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Review

New Ways to Modelling and Predicting Ionosphere Variables

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Abstract: The new way of thinking science from Newtonian determinism to nonlinear unpredictability and the dawn of advanced computer science and technology can be summarized in the words of the theoretical physicist Michel Baranger, who, in 2000, said in a conference: "Twenty-first-century theoretical physics is coming out of the chaos revolution; it will be about complexity and its principal tool will be the computer.". This can be extended to natural sciences in general. Modelling and predicting ionosphere variables have been considered since many decades as a paramount objective of research by scientists and engineers. The new approach to natural sciences influenced also ionosphere research. Ionosphere as a part of the solar–terrestrial environment is recognized to be a complex chaotic system, and its study under this new way of thinking should become an important area of ionospheric research. After discussing the new context, this paper will try to review recent advances in the exploration of ionosphere parameter time series in terms of chaos theory and the use of machine-learning algorithms.

Keywords: ionosphere; modelling; complex systems; chaos theory; machine learning

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1. Introduction

1.1. About Linear and Complex Systems

In April 2000, the French-US theoretical physicist Michel Baranger gave a "physics talk for non-physicists" on chaos, complexity, and entropy at the New England Complex Systems Institute of Cambridge, Massachusetts [1]. In his initial words, he said, "Twentieth-century theoretical physics came out of the relativistic revolution and the quantum mechanical revolution. It was all about simplicity and continuity (in spite of quantum jumps). Its principal tool was calculus. Its final expression was field theory. Twenty-first century theoretical physics is coming out of the chaos revolution. It will be about complexity and its principal tool will be the computer. Its final expression remains to be found.". I am convinced that we can extend his scientific vision about the 21st century by saying that "In the 21st century, natural sciences, including space and earth sciences, will benefit from the chaos revolution, will deal with complexity, and will have as means machine-learning tools.". In essence, natural sciences have to shift from a "linear approach" to a "complex approach". I will try to support my statement in what follows.

To start, I would like to clarify the meaning of some words. The "solar–terrestrial physics" phrase has been replaced in the last few decades by "space weather". This was carried out to make the subject more appealing to the public and politicians and also to stress the effect of solar–terrestrial physics on technology. However, space weather should be considered just a part of solar–terrestrial physics, recognizing that it is the "star" of this field. In this paper, "solar–terrestrial environment" will be used referring to the physical region where the solar system interacts with the earth system of systems.

All physical sciences of the 20th century, including relativity and quantum mechanics, were based on "calculus" introduced by Newton and Leibnitz, by itself a key example of linear approach. Space and earth system sciences are data-driven, and they always had to rely on time series of observations of specific variables intrinsically not repeatable. Their time variations were analyzed, modelled, and forecasted on the basis of the model adopted.

Models were grounded for a long time on linear approaches not only following Newton's and Leibnitz's "calculus" but also because of the reduced number of data available.

A linear system has a fixed proportional relationship between the input and output; it is predictable and stable. In addition, the relationship between variables x and y can be graphically represented by a straight line. The linear modelling efforts to explain the variability of data time series played an important role in understanding the basic behavior of natural phenomena. However, most natural processes are nonlinear, and, thus, linear models can only approximate real-world systems to a certain extent. A typical linear system approach is given by the Maxwell equations.

The advancement of experimental data sources, their increase in number, and particularly the advent of the space era and the enormous amount of space and ground data now available completely changed the perspective of solar–terrestrial physics/space weather. We have understood that a linear approach cannot deal anymore with what this amount of data is revealing. It now becomes evident that the solar–terrestrial system is a complex system of interacting complex systems. Ionosphere is one of such complex systems.

1.2. About Complex Systems and Chaos

One of the characteristics of a complex system is its nonlinearity, and its modelling shows nonlinear relationships between inputs and outputs, as well as chaotic behavior often present in natural systems. When we say that a certain system "exhibits chaos", it means that the system obeys deterministic time evolution, but that the outcome is highly sensitive to small uncertainties in the specification of the initial conditions, as indicated in the pioneering work of Lorenz (1963) [2]. In terms of predictability of the time evolution of a certain variable, it says that, after some time, we are not able to usefully predict such evolution anymore.

A way to quantify the presence and degree of chaos in a complex system is to measure its correlation dimension (D_2) and the Kolmogorov entropy (K_2) (Abarbanel and Parlitz, 2006) [3], which can be calculated with the method given by Grassberger and Procaccia (1983a) [4].

