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Review

Predictive Production Models for Mountain Meadows: A Review

Adrián Jarne, Asunción Usón and Ramón Reiné *

Departamento de Ciencias Agrarias y del Medio Natural, Escuela Politécnica Superior, Universidad de Zaragoza, Ctra Cuarte s/n, 22071 Huesca, Spain; ajarne@unizar.es (A.J.); mauson@unizar.es (A.U.)
* Correspondence: rreine@unizar.es

Abstract: Meadows are the most important source of feed for extensive livestock farming in mountainous conditions, as well as providing many environmental services. The actual socioeconomic situation and climate change risk its conservation. That is why finding its optimal management is important. To do so, predictive models are a useful tool to determine the impact of different practices and estimate the consequences of future scenarios. Empirical models are a good analytical tool, but their applications in the future are limited. Dynamic models can better estimate the consequences of newer scenarios, but even if there are many dynamic models, their adaptation into grassland production estimation is scarce. This article reviews the most suitable predictive models for grass production in mountain meadows when data on agricultural management (mowing, grazing, fertilization) and forage value are available, considering the conservation of plant biodiversity.

Keywords: grassland; modeling; agricultural management practices

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1. Introduction

Traditional livestock farming in mountainous areas is strongly dependent on hay meadows [1]. These meadows are communities formed by different plant species from different botanical families that grow together as a single crop. On those farms, meadows are cut during the summer, and if the summer is wet enough, they can be cut a second time. They are also used for grazing in spring and autumn. That is why they constitute the keystone of traditional livestock farming [2–4].

Not only do they help farmers meet their feeding needs, but they also provide environmental services. Due to their dynamics, meadows can act as carbon and nitrogen sinks by capturing those elements into organic matter in the soil, helping in climate change mitigation [5,6]. They are an important biodiversity reservoir, providing adequate ecological niches for many plants and animals [7,8]. Lastly, it should be noted the great landscape value that they have, making the rural environment more bucolic [9].

Those services can be affected by changes in management. Given the actual climatic conditions, where heat stress days and drought days are increasing, meadows can pivot from being a carbon sink into a carbon emitter, especially if they are heavily fertilized or if there is overgrazing [5].

System biodiversity is also driven by management practices, mainly mowing, grazing, and fertilization [10]. If there are changes in those practices, be they in excess or absent, there will be changes in vegetation dynamics, species distribution, and landscape biodiversity [8].

Meadows are a more complex crop system than conventional monocultures [11]. Instead of having a single species, we have a community formed not only by different species but also by different botanical families, each one behaving and responding differently to farm management and climatic conditions [12]. Given that complexity, it is difficult to establish which practices are beneficial for the whole meadow. For example, nitrogen fertilization would be beneficial for grasses but detrimental for legumes [8]. On the other hand, biodiversity gives meadows a higher resiliency, adapting better to stressful situations like floods, heat stress, or drought [13].

Abandonment of traditional livestock farming, especially in disadvantaged areas like mountainous areas, has been a constant issue since the 1980s, leading to a decrease in meadow area [2]. Although biodiversity usually increases right after meadow abandonment, in the long term, it will be significantly lower than it was when it was managed [14]. Intensification of production also decreases biodiversity due to the higher fertilization rates and the increase in grazing days [14,15].

In order to preserve meadows and maintain the ecosystemic services they bring, their management must be profitable [16]. Finding a balance between profit and conserving biodiversity while adapting to climate change is quite a challenge [17,18]. Actually, permanent grasslands in Europe occupy 33% of the agricultural area, or about 56.9 Mha (https://ec.europa.eu/eurostat/data/database, accessed on 9 April 2024).

During the past four years, the production, forage quality, and floristic diversity of several hay meadows in the Aragonese Pyrenees have been quantified. Agricultural management practices and meteorological variables have also been recorded during this period. With this information, we intend to calibrate a prediction model that will allow us to evaluate the production–conservation binomial of these meadows in the future under different management.

