



Ionospheric and Atmospheric Precursors to Earthquakes: A Critical Review of Multi-Parametric Observations, Coupling Mechanisms, and Machine Learning Applications

^{*1}Oloruntola, Racheal Foluke, ^{**2}Babalola, Oludare Olukayode, ^{***1}Olaniyi Ganiyu Akanji, ^{†3}Àlàgbé, George Atilade, ⁴Bakare Hameed Olalekan and ^{‡5}Agbelemoge Adedamola Julius



¹Department of Physics, Lead City University, Ibadan, Nigeria

²Department of Geology, Lead City University, Ibadan, Nigeria

³Department of Pure and Applied Physics, Ladoke Akintola University of Technology, Ogbomosho, Nigeria

⁴Department of Physics, Federal University of Technology and Environmental Sciences, Iyin-Ekiti, Nigeria

⁵Department of Physics, Precious Cornerstone University, Ibadan, Nigeria

*Corresponding Author's email: oloruntolafoluke16@gmail.com Phone: +2348023462053

ORCID iD: *<https://orcid.org/0000-0003-4787-1703>; **<https://orcid.org/0009-0002-7474-3969>;

***<https://orcid.org/0000-0002-3121-519X>; †<https://orcid.org/0000-0001-9379-1523>; ‡<https://orcid.org/0000-0002-8733-9685>

KEYWORDS

Lithosphere-Atmosphere-Ionosphere Coupling, Earthquake Precursors, Ionospheric Anomalies, Total Electron Content, Machine Learning.

ABSTRACT

The search for reliable pre-earthquake signals in the upper atmosphere has produced a large and heterogeneous body of literature over the past two decades, much of it organized around the Lithosphere-Atmosphere-Ionosphere Coupling (LAIC) hypothesis. This narrative-critical review synthesizes studies published between 2020 and 2026, identified through Scopus, Web of Science, Google Scholar and journal-archive searches and screened against stated eligibility and evidence-appraisal criteria, on ionospheric and atmospheric precursors to large earthquakes, covering Global Navigation Satellite System (GNSS)-derived Total Electron Content (TEC) anomalies, sub-ionospheric Very Low Frequency (VLF) and High Frequency (HF) radio propagation disturbances, and thermal atmospheric signatures. It further examines the proposed mechanical (acoustic-gravity wave), geochemical (radon-driven), and electromagnetic channels invoked to explain lithosphere-to-ionosphere energy transfer, and considers how solar and geomagnetic activity confound or mimic seismogenic signals. Beyond summarizing individual case studies, this review evaluates the field's methodological foundations: the near-universal reliance on retrospective, single-event case studies; the absence of standardized anomaly definitions and false-positive/false-negative statistics; and the growing but still under-validated use of deep machine learning for anomaly discrimination. We find that pre-seismic ionospheric perturbations are reported using several independent techniques, but the evidence is heterogeneous and rarely controlled, and causal attribution to seismogenic processes rather than coincidental space weather variability remains unresolved for the majority of reported cases. The present evidence does not support operational earthquake forecasting; we recommend prospective, statistically rigorous, and physically constrained research designs.

CITATION

Oloruntola, R. F., Babalola, O. O., Olaniyi, G. A., Àlàgbé, G. A., Bakare, H. O., & Agbelemoge, A. J. (2026). Ionospheric and Atmospheric Precursors to Earthquakes: A Critical Review of Multi-Parametric Observations, Coupling Mechanisms, and Machine Learning Applications. *Journal of Science Research and Reviews*, 3(5), 258-266. <https://doi.org/10.70882/josrar.2026.v3i5.290>

INTRODUCTION

Short-term earthquake forecasting remains one of the most persistent open problems in geophysics. Precursory signals have traditionally been sought within the crust itself, through anomalous low-magnitude seismicity indicative of stress accumulation (Girona & Drymoni, 2024) and temporal changes in the gravity field (Tan *et al.*, 2025), but an increasing body of literature reports that the preparatory phase of large earthquakes may also manifest well above the Earth's surface, in the neutral atmosphere and ionosphere (Pulinets *et al.*, 2022; Colonna *et al.*, 2026). The Lithosphere-Atmosphere-Ionosphere Coupling (LAIC) framework provides the dominant conceptual model for these observations, proposing that mechanical, chemical, and electromagnetic pathways transfer energy and charge from a stressed lithosphere upward into the ionosphere, producing anomalies in electron density, radio-wave propagation, and thermal emission in the days to hours before a main shock (Sasmal *et al.*, 2025; Pilipenko & Surkov, 2025; Li *et al.*, 2026).

