March 2015 was a common kind of storm: G4 levels are reached about 100 times, on about 60 days, in a solar cycle [5]. Its −234 nT was well short of March 1989's −589 nT (final) and May 2024's −406 nT (provisional) [7], and far short of the Carrington storm of 1859, as our page on the Sun's worst cases sets out. With one storm there is no dose and response to extend to a greater one, the abstract proposes no mechanism [1 ¶5], and nothing in it bears on a weakening or reversing field. If every G4 storm cut cardiac arrests by 6–9% for two weeks, the effect would recur several times a year near solar maximum, and our check of national deaths found none after the three G4 storms of 2014–2019, within its limits [15].

11 · LIMITS

What this check can't tell us

An abstract, not a paper

We read 276 words. The poster may answer some of our questions: the model, the window, placebo checks, the June storm [1].

The data aren't public

NEMSIS's research data need an agreement, and the author's Zenodo files are restricted, so we couldn't rerun anything [2][9 Data Subsets].

Approximations from rounded numbers

Our tests of the differences read four rounded p-values through a normal approximation; the author's full results could differ somewhat, though not enough to make a 2.6-point gap with p ≈ 0.55 significant. The 4.7-point age gap is closer: p ≈ 0.08 at the most favourable of our readings (the two estimates' errors correlated at 0.5), still short of 0.05; read as two-sided, which the package's p-values are not [13 Manual], and with correlated errors, it could fall below 0.05.

Deaths are not cardiac arrests

The national check counts deaths from heart disease. Arrests that people survive, or that have other causes, aren't in it, and many heart-disease deaths aren't sudden [15].

Searches miss things

The earlier 6.4% may exist somewhere we didn't look, such as a talk or a thesis.

Small slips we noticed

None of these changes a verdict. The abstract speaks of "the G4 solar storm in 2015" [1 ¶2], but 2015 had two: NOAA reported severe storm levels on March 17 and on June 22–23 [3 p. 1][4 p. 1], and GFZ's Kp reached 8− and 8+ [6]. And it studies cardiac arrests "in the entire U.S." [1 ¶2], while NEMSIS's data for 2015 came from about 79% of counties, by voluntary submission [10 Methods][9 What is NEMSIS].

What would change these verdicts

01
The poster or a paper giving the model, its fit before the storm and a placebo check; the same analysis run for the June 2015 storm, and for other years, finding the drop again, would move the first claim toward True.

02
A test of the difference between women and men, or between age groups, in the full results, or the same differences found after other storms.

03
The earlier 6.4% result, identified: from independent data, it would make the fifth claim a real confirmation to weigh; from the same 2015 data, a restatement.

12 · REPEAT OUR NUMBERS

The rules, the scripts and our derived numbers; the data stay with their owners

Each rules file was written and hashed before the test it governs; the two descriptions made afterwards say so. The scripts fetch their public inputs by URL under a plain client name and check them against the copies we used.

TXT **README.txt, HASHES.txt and HASHES-abstract.txt**
How to run everything, in order; the SHA-256 of every file and input, and when each rules file was hashed · 21 KB

PY **fetch_inputs.py**
Fetches GFZ's Kp file and the NCHS death counts and checks them against our copies; standard library · 6 KB [6][15]

PY **exposure.py and exposure_check.py**
The 2015 storms in GFZ's Kp and Ap, NOAA's G levels, and the 14-day windows, section 2, with a separately written check · 20 KB

CSV **ap_daily_2015.csv, kp_3h_2015.csv, storms_2014_2019.csv, exposure_2015.json and chart_ap_2015.json**
Daily Ap and three-hour Kp of 2015, the storms of 2014–2019, every answer of the rules and the chart's data · 119 KB

PY **weekly_deaths.py and weekly_deaths_check.py**
The national check of section 7, with a separately written check of its primary result; numpy and pandas, seeded · 17 KB

CSV **weekly_deaths_us.csv, placebo_deltas.csv, weekly_deaths_results.json and chart_weekly_deaths.json**
The 313 U.S. weeks used, every two-week window's change, the results and the charts' data · 85 KB

PY **arithmetic.py, abstract_arithmetic.py and their outputs 1, 2**
Two separate versions of the arithmetic on the abstract's numbers, section 5; standard library · 16 KB