Therefore, a literature review of the use of models in different types of grasslands and productive environments is carried out, with special emphasis on the quantity and quality of the data necessary for their application. It also considers the way in which agrarian management is treated, namely, the quantity and timing of cuttings and grazing, the type and quantity of fertilization, etc. Finally, consideration is given to the way in which such models value changes in plant biodiversity in these systems.

2. Crop Predictive Models

Meadow profitability can be improved by optimizing farm management by adjusting fertilizing rates, mowing times, and grazing days. But knowing how to adjust those practices is quite difficult; it would take thorough research for each practice on each meadow to measure the impact of each practice. To facilitate this enormous task, there are predictive models that allow us to infer the impact of different practices and scenarios on production [19].

Predictive models allow us to precisely predict crop reality given specific management, soil, and climatic conditions at various temporal resolutions [20]. They are able to simulate the entire field situation by using relatively little field data [19].

Predictive models are mathematical approximations of the phenomena that happen in the atmosphere–plant–soil system, integrating all natural processes that influence these phenomena [21]. Each model uses a different mathematical approximation because there are different hypotheses in the different fields of study for the different natural processes. Usually, those approximations have no linear dependence on each other, which leads to important changes in the results with minimum changes in the input [21]. But it is important to be precise about what we want to predict and what the specific model requirements are [17].

They suppose a handy tool to analyze different scenarios given hypothetical situations and to know the previsible impact that those changes determined in the hypothesis will have on the modeled parameters [13,21,22].

One of their main uses is food security [23]. Because it allows us to predict the amount of food that will be available. That is especially useful with the current climate change situation. Despite the uncertainty of how the climate in the future will be, using predictive models, we can estimate the impact of long heat waves, droughts, etc. that are previsible to be more frequent [24].

We can classify predictive models according to their type as follows: they can be empirical (static), or they can be dynamic.

Empirical models are only built based on field data. They are statistical constructions to explain data variability given determined conditions at a specific moment. Usually, they are based on regressions, and although they are useful to describe and analyze, they cannot make predictions outside the field data range. The extrapolation of the result is at least very speculative [25].

On the other hand, dynamic models are based both on field data and equations that represent natural processes. They are more complex to parametrize and validate, but at the same time, they can be used for more situations than the empirical models [25].

We can also look at the complexity of the model; as the model gets more complex, it will better explain the entity and be more robust. But as a consequence, analyzing the impact of the different factors will be more difficult; there will be more correlations between parameters, and there will be a higher demand for calibration and validation [21,26].

On the contrary, as the model gets simpler, it will be easier to evaluate the impact of each factor, there will be less correlation between parameters, and validation and calibration will be simpler. But as a consequence, the model will be less robust, and there will be more differences between observed values and predicted values [21,26].

The area of application is one of the major drivers of complexity. Globalist models can be applied to many different situations, but they are more complex than other models that are more local [17].

There is a need to find a balance between explaining variability properly and having a manageable number of variables. If we use many variables, the model can get so complex that it will require enormous computing power to run simulations [27].

In our case of study, that is, meadows, there are specific parameters that should be considered that are not necessary for other crops. As meadows are used for animal feed, it is important to know what the impact on nutritional value will be. There are many factors that affect it, such as the diversity of species, which will change its nutritional value depending on the species that it contains and the quantity in which they are present [25]. Phenology will also play a key role in nutritional value because, as phenology advances, digestibility will decrease [28]. In addition, fertilization will be another factor that will affect nutritional value, especially nitrogen fertilization [28].

The impact of each factor will be different than in conventional crops, with biodiversity having one of the highest impacts [29]. But other parameters, like carbon, will have different impacts depending on the diversity of species [14].

Meadow management is also more complex than the management of other crops. There is a need to take into account practices like mowing or grazing, which implies that there is more than one type of harvest and more than one harvest per year, in contrast with other crops where there is only one harvest per year [13]. Current developments in remote sensing open new opportunities to measure objectively more parameters at a relatively low cost [30,31].

2.1. Empirical Models

This type of model is mainly used to describe and analyze observed situations. But there are studies where they have to infer conclusions based on the empirical model [32].