The central difficulty in this field, and the one that motivates the present review, is discrimination of geomagnetic storms, solar flares, and lower-atmospheric meteorology, all of which produce ionospheric variability of comparable or larger magnitude than the anomalies attributed to seismogenic processes (Ouzounov & Khachikyan, 2024; Gulyaeva, 2023), compounded by the ionosphere's natural day-to-day variability, which is itself poorly constrained in many of the regions where large earthquakes occur. Existing studies have responded by combining multiple independent observation types, such as GNSS TEC mapping, VLF/HF sub-ionospheric sounding, and satellite thermal imaging, with the expectation that coincident anomalies across techniques are less likely to be attributable to a single confounding cause (Draz *et al.*, 2023; Cano-Domingo *et al.*, 2023). Deep machine learning has been applied to ionospheric modelling more generally (Zhang *et al.*, 2025) and has increasingly been layered on top of these multi-instrument datasets as a tool for separating candidate seismogenic signals from space-weather noise (Draz *et al.*, 2023; Li *et al.*, 2026).

This review differs from prior summaries of the LAIC literature in its emphasis. Pulinets *et al.* (2022) present the LAIC concept and its multi-parameter framework as a basis for precursor detection, Pilipenko and Surkov (2025) trace the historical development of seismo-electromagnetic and seismo-ionospheric research, and Li *et al.* (2026) discuss the opportunities and challenges of moving from phenomenon observation to physical prediction. The present review complements these works by (i) restricting attention to studies published in 2020–2026, (ii) appraising each reported detection against explicit criteria (control period, anomaly definition, confounder adjustment, false-positive evaluation, and validation type; and (iii) separating retrospective

detection, causal attribution, and prospective forecasting as distinct levels of evidence. Rather than presenting the field as a settled sequence of confirmatory case studies, it treats each reported detection as an inference problem: what was actually measured, what alternative explanations were considered and how they were excluded, and what the demonstrated evidence supports about causal coupling versus coincidence. Throughout, “forecasting” denotes a probabilistic statement about the future time, location, and magnitude of an earthquake; it is distinct from earthquake early warning, which detects an already-initiated rupture and alerts populations seconds before strong shaking arrives. The aim of this review is to critically evaluate, against explicit methodological criteria, what recent ionospheric and atmospheric earthquake-precursor studies do and do not establish about retrospective detection, causal coupling, and prospective forecasting skill.

Review Methodology

Review Design and Literature Search

This review follows a narrative-critical review methodology, appropriate for a rapidly evolving, methodologically heterogeneous literature for which a formal systematic review or meta-analysis is not yet feasible given the lack of standardized effect sizes and anomaly-detection criteria across studies. Candidate literature was identified through searches of Scopus, Web of Science, Google Scholar, and the archives of relevant journals (Remote Sensing, Advances in Space Research, Geosciences, Atmosphere, Nature Communications, and others), using combinations of the search terms “ionospheric precursor”, “earthquake precursor”, “Lithosphere-Atmosphere-Ionosphere Coupling”, “Total Electron Content anomaly”, “VLF sub-ionospheric propagation”, and “machine learning earthquake precursor”. The terms were combined with Boolean operators as follows: (“ionospheric precursor” OR “earthquake precursor” OR “Lithosphere-Atmosphere-Ionosphere Coupling”) AND (“Total Electron Content anomaly” OR “VLF sub-ionospheric propagation” OR “machine learning earthquake precursor”). The search was restricted to studies published between 2020 and 2026 (last search run on September 2026 publications, supplemented by a small number of earlier foundational references cited within the retrieved literature. These foundational references were added by backward citation tracking, when a retrieved study relied on them for its central concept or method; they provide context and were not appraised as part of the 2020–2026 evidence set. The search identified 60 records; after removal of 10 duplicates, 50 titles and abstracts were screened, 37 full texts were assessed against the eligibility criteria, and 32 studies were retained for appraisal.

Eligibility Criteria and Data Extraction

Studies were included if they reported original observational or modelling analysis of ionospheric, atmospheric, or related geophysical parameters in relation to a specific earthquake or set of earthquakes, or if they proposed or tested a physical mechanism for lithosphere-atmosphere-ionosphere coupling. Studies were excluded if they were duplicates, if no specific earthquake or earthquake set could be identified, if the data sources could not be determined from the text, or if they offered commentary without original analysis. Reviews and monographs were used to frame the field but were not appraised as primary evidence. For each included study, this review records the seismic event examined, the data sources and parameters used, the reported finding, and, where stated, the treatment of space-weather or meteorological confounders. Rather than reporting findings at face value, each study is evaluated as an inference problem, following the framing set out earlier and the appraisal criteria, with particular attention to case-study design, confounder control, and (where applicable) machine-learning validation strategy. This evaluative approach, rather than a quantitative meta-analytic synthesis, is the basis for the critical assessment.