The correlation dimension D_2 is a non-integer value and gives a lower limit of the number of independent variables or the degree of freedom of the system. It indicates the minimum number of differential equations needed to fully describe the system itself. A value of $K_2 = 0$ indicates a fully predictable evolution of the system, a finite $K_2 > 0$ indicates a chaotic system, and a value $K_2 = \infty$ indicates a fully stochastic system. An estimate of time predictability of a system variable is given by $1/K_2$. Some other relevant references about chaos theory and its application to geophysics are Grassberger and Procaccia (1983b) [5], Zeng (1992) [6], and Vassiliadis et al. (1990) [7]. Figure 1 shows in a simple way the relation between the dimension of a complex system and its predictability.

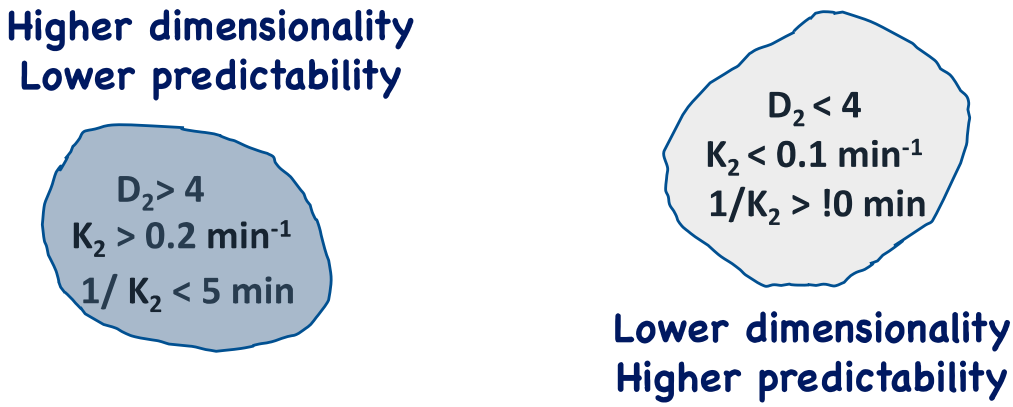

Figure 1. Relationship between complex system dimension and its predictability. (Adapted from Consolini et al. 2018 [8]).

1.3. Solar–Terrestrial Physics/Space Weather and Chaos

Time series of observable variable data, processing of such data, modelling, and prediction are the essential steps of solar–terrestrial physics/space weather, including ionosphere research.

Let us assume that all the systems involved in the solar–terrestrial environment are complex. It is important to investigate if these complex systems exhibit chaotic behavior. This can be performed in terms of the correlation dimension and the Kolmogorov entropy mentioned above.

Considering that all the systems of the complex solar–terrestrial system are mutually interacting as indicated in Figure 2, those that are going to be analyzed in the discussion that follows are indicated in orange.

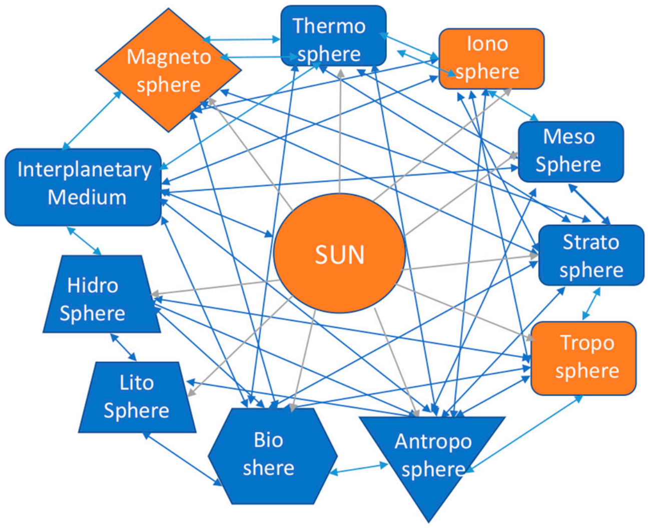

Figure 2. The assumed complex solar–terrestrial system of interacting complex systems (both blue and orange). In orange are those systems that are going to be considered in the text discussion. Light grey arrows indicate that the Sun act on all the other systems and blue arrows indicates that all the other systems may act among them.

Several authors investigated the chaos characteristics of the solar–terrestrial systems shown in orange in Figure 2 using different chaos indicators. Those shown in orange used the D_2 and K_2 indicators. Table 1 presents the results of such investigations.

Table 1. Solar–terrestrial systems investigated using D_2 and K_2 indicators of chaos. Asterisk indicates that the referenced paper uses a different denomination for the correlation dimension and Kolmogorov entropy.

