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Developments in Bioelectricity and Perspectives in Italy: An Analysis of Regional Production Patterns

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Abstract: Bioenergy is being increasingly used worldwide to generate energy from biogas, biomethane, and other biofuels, bringing significant environmental and economic benefits. In Italy, biogas can significantly contribute to the achievement of the renewable energy targets set at the national and European levels. The exploitation of this energy source in a particular area is determined by its environmental and anthropic properties, as well as by the incentive system and the political will of decision makers. This paper analyzes the socioeconomic drivers and natural conditions triggering bioelectricity production in Italian regions. The analysis proposed here was performed in two steps—first, by identifying groups of similar regions for some natural, social, and economic variables, and then by modeling the historical trajectory of bioelectricity production for each identified group with innovation diffusion models. As a general finding, regions pertaining to the same group in terms of natural and socioeconomic conditions revealed a similar production pattern for bioelectricity, as confirmed by the results of diffusion modeling. On the basis of the diffusion modeling procedure, some scenario simulations were performed, which suggested the set-up of suitable policy actions for each group of regions.

Keywords: bioelectricity; bioenergy; regional production; cluster analysis; innovation diffusion modeling; scenario simulations

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1. Introduction

Countries worldwide are facing the challenge of transitioning from fossil-fuel-based energy systems to renewable and sustainable economies due to the multiple threats represented by climate change, energy security problems, biodiversity loss, and rapid depletion of natural resources [1]. In this scenario, the Renewable Energy Directive (RED) [2] has set targets for the EU Member States to reach a 32% renewable energy share by 2030. Furthermore, this target was raised to 40% [3], and a specific renewable energy share target of 14% was established for the transport sector; in particular, a 2.2% share of the total was set aside for biofuels. This proves the interest in and importance of this resource in EU plans. Therefore, all renewable energy sectors must be investigated to implement innovative and practical solutions for achieving such targets. Currently, the most popular renewable energies are solar, wind, hydropower, and bioenergy. Hydropower allows the construction of large power plants that are capable of producing significant amounts of energy [4]. However, their construction depends on the presence of particular geographical conditions; in addition, this process results in significant environmental damage in the affected area. Solar and photovoltaic modules make it possible to take advantage of an energy source that is widespread everywhere, albeit at very different levels [5]. It also allows the installation of both large industrial plants and small domestic ones. The problems of these systems lie in the large area used and, above all, in the variability of solar radiation, which depends not only on the alternation between day and night, but also on weather conditions. This implies a problem of excess energy at certain times and a shortage of the same at certain others. Wind power plants allow for the economic exploitation of an available and free resource [6]. However, this system presents the same problems as solar energy. The intensity of the wind and the environmental factors that determine it are completely independent of human control. For these energies, there is the problem of storing the excess electricity produced and needed during periods of low production. Among the various proposed solutions, an interesting opportunity is green hydrogen, that is, hydrogen produced through electrolysis with electricity from renewable energy sources [7]. Hydrogen cell storage systems are an interesting opportunity, so many researchers and companies are investing considerable resources in developing these storage systems. The technological aspects of these solutions have been discussed, among other places, in [8,9]. In this renewable energy context, significant development is expected for the bioenergy sector, which has become an exciting sector for many stakeholders and researchers in recent years [10]. Bioenergy is a form of renewable energy derived from recently living organic materials known as biomass, which can be used to produce transportation fuels, heat, electricity, and products [11]. The use of biomass for energy and electricity production has the potential to imply crucial benefits, such as improved energy security, thanks to a smaller dependence on fossil fuel supply, reduction of greenhouse gas emissions and related climate impact, and revitalization of rural economies with new job opportunities [12]. As suggested by [13], multiple services and benefits to the energy system can deploy sustainable biomass utilization under changing operating conditions and limitations, contributing to energy security beyond the power grid. From this perspective, the generation of bioenergy and bio-products from bio-waste streams has called attention to the achievement of a cutting-edge circular economy [14]. The increasing importance of bioenergy requires analyses based on several economic, social, and environmental conditions in order to improve consciousness regarding their impact on the territory and communities [15]. Although bioenergy is a promising opportunity for developing an energy system based on renewable energies [10], its exploitation still needs careful consideration of the technical, economic, social, and environmental aspects of production [16]. For this reason, many authors have dedicated their research to assessing these aspects. The transport of biomass, particularly the raw material, with road vehicles involves the emission of GHGs [17]. Thus, it is essential to consider the transport network to ensure a bioenergy production system's economic and environmental sustainability. Another critical problem of bioenergy facilities is soil sealing [18]: The large covered areas of biomass plants (BPs) could cause local waterproofing problems [19]. Furthermore, the location of the plants must consider the potential negative consequences for the environment and the *not-in-my-backyard* (NIMBY) beliefs in the local population. To determine the impacts of the facilities on local communities and evaluate their social acceptance, authors are used to discriminating among the issues by using three main fields: (i) social, (ii) economic, and (iii) environmental. Biomass facilities cause direct or indirect negative social consequences for local communities. The bio-digestion process and the agricultural and livestock activities that supply the feedstock are sources of noise and smell [20]. The affected population is limited because the involved space is a limited area close to the plants. Thus, the degree to which local communities are disturbed depends on the distance from the energy production site, especially if enterprises do not implement efficient environmental mitigation solutions. New bioenergy facilities allow the creation of jobs and stimulate the local circular economy, so they can be an excellent economic opportunity [21]. Again, knowing the economic context of the area, it is possible to plan the exploitation of the heat produced in the plants for the local settlements. The profitability of a bioenergy system deeply depends on the availability of bioresources [22]. Furthermore, using by-products and waste can be an additional source of income and a positive externality for the environment. An example is the use of urban waste for biogas production and livestock effluent treatment: Nitrogen emissions can be controlled by collecting and treating livestock waste in biogas plants [23]. The analysis of environmental conditions must consider anthropic elements: land use, crops cultivated in the area, cultural and historical sites, and natural features, such as the hydrographical network, natural spaces, and climate conditions [24]. Moreover, areas with high hydrological risk, such as those susceptible to flooding and earthquakes, should be avoided. Considering all of the factors mentioned above, the policy decisions, regulations, and incentives implemented by institutions gain crucial importance. Italy is a European country that mostly focuses on biomethane production development. Since 2008, bioenergy production has been directed to the production of electricity through biogas usage; by 2021, 2010 biogas plants were operating in Italy (GSE, 2021). With the entry into force of the Biomethane Decree in 2018, the interest was shifted toward biomethane production. From 2019 to 2021, 25 new biomethane plants came into operation, with a total theoretical capacity of 18.2 tCH4/h. The incentives also determine the feedstock of bioenergy plants; only livestock waste, second-crop crops, agricultural by-products, and organic fractions of municipal solid waste can be used. Recent studies have demonstrated that the incentives of the Biomethane Decree can make investments in upgrading technologies profitable for existing plants, but not for new plants [25].

Among the countries that are currently investing in bioenergy, Italy may represent an interesting case study because of its natural and socioeconomic characteristics. In fact, numerous measures have been approved in recent years to incentivize biogas production. Strong incentives in 2009 for combined heat and power from biogas (EUR 280/MWh for plants below 1 MW) determined the sector's rapid development, which was, notably, based on energy crops. In 2018, the Biomethane Decree was adopted to support biomethane and advanced biofuel development for the transportation sector [26].

Today, Italy is one of the European countries that has shown the most willingness to support bioenergy [27]. An illustration of the Italian context was provided in [28], with a focus on Italian strategies for bioeconomy. The authors discussed the strengths and weaknesses of the sectors involved, reporting the measures, regulatory initiatives, and monitoring actions undertaken. Many authors have analyzed the conditions that influence the development and location of biogas plants. Small [29] and very large [30] study areas have been considered; in addition, different types of biomass have been investigated based on available crops, such as industrial olive by-products [22], straw [31], livestock manure [16], and a mixed supply [32]. Moreover, the problem of environmental impact was studied by [19], who conducted an analysis of the land consumption that occurred because of the construction of agricultural biogas plants in the Italian territory. In [33], the authors compared two regional cases to explore the overall impacts of proposed policy schemes on biogas upgrading potentials and the relevant environmental impacts. However, although important contributions concerning technical aspects have been provided in the literature, more analyses on bioenergy development in Italy are still needed.

Notwithstanding the role of technical aspects, in this paper, a different perspective is adopted in an attempt to analyze the socioeconomic drivers and natural conditions that may stimulate bioenergy production in Italian regions. In fact, Italy is divided into 20 regions, which have their own specificities in terms of both geographic and territorial traits and socioeconomic features that may trigger or hinder the development and diffusion of bioenergy systems. We believe that an analysis at the regional level is essential because the local scale is recognized as the primary context in which both active citizens and local institutions can play a leading role in energy and climate policies [34,35]. In fact, active protection of the local climate and environment is closely linked to sustainable energy policy [36]. As highlighted by [37], investigating at a regional level allows for deep comparison of fundamental specificities related to cultural, political, and socioeconomic contexts.

To this end, in this paper, the analysis was performed in two steps: The first step was aimed at identifying groups of similar regions for some natural, social, and economic variables; then, once these groups were identified, the second step was dedicated to modeling the historical trajectory of bioelectricity production for each region in order to analyze and discuss whether there were similar diffusion characteristics within the groups. This modeling exercise allowed some scenario simulations that may be the base for setting up suitable policy actions, given that adequate predictive scenarios are necessary in order to enable operators to move effectively inside the various markets [38]. Simulations provide a useful indication of how renewable energy may be stimulated as a result of well-specified policies [39]. From a methodological point of view, the analysis combined a clustering method for the identification of groups of regions and innovation diffusion modeling to describe and simulate the scenario's prediction of historical bioelectricity production patterns.