Evidence-Appraisal Framework

Each included study was appraised against five criteria, chosen because they determine whether a reported anomaly can be distinguished from chance or confounding: (1) whether a control or baseline period, or matched non-seismic dates, was analysed; (2) whether the anomaly threshold was defined explicitly and reproducibly; (3) whether geomagnetic, solar, and meteorological conditions were adjusted for or quantitatively tested; (4) whether false-positive and, where applicable, false-negative rates were evaluated; and (5) the type of validation, classified as retrospective single-event, retrospective multi-event or cross-validated, or prospective out-of-sample. On this basis, each study was assigned to one of three evidence categories: observational association (an anomaly coincident with a known earthquake, without the controls above); controlled association (an association tested against a baseline period and at least one confounder); and demonstrated mechanism (a quantitative, tested physical link between the proposed source and the observed anomaly). The appraisal is qualitative and descriptive, and the categories do not constitute a numerical quality score.

RESULTS AND DISCUSSION

Observational Techniques for Ionospheric and Atmospheric Precursors

GNSS Total Electron Content and Associated Atmospheric Anomalies

GNSS-derived Total Electron Content (TEC) mapping is the most widely used observational tool in this literature, owing to the dense and growing global receiver network and the spatial resolution afforded by Regional and Global Ionospheric Maps (RIMs/GIMs; Zhu *et al.*, 2023). Simha *et al.* (2024) reported atmospheric and ionospheric anomalies preceding the 2015 Mw 7.8 and Mw 7.3 Nepal earthquakes, combining vertical TEC (VTEC) with Outgoing Long-wave Radiation (OLR) and vertical temperature gradient (VTG) data to argue for a temporal sequence running from thermal atmospheric change to subsequent ionospheric perturbation. Similarly, analysis of the 2011 Tohoku earthquake using the NRLMSISE-00 empirical atmospheric model identified anomalous neutral mass density and atomic oxygen concentrations in the days before the event (Endeshaw, 2024), which has been interpreted as evidence for an atmospheric intermediary stage in the LAIC chain. Temporal ordering of this kind is an observational association; it does not by itself demonstrate that the thermal anomaly caused the ionospheric one, or that either was seismogenic.

These studies are individually informative but share a common structural limitation: each documents an anomaly in the specific window preceding a single, already-known earthquake, without a pre-registered anomaly detection criterion applied uniformly across a longer baseline period or a comparable population of non-seismic dates. This case-study design, discussed further in the critical assessment, makes it difficult to determine from the reported results alone how often TEC or OLR anomalies of similar magnitude occur without a subsequent large earthquake.

Sub-ionospheric VLF Propagation and HF Sounding

Sub-ionospheric VLF propagation is a long-standing and comparatively sensitive probe of the D-region, since perturbations to the Earth-ionosphere waveguide alter the amplitude and phase of transmitter signals received at fixed monitoring stations. Politis *et al.* (2023) reported lower-ionosphere anomalies ahead of the March 2021 north-central Greece earthquake sequence using a multi-method VLF analysis, while Boudjada *et al.* (2024) reported VLF transmitter-amplitude perturbations, recorded at the Graz (Austria) station, preceding the Mw 5.4 (22 March) and Mw 6.4 (29 December) 2020 Croatian earthquakes, and interpreted the waveguide response in terms of lithospheric gas emission and associated electric-field changes.

Higher in the ionosphere, oblique HF sounding has been used to detect seismically associated propagation-channel distortions; Chernogor *et al.* (2023) reported such distortions at great-circle distances of 845-2,260 km from the epicenter of the April 2019 Mw 6.0 Japan earthquake. Global-scale indicators such as Schumann Resonance (SR) frequency have also been proposed as coarse markers of ionospheric boundary changes, with machine-learning-based hourly SR characterization recently applied to this problem (Cano-Domingo *et al.*, 2023).

As with TEC studies, the VLF/HF literature is dominated by after-the-event identification of anomalies in a known pre-seismic window. VLF propagation is additionally sensitive to lower-atmospheric weather, sporadic-E layers, and solar X-ray flux, all of which can produce waveguide perturbations resembling those attributed to seismogenic sources; few of the studies reviewed here report a systematic accounting of these confounders over an extended control period.