System	Parameter	D_2	K_2	Authors
Sun	Radio pulsations	3.2–3.8	0.04	[9] Kurths Herzel (1987)
	F10.7	3.3–4.5	0.02–0.04	[10] Romanelli et al (1987)
	F10.7	3.5	0.07	[11] Romanelli et al. (1988)
Magnetosphere	AE	3.3	0.08	[11] Romanelli et al. (1988)
	AE	3.6	0.2	[7] Vassiliadis et al. (1990)
	AE & SYM-H	1–4	0.2–0.02	[8] Consolini et al. (2018)
Ionosphere	foF2	3.4	0.04	[11] Romanelli et al. (1988)
	TEC	2.78	0.12–0.13	[12] Materassi et al. (2023)
Troposphere	Annual mean global surface temperature (1856–1998)	1.99–3.25 *	0.137 *	[13] Gimeno et al. (2001)

These results suggest that the interacting systems shown have a similar low correlation dimension D_2 that essentially indicates that they are low-dimensional systems. This means that they can be modelled with a number of "dominant" variables around 3 ($D_2 < 4$ in Figure 1). Most of the Kolmogorov entropy K_2 values in Table 1 show $K_2 < 0.1$ to K_2 not above 0.2. These results indicate that the interacting systems of the solar–terrestrial system considered have similar chaos characteristics when D_2 and K_2 are considered. Differences found in the values reported can be related to the different time series scales considered in the different investigations.

1.4. The Advent of Machine Learning

From the start of the space era by the middle of the last century and the development of higher and higher computing capacity, the amount of solar–terrestrial environment data available increased in a remarkable speed. Data processing and modelling become a pressing challenge for researchers, and new methods of analysis have been developed. In addition to the classical approaches based on the use of physical causality models, new methods to analyze the large amount of data and predict their evolution have been developed. Machine-learning (ML) methods have emerged and became widely used in solar–terrestrial physics/space weather research (Baker, 2020) [14]. They have been applied also in a myriad of other fields of science and technology. Such fields go from life sciences (Gosh and Dasgupta, 2022) [15] to urban traffic (Genser, 2022) [16] and cybersecurity (Musser and Garriot, 2021) [17]. The difference between classical and ML approach in dealing with the solar–terrestrial environment is indicated in Figure 3.

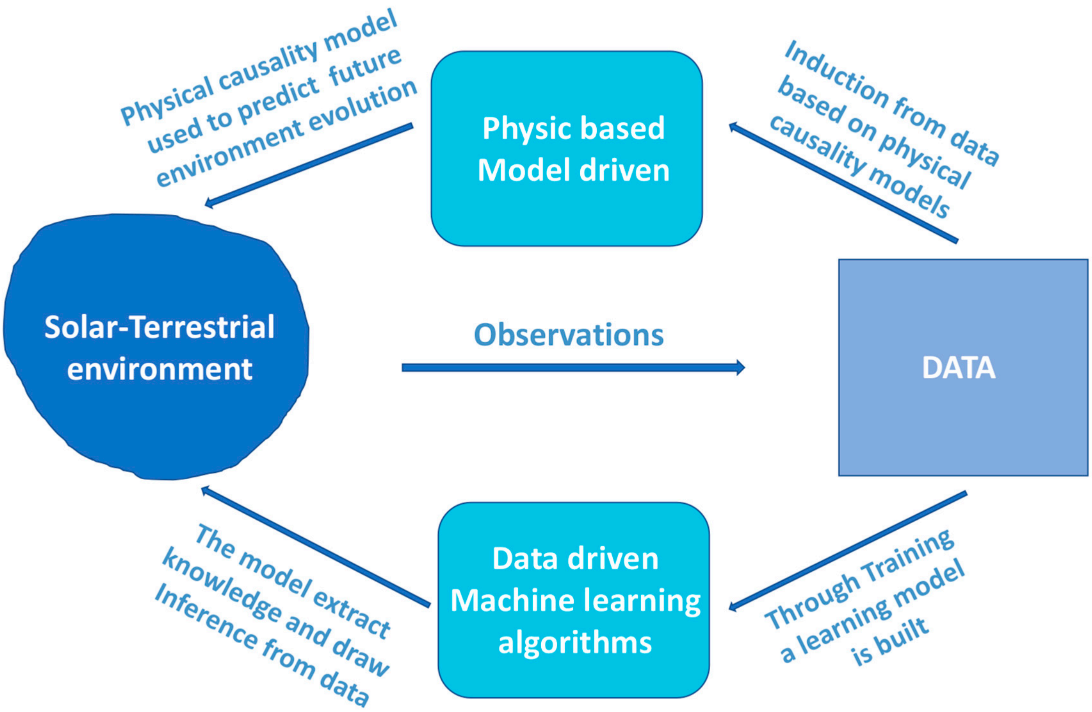

Figure 3. The physics-based model-driven approach and the data-driven ML approach to study the solar–terrestrial environment.