The remainder of the paper is organized as follows: Section 2 illustrates the data and the methods employed in the analysis. Section 3.1 describes the results of the clustering procedure and describes the profiles of the identified groups of regions. Section 3.2 describes the development of the innovation diffusion modeling procedure in order to capture the different production patterns of each group and, on this basis, proposes a scenario simulation. Section 4 draws some conclusions from the obtained results. Appendix A shows an illustrative example to explain the prediction method, and Appendix B presents a study on the Bass model estimation method by considering a portion of the available data for validation purposes.

2. Materials and Methods

This section describes the data used to identify groups of regions and the subsequent analysis of historical bioelectricity production patterns under the innovation diffusion approach. A description of the main features of the selected clustering procedure that was based on the model-based clustering method and of the innovation diffusion model used, i.e., the standard Bass model by [40], is also provided.

2.1. Data Description

In order to extract groups of regions that may be similar in terms of bioelectricity production, several measures that may provide relevant insights were explored. In doing so, selected variables at a fixed point in time were considered, taking the 2020 data point as a reasonable reference. In the variable selection procedure, some synthetic indicators were employed, accounting for natural, social, and economic conditions that may be seen as potential determinants of the bioenergy production chain.

The variables considered for creating the groups of regions, which were called *grouping variables*, may be divided into three categories: economic factors, social factors, and natural factors.

- *Economic factors.* In line with the concept of circular economy, a crucial step for shifting to a bioenergy system is the use of waste in order to produce energy. Environmental problems associated with global energy supply systems and increasing solid waste generation worldwide are triggering a shift toward greater reliance on biomass waste [41]. Thus, two indicators that may directly influence the amount of biomass production were selected:

    Production: production of goods and services at base prices, consisting of the products resulting from the activities of agriculture, forestry, and fishing as a whole in 2020 (Source: ISTAT [42]).

    Waste: total urban waste production for a region in 2020 (Source: ISPRA [43]).

- *Social factors*. The diffusion of a new technology is highly stimulated by communication between people and imitation dynamics [44]. Social contacts obviously affect the possibility of communicating and interacting with others, influencing the expectations for technology adoption [45]. Therefore, in order to have a density indicator that affects social contacts, the following variable was considered:

    Density: population over km^2 in 2020 (Source: EUROSTAT [46]).

- *Natural factors*. One of the major components of biomass is the large amount of agricultural waste produced [47]. From this perspective, the authors of [48] showed how climate change affects biodiversity loss, confirming the close association between geotechnical factors and functional ecosystem processes. Based on these, two natural factors that may impact agricultural biomass production were included:

    Rainfall: total annual precipitation in the regional capitals in 2020 (Source: ISTAT [42]).

    Temperature: average annual temperature in regional capitals in 2020 (Source: ISTAT [42]).

Concerning the second step of the analysis, for each Italian region, a measure called *regional bioelectricity density* was calculated by considering, as the primary element, the regional yearly net electricity production from biomass (in MWh), which was considered in the period 2000–2020. To conduct a comparative study between regions, this variable was normalized to analyze the energy performance in a homogeneous setting between regions. The variable employed for the normalization was the regional surface (in km^2). The data of the regional yearly net electricity production from biomass were taken from the TERNA website (https://www.terna.it, accessed on 10 February 2021), while information concerning regional areas was based on ISTAT [42]. The resulting normalized variable, *regional bioelectricity density*, came from the ratio between the regional yearly net electricity production from biomass and the regional surface (in MWh/km^2). These data are displayed in Figure 1.

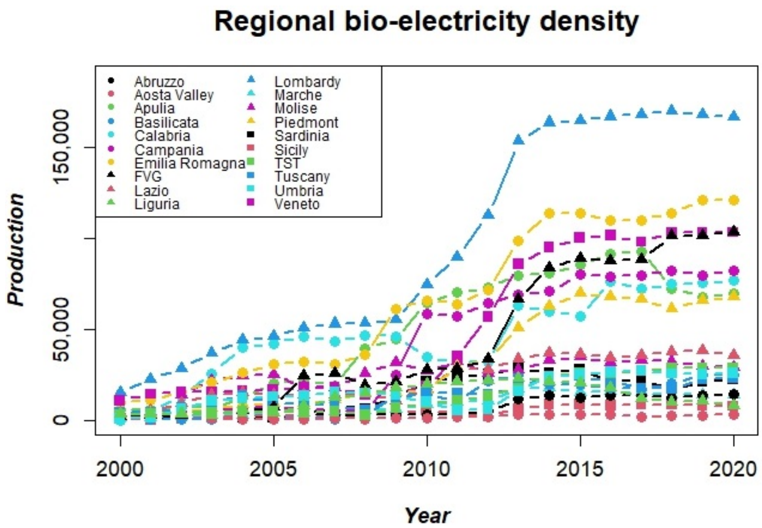

Figure 1. Regional bioelectricity density in Italy, 2000–2020 (in MWh/km^2).

2.2. Cluster Analysis

Cluster analysis is a set of statistical techniques designed to identify groups of units that are similar to each other with respect to a set of characters that are taken into account and according to a specific criterion [49]. In order to identify similar regions, a cluster analysis was implemented by using a *model-based approach*. In contrast to heuristic techniques, model-based clustering permits a robust approach to parameter estimation and objective inference on the number of clusters while providing a clustering solution that accounts for uncertainty in cluster membership [50]. Model-based methods assume that the true segmentation solution—which is unknown—has the following two general properties: (i) Each segment has a certain size, and (ii) if an entity belongs to segment A, that entity will have characteristics that are specific to members of segment A [51]. These two properties are assumed to hold, but the exact nature of these properties—the sizes of these segments and the values of the segment-specific characteristics—is not known in advance. These methods use empirical data to find the values for segment sizes and segment-specific characteristics that best reflect the data. Specifically, the model-based method used in this analysis is a *finite mixture model* because the number of segments is finite, and the overall model is a mixture of segment-specific models.

This method postulates a formal statistical model for the population from which the data are sampled, known as the finite density mixture model, which characterizes each cluster with a different multivariate probability density function. Property (i) implies that the segment membership z of a unit is determined by the multinomial distribution with segment sizes π:

$$z \sim Multinomial(\pi)$$

Property (ii) states the presence of segment-specific characteristics for members of each segment. These segment-specific characteristics are captured by vector θ, containing one value θ_h for each segment h. These θ_h parameters are estimated by fitting the $f()$ distribution on the segment variables that are available. The probability of observing specific values y in the empirical data is captured by function $f(y|x, \theta_h)$, given the unit segment membership h and, potentially, some additional information x for that unit [51]. Segment-specific models refer to these functions, which correspond to statistical distribution functions and lead to the following finite mixture model:

$$\sum_{h=1}^{k} \pi_h f(y|x, \theta_h) \qquad \pi_h > 0, \qquad \sum_{h=1}^{k} \pi_h = 1$$

By adopting this approach, the clustering problem becomes the estimation of the parameters of the assumed mixture and then the use of the estimated parameters to calculate the probabilities of each cluster membership:

$$Prob(z = h|x, y, \pi_1, ..., \pi_k, \theta_1, ..., \theta_k) = \frac{\pi_h f(y|x, \theta_h)}{\sum_{j=1}^{k} \pi_j f(y|x, \theta_j)}$$

Furthermore, the determination of the number of clusters is reduced to a model selection problem for which objective procedures exist; units are assigned to the segment with the highest probability. In this analysis, the fitting of the model was performed with the R package *mclust* [52], as detailed in Section 3.1.

In this analysis, the simplest case of model-based clustering was used, with no independent variables x, and a *finite mixture of distributions* was used. A finite mixture of distributions model can be defined as:

$$\sum_{h=1}^{k} \pi_h f(y|\theta_h) \qquad \pi_h > 0, \qquad \sum_{h=1}^{k} \pi_h = 1$$

where π_h identifies the segment size h, θ_h refers to the segment-specific characteristics, $f(y|\theta_h)$ is the segment-specific model that corresponds to a determined distribution, and $f()$ is a multinomial distribution [51]. In this case, a multivariate normal distribution was assigned to $f()$, so the finite mixture model was a mixture of several multivariate normal distributions:

$$f(y|\theta_h) \sim Normal(\mu_h, \Sigma_h)$$

The multivariate normal distribution can easily model the covariance between variables. Mathematically, $f()$ is a multivariate normal distribution with two sets of parameters–the mean and variance–that identify the segment-specific characteristic θ_h. If k segmentation variables are used, each segment has a segment-specific mean vector μ_h of length k containing the segments' mean variables' values. In addition, the covariance structure can be modeled, resulting in a $k \times k$ covariance matrix Σ_h for each segment. The covariance matrix Σ_h contains the variances of the k segmentation variables in the diagonal and the covariances between pairs of segmentation variables in the other entries. The covariance matrix is symmetric and contains $k(k+1)/2$ unique values. As performed in this analysis, the parameters of the density of the subpopulations are typically estimated via maximum likelihood using the expectation-maximization algorithm.