PY **posthoc_2015_excess.py, posthoc_flu_deaths.py and their outputs 1, 2**
The two descriptions made after the national check had run: the winter excess, and the influenza-and-pneumonia deaths, section 6 · 11 KB

PY **fetch_dst_2015.py, kyoto_dst_final.py and kyoto_dst_final_2015_storms.txt**
Kyoto's final Dst for 2015 and the year's intense storms, section 2; standard library · 8 KB [7]

PY **context_arithmetic.py and context_arithmetic.txt**
The abstract's drop at national scale and the check's flag line, section 7; the seasonal counts and the temperatures, section 6; the age gap read as two-sided, section 11; standard library · 10 KB [11][17][21]

PY **calendar_2015.py and calendar_2015.txt**
Daylight saving time, Easter and the possible windows, section 6 · 3 KB

TXT **RULES_exposure.txt, RULES_weekly_deaths.txt, RULES_arithmetic.txt, RULES_abstract_arithmetic.txt, RULES_zenodo_ap.txt, RULES_posthoc_2015_excess.txt and RULES_posthoc_flu_deaths.txt**
The rules, each written before its run; the last two after the national check, as they say · 25 KB

Run it

`python3 fetch_inputs.py inputs` fetches GFZ's and NCHS's files; then, for example, `python3 -I exposure.py inputs/gfz-kp/Kp_ap_Ap_SN_F107_since_1932.txt results`. README.txt gives every command in order, and HASHES-abstract.txt the commands for our arithmetic, Kyoto's Dst and the calendar. The national check and exposure_check.py need numpy and pandas; everything else needs only Python 3.9 or later.

What we don't host

The abstract, which carries no licence [1]; GFZ's Kp file, NCHS's death counts, Kyoto's Dst and NOAA's temperature series as published, which the scripts fetch from their owners [6][15][7][21]; and the author's data, which we couldn't read [2]. We host our own rules, code and derived numbers, with the extracts of public data they use, credited: GFZ's Kp and Ap for 2015 (CC BY 4.0) and NCHS's 313 U.S. weeks (public domain).

Related checks

UNSUPPORTED The Sun and wars, crime and revolutions The Disaster Cycle, Fact-Checked

Sources

Bracketed numbers refer to this list. For the abstract [1], ¶ counts its paragraphs as AGU's page shows them, from ¶1 ("Previous research…") to ¶5 ("These results confirm…"), and Title is its title. For NOAA's weekly reports [3] and [4], p. gives a page of the report; for Liu et al. [8], a page of the arXiv version; for Brodersen et al. [12], the journal's page. For NEMSIS [9], the locator names the page; for the CausalImpact package [13], Vignette, Manual and Source name its vignette, reference manual and R source. Elsewhere, Abstract means the abstract and other names give a section or table; where only an abstract or a record was read, the entry says so. Links checked November 21, 2026.

1 Marschollek, M. (2026). Age and Sex Differences in Causal Impact of Geomagnetic Ap on Cardiac Arrest Incidence during and after Solar Storms. Abstract GH11D-VR9816 (Paper 2071962), AGU26, the AGU Annual Meeting 2026, poster session GH11D "Data-Driven Frontiers in GeoHealth: Exposure, Disasters, and Human Health I", December 7, 2026. Conference abstract, not peer reviewed; no DOI and no licence stated, so it is quoted here and not reproduced. We read the full abstract on AGU's meeting site on November 20, 2026; the site loads it by script, and our tools receive only its title and first 80 characters.

2 Marschollek, M. (2026). Data of geomagnetic variation, solar flux and temperature averages the the U.S. for 2015 [sic]. Zenodo, published April 1, 2026. CC BY 4.0. Record only: the record is public, but its files are restricted.

3 NOAA Space Weather Prediction Center (2015). Preliminary Report and Forecast of Solar Geophysical Data, SWPC PRF 2064, March 23, 2015, for March 16–22, 2015, from NOAA NCEI's archive. Public domain. p. gives its page.

4 NOAA Space Weather Prediction Center (2015). Preliminary Report and Forecast of Solar Geophysical Data, SWPC PRF 2078, June 29, 2015, for June 22–28, 2015, from NOAA NCEI's archive. Public domain. p. gives its page.