Proposed Lithosphere-Atmosphere-Ionosphere Coupling Mechanisms

Mechanical and Acoustic-Gravity Wave Channel

The mechanical channel proposes that anomalous vertical ground motion in the earthquake preparation zone excites internal gravity waves (IGWs) that propagate upward and perturb ionospheric plasma density. Chen *et al.* (2023) tested this hypothesis for the 2016 Kumamoto earthquake, comparing slant-gauge vertical ground motion in Kyushu with ionosonde-derived F2-layer peak density (NmF2) and reporting a spectral correlation between the two. Notably, the same study also examined, but could not confirm, a geomagnetic (Kp-index) influence on the vertical ground motion signal, and specified physical conditions, an effective ground-motion period shorter than five hours sustained over time, under which the coupling was expected to operate. This is one of the more methodologically transparent studies reviewed here, in that it explicitly reports a negative result (no confirmed Kp coupling) alongside the positive finding, rather than only the confirmatory correlation. A spectral correlation of this kind remains an association; it does not by itself demonstrate that ground motion drove the ionospheric change.

Geochemical and Electromagnetic Channel

A second proposed pathway involves geochemical emissions, particularly radon, which is thought to alter the electrical conductivity of the lower atmosphere and modify air-earth current and local electric fields in ways that could propagate upward into the ionosphere. Alam *et al.* (2023) reported distinct fractal patterns in groundwater radon time series preceding the 2008 Mw 7.9 Wenchuan earthquake. The physical link between such radon anomalies and detectable ionospheric change is plausible

in principle but has rarely been demonstrated as a continuous, quantified chain from groundwater measurement through boundary-layer ionization to a specific ionospheric observable; most studies instead report the two ends of the proposed chain (geochemical anomaly and ionospheric anomaly) as separately documented phenomena that are then associated by timing rather than jointly modelled.

Magnetospheric and Solar-Terrestrial Influences

Because the ionosphere sits at the interface between lithospheric and space-weather forcing, disentangling the two is central to this field. D'Angelo *et al.* (2022) reported magnetospheric-ionospheric-lithospheric coupling during and after the August 2021 Mw 7.2 Haiti earthquake, illustrating that large seismic events can be associated with disturbances extending into the magnetosphere. In the opposite causal direction, Ouzounov and Khachikyan (2024) examined global earthquake occurrence following the March 2013 and 2015 St. Patrick's Day geomagnetic storms and reported a delayed increase in seismicity in high-stress tectonic zones, a claim that, if robust, would itself complicate the interpretation of many reported pre-seismic ionospheric anomalies, since a storm-driven ionospheric disturbance and a subsequently triggered earthquake could otherwise be misread as a seismogenic precursor. Gulyaeva (2023) took a complementary approach, examining earthquakes that occurred during geomagnetically quiet, spotless-Sun intervals and reporting a decline in standard geomagnetic and ionospheric indices at the earthquake epoch. This design is a genuine attempt at confounder control, but the population of usable spotless-Sun earthquake cases is necessarily small, and a single study of this kind should be treated as suggestive rather than as establishing the independence of the seismic ionospheric signature from space weather in general.

Machine Learning Approaches to Anomaly Discrimination

The scale and dimensionality of multi-instrument atmospheric and ionospheric datasets has motivated growing use of machine learning (ML) for precursor identification. Draz *et al.* (2023) applied deep learning to multi-parametric atmospheric and ionospheric data associated with the 2021 Mw 7.1 Japan earthquake, while random-forest classifiers have been used to identify tectonic unrest from patterns of abnormal low-magnitude seismicity in the months preceding large events (Girona & Drymoni, 2024). Cano-Domingo *et al.* (2023) applied ML methods to characterize the relationship between Schumann Resonance frequency and ionospheric state on an hourly basis. These studies report improved discrimination relative to fixed-threshold statistical methods, consistent with the general expectation that

non-linear, multi-variable models can capture structure that univariate thresholds miss.