2.3. Innovation Diffusion Modeling

Innovation diffusion models are typically used to describe and predict the evolution of a new product or technology being accepted in a market over time. Originally developed in the commercial and marketing field, these models have been successfully employed in the energy domain in order to capture the process of adoption of renewable energy technologies and the possible decline of fossil fuels. For a review, see, for instance, [53,54]. The most famous and most commonly employed innovation diffusion model—also in the energy context—is the Bass model from [40]. The Bass model is described by a first-order differential equation:

$$z'(t) = \left\{ p + q\frac{z(t)}{m} \right\} \{ m - z(t) \}$$

where $z'(t)$ is the variation in adoption of the technology over time, which is proportional to a residual market, $m - z(t)$, calculated as the difference between the market potential m and the cumulative adoptions at time t, $z(t)$. The residual market is multiplied by two coefficients p and q, which, respectively, characterize two categories of individuals, the *innovators* and the *imitators*. The innovators are pioneers in adopting the new technology, while the imitators wait and see the consequences of technology adoption for others before accepting it. The Bass model was found to be a simple and powerful tool for describing the take-off of renewable energy technologies and for predicting their evolution over time, and we found it reasonable to use it also in the bioenergy case. However, it should be noticed that the diffusion processes of renewable energies are often very perturbed because of hindering factors that may slow down growth, on the one hand, and, on the other, the effects of incentive measures that may accelerate it. Therefore, the resulting observed pattern is not as smooth as the Bass model would envisage, and models able to account for these perturbations may prove useful. For example, the Generalized Bass model from [55] could be used to account for structured perturbations due to policy actions that may change the form and the timing of the diffusion process. Several research contributions have employed the Generalized Bass model to renewable energy diffusion, as reviewed in [53], in order to analyze the effects of incentives on the adoption of solar photovoltaic energy. Moreover, competition with other energy technologies may have a perturbing effect on the diffusion of renewable energy. Studies that considered this competitive environment have been proposed in the recent literature. For recent reviews, see, for instance, [53,54]. In this paper, in order to use a common and reasonable model for all of the regions, the Bass model was employed to obtain a sound description of bioelectricity production at a regional level, even though possible perturbations in single trajectories were not accounted for.

3. Results

3.1. Groups of Regions

In this section, the results of the cluster analysis based on the grouping variables described before are illustrated. The fitting of the mixture of normal distributions was performed with the R package *mclust* [52]. In order to implement the finite mixture of normal distributions method, all of the variables were standardized. The best model obtained according to the Bayesian Information Criterion identified four groups, which are reported below and displayed in Figure 2:

1. Abruzzo, Aosta Valley, Basilicata, Molise;
2. Apulia, Calabria, Marche, Sardinia, Sicily;
3. Campania, Emilia Romagna, Lazio, Lombardy, Piedmont, Tuscany, Veneto;
4. Friuli-Venezia Giulia, Liguria, Trentino-South Tyrol, Umbria.

Figure 2. Group distribution: Group 1 (brown), Group 2 (beige), Group 3 (light blue), and Group 4 (green).

Figure 2 outlines the geographical distribution of the groups. A profiling analysis helped better capture the characterizing features of these groups.
Bonferroni correction [56] was used to evaluate whether the differences between the groups obtained were significant. This test highlighted that the four identified groups were significantly diverse based on the variables utilized in the clustering procedure.

Group Profiles

Providing a profile for each of the four groups is critical for recognizing similarities and differences across the groups regarding the factors that may enable bioelectricity production. Table 1 reports the different means of the grouping variables employed, and Figure 3 shows boxplots that help one appreciate the distribution of these variables.

Table 1. Group profiles: means of the variables for each group.

	Prod. (mln)	Density (p./km^2)	Rainfall (mm)	Temp. (°C)	Waste (kt)
Group 1	0.81	69.10	571.25	13.07	239.70
Group 2	3.15	147.20	544.64	17.78	1236.81
Group 3	5.08	279.22	643.47	16.31	2780.26
Group 4	1.26	153.31	936.47	15.57	585.09
mean	2.98	179.01	662.92	15.89	1447.26

The results of this analysis may be summarized as follows:

1. *Group* 1: Abruzzo, Aosta Valley, Basilicata, and Molise. This group is characterized by almost all of the smallest mean values. The regions of this group are the least densely populated, have the coldest temperatures, and, on average, receive less rain than those in groups 3 and 4; moreover, these regions have the smallest values of production and waste with respect to the other groups.

2. *Group* 2: Apulia, Calabria, Marche, Sardinia, and Sicily. As it was reasonable to expect, this group is characterized by higher temperatures with respect to the Italian average and less rainfall. It presents a slightly smaller value of density and waste compared to the Italian average; instead, it shows a production value over the mean and is just smaller than that of group 3.
3. *Group* 3: Emilia Romagna, Lombardy, Piedmont, Veneto, Tuscany, Lazio, and Campania. This group is formed from the regions with the greatest populations and with the highest production and waste values. The rainfall and temperatures essentially reflect the Italian average.
4. *Group* 4: Friuli-Venezia Giulia, Liguria, Trentino-South Tirol, and Umbria. This group is characterized by the highest value of rainfall and slightly smaller values of temperature and density compared to the Italian average. The production and waste values are smaller than the Italian average and those of groups 2 and 3.

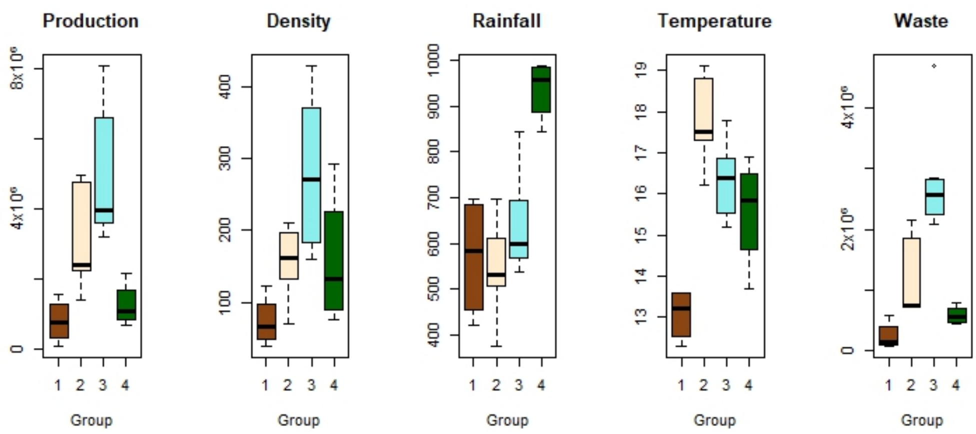

Figure 3. Boxplots of the grouping variables: Group 1 (brown), Group 2 (beige), Group 3 (light blue), and Group 4 (green).

3.2. Modeling Historical Production Patterns

Once the groups were identified, the second step of the analysis involved a quantitative comparison of their bioenergy production patterns by considering the bioelectricity density trajectories, which are displayed in Figure 1. To do so, the standard Bass model was estimated for each region in order to provide a reasonable description of the growth of bioelectricity at the local level. Specifically, the parameters of the Bass model, i.e., m, p, and q, provided relevant insights into the growth of this form of energy in Italy and allowed an understanding of how the groups could differ in terms of the speed and magnitude of this growth.

Table 2 illustrates the results of the model estimation, while Figures 4–7 show the model fit in all regions, divided by group; as a general note, we may observe that the model reasonably fit all of the regional data, as can be observed in the figures, although in some cases, the variability around the mean was especially strong (e.g., in Basilicata). This variability would probably suggest the use of more complex diffusion models that are able to capture the perturbations occurring within the data, such as the Generalized Bass model, but this would require the usage of one specific model tailored to each data series. Instead, to meet the purpose of this analysis, the simple Bass model was used in all cases, even in those where the fit was not completely satisfactory, in order to have an intuition of the evolution of growth with a unique and common model. This choice was especially suitable for performing some comparisons between different groups of regions.

For validation purposes, an estimation exercise using the Bass model with a truncated data series (until 2017) was performed, and the results are commented upon in Appendix B. However, given the sensitivity of the Bass model's estimates to the amount of data available, we chose to perform our analysis by considering all of the available data (until 2020) and to develop a prediction method that produced some scenario simulations based on reasonable assumptions about the set-up of the targeted policy measures, which allowed a wider perspective on the possible evolution of the process in each region. This procedure, along with the obtained results, is described in the following sections.

Table 2. Bass model parameter estimates for regional bioelectricity production density ordered by group (Group 1, Group 2, Group 3, and Group 4) and for Italy.

Regions	*m*	*p*	*q*
Abruzzo	1,890,445	0.00762	0.29614
Aosta Valley	58,308	0.01001	0.19466
Basilicata	274,713	0.00172	0.34786
Molise	1,030,369	0.01697	0.08896
Apulia	1,258,765	0.00310	0.28419
Calabria	2,429,063	0.00664	0.11623
Marche	263,028	0.00398	0.24071
Sardinia	320,590	0.00154	0.36669
Sicily	182,907	0.00408	0.19062
Campania	1,072,933	0.00131	0.32963
Emilia-Romagna	2,231,204	0.00414	0.20676
Lazio	966,508	0.00596	0.15272
Lombardy	3,657,533	0.00423	0.18895
Piedmont	1,010,660	0.00171	0.27614
Tuscany	700,821	0.00741	0.11778
Veneto	2,051,884	0.00228	0.22101
Liguria	291,322	0.00546	0.30365
Friuli-Venezia Giulia	1,533,934	0.00147	0.26732
Trentino-South Tirol	728,901	0.00234	0.18907
Umbria	8,147,832	0.00073	0.08288
Italy	19,726,838	0.00398	0.20882