ML, the computer management of data and algorithms to learn without giving precise instructions (Batta, 2018) [18], is a subclass of artificial intelligence, that is, the ensemble of theory and development of computer systems able to achieve or exceed human intelligence (Brunette et al., 2009) [19]. The core of ML is deep learning, which uses a complex ensemble of computer algorithms inspired by the human brain behavior. It derives from the more conventional neural network algorithms, but it is much more advanced (Alzubaldi et al., 2021) [20]. Neural network algorithms were introduced already in the 1950s and are designed to allow computers to recognize patterns without being explicitly programmed to do so. They are a group of interconnected nodes that resemble human neurons (Saha et al., 2023) [21]. Figure 4 shows the relationship among the different sets or classes included in what is called artificial intelligence.

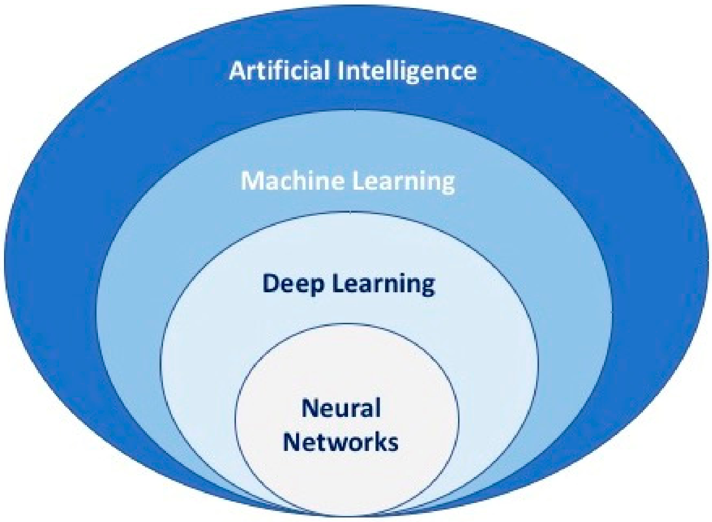

Figure 4. Setting relationship among the different sets or classes included in artificial intelligence.

1.5. The Machine-Learning "Black Box" Problem

In machine learning, predictive models can be very complicated functions of the variables. No human can understand how the variables are related to each other to reach the prediction. Such models are called "black box" models because the input and output are known, but researchers cannot fully understand how the model makes the prediction. This limitation makes it difficult in many science quarters to support the use of ML methods. They consider that the very wide use of the scientific use of ML "black box" methods is producing a "science crisis" because of the lack of reproducibility of their results. An intense discussion is going on between those scientists who defend the importance of using "black box" ML and those who reject such use. The creation of new paradigms like the combination of physics-based and ML approaches ("gray box") as introduced by Camporeale et al. (2018) [22] or the more recent interpretable ML procedure (Li et al., 2023) [23] are promising compromising solutions. These new approaches can make the "black box" more transparent and can allow a convergence of interests among those who fully support ML and those who are opposed to it. It is of interest to note that both these two papers just mentioned deal with solar–terrestrial environment problems.

2. The Need of a New Approach to Ionosphere Research

The long introduction had the intention to make clear to the young generation of scientists that the research panorama in general and particularly the one dealing with the solar–terrestrial environment has changed. It means that the research approach, including ionosphere research itself, has to change due to the advanced level of measuring capability of its variables and what it has revealed and will reveal.

For decades, ionosphere variable data like, as mere examples, foE or foF2 (and its equivalent NmF2) have been interpreted in terms of the genial and fundamental Chapman theory of ionization of atmospheric gases by solar radiation (Chapman, 1931) [24]. Very soon, temporal or spatial behavior of the ionosphere variables appeared diverging from the Chapman theory, and the departures from that theory started to be called "anomalies" and we continue to call them in the same way. Possibly the most famous ionosphere "anomaly" is the so-called equatorial ionospheric anomaly (EIA). The peculiar characteristics of the equatorial and low-latitude foF2 were found by Japanese scientists in Southeast Asia during World War II (Nishida, 2010) [25]. A short Letter to the Editor of *Nature* by E. V.

Appleton (Appleton, 1946) [26] described the characteristics of the equatorial and low-latitude ionosphere foF2, which was later called the equatorial ionospheric anomaly. The name, which remains to this day, describes the actual behavior of the low-latitude and equatorial ionosphere. It is known that the low-latitude F region is strongly controlled by the geomagnetic field and E region equatorial Electrojet variations in a complex way (Balan et al., 2018) [27]. This behavior is a good example of the complexity of the ionosphere system that interacts with other components of a more complex system, the earth system.