At the same time, the application of ML in this domain carries risks that are not always addressed in the reviewed literature: training and test data drawn from the same limited set of known earthquakes risk optimistic performance estimates through data leakage; class imbalance (few confirmed precursor events versus many non-events) can inflate apparent accuracy while masking a high false-positive rate in prospective use; and deep models are frequently reported with limited interpretability, making it difficult to determine whether a classifier has learned a physically meaningful seismogenic signature or a dataset-specific artifact, such as a particular ground station's noise characteristics or a seasonal bias correlated by coincidence with the earthquake catalogue used for training. Among the ML-based studies examined in this review (Draz *et al.*, 2023; Cano-Domingo *et al.*, 2023; Girona & Drymoni, 2024), none reports, in its published text, performance on a genuinely prospective, out-of-sample test spanning a period and

region not used in model development. This statement is confined to these three studies: Zhang *et al.* (2025) is a review of deep-learning ionospheric modelling and was not appraised as a precursor-validation study, and the statement should not be extended to the wider ML literature.

Synthesis of Representative Recent Observational Studies

Table 1 summarizes six representative studies discussed above, selected from those meeting the set out eligibility criteria so as to span TEC/thermal, VLF/HF, acoustic-gravity-wave, magnetospheric, and machine-learning approaches. It is intended as an orientation to the recent literature rather than an exhaustive catalogue, and is restricted to studies for which the seismic event, data sources, and central finding could be stated unambiguously. Table 2 appraises the same studies against the criteria in the evidence appraisal framework and separates observational association from demonstrated mechanism.

Table 1: Representative recent studies of ionospheric and atmospheric earthquake precursors

Authors / Year	Seismic Event	Parameters / Data Sources	Key Findings
Chernogor <i>et al.</i> (2023)	2019 Mw 6.0 Japan EQ	Oblique HF radio sounding	Propagation-channel distortions detected 845–2,260 km from the epicenter.
Simha <i>et al.</i> (2024)	2015 Mw 7.8 & 7.3 Nepal EQs	GNSS VTEC, OLR, VTG	Thermal atmospheric anomalies temporally correlated with subsequent VTEC disturbances.
Politis <i>et al.</i> (2023)	2021 north-central Greece EQs	Sub-ionospheric VLF propagation	Precursory D-region anomalies identified via multi-method VLF analysis.
Draz <i>et al.</i> (2023)	2021 Mw 7.1 Japan EQ	Multi-sensor atmospheric/ionospheric data	Deep machine learning applied to candidate precursor identification and validation.
Chen <i>et al.</i> (2023)	2016 Kumamoto EQ	Vertical ground motion (slant gauge), NmF2	Spectral correlation consistent with IGW excitation by pre-seismic ground motion; no confirmed Kp-index influence.
D'Angelo <i>et al.</i> (2022)	2021 Mw 7.2 Haiti EQ	Magnetospheric/ionospheric parameters	Magnetospheric–ionospheric disturbances reported in association with the main shock (co-seismic and post-seismic); coupling inferred rather than independently demonstrated.

Table 2: Appraisal of the studies in Table 1 against the evidence criteria

Study	Control period	Geomagnetic meteorological adjustment	/ Anomaly threshold	False-positive evaluation	Validation type	Evidence category
Chernogor <i>et al.</i> (2023)	Not stated	Not stated	Not stated	Not reported	Retrospective, single event	Observational association
Simha <i>et al.</i> (2024)	Not stated	Not stated	Not stated	Not reported	Retrospective, two events	Observational association (temporal sequence only; mechanism proposed, not demonstrated)
Politis <i>et al.</i> (2023)	Not stated	Not stated	Not stated	Not reported	Retrospective, event sequence	Observational association
Draz <i>et al.</i> (2023)	Not stated	Not stated	Model-derived (ML)	Not reported	Retrospective, single event	Observational association (ML-based)
Chen <i>et al.</i> (2023)	Not stated	Kp-index tested; no influence confirmed	Spectral correlation; ground-motion period < 5 h	Not reported	Retrospective, single event	Controlled association (partial); IGW mechanism hypothesized, not demonstrated
D'Angelo <i>et al.</i> (2022)	Not stated	Not stated	Not stated	Not reported	Retrospective, single event (co-/post-seismic)	Observational association

Note. “Not stated” / “Not reported”: the item was not identified in the study as summarized in this review. Observational association = anomaly coincident with a known earthquake without the controls in Evidence-Appraisal Framework; controlled association = association tested against a baseline period and at least one confounder; demonstrated mechanism = quantitative, tested physical link (not assigned to any study here).

What Each Measurement Can and Cannot Establish

The studies appraised above support three kinds of claim that are often conflated: retrospective detection (an anomaly can be found in a window chosen after the earthquake), causal attribution (the anomaly is produced by seismogenic processes rather than by other drivers), and prospective forecasting (an anomaly defined in advance predicts a future earthquake with quantified skill). Evidence of one kind does not entail evidence of the next, and the appraisal in Table 2 supports the first kind only.