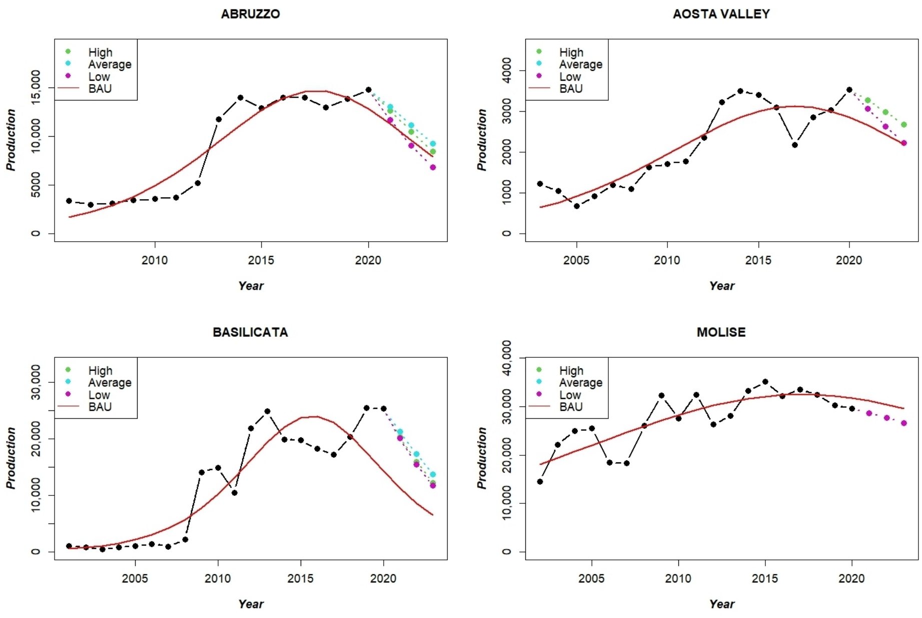

Figure 4. Predictions with the Bass model and scenario simulations for Group 1.

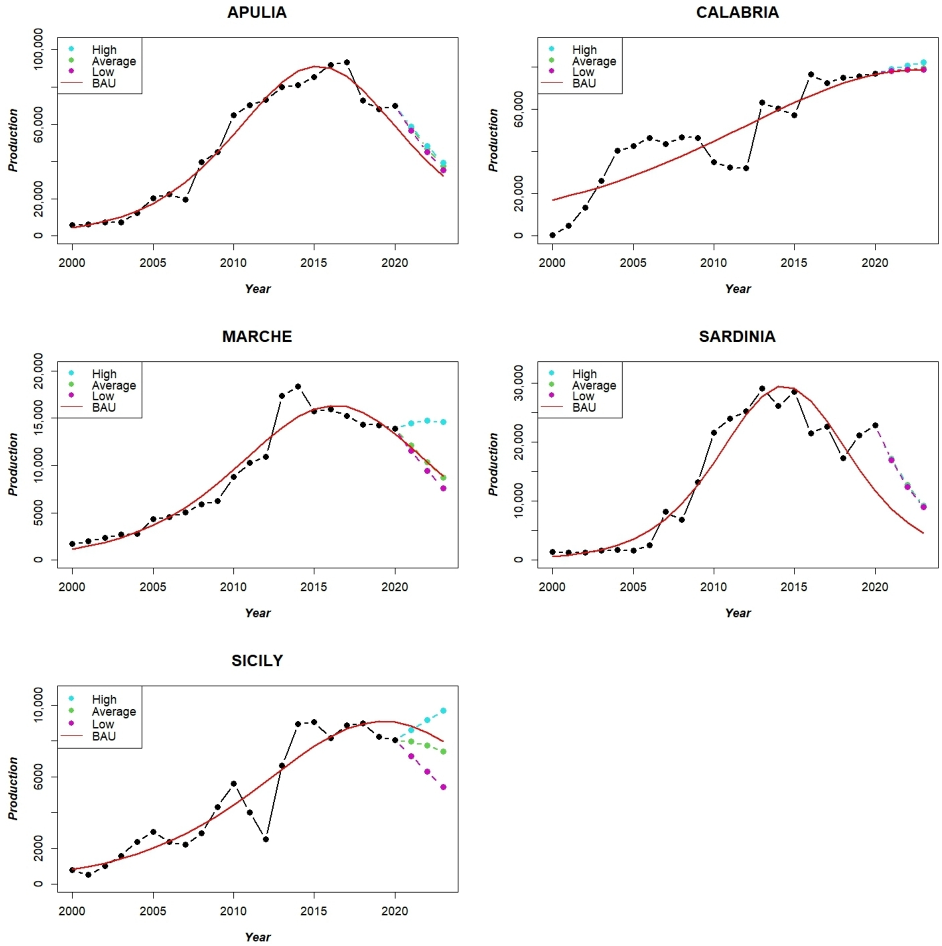

Figure 5. Predictions with the Bass model and scenario simulations for Group 2.

3.2.1. Predictions and Scenario Simulations

A crucial aspect when studying the diffusion of a renewable energy source is the ability to predict its possible future development. Given that renewable energy sources are subject to sudden changes caused by the implementation of specific policies, in this paper, a prediction method based on the Bass model was designed to detect phases within the growth process that determined specific trends or perturbations. These perturbations may have been the consequences of specific policy actions that were undertaken in those periods. Coherently, it was assumed that future growth could be determined by a new set-up of policies, and three different scenarios were considered: one corresponding to an intense policy action (High), one corresponding to a mild policy action (Average), and one corresponding to a weak policy action (Low). These scenarios were also compared to that of the Bass model, which was considered as the "Business as Usual" (BAU) scenario in which no policy was implemented. The more changes are required by any proposed policy measure, the more difficult it may be to implement them within a reasonable time frame [57]. From this perspective, the main goal was to provide a short-term prediction with a time span of three years. This is a reasonable timing to allow local governments to envisage their policy choices and decisions on investment.

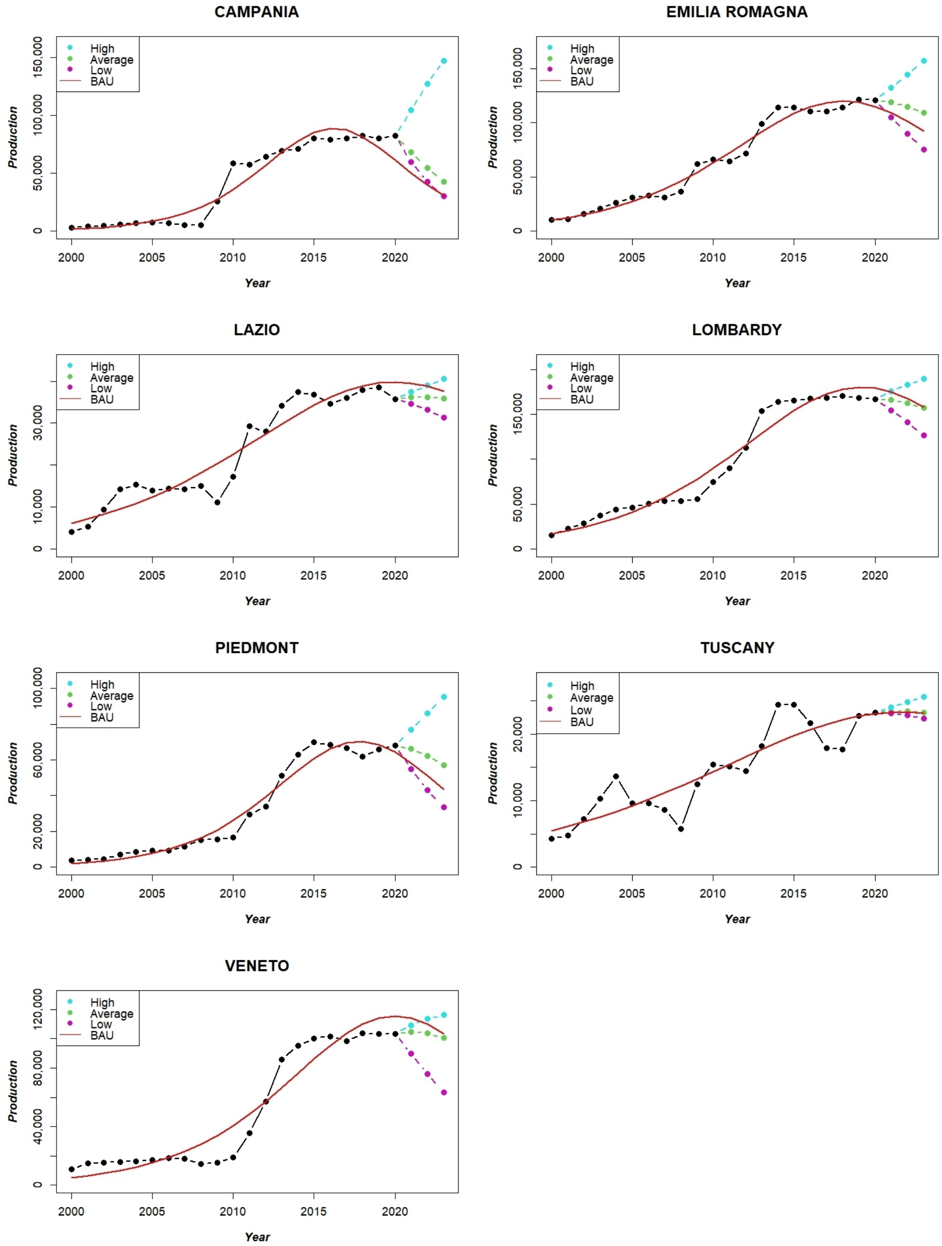

Figure 6. Predictions with the Bass model and scenario simulations for Group 3.