Limiting this discussion to the F2 layer, there are other well-known "anomalies" that reflect the complexity of the ionosphere system. Some of them are the "winter anomaly", the "seasonal anomaly", the "annual anomaly", and the "semi-annual anomaly" (Rishbeth, 1998, Rishbeth and Mendillo, 2001; Yu et al., 2004) [28–30]. To give an explanation for the departures from the Chapman layer theory, it was necessary to accept the fact that other components of a larger complex system are interacting with the ionosphere system. Some of these interactions have been discovered and are studied like the interactions with the sun, the magnetosphere, the thermosphere, the stratosphere, and the troposphere. Other interactions may be found in the future. It shows that what we continue to call "anomalies" are just the behavior of the real ionosphere. It reveals the complexity of the interaction between the atmosphere plasma with other elements of the complex solar–terrestrial environment.

The continued use of the term "anomaly" when data show regular departures from the basic Chapman theory tells the fact that scientists are reluctant to abandon the linear approach. This approach is based on a form of reductionism: the reduction of a system to simpler parts that appear to be easier to analyze in detail. Reductionism approach has been very successful to understand basic natural phenomena and also the basic behavior of the ionosphere, and it was a logical manner to start research. For a more in-depth discussion about reductionism, complexity, and chaos, I suggest the reader of this article to refer to the book by Chibbaro et al. (2014) [31]. However, it is now evident that all the natural sciences, including solar–terrestrial physics/space weather, deal with complex nonlinear systems that require a change of approach.

3. An Overview on Ionosphere Variability

The multifaceted variability of the ionosphere due to the fact that it is a complex system interacting with complex systems is summarized in Figure 5.

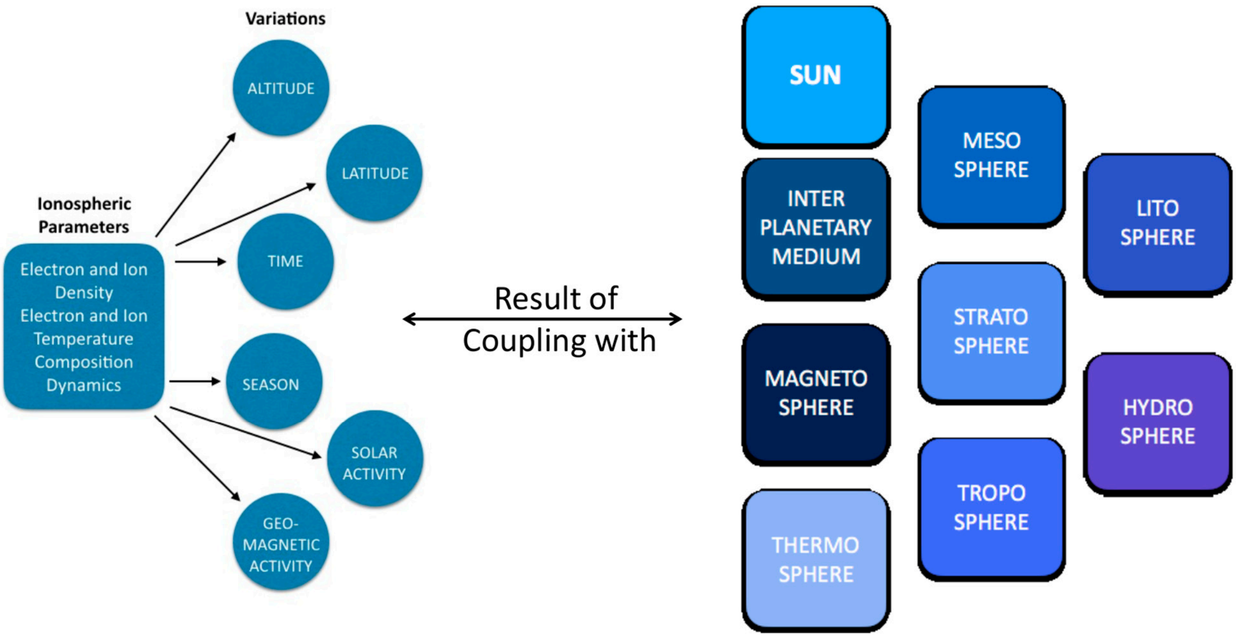

Figure 5. Ionospheric variation result of interactions with other complex systems.

Before reviewing research carried out on the chaotic characteristics of some of the basic ionosphere parameter time series data, and the use of ML methods to study them, the issue of their variability needs to be briefly considered. The parameters chosen are the ionosphere peak electron density NmF2 (measured by different experimental means) and the total electron content (TEC). Their day-to-day variability that essentially represents the "ionospheric weather", an important part of solar–terrestrial physics/space weather, requires particular attention due to the need to model and forecast such variability also for technology applications. The discussion that follows will be based on the day-to-day variability of NmF2 and TEC.