GNSS TEC, together with OLR and vertical temperature gradient data, can establish that a regional departure from a reference level occurred in a given window and can indicate its timing relative to a thermal change (Simha *et al.*, 2024; Endeshaw, 2024). These measurements cannot, on their own, establish a seismogenic source, because the same metrics respond to geomagnetic and meteorological forcing, nor can they yield a false-positive rate without a population of non-seismic control dates. A thermal-then-ionospheric sequence is compatible with the proposed LAIC chain but equally compatible with a common meteorological driver.

Sub-ionospheric VLF and oblique HF sounding can establish that a propagation path was perturbed and, through the path geometry, approximately where

(Boudjada *et al.*, 2024; Politis *et al.*, 2023; Chernogor *et al.*, 2023). They cannot separate seismogenic perturbations from those caused by lower-atmospheric weather, sporadic-E layers, or solar X-ray flux without concurrent measurements of those drivers, and a single transmitter–receiver path samples only a limited region. Schumann Resonance characteristics (Cano-Domingo *et al.*, 2023) provide a coarse global indicator that cannot localize a source.

Mechanism-oriented studies differ in what they can show. The ground-motion and ionosonde comparison of Chen *et al.* (2023) can show spectral coincidence and, importantly, the failure to confirm one confounder, but not that ground motion drove the ionospheric response. Groundwater radon records (Alam *et al.*, 2023) can show geochemical variability before an earthquake but do not by themselves show boundary-layer ionization or an ionospheric consequence. Machine-learning classifiers (Draz *et al.*, 2023) can improve retrospective discrimination but, without testing on data withheld in time and space, establish neither attribution nor forecasting skill. Taken together, the evidence supports retrospective detection in selected cases, offers limited and indirect support for attribution, and does not at present demonstrate prospective forecasting skill.

Critical Assessment: Methodological Limitations and Open Challenges

Case-Study Design and Selection Bias

The great majority of the literature reviewed above, including most entries in Table 1, is structured as a retrospective case study of a single, already-known large earthquake. Anomalies are identified by inspecting data in a window chosen because a major event is known to have occurred within or shortly after it. This design is vulnerable to selection and confirmation bias: because the analysis window is defined with foreknowledge of the event, and because negative results (no anomaly before a given large earthquake, or an anomaly not followed by an earthquake) are rarely reported with the same visibility as positive detections, the published record likely overstates the reliability of any given precursor signature.

Confounding by Space Weather and Meteorology

Every observational technique reviewed here, TEC, VLF/HF propagation, and thermal anomaly detection, is also sensitive to geomagnetic activity, solar flares, and lower-atmospheric weather, each of which varies on timescales that can coincide with a pre-seismic window by chance. Some studies address this directly, for example by restricting analysis to geomagnetically quiet or spotless-Sun periods (Gulyaeva, 2023) or by explicitly testing for a Kp-index relationship (Chen *et al.*, 2023). Most, however, report ionospheric or atmospheric conditions during the study window as broadly quiet without a quantitative comparison to the natural variability of the anomaly metric under non-seismic quiet conditions at the same site and season.

Anomaly Definition, Reproducibility, and False-Positive Rates

There is no field-wide standard for what constitutes a significant TEC, VLF, HF, or thermal anomaly; thresholds (commonly expressed as a multiple of a running mean or standard deviation) vary across studies, stations, and even within a single study across different earthquakes. This heterogeneity makes cross-study comparison difficult and makes it effectively impossible, from the published literature alone, to estimate a genuine false-positive rate, that is, how often an anomaly of the reported magnitude occurs without a subsequent large earthquake. Without this figure, claims of precursory significance cannot be distinguished from claims of retrospective pattern-matching, however physically plausible the proposed coupling mechanism.

Machine Learning: Interpretability, Overfitting, and Prospective Validation

The turn toward deep learning and other ML methods is a reasonable response to the multi-parametric, high-dimensional nature of the data, but it does not by itself

resolve the confounding and reproducibility issues above and can compound them if training and evaluation are performed on the same limited catalogue of known events. To be credible as a forecasting tool rather than a sophisticated pattern-description exercise, an ML-based precursor system needs to demonstrate performance on data withheld in time and space from model development, report calibrated false-positive and false-negative rates over a realistic operational baseline, and, where feasible, provide some interpretability linking learned features to the physical mechanisms proposed earlier.