In detail, starting from 2006, the yearly evolution of each regional series was analyzed through a careful analysis of the estimated Bass model parameters (i.e., p and q) by first calculating the yearly rates of change of these parameters and then connecting them with the regional policies, whose details are provided by GSE [58]. In this way, the variations in the parameters could provide an indication of the intensity of a policy action. Then, by inspecting the graphical trajectories of each region and considering the regional policies enacted, the significant yearly variations in the most likely policy scenario (high, average, low) were assigned. A thorough description of the scenario method, along with the variations employed for each regional policy scenario, are reported in Appendix A. In what follows, the results are presented for each group in order to identify common traits and differences in the predictions between regions with similar regional electricity production.

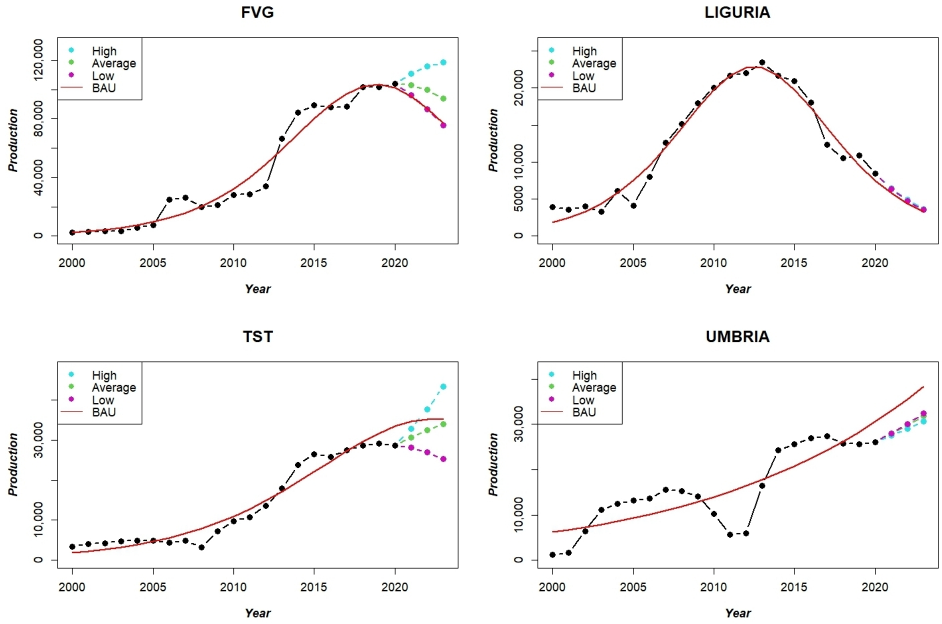

Figure 7. Predictions with the Bass model and scenario simulations for Group 4.

3.2.2. Discussion

This section discusses the estimates—which were based on nonlinear least squares and performed by using the Levemberg–Marquardt algorithm (see [59])—of the Bass model, and it illustrates the predictive scenario simulations based on m, p, and q parameters. As a general insight, the findings show that regions pertaining to the same cluster exhibited a similar production pattern for bioelectricity, as testified by the results of diffusion modeling. So, regions that were similar for some natural or socioeconomic conditions were also characterized by similar bioelectricity diffusion trajectories.

However, before going into the details of the results, it should be observed that the Bass model was able to describe the mean behavior of the series, while it did not account for the variability of the data, which was possibly due to the effect of a serial correlation or local perturbations related to exogenous factors. This implies that in some regions, the description provided by the model proved satisfactory, while in others, it was less reasonable. This instability in the observed regional patterns is arguably due to the fact that bioenergy is still a relatively new form of energy, and its process of diffusion through bioelectricity production is not smooth and is characterized by a degree of uncertainty, which is clearly reflected in the observed data. Despite this clear drawback, the model was chosen as a general descriptive and predictive tool in order to offer a perspective on how this form of energy is evolving in the different regions of Italy.

Group 1

This group was composed of the most recent regions to start producing bioelectricity. Specifically, Abruzzo started in 2006, Aosta Valley in 2003, Molise in 2002, and Basilicata in 2001. From Table 2, it emerged that three of the four regions of this group had the highest values of p (Abruzzo, Aosta Valley, and Molise). The reason for these high p values was the fast-increasing trend in the early stages of the series. This would suggest that these regions experienced a faster take-off in bioelectricity production (but starting later than other regions) by taking inspiration from the successfully adopted solutions and policies implemented by the other regions of Italy.

Instead, Basilicata presented a low p, which is reasonable if we look at its low diffusion in the early stages. On the other hand, this region was characterized by a very high q value (second among all Italian regions), which is coherent with the rapid diffusion that bioelectricity had from 2009, which was caused primarily by two evident shocks (2009 and 2012). In addition, Abruzzo presented a high q value, which outlined the increase in bioelectricity production density from 2011.

By analyzing the predictions, this group presented unique scenario simulations compared to the results for the other groups. The regions that comprised this group had particular trends that the Bass models already estimated in a clearly declining phase. This trend dramatically affected the possibility of identifying three policies that were able to show different results. In fact, from Figure 4, it is evident that all of the assumed policies involved a downward trend. Moreover, we could not estimate all policies for Aosta Valley and Molise. Specifically, the particular trend in these series did not allow the estimation of various Bass patterns over the years, making it impossible to identify positive variations in the parameters. This result suggests that a deeper analysis of these regions should be carried out to find a possible solution for inverting the negative trend that characterizes the historical trajectories.

Group 2

Apulia, Marche, and Sicily had similar trajectories that were reflected in the similar p and q values in Table 2. These regions had p values near the Italian average, representing a start of diffusion with a medium slope, and high q values, which outlined rapid growth after the initial phase. However, Sardinia presented a low p value, representing its stationary trajectory and shallow start. On the other hand, it had the highest q value (among all Italian regions), which is coherent with the exponential growth after 2008. According to its trajectory, Calabria was characterized by a high p value and a more moderate q value, which started with high intensity and was then dampened. The scenario simulations in Figure 5 show the different evolutionary patterns inside this group. Even though their trend in recent years was slightly decreasing, Marche and Sicily presented conditions that were sensitive to the choices made and had results in line with what might be expected for the three different types of policies. The implementation of a strong policy could lead to a positive exponential shock that should push the bioelectricity density diffusion (more evident in Sicily); the Average scenario reflected a more conservative trend in Sicily and a slight increase in Marche; finally, the Low scenario could produce a decreasing trend. Given these results, these regions have a solid foundation that can give rise to an increase in biolectricity production thanks to a boost that can come from a reasonably effective policy.

Despite its trend being full of ups and downs, Calabria showsed a unique, slightly increasing direction for the three scenarios simulated. This could lead to the further investigation of the previous shocks that characterized its trend to understand the causes of these accelerations.

Instead, Apulia and Sardinia presented only negative scenarios. These regions did not have many change rates to be explored because the standard Bass models that were estimated were only reliable since 2014. The rate of change in their increasing part could not be considered, which limited the simulation scenarios in these regions. Other than this, these negative trends also appeared because the trajectories of the last years were decreasing, a fact that negatively influenced the simulation results of the three policies. A substantial change caused by a strongly positive and effective policy would be needed to boost diffusion in these two regions.

Group 3

Group 3 contained regions with similar bioelectricity production diffusion. They all exhibited an acceleration between 2008 and 2014, while it was mostly linear in the other periods. In particular, Lombardy, Emilia Romagna, and Lazio revealed similar trends and very close p and q parameters, as can be observed in Table 2. What really distinguished the three regions was the scale of the process, parameter m, i.e., the trajectories were similar, but the regional processes differed in terms of size. Campania, Piedmont, and Veneto seemed to follow the development of these first three regions, but with a dampened increasing trend; in fact, except for the strong growth between 2010 and 2012, the preceding and following phases were flatter than those of Lombardy, Emilia Romagna, and Lazio, although the trends were very similar. This was also evidenced by a lower p value and a higher q value. However, Tuscany presented a particular series; after a strong start (it showed the highest p value within this group), it had difficulty in expanding (lowest q value).

This points to a situation in which bioelectricity density has all of the favorable elements to continue developing—taking cues from neighboring regions and encouraging their production. In fact, looking at the prediction scenarios in Figure 6, almost all of the regions in this group presented situations that were sensitive to the choices made and presented results in line with what could be expected. Implementing a solid policy could lead to a positive exponential shock that would push the diffusion of bioelectricity; the stable situation reflected a more conservative trend, and the disinvestment situation could produce a decreasing trend. The only region that did not show three different scenarios was Campania, which had just two options because the stable scenario, in this case, could not be easily estimated. To sum up, based on these findings, these regions have a solid basis that can support an increase in biolectricity production thanks to a stimulus coming from a reasonably robust policy measure.

Group 4

The fourth group incorporated Liguria and Umbria, which showed particular trends, and Friuli–Venezia Giulia and Trentino–South Tirol, which were more in line with what was found in the other northern regions. Umbria had the most particular trajectory, which was characterized by the evident drop between 2008 and 2010. The Bass model did not capture this peculiar trajectory well, as evidenced by the non-significant estimates of parameters m and p reported in Table 2. In addition, Liguria had a particular trend that seemed to be essentially declining. Instead, Friuli–Venezia Giulia and Trentino–South Tirol had similar and more positive trajectories; in particular, it appeared that Trentino–South Tirol followed the trend of Friuli–Venezia Giulia, with a few lags of delay. This was also emphasized by the parameter estimates: Trentino–South Tirol was characterized by a slightly higher p and a marginally lower q than those of Friuli–Venezia Giulia. In addition, the m estimate showed that Friuli–Venezia Giulia was the leading region in this group.