Following Mendillo (2020) [32] and the method developed by Rishbeth and Mendillo (2001) [29], three main sources of the day-to-day variability σ_{total} of NmF2 can be identified, where σ_{total} is the standard deviation of NmF2 daily values within every month. These are changes of ionizing photon solar radiation σ_{sun}, solar-wind-induced geomagnetic activity σ_{mag}, and meteorological coupling from the troposphere σ_{met}. Our chosen groups of years can be written as

$$[\sigma_{total}]^2 = [\sigma_{sun}]^2 + [\sigma_{mag}]^2 + [\sigma_{met}]^2$$

Under nominal conditions (in the absence of solar or geomagnetic events), Mendillo (2020) [32] considers that the total variability and contribution of each component of this variability in percentage (see the equation above) is

$$[20\text{–}25\%]^2 = [3\text{–}6\%]^2 + [14\text{–}17\%]^2 + [14\text{–}17\%]^2$$

He concludes that the influence of ionizing photon solar radiation is minimal in comparison with solar wind magnetospheric sources and tropospheric sources, with the latter two being comparable. The same author considers that the results for NmF2 are also valid for the day-to-day variability of the TEC.

A very detailed and exhaustive analysis of the state of the art about the ionosphere–thermosphere (IT) complex system day-to-day variability is given by Liu et al. (2021) [33]. According to Mendillo (2020) [32], the results of these authors confirm that the main sources of variability are the ionizing solar photon radiation, the solar wind/geomagnetic activity, and the upward effect of tropospheric activity. They review past research results and identify also a series of issues about day-to-day variability that need future research efforts. The first two of these, which are, I quote, "(1) How to systematically quantify day-to-day variability of the global IT system, (2) how does the day-to-day variability in key IT parameters change in space and evolves with time", are considered of particular importance. To be able to make possible these efforts, an important paper by Tsagouri et al. (2023) [34] describes the present status of the availability of relevant data to investigate ionosphere variability. It stresses also the need for an interdisciplinary and international approach to connect all the available data sources recognizing the progress already reached in this direction.

4. Chaos Theory and the Ionosphere

The analysis that follows will be centered on those studies that treat time series data of foF2 and TEC in terms of correlation dimension. Possible convergent or divergent results from different authors using diverse time series lengths and sampling rates will be evidenced in Tables 2 and 3.

Regarding foF2 data, I found only two papers analyzing the chaos characteristics of the time series. As shown in Table 2, the first study reporting the existence of a low dimension in an foF2 data series was the one of Romanelli et al. (1988). These authors used a time series of hourly values of foF2 obtained at Argentine Island (65.25° S, 64.27° W) for the years 1977–1978. A recent paper by Mendez (2022) [35] reports the study of chaos characteristics obtained from two foF2 time series obtained at Juliusruh (54.6° N 13.4° E) from 1 November 1987 to 10 February 1988 and from 1 November 2002 to 10 February 2003.

Table 2. Correlation dimension of the deterministic chaos found in foF2 time series by two different authors under different conditions. Geomagnetic activity not specified.

Latitude	Solar Activity (F10.7)	Geomagnetic Activity	foF2 Time Series Length	foF2 Sampling Rate	D	Authors
High	Low	---	2 years	1 h	3.4	Romanelli et al., 1988 [11]
Middle high	Low	---	83 days	1 h	3.0	Mendez, 2022 [35]
Middle high	Low	---	83 days	1 h	3.3	Mendez, 2022 [35]

The large amount of TEC now available has allowed the study of the chaoticity of this ionosphere parameter by several authors.

Kumar et al. (2004) [36] reported the chaotic behavior of time series of TEC at a 15 min sampling rate at Goose Bay (47° N, 286° E) during the period February to April of the solar minimum year 1976. The TEC was measured by Faraday rotation technique using the trans-ionosphere signal from the satellite GOES-2.

Unnikrishnan (2010) [37] analyzed the chaos characteristics of GNSS-derived TEC data from three stations located at the low-latitude ionosphere crests and trough of the so-called EIA: Agatti, 10.75° N, 72.5° E (trough); Mumbai, 18.5° N, 78.5° E (near Southern crest); and Jodhpur, 26.3° N, 77° E (near Northern crest). TEC time series data used were taken at a 1 min sampling rate for four days: 7–10 June 2005 (geomagnetically quiet period) and 11–14 June 2005 (geomagnetically disturbed period).

Ogunsua et al. (2013) [38] were looking for the chaoticity of TEC time series measured at a 1 min sampling rate for the period January to December 2011 from three different stations, namely Birnin Kebbi (12.53° N, 4.2° E), Enugu (6.43° N, 7.5° E), and Lagos (6.45° N, 3.38° E).