5 NOAA Space Weather Prediction Center. NOAA Space Weather Scales and the Planetary K-index page, read November 20, 2026. Public domain.

6 Matzka, J., Bronkalla, O., Tornow, K., Elger, K., and Stolle, C. (2021). Geomagnetic Kp index, V. 1.0. GFZ Data Services. The definitive Kp, ap and Ap from GFZ's file Kp_ap_Ap_SN_F107_since_1932.txt, read November 20, 2026. CC BY 4.0. The indices are described in Matzka, J., Stolle, C., Yamazaki, Y., Bronkalla, O., and Morschhauser, A. (2021), The geomagnetic Kp index and derived indices of geomagnetic activity, *Space Weather* 19(5), e2020SW002641.

7 Nose, M., Iyemori, T., Sugiura, M., and Kamei, T., World Data Center for Geomagnetism, Kyoto (2015). Geomagnetic Dst index: final hourly values for 2015 and March 1989, and provisional values for May 2024, from the WDC's monthly pages, read November 20, 2026, under the WDC's data usage rules: scientific use, no commercial use, with acknowledgement of the WDC and of the observatories that supply the data (Kakioka, Honolulu, San Juan, Hermanus and Alibag). No real-time value is used.

8 Liu, Y. D., Hu, H., Wang, R., Yang, Z., Zhu, B., Liu, Y. A., Luhmann, J. G., and Richardson, J. D. (2015). Plasma and Magnetic Field Characteristics of Solar Coronal Mass Ejections in Relation to Geomagnetic Storm Intensity and Variability. *The Astrophysical Journal Letters* 809(2), L34. We read the accepted version, arXiv:1508.01267; p. gives its page.

9 NEMSIS Technical Assistance Center. National Emergency Medical Services Information System, nemsis.org: What is NEMSIS, History of NEMSIS, Request Research Data, Research Data Resources and NEMSIS Data Subsets, with its terms of use, read November 20, 2026. The locator names the page.

10 Kahn, P. A., Dhruva, S. S., Rhee, T. G., and Ross, J. S. (2019). Use of Mechanical Cardiopulmonary Resuscitation Devices for Out-of-Hospital Cardiac Arrest, 2010–2016. *JAMA Network Open* 2(10), e1913298. CC BY 4.0. We read the full text in Europe PMC (PMC6806423).

11 Chan, H. K., Okubo, M., Callaway, C. W., Mann, N. C., and Wang, H. E. (2020). Characteristics of adult out-of-hospital cardiac arrest in the National Emergency Medical Services Information System. *JACEP Open* 1(4), 445–452. CC BY-NC-ND 4.0. We read the full text in Europe PMC (PMC7493527).

12 Brodersen, K. H., Gallusser, F., Koehler, J., Remy, N., and Scott, S. L. (2015). Inferring causal impact using Bayesian structural time-series models. *The Annals of Applied Statistics* 9(1), 247–274. We read the reprint posted as arXiv:1506.00356; p. gives the journal's page.

13 Brodersen, K. H., and Hauser, A. CausalImpact: Inferring Causal Effects using Bayesian Structural Time-Series Models, R package version 1.4.1, Google, doi:10.32614/CRAN.package.CausalImpact. Apache License 2.0. We read its vignette and reference manual on CRAN and its R source on GitHub, November 20, 2026.

14 Gelman, A., and Stern, H. (2006). The Difference Between "Significant" and "Not Significant" is not Itself Statistically Significant. *The American Statistician* 60(4), 328–331. Record only, through Crossref.

15 National Center for Health Statistics. Weekly Counts of Deaths by State and Select Causes, 2014–2019, Data set 3yf8-kanr, data.cdc.gov, read November 20, 2026. Public domain. We used the United States rows: deaths from diseases of the heart, from influenza and pneumonia, and from all causes.

16 Bagai, A., McNally, B. F., Al-Khatib, S. M., Myers, J. B., Kim, S., Karlsson, L., et al. (2013). Temporal Differences in Out-of-Hospital Cardiac Arrest Incidence and Survival. *Circulation* 128(24), 2595–2602. We read the abstract (PubMed 24045044).