Looking at the scenario simulations in Figure 7, Friuli–Venezia Giulia and Trentino–South Tirol showed results that were sensitive to the choices made. However, Umbria and Liguria had particular situations. The first was characterized by an increase regardless of the type of policy implemented, and the second was characterized by a decrease. Liguria seemed to have left this type of technology; in fact, the forecasts were pessimistic even if we simulated a strong policy scenario. So, in this region, a rethinking of objectives regarding bioelectricity diffusion would be necessary, as probably occurred in Umbria between 2010 and 2012. After this drop, Umbria started a positive trend that will likely continue in the following years, as confirmed by the simulations.

4. Conclusions

Policy decisions may produce different effects when there is a strong heterogeneity between the regions of a given country. The Italian evidence indicates that northern regions and those with better socioeconomic conditions are more actively drawing policy lessons. Indeed, in agreement with [60], our findings suggest that the southern regions of Italy, while tending to enjoy a robust economic base in primary production, lag far behind the national average in bioeconomy performance.

Moreover, our analysis confirmed that socioeconomic conditions in different regions significantly affect the predictability of bioelectricity production. Regions with solid bioelectricity development will likely continue their positive evolution, while more resources should be implemented in underdeveloped regions in order to meet future sustainability purposes. The two key examples of these different scenarios were represented by Group 3 and Group 1. On the one hand, Group 3 had the best conditions for strengthening future developments; consequently, it was possible to produce an interesting scenario simulation with different alternatives. On the other hand, Group 1 was characterized by several weaknesses, as also confirmed by the predictions with the Bass model, which did not find a solid basis for implementation. This clearly indicates that the differences in regions significantly affect the predictability (and the future development) of this form of energy.

Indeed, the difficulty of estimating the Bass model in all years for all of the regions is surely a limitation of this study, as it caused some loss of information. As observed earlier in the paper, this difficulty was especially evident in the regions in which the observed trajectory was particularly perturbed. These perturbations can be imputed to the effects of exogenous shocks, but we may observe that the general variability characterizing essentially all of the regional patterns could be motivated by the relative newness of bioenergy, which has prevented smooth growth so far. A possible solution in some cases could be the use of the Generalized Bass model in order to capture the effects of possible shocks. However, in order to provide a general overview of the development of bioenergy in Italy, in this paper, we chose the Bass model as a unique, simple, and interpretable basis for the proposed prediction method.

In particular, the comparison of the three scenarios and the BAU provided some crucial insights. Despite the difficulties encountered in some regions, the obtained results support the trend towards deployment of bioelectricity through a system of incentives, which can then be carried forward over the years by a strong institutional commitment. In regions with no optimal conditions for bioenergy development and where there has been a decline in recent years, it will be necessary to plan a strong and manageable recovery. As a matter of fact, predicting an increase in bioelectricity production density when the Bass model estimated a process already in the decline phase was almost impossible, even when using the most optimistic scenario.

As a future development of this work, it would surely be of interest to perform new analyses to investigate the shocks that characterized regional trends when new data become available. With the availability of longer time series, a specific understanding of the substantial changes that cause the positive and negative effects in Italian regions could be crucial for boosting the growth of bioelectricity.

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Data Availability Statement: All the data used in this analysis are public. As reported in Section 2, the sources are: ISTAT http://dati.istat.it/?lang=en (accessed on 17 February 2022), ISPRA https://www.catasto-rifiuti.isprambiente.it/index.php?pg=regione (accessed on 18 February 2022), EUROSTAT https://ec.europa.eu/eurostat/web/main/data/database (accessed on 18 February 2022), and TERNA https://www.terna.it/it/sistema-elettrico/transparency-report/download-center (accessed on 10 February 2022).

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. Method of Prediction and Scenario Simulation

In order to explain our prediction method in detail, the Lombardy case is considered as an illustrative example. The steps described below were implemented for all twenty Italian regions (Table A3 shows the information concerning all regions).

Starting from 2006, a careful analysis of the yearly evolution of the series was performed. Bass models were estimated for all years in the period 2006–2020. However, for the Lombardy series, there were difficulties in the period 2012–2017 because of highly intense perturbations that occurred in those years (we encountered similar problems in almost all regions).

As illustrated in Figure A1, for Lombardy, it was possible to adequately estimate the Bass model for the years 2006–2011 and 2018–2020. This sequence of models for capturing the yearly evolution of the series deeply analyzed the estimated Bass model parameters p and q. In Figure A1, black-colored lines represent the observed data, red-colored lines predictions with Bass model. The parameter estimates of p and q for each year considered are reported in the legend.

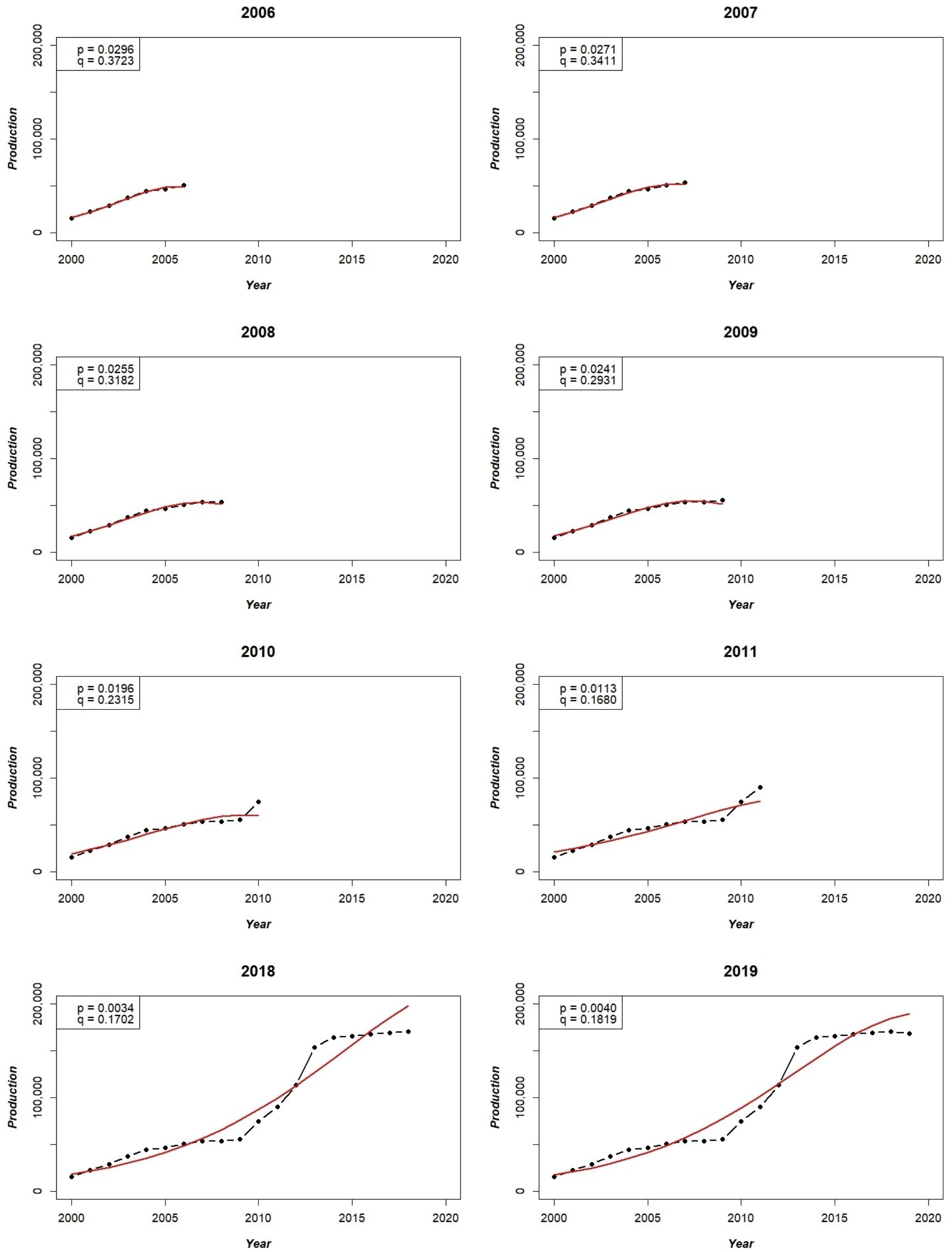


Figure A1. *Cont*.

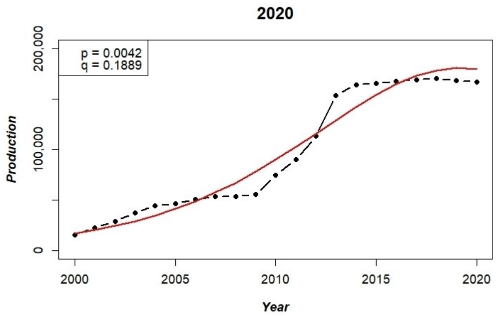


Figure A1. Sequential Bass model analysis for Lombardy: 2006–2011, 2018–2020.

After estimating the p and q values, the yearly rates of change of these parameters were calculated by using the following formulas:

$$\Delta p_t = \frac{p_t - p_{t-1}}{p_{t-1}} \qquad \Delta q_t = \frac{q_t - q_{t-1}}{q_{t-1}} \qquad t = 2007, \ldots, 2020$$

The results of this procedure are summarized in Table A1.

Table A1. Yearly rates of change of p and q and identification of the scenarios in Lombardy.