They can properly determine tendencies within actual management under actual practices, given that information is available to predict results within those conditions [33]. But the main purpose of the study must be clear, because depending on the goal, different types of results will be needed, and as a consequence, there will be certain statistical tools [34]. It is important not to try to infer conclusions outside of the range of field data due to the uncertainty outside this range [35].

Many empirical models are based on remote sensing. This is a cost-effective technique to get data objectively, and that is why it is widely used [36,37]. Most of them use the Normalized Vegetation Index (NDVI) to determine the amount of biomass present in the meadow [38]. Many of them are based on satellite imagery, which has the drawback of having low resolution, and as a result, it can only be successfully used when the area is large and homogenous [39]. In order to improve resolution, there are studies that use Unmanned Aerial Vehicles (UAV), and in these cases, small fields with higher heterogeneity can be studied [40]. Another remote sensing technique that has been applied to build empirical models is Lidar. This technology allows for the creation of a three-dimensional map from which it is possible to calculate biomass volume. Although it is considered a promising technology, its cost is still too high [41].

Recently, the development of friendly use of new Artificial Intelligence (AI) techniques has allowed us to let them use them in crop modeling [42]. There are many AI tools like Random Trees, CHAID, K-Nearest Neighbor, or Naïve Bayes [43]. Although they are not so new, Artificial Neural Networks (ANN) have been used for years as a way to develop models based on data classification [35,42]. The combination of AI technologies and UAV imagery provides a robust modern base for developing new cost-effective empirical models, but there is still much research needed to improve their accuracy [44].

2.2. Dynamic Models

Dynamic models are based on mathematical approximations of natural processes, based on equations that have no linear behavior and have an important number of variables. There are many processes that have been incorporated into the dynamic models; the most common are the carbon cycle, nitrogen cycle, water dynamics, plant growth, and plant competition [25].

Using a dynamic model must be performed carefully; all the variables must be used according to model requirements, and in some cases, their objective determination is not easy and requires indirect determination from other parameters. This does not only increase correlation between variables; it is also a common source of error [21]. Most dynamic models are built on modules that simulate a specific cycle or process. Although those modules are often independent, their results will have an impact on the rest; the impact is usually not linear, so small changes in one module can lead to great differences in the result as a result of losing precision [45]. To be widely used, the model must be easy to use, have as few variables as possible, and be parametrized for as many conditions as possible. But finding a balance between user friendliness and accuracy is a complex challenge. As a result, precision increases its usability, and as a consequence, the number of users decreases [46–48].

In the case of meadows, the number of variables increases compared to other crops. Each species has a different lifespan; some plants are annual and others are pluriannual; their phenology varies between species; surviving rates will change depending on management, climate, and species. All this complexity leads to more challenging model-building [10,28]. To solve this problem, some models have simplified this process, and in some cases, they have obviated it, but at the cost of reducing model precision [49,50]. Simplification can be performed by aggregating growing patterns of vegetation and considering it as a single crop, making modeling easier [49].

One of the first models developed for meadows was the Hurley Pasture Model. It is a generic, deterministic, dynamic, and mechanistic model where the cycles of carbon, nitrogen, and water are simulated using modules to independently simulate each cycle in the soil, plant, and animal and apply its result to the rest of the modules. This model uses parameters like Leaf Area Index (LAI), Net Primary Productivity (NPP), root-shoot partitioning, C/N ratio, soil organic matter, etc. Some dynamical models have integrated this model into them as the backbone of meadow simulation [51].

There are many different dynamic models, but we can classify them according to their characteristics [25], as follows:

- Ecological model: they are small models focusing on biotic interactions using elegant equations. Those models explain general ecological patterns, including species interactions, but abiotic effects and spatial heterogeneity are poorly accounted for.
- Biogeochemical: they are parameter-rich models of the cycling of carbon, nutrients, and water. They make long-term predictions about biogeochemical cycles and soil pools. On the other hand, they usually have limited capacity for yield forecasting and limited capacity for heterogeneity and biodiversity.

- Agricultural: they are rich-parameter models focusing on phenology and yield formation. They make short-term predictions of productivity, but they lack long-term predictive capacity and admit no spatial heterogeneity or biodiversity.