17 El Sibai, R. H., Bachir, R. H., and El Sayed, M. J. (2021). Seasonal variation in incidence and outcomes of out of hospital cardiac arrest: A retrospective national observational study in the United States. *Medicine* 100(18), e25643. CC BY-NC 4.0. We read the full text in Europe PMC (PMC8104224).

18 Appiah, G. D., Blanton, L., D'Mello, T., Kniss, K., Smith, S., Mustaquim, D., et al. (2015). Influenza Activity — United States, 2014–15 Season and Composition of the 2015–16 Influenza Vaccine. *Morbidity and Mortality Weekly Report* 64(21), 583–590. Public domain. We read the full text in Europe PMC (PMC4584770).

19 Onozuka, D., and Hagihara, A. (2018). Extreme influenza epidemics and out-of-hospital cardiac arrest. *International Journal of Cardiology* 263, 158–162. We read the abstract (PubMed 29754914).

20 Gasparrini, A., Guo, Y., Hashizume, M., Lavigne, E., Zanobetti, A., Schwartz, J., et al. (2015). Mortality risk attributable to high and low ambient temperature: a multicountry observational study. *The Lancet* 386(9991), 369–375. CC BY 4.0. We read the full text in Europe PMC (PMC4521077).

21 NOAA National Centers for Environmental Information. Climate at a Glance: National Time Series, contiguous U.S. average temperature for February and for March, 1895–2026, read November 20, 2026. Public domain. The departures from the 1991–2020 average are our arithmetic.

22 15 U.S.C. § 260a, Advancement of time or changeover dates. Read at the Legal Information Institute, Cornell Law School, November 20, 2026.

23 Sandhu, A., Seth, M., and Gurm, H. S. (2014). Daylight savings time and myocardial infarction. *Open Heart* 1(1), e000019. CC BY-NC 3.0. We read the full text in Europe PMC (PMC4189320).

24 Manfredini, R., Fabbian, F., Cappadona, R., De Giorgi, A., Bravi, F., Carradori, T., Flacco, M. E., and Manzoli, L. (2019). Daylight Saving Time and Acute Myocardial Infarction: A Meta-Analysis. *Journal of Clinical Medicine* 8(3), 404. CC BY 4.0. We read the full text in Europe PMC (PMC6463000).

25 Zilli Vieira, C. L., Alvares, D., Blomberg, A., Schwartz, J., Coull, B., Huang, S., and Koutrakis, P. (2019). Geomagnetic disturbances driven by solar activity enhance total and cardiovascular mortality risk in 263 U.S. cities. *Environmental Health* 18, 83. CC BY 4.0. We read the full text in Europe PMC (PMC6739933); also cited on our check Storms, auroras and the brain.

26 Feigin, V. L., Parmar, P. G., Barker-Collo, S., Bennett, D. A., Anderson, C. S., Thrift, A. G., et al. (2014). Geomagnetic Storms Can Trigger Stroke: Evidence From 6 Large Population-Based Studies in Europe and Australasia. *Stroke* 45(6), 1639–1645. As cited on our check Storms, auroras and the brain; not re-read for this page.

27 Gaisenok, O., Gaisenok, D., and Bogachev, S. (2025). The Influence of Geomagnetic Storms on the Risks of Developing Myocardial Infarction, Acute Coronary Syndrome, and Stroke: Systematic Review and Meta-analysis. *Journal of Medical Physics* 50(1), 8–13. CC BY-NC-SA 4.0. We read the full text in Europe PMC (PMC12005662).

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29 Vencloviene, J., Krikscionaitiene, A., Darginavicius, L., Baksevice, D., Vaitkaitiene, E., Vaitkaitis, D., and Dobozinskas, P. (2026). Association Between Geomagnetic Activity and Unsuccessful Out-of-Hospital Cardiac Arrest. *GeoHealth* 10(6), e2025GH001721. CC BY-NC 4.0. We read the full text in Europe PMC (PMC13288371).

30 Stoupel, E. (1993). Sudden cardiac deaths and ventricular extrasystoles on days with four levels of geomagnetic activity. *Journal of Basic and Clinical Physiology and Pharmacology* 4(4), 357–366. We read the abstract (PubMed 8664252).