Year	Δp_t	Δq_t	Policy
2007	−8.47	−8.38	Average
2008	−5.74	−6.70	Average
2009	−5.75	−7.90	Average
2010	−18.51	−21.02	High
2011	−42.23	−27.42	High
2018	189.06	−70.17	–
2019	18.34	6.83	Low
2020	5.76	3.90	–

Whenever possible, these parameter variations were associated with the regional policies implemented, the details of which are provided by GSE [58]. In this way, the variations in the parameters provided an indication of the intensity of policy actions. Then, by inspecting the graphical trajectories and considering the regional policies enacted, the significant yearly variations were assigned to the most likely policy scenario, i.e., High, Average, and Low. Each year was assigned to one of the three scenarios considered whenever possible. Table A1 also reports the information about the allocation of the policies for the Lombardy case. In particular, in the case of Lombardy, the following policies were considered: the effects of a policy enacted in 2006 that regulates the energy production of agro-forestry origin for the Average scenario; the consequences of the important reform for biomass facilities of 2012 for the High scenario; the guidance on bio-methane production from waste recovery facilities established in 2019 for the Low scenario. In graphical terms, Figure A2 shows the periods analyzed for each policy scenario with the colored lines.

After determining which scenario to assign to each variation, mean values of Δp_t and Δq_t were calculated by scenario type. Specifically, in this example, in order to determine the mean Δp_{av} and Δq_{av} for the Average scenario, the corresponding Δp_t and Δq_t values of the years 2007, 2008, and 2009 were averaged. This mean value indicates how much the estimated parameter values have to be changed if we want to simulate an Average policy. The results of these calculations for the Lombardy case are expressed in Table A2.

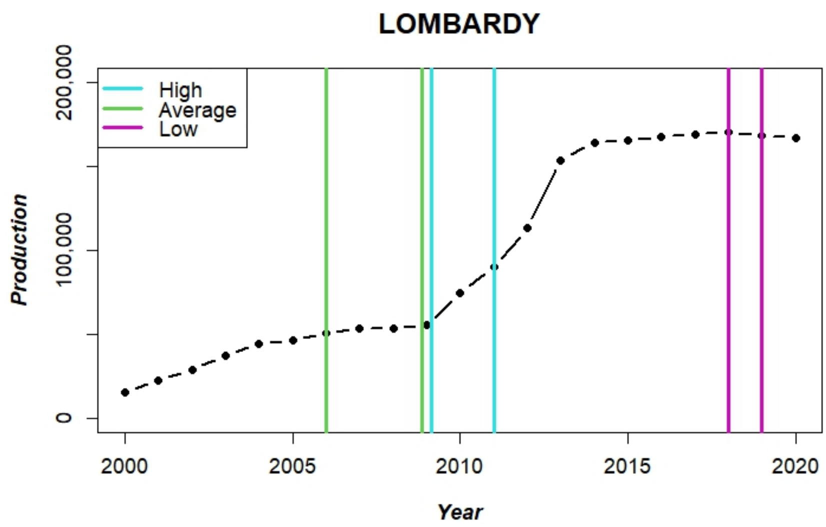


Figure A2. Bioelectricity production density in Lombardy with the policy periods highlighted.

Table A2. Average rates of change for each scenario in Lombardy.

Policy	Δp_{av}	Δq_{av}
Average	−6.65	−7.66
High	−30.37	−24.22
Low	18.34	6.83

Once Δp_{av} and Δq_{av} were calculated for each policy scenario, these variations were applied to the estimated parameters of the models implemented on the entire technology life cycle (p_{2020} and q_{2020}) with the following formulas:

$$p_{new} = p_{2020} * (1 + \frac{\Delta p_{av}}{100}) \qquad q_{new} = q_{2020} * (1 + \frac{\Delta q_{av}}{100})$$

Finally, for each scenario, by employing the Bass equation with the new parameter values p_{new} and q_{new} and considering $z'(t)$ equal to the last observed data point of the series, three 'new' observations were predicted. For the Lombardy case, the main results are reported in Figure A3. A detailed description of the results for Lombardy is reported in Section 3.2.2 with Group 3.

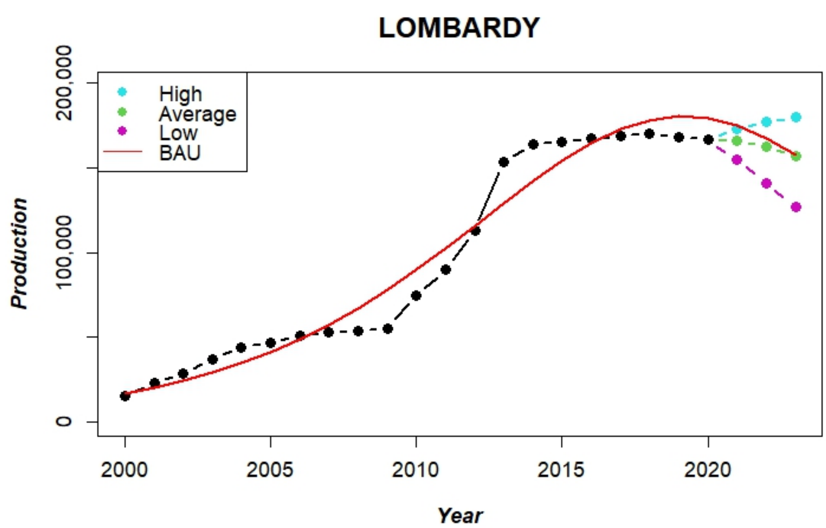


Figure A3. Predictions with the Bass model and scenario simulations for Lombardy.

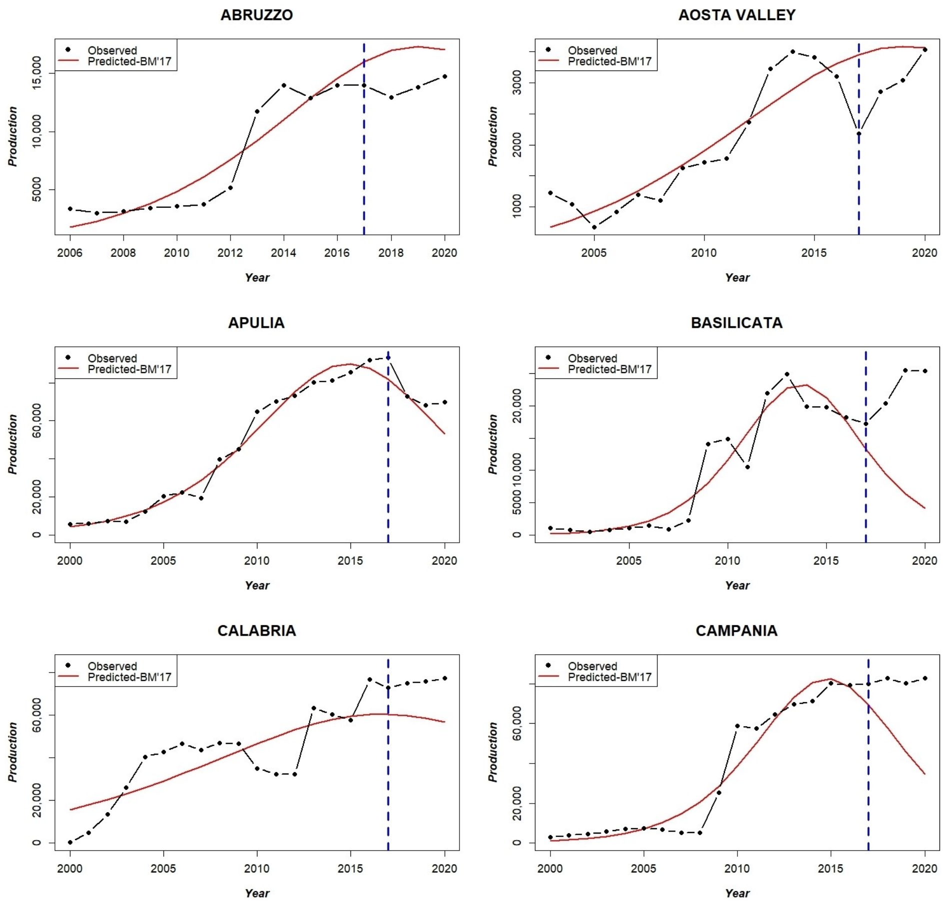
Table A3. Scenario identification in the Italian regions.

Regions	Policy	Years	Δp	Δq
Abruzzo	Average	2019	0.91	1.55
	High	2020	−0.79	−3.49
	Low	2018	19.84	11.71
Aosta Valley	Average	2020	−0.17	−1.30
	High			
	Low	2019	21.04	12.69
Basilicata	Average	2005, 2020	13.91	−6.33
	High	2013	2.09	−10.27
	Low	2016, 2017	11.17	−4.00
Molise	Average			
	High			
	Low	2017, 2018, 2019, 2020	7.41	5.04
Apulia	Average	2015, 2020	0.38	−1.38
	High	2016, 2017	−0.29	−3.82
	Low	2014	2.88	2.11
Calabria	Average	2008, 2019, 2020	6.81	−10.52
	High	2013, 2016, 2018	−5.54	−17.42
	Low	2010, 2011, 2012	5.68	−6.80
Marche	Average	2019, 2020	−24.16	−0.01
	High	2016	−73.66	−3.36
	Low	2017, 2018	20.15	8.22
Sardinia	Average	2017, 2019, 2020	11.41	−4.62
	High	2015	4.33	−3.14
	Low	2018	5.56	−2.35
Sicily	Average	2007, 2013	−5.88	−5.37
	High	2009, 2018	−41.63	−31.35
	Low	2012, 2019	32.56	15.09
Campania	Average	2016, 2017	5.45	−3.84
	High	2014	−97.69	10.48
	Low	2007	8.38	14.12
Emilia-Romagna	Average	2008	−8.51	−10.20
	High	2009	−67.82	−40.91
	Low	2016	62.43	8.09
Lazio	Average	2007, 2008	−0.27	−14.95
	High	2011	−30.51	−44.63
	Low	2020	9.10	4.85
Lombady	Average	2007, 2008, 2009	−6.65	−7.66
	High	2010, 2011	−30.37	−24.22
	Low	2019	18.34	6.83
Piedmont	Average	2007	−14.60	−10.35
	High	2009	−61.174	−30.94
	Low	2018	33.44	10.83
Tuscany	Average	2008	1.01	−3.42
	High	2009, 2010, 2019	−28.13	−38.32
	Low	2020	8.47	3.87
Veneto	Average	2007, 2009	−7.32	−6.96
	High	2010	−11.46	−19.68
	Low	2008	17.55	20.22
Friuli–Venezia Giulia	Average	2011	11.38	−13.36
	High	2012, 2013	−13.25	−23.19
	Low	2020	−0.04	−0.09
Liguria	Average	2015	0.37	0.90
	High	2019	−0.13	0.14
	Low	2014	3.14	3.06
Trentino–South Tirol	Average	2007	−11.08	−17.39
	High	2020	−97.18	−25.69
	Low	2008	6.09	12.72
Umbria	Average	2007, 2012	5.59	−10.50
	High	2013, 2014, 2015	5.99	−28.54
	Low	2010, 2011	1.14	−3.37