Eapen et al. (2018) [39] reported their results on the search for TEC time series chaoticity using data from the MIT Madrigal database. They selected one location each from the low latitude, (28° N and 82° W), midlatitude, (40° N and 119° W), and high latitude (60° N and 150° W) for the period from 1 January to 30 April of the solar minimum year 2008. The sampling rate was 5 min.

Materassi et al. (2023) [12] analyzed two year-long TEC time series from the location of Matera (40.65° N, 16.70° E) that corresponded to the years 2001 (high solar activity) and 2008 (low solar activity) searching for chaos signatures. The sampling rate of the TEC was 50 s.

These references were chosen because, in all of them, the correlation dimension is calculated. As indicated in the introduction, the correlation dimension is a good indicator of the type of chaoticity found in an experimental time series. Table 2 summarizes their results in terms of correlation dimension (D). It is organized by the latitude of the location considered and solar activity and by considering the geomagnetic activity also. The intention is to see if the results of different authors and calculation techniques, using the distinct length of the time series and data sampling rates, show a consistent picture.

From the papers mentioned and the data reported in Tables 2 and 3, some conclusions can be obtained. All the authors mentioned in these tables coincide in affirming that the time series analyzed (of different size and sampling rates) show the existence of low-dimensional deterministic chaos. In other words, it should be possible to model and predict the evolution of such time series with a limited number of nonlinear differential equations. Based on the reported values of correlation dimension, it does not appear that such values indicate clear patterns in terms of latitude or solar or geomagnetic activity. The main reason can be the variety of calculation techniques used or the size and sampling rate of the time series analyzed. This suggests that the use of uniform time series data in terms of size and sampling rate, now available thanks to the available databases (see Tsagouri et al., 2023), can determine if the ionosphere chaoticity depends on location or solar and geomagnetic activity or other interacting systems.

Table 3. Correlation dimension of the deterministic chaos found in TEC time series by different authors under different conditions. The asterisk means that the values are the averages of those shown in Tables 1 and 2 of the paper mentioned (Eapen et al., 2018). "---" indicate that the geomagnetic activity is not specified.

Latitude	Solar Activity (F10.7)	Geomagnetic Activity	TEC Time Series Length	TEC Sampling Rate	D	Authors
Low	Low	Quiet	4 days	1 min	2.23–2.74	Unnikrishnan (2010) [37]
Low	Low	Disturbed	4 days	1 min	3.37	Unnikrishnan (2010) [37]
Low	Low	Monthly 5 quiet days	1 year	1 min	3.5	Ogunsua (2013) [38]
Low	Low	Monthly 5 disturbed days	1 year	1 min	2.8	Ogunsua (2013) [38]
Low	Low	Quiet	4 months	5 min	4.61 *	Eapen et al. (2018) [39]
Low	Low	Disturbed	4 months	5 min	3.74 *	Eapen et al. (2018) [39]
Middle	Low	Quiet	4 months	5 min	4.63 *	Eapen et al. (2018) [39]
Middle	Low	Disturbed	4 months	5 min	3.81 *	Eapen et al. (2018) [39]
Middle	Low	---	1 year	1 min	2.78	Materassi et al. (2023) [12]
Middle	High	---	1 year	1 min	2.78	Materassi et al. (2023) [12]
High	Low	Two intense storms in the period	3 months (February–April)	15 min	5.63	Kumar et al. (2004) [36]
High	Low	Quiet	4 months	5 min	6.22 *	Eapen et al. (2018) [39]
High	Low	Disturbed	4 months	5 min	3.77 *	Eapen et al. (2018) [39]

Machine Learning and the Ionosphere

Machine learning (ML) has been increasingly applied to ionosphere time series data analysis in the past several decades to model and forecast their evolution. Research started by using artificial neural networks or, in brief, NNs. The first steps on NNs came in the 1940s, but it was in the 1980s when they evolved to what is now known about them. Between 2009 and 2012, the recurrent NNs and deep feedforward NNs were developed (Schmidhuber, 2014 [40]). Later on, NNs became the basis of what is known as deep learning (DL), a set or branch of ML. NNs are systems or hardware designed to operate in a way that imitates the work of human neurons. The simplest type of NNs is the feedforward NNs where the information moves in one direction, from the input nodes to the output nodes. The other main type of NNs is the recurrent NN that allows the output from some nodes to affect the subsequent input to the same nodes. Since the early 1990s, NNs of different type evolved to more advanced DL tools that have been used in ionosphere research with relevant success. They were performed to model and predict particularly the behavior of the TEC obtained from GNSS signals (most of them from the GPS constellation). A short list of these research activities will be mentioned below.