31 Stoupel, E., Domarkiene, S., Radishauskas, R., and Abramson, E. (2002). Sudden cardiac death and geomagnetic activity: links to age, gender and agony time. *Journal of Basic and Clinical Physiology and Pharmacology* 13(1), 11–21. We read the abstract (PubMed 12099401).

32 Stoupel, E. (2006). Cardiac arrhythmia and geomagnetic activity. *Indian Pacing and Electrophysiology Journal* 6(1), 49–53. We read the abstract (PubMed 16943895).

33 Ebrille, E., Konecny, T., Konecny, D., Spacek, R., Jones, P., Ambroz, P., et al. (2015). Correlation of Geomagnetic Activity With Implantable Cardioverter Defibrillator Shocks and Antitachycardia Pacing. *Mayo Clinic Proceedings* 90(2), 202–208. We read the abstract (PubMed 25659238).

34 Messner, T., Häggström, I., Sandahl, I., and Lundberg, V. (2002). No covariation between the geomagnetic activity and the incidence of acute myocardial infarction in the polar area of northern Sweden. *International Journal of Biometeorology* 46(2), 90–94. We read the abstract (PubMed 12135204).

35 SpaceWeatherNews (S0) (November 20, 2026). Solar/Pole Shift Impact: Insects, Plants, Humans | S0 News Nov.20.2026. YouTube video. Linked the source; no transcript was available, so nothing the episode said is rated here.

METHOD

How this was checked

On November 20, 2026, we checked every statement, number and quotation on this page against its source: the abstract as AGU's meeting site shows it, read in full in a browser because the page gives scripted readers only its title and first 80 characters [1]; NOAA's weekly reports on the two G4 storms of 2015 [3][4], GFZ's definitive Kp and Ap [6] and Kyoto's final Dst [7]; the method's paper and the CausalImpact package's documentation and code [12][13]; NEMSIS's own pages [9] and two studies of its data [10][11]; and 19 other studies, ten read in full, seven in abstract and two through their records or our earlier check: 35 sources in all. We searched seven indexes and AGU's 2025 and 2026 meeting programmes for the earlier result the abstract cites, and didn't find it.

The verdicts and the items tagged "Our analysis" are our own assessment, built on the cited sources. They include the arithmetic on the abstract's printed numbers (the case counts, the drops in people, the uncertainty its p-values imply, the tests of the sex and age differences, and four tests at once), the storm's numbers in GFZ's and Kyoto's indices, a pre-registered check of U.S. weekly death counts around every G4 storm of 2014–2019, and two descriptions made after that check had run: how 2015's winter excess of heart-disease deaths faded, and when that winter's excess of influenza-and-pneumonia deaths ended. Feigin et al. (2014) is cited as our check of a 2026 review cites it.

Every number of ours can be repeated with the hosted files: each test's rules were written and hashed before it ran, and the scripts fetch their public inputs and check them against the copies we used. We couldn't recheck the abstract's own analysis: its model and its NEMSIS series aren't published, the author's files on Zenodo are restricted, and the poster hasn't been presented. The national check counts heart-disease deaths, not cardiac arrests, and could not reliably detect a change of the size the abstract reports.

This page was researched and written with Claude, an AI assistant made by Anthropic, and then re-checked against its sources in a separate verification pass.

The verdicts on this page

OVERSTATED	Has some basis but claims much more than the evidence supports.
UNSUPPORTED	No evidence we could find backs it up, though it hasn't been strictly disproven.
UNCONFIRMED	Rests on a preliminary result that hasn't been confirmed.
UNVERIFIED	We couldn't find the source or record it depends on.

All ten verdicts, and how we check

CORRECTIONS

Corrections and changes

If we get something wrong, we fix it and record the change below with the date. If a correction changes a verdict, the log says what the old verdict was.

Change log

`Nov 21, 2026` Published on factchecked.science after a full check against the sources. Built from the abstract as AGU's meeting site shows it, NOAA's and GFZ's records of the 2015 storms, Kyoto's final Dst, the method's documentation and the studies of storms and the heart, with our own arithmetic on the abstract's numbers and a pre-registered check of U.S. weekly death counts. Five claims rated on the site's scale: Unconfirmed, Overstated, Unsupported, Overstated and Unverified.

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Last updated Nov 21, 2026