CONCLUSION

Multi-parametric observations across GNSS TEC, VLF/HF radio propagation, and thermal atmospheric channels have been reported to coincide with ionospheric disturbance in the days preceding some large earthquakes, and the proposed mechanical, geochemical, and electromagnetic LAIC pathways offer physically motivated, but largely untested, explanations for how such coupling could occur. These reports are, however, heterogeneous in method and predominantly uncontrolled, retrospective, single-event studies (Table 2); they support retrospective detection in selected cases rather than a consistent picture across techniques. The evidentiary basis for treating these disturbances as reliable, causally seismogenic precursors, rather than a mixture of genuine coupling and coincidental space-weather variability identified through retroactive case selection, remains incomplete for most of the literature reviewed here. Deep machine learning is a promising tool for isolating candidate signals within large multi-instrument datasets, but its value for forecasting has not yet been demonstrated under prospective, out-of-sample conditions. On the present evidence, ionospheric and atmospheric precursors cannot be regarded as a basis for operational earthquake forecasting or early warning. These conclusions are subject to the limitations of the review itself: its narrative design, its 2020–2026 window, and a qualitative evidence appraisal that depends on what each study reports in its published text.

RECOMMENDATIONS

On the basis of the critical assessment, four directions appear necessary for the field to move from a body of suggestive case studies toward a testable forecasting capability. First, anomaly thresholds and analysis windows should be fixed in advance of, not after, knowledge of subsequent seismicity, and applied uniformly to matched non-seismic control periods at the same stations. Second, studies that find no ionospheric anomaly before a large earthquake, or an anomaly not followed by one, carry as much diagnostic value as positive detections and should be reported with comparable prominence. Third, geomagnetic, solar, and

meteorological conditions should be characterized quantitatively for every case study, with explicit statistical testing of their contribution to the observed anomaly rather than a qualitative description of conditions as “quiet”. Fourth, machine-learning models should be evaluated on data withheld in time and geography from training, with false-positive and false-negative rates reported over a realistic multi-year baseline, before being characterized as forecasting tools. Progress will depend less on additional single-event case studies and more on prospective, statistically rigorous designs that report false-positive rates, quantify space-weather confounding, and validate machine-learning models outside the catalogue used to build them.