In this paper, we have revised some of the dynamic models that have been used for meadow production. The selection criterion was the existence of bibliographical references regarding the application of the model for grassland management. Most of them are agricultural models due to their inherent focus on production. Ecological models, as they are not well suited for production, have not been considered. Some biochemical models, although they are not focused on production, can accurately predict production. All of them have global scope. Although some models are not calibrated for meadow production, there are popular agricultural models that have great potential in meadow modeling, and there are some studies where they have calibrated them for meadows in certain environments. There could be more models, such as GrassProg or CosMo, but putting more models into the review could be redundant, as some of the nonstudied models have a similar structure as the chosen ones. Table 1 shows some characteristics of these models and their main bibliographical references.

Table 1. Summary of the analyzed models.

Model	Type	Grassland Calibrated	Area of Study	References
APSIM	Agricultural	Yes	Europe, Oceania	[52–60]
STICS	Agricultural	No	Europe, North America	[61–67]
LINGRA	Agricultural	Yes	Europe	[68–74]
CROPSYST	Agricultural	No	Europe	[75–81]
WOFOST	Agricultural	No	China, Europe	[82–88]
PaSIM	Biogeochemical	Yes	Europe	[89–95]
Biome-BCG	Biogeochemical	Yes	China, Europe, North America	[96–102]
CenW	Biogeochemical	Yes	Europe, Oceania, North America	[103–110]

Table 2 provides additional information on the use of the models of management practices parameters (mowing, grazing, and fertilization), biodiversity parameters, and the volume of data needed to run them.

Table 2. Parameters included in the models.

Model	Mowing	Grazing	Biodiversity	Fertilization	Amount of Data Required
APSIM	Yes	Yes	Yes	Yes	Medium
STICS	No	Yes	No	Yes	Medium
LINGRA	No	Yes	No	Yes	Low
CROPSYST	No	Yes	No	Yes	Medium
WOFOST	No	No	No	Yes	Low
PaSIM	Yes	Yes	Yes	No	High
Biome-BCG	Yes	Yes	Yes	No	High
CenW	No	No	Yes	No	High

2.2.1. APSIM

The Agricultural Production System Simulator (APSIM) was originally developed in Australia, but it now suits all global conditions. Its aim is to have an easy-to-use model able to predict harvest according to different situations and to give the manager a useful tool to help in decision making. It has been parametrized for multiple crops, including meadows [52,53]. It has a modular architecture where different components represent specific processes in the system, like soil, weather, crop, and nutrients, where each component interacts with another [54]. For modeling crop growth, it simulates key processes such as photosynthesis, respiration, transpiration, and phenology using factors such as climate factors (temperature and solar radiation) and soil factors (soil moisture and nutrient availability), whereas crop development stages are tracked based on thermal accumulation [55]. It also models nutrients and water dynamics using soil properties, management practices, and crop characteristics to model soil water movement, evaporation, nutrient cycling, and water and nutrient uptake by the crop [56,57].

One of the greatest strengths of this model is its capability to define a wide range of management practices, like sowing, irrigation, fertilization, mowing, or grazing. Each practice can be customized to the studied conditions [58]. It is also noticeable for its ability to infer the growth of each species, simulating the effects of competition and grazing [59,60].

2.2.2. STICS

Simulateur mulTIdisciplinaire pour les Cultures Standard STICS, a model developed by the French National Institute for Agronomic Research (INRA), consists of a yield-focused agricultural model [61,62]. It also has a modular design where each module represents different aspects of the crop system, namely, soil, climate, crop, and management. Those modules interact with each other to simulate crop growth and development [62,63]. Plant growth is based on temperature using degree-fays, but it also considers other factors such as solar radiation, water, and nutrient availability [64]. It incorporates management data such as irrigation and fertilization [65].

Although its focus is on yield forecasting, it can also predict quality [66]. Another strength is that it makes it easy to change management dates, such as the sowing date or the mowing date, to evaluate their impact [67].