Cander (1998) [41] gave a review of the early use of NNs in ionosphere research particularly focused on the time series of foF2 and TEC. In her paper, she stressed the value of the NN approach to advance from a climatic specification of the ionosphere parameters to what now we call an "ionosphere weather" specification.

Tulunay et al. (2006) [42], using a feedforward NN, successfully forecasted TEC maps over Europe during a period with a strong solar–terrestrial physics event with relevant space weather effects.

Habarulema et al. (2007, 2009 and 2011) [43–45] used NNs to produce regional models of TEC for Southern Africa.

Huang and Yuan (2014) [46] used a NN to produce single-station short-term TEC forecast.

Tebabal et al. (2018) [47] presented modelling efforts of TEC for one low-latitude and one middle-latitude location using feedforward NNs, with a Bayesian regularization back-propagation algorithm. Data used were TEC times series from the years 2011 to

2014 for training and 2015 for testing. The main results show that the model adopted reproduces reasonably well the climatic and the day-to-day variability of the experimental time series data of the two stations and has forecasting capabilities. However, the model does not reproduce well the experimental TEC of the middle-latitude station during a large solar–terrestrial physics event with space weather effects.

Tebabal et al. (2019) [48] employed a multilayer feedforward network with a back-propagation learning algorithm investigating the possibility of regional modelling and of TEC in the East African region with forecasting possibilities. Their modelling efforts show very promising results.

Particularly since 2020, more sophisticated DL tools have been applied to model and forecast the variability of ionospheric parameters like foF2 and TEC. Without any doubt, the huge availability of TEC data of recent years makes its time series the preferred parameter to be used for ionosphere research.

Li et al. (2021) [49] used a DL long short-term memory (LSTM) network that is a recurrent neural network (RNN) to forecast foF2. Time series of hourly values of foF2 from 10 ionospheric stations in China and Australia from 2006 to 2019 were used for training and verifying. The results are compared with those obtained by using a back-propagation neural network (BPNN) and a genetic algorithm optimized back-propagation neural network (GABP). The authors found that the results obtained with the LSTM model give the best forecasting results.

Tang et al. (2022) [50] developed a global ionospheric TEC prediction model combining indirect forecasting methods from previous studies with the machine-learning Prophet model (Taylor and Letham, 2018) [51] to forecast a global TEC map for the next two days. The results show that the technique used forecast TEC with good accuracy.

Bi et al. (2022) [52] successfully used a state-of-the-art hybrid NN combined with a quantile mechanism to forecast foF2 parameter variations under low and high solar activity years including solar–terrestrial physics/space weather events.

Reddybattula et al. (2022) [53] adopted a long short-term memory (LSTM) DL network model to forecast TEC from GPS signals at a low-latitude location during about eight years of data for training and validation. One year of data was used for independent testing and forecasting of the TEC.

Smirnov et al. (2023) [54] developed a novel model of the ionosphere topside by combining four NNs that reproduce the parameters of the linear alpha-Chapman equation based on location, season, magnetic local time, and solar and geomagnetic activity.

Priyadarshi and Syam (2023) [55] showed a slant TEC forecasting machine-learning (ML) model for the regions of Europe and North Africa, making use of spatial as well as temporal information.

It has to be noted that in all the mentioned investigations, the comparison between the novel technique used with other more traditional ones has shown that the technique introduced by the authors gave better results.

5. Conclusions

To conclude this paper, I like to go back to my paraphrase and extension of what the theoretical physicist M. Baranger (see Section 1) said about the importance of chaos theory and computers in this century. I wrote, "In the 21st century, natural sciences, including space and earth sciences, will benefit from the chaos revolution, will deal with complexity, and will have as means machine-learning tools." In addition, I like to quote the concluding remarks of a recent paper on the present and future of DL research in geophysics: "With the development of new artificial intelligence models beyond DL (Deep Learning) and advances in research into the infinite possibilities of applying DL in geophysics, we can expect intelligent and automatic discoveries of unknown geophysical principles soon" (Yu and Ma, 2021 [56]). However, I expect to see in the future that the physics behind the evolution of time series like those of interest to ionosphere research will become clearer with the help of machine-learning methods. I believe that what Duncan and Rath say in their recent paper is the novelty that will change the way to do research in many natural sciences including solar–terrestrial physics/space weather and, of course, ionosphere research. They write, "combinations of machine learning and physical knowledge are attributed to the important emerging field called *theory-guided data science*, which seeks to exploit the promise of data science without ignoring the treasure of knowledge accumulated in scientific principles" (Duncan and Rath, 2023) [57]. In this paper, I tried to help evidencing that these quotes are valid in the case of solar–terrestrial physics/space weather research and particularly ionosphere studies.

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