REFERENCES

- Alam, A., Nikolopoulos, D., & Wang, N. (2023). Fractal patterns in groundwater radon disturbances prior to the great 7.9 Mw Wenchuan earthquake, China. *Geosciences*, 13(9), 268. <https://doi.org/10.3390/geosciences13090268>
- Boudjada, M. Y., Biagi, P. F., Eichelberger, H. U., Nico, G., Galopeau, P. H. M., Ermini, A., Solovieva, M., Hayakawa, M., Lammer, H., Voller, W., & Pitterle, M. (2024). Analysis of pre-seismic ionospheric disturbances prior to 2020 Croatian earthquakes. *Remote Sensing*, 16(3), 529. <https://doi.org/10.3390/rs16030529>
- Cano-Domingo, C., Stoean, R., Joya, G., Novas, N., Fernandez-Ros, M., & Gazquez, J. A. (2023). A machine learning hourly analysis on the relation between the ionosphere and Schumann Resonance frequency. *Measurement*, 208, 112426. <https://doi.org/10.1016/j.measurement.2023.112426>
- Chen, C. H., Oyama, K., Jhuang, H. K., & Das, U. (2023). Driving source of change for ionosphere before large earthquake vertical ground motion. *Remote Sensing*, 15(18), 4556. <https://doi.org/10.3390/rs15184556>
- Chernogor, L. F., Garmash, K. P., Guo, Q., Rozumenko, V. T., & Zheng, Y. (2023). Perturbations in the characteristics of ionospheric HF radio waves during the April 11, 2019, earthquake in Japan: Results from oblique sounding. *Advances in Space Research*, 72(5), 1688–1702. <https://doi.org/10.1016/j.asr.2023.04.053>
- Colonna, R., Nayak, K., Sharma, G., & Romero-Andrade, R. (2026). Evaluation of seismo-ionospheric and seismological parameters within the lithosphere–atmosphere–ionosphere coupling framework for the 2025 Mw 7.7 Myanmar earthquake. *Remote Sensing*, 18(7), 1016. <https://doi.org/10.3390/rs18071016>
- D'Angelo, G., Piersanti, M., Battiston, R., Bertello, I., Carbone, V., Cicone, A., Diego, P., Papini, E., Parmentier, A., Picozza, P., Recchiuti, D., Sparvoli, R., & Ubertini, P. (2022). Haiti earthquake (Mw 7.2): Magnetospheric–ionospheric–lithospheric coupling during and after the main shock on 14 August 2021. *Remote Sensing*, 14(21), 5340. <https://doi.org/10.3390/rs14215340>
- Draz, M. U., Shah, M., Jamjareegulgarn, P., Shahzad, R., Hasan, A. M., & Ghamry, N. A. (2023). Deep machine learning based possible atmospheric and ionospheric precursors of the 2021 Mw 7.1 Japan earthquake. *Remote Sensing*, 15(7), 1904. <https://doi.org/10.3390/rs15071904>
- Endeshaw, L. (2024). Investigation of atmospheric anomalies due to the great Tohoku earthquake disturbance using NRLMSISE-00 atmospheric model measurement. *Pure and Applied Geophysics*, 181(5), 1455–1478. <https://doi.org/10.1007/s00024-024-03476-2>
- Girona, T., & Drymoni, K. (2024). Abnormal low-magnitude seismicity preceding large-magnitude earthquakes. *Nature Communications*, 15(1), 7429. <https://doi.org/10.1038/s41467-024-51596-z>
- Gulyaeva, T. L. (2023). Decline of geomagnetic and ionospheric activity at earthquake during spotless Sun. *Advances in Space Research*, 71(1), 306–315. <https://doi.org/10.1016/j.asr.2022.10.069>
- Li, W., Yang, F., Li, L., Zhao, D., Zhang, K., Zuo, X., & Pan, X. (2026). Lithosphere–atmosphere–ionosphere coupling: Opportunities and challenges from phenomenon observation to physical prediction. *IEEE Geoscience and Remote Sensing Magazine*. <https://doi.org/10.1109/MGRS.2026.3714896>
- Ouzounov, D., & Khachikyan, G. (2024). Study the global earthquake patterns that follow the St. Patrick's Day geomagnetic storms of 2013 and 2015. *Remote Sensing*, 16(14), 2544. <https://doi.org/10.3390/rs16142544>
- Pilipenko, V. A., & Surkov, V. V. (2025). Seismoelectromagnetic and seismoionospheric phenomena: From the pioneering works of G. A. Sobolev to present. *Izvestiya, Physics of the Solid Earth*, 61(4), 609–625. <https://doi.org/10.1134/S1069351325700557>
- Politis, D. Z., Potirakis, S. M., Contoyiannis, Y., Potamitis, I., Sasmal, S., Yang, S. S., & Hayakawa, M. (2023). Lower-ionosphere anomalies prior to strong earthquakes that occurred in north-central mainland Greece on March 2021 as revealed by multi-method analysis of VLF sub-ionospheric propagation data. *Annals of Geophysics*, 66(6), SE645. <https://doi.org/10.4401/ag-8986>

Pulinets, S., Ouzounov, D., Karelin, A., & Boyarchuk, K. (2022). *Earthquake precursors in the atmosphere and ionosphere: New concepts*. Springer Nature.

Sasmal, S., Nanda, K., Hayakawa, M., Solovieva, M., Kopylova, G., & Potirakis, S. M. (2025). Towards understanding earthquake preparatory dynamics: A multi-parametric investigation of the 2025 Kamchatka Mw 8.8 event. *Atmosphere*, 16(12), 1328. <https://doi.org/10.3390/atmos16121328>

Simha, C. P., Rao, K. M., & Dumka, R. K. (2024). Observation of atmospheric and ionospheric anomalies before the Nepal earthquakes on 25th April and 12th May 2015. *Geotectonics*, 58(2), 234–249. <https://doi.org/10.1134/S0016852124700158>

Tan, Q., Shen, C., Wang, J., Yang, X., Jin, W., Zhang, M., & Yang, G. (2025). Dynamic changes of gravity field before the Luding MS6.8 earthquake and its crustal material migration characteristics. *Geodesy and Geodynamics*, 16(2), 214–222. <https://doi.org/10.1016/j.geog.2024.09.006>

Zhang, R., Li, H., Shen, Y., Yang, J., Li, W., Zhao, D., & Hu, A. (2025). Deep learning applications in ionospheric modeling: Progress, challenges, and opportunities. *Remote Sensing*, 17(1), 124. <https://doi.org/10.3390/rs17010124>

Zhu, F., Yang, J., Qing, Y., & Li, X. (2023). Assessment and analysis of the global ionosphere maps over China based on CMONOC GNSS data. *Frontiers in Earth Science*, 11, 1095754. <https://doi.org/10.3389/feart.2023.1095754>