Appendix B. Bass Model Estimation with Truncated Data

For validation purposes, a study on Bass model estimation, which was considered in this paper as the BAU, was performed. The results of this analysis were useful for supporting the implementation of a prediction method through scenario simulations. This appendix presents the Bass model estimation on the truncated series up to 2017 with out-of-sample predictions up to 2020 for each region. In this way, it is possible to compare the predicted values with the observed data for a time window of three years, i.e., the one that was also used in the scenario simulations.

As shown in Figures A4 and A5, the model did not capture the variability and perturbations well in the studied regions. Therefore, the particular nature of the series analyzed and the structure of the model used did not allow a precise prediction analysis through the BAU. Comparing these outcomes with those in Section 3.2.1, it is crucial to underline some characteristics of the Bass model that led to different results. Looking at Figures A4 and A5, it may be noticed that the model failed to capture the periods of stationarity that characterized some of these series in the years 2018–2020, such as in Campania, Lombardy, Piedmont, Trentino–South Tyrol, and Veneto. The primary cause was the model's sensitivity to the amount of data used for estimation. In fact, in Section 3.2.1, the BAU fit the data better because of the greater number of data points, allowing a better performance of the model. On the other hand, the BAU predictions, especially in some cases, could not be considered highly reliable due to the structure of the series, which were strongly perturbed by policy interventions. For these reasons, the BAU was only used to perform a baseline study of the series and as a starting point for the new prediction method that we propose in this paper, which gave us the opportunity to provide a wider perspective on the future evolution of the development of bioelectricity in each Italian region.



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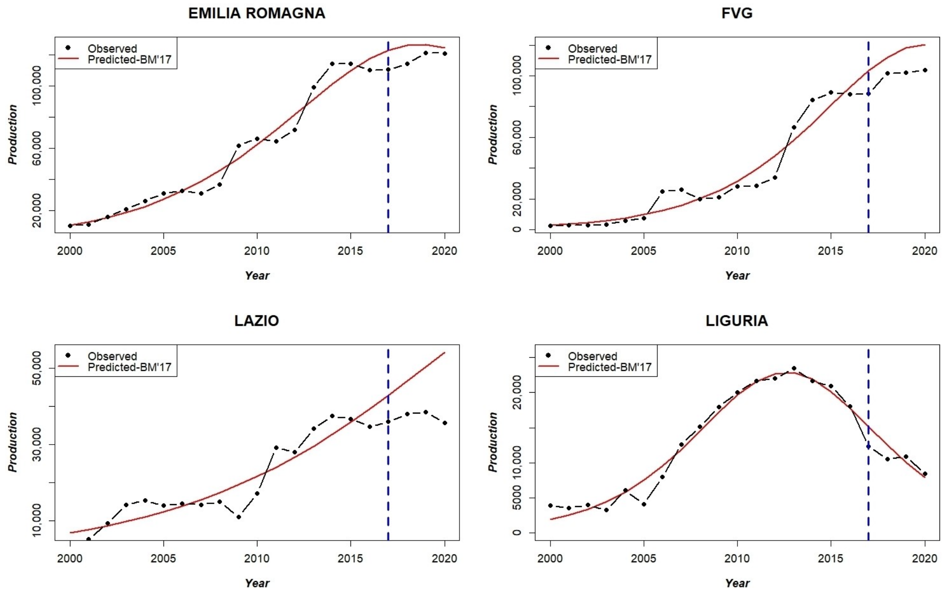
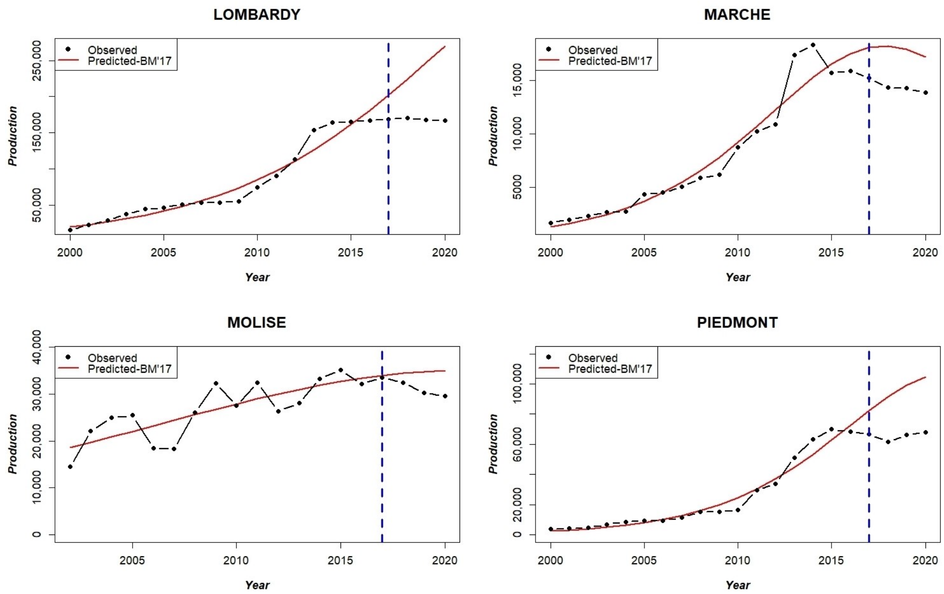


Figure A4. Bass model estimation until 2017: from Abruzzo to Liguria in alphabetical order (the vertical blue line represents the point in time where data have been truncated).



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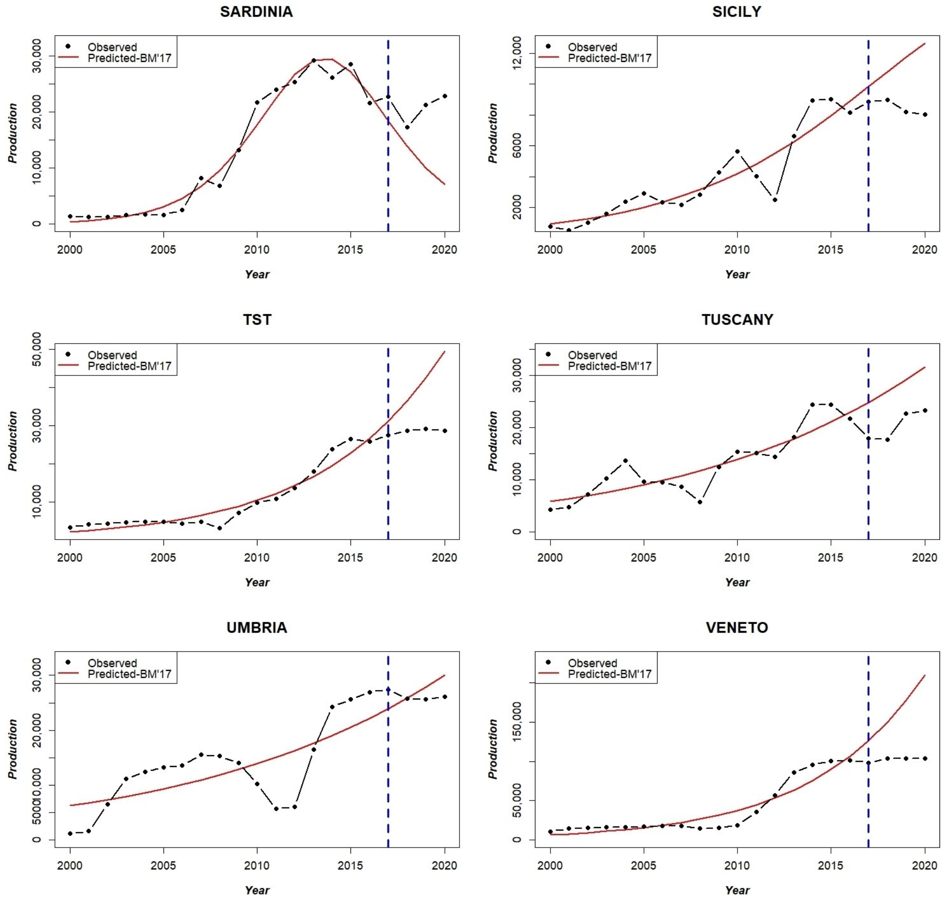

Figure A5. Bass model estimation until 2017: from Lombardy to Veneto in alphabetical order (the vertical blue line represents the point in time where data have been truncated).

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