2.2.3. LINGRA

This model is especially designed to simulate grassland growth under various conditions [68,69]. It is simpler than other models and calculates three types of production, namely, potential production, water-limited production, and nitrogen-limited production [70]. It requires less input than other models. For weather, it only needs solar radiation, minimum and maximum temperatures, vapor pressure, wind speed, and rainfall. For the soil analysis, it just needs soil depth, moisture content at field capacity, saturation, and wilting point. And finally, for management, it only needs to know when the harvest is performed and when and how much fertilization is applied [69,71].

Its stronger point is its simplicity; it can even be run on Excel 17.0 [72]. It has been used successfully to estimate forage production in the European Union and is the model that better represents physiological mechanisms that take part in defoliation and regrowth [73].

As a drawback, it lacks reproductive growth, herbage growth from nitrogen fertilizer, species proportion, and herbage quality. Some studies have improved those parameters [74].

2.2.4. CROPSYST

This agricultural model is a multiyear, multicrop model that simulates crop growth on a daily basis. It is one of the most used models due to its user-friendly environment and its wide range of parametrized crops and conditions [75,76]. It has various modules that simulate the soil water budget, soil and plant nitrogen budget, crop growth, dry matter production, yield formation, residue production and decomposition, and soil erosion [77]. It calculates crop growth based on the thermal accumulation needed to reach a specific phonologic phase, although it also takes into account the limitations of water, nitrogen, light, or temperature [78].

It has the strength of being able to accurately predict the consequences of extreme climate events on crop phenology and development [79]. It has been bundled with ClimGen, a generator of weather conditions for places where there is not much data available. And it can be improved by the use of GIS [80]. Although there are many parametrized crops, meadows are not one of them, but some studies have parameterized them for certain meadow situations [81].

2.2.5. WOFOST

It is the acronym for WOrld FOod STudies (WOFOST), a mechanistic and dynamic agricultural model. It was developed by the Center for World Food Studies in collaboration with Wageningen University and Research [82,83]. It simulates crop growth on a daily basis, modeling natural processes like photosynthesis and respiration. It also considers limitations caused by temperature, light, water, and soil properties [84]. When the crop is parametrized, it requires little input about climate, management, and soil, making it easy to use [85]. As outputs, it gives the maximum yield achievable under optimal conditions, biomass accumulation, water use efficiency, and actual production [86].

This model is used worldwide to estimate crop yields around the globe, and their output is given by maps of yields. Despite being designed for crop yield estimation, it shows more accuracy in predicting crop growth and development than yield. In addition, remote sensing has been shown as a possible tool to improve its accuracy [85]. Unfortunately, it is not officially parametrized for grassland; some studies have achieved it [87,88].

2.2.6. PaSIM

It is the acronym for Pasture Simulation Model. It is a biochemical model designed to simulate grassland ecosystems by the INRA [89]. It is focused on carbon, nitrogen, and water flux throughout the soil–plant–atmosphere system. It accounts for net primary productivity, forage intake by domestic herbivores, and energy dynamics [90,91]. It requires a huge number of variables, accounting for more than 100, but only 27 have a significant impact [91]. As a difference from other models, it uses an hourly time step, allowing more detailed dynamics [92,93].

It is one of the most complete models, having a complete simulation of all the processes that affect meadows [94], even tackling the impact of grazing on production, but due to its complexity, it requires a fairly large amount of calibration study [95].

2.2.7. Biome-BCG

This model, originally developed by the University of Montana to simulate forest conditions, is a combination of a biogeochemical and an ecological model. It is capable of modeling interactions between nutrients and water cycles with species mortality and expansion [96,97]. It operates at a daily time step and requires a vast number of parameters, aggregated in four files, namely, one for initial conditions, a second for meteorological data, a third for eco-physiological constants, and the last with soil properties [98]. It is able to incorporate management information such as fertilization and grazing using a management file [99,100]. As an additional parameter, we can use NDVI, improving its accuracy [101].

It has the strength of being able to simulate all processes involved in meadows, giving precise information about not only yield but also carbon and nitrogen fluxes in the soil [97]. As a setback, it requires a lot of data to be calibrated because each meadow community will have a different behavior [102].

2.2.8. CenW

Acronym for Carbon Energy Nutrients Water is a biogeochemical model designed to study environmental responses to changes in the ecosystem [103]. It is mainly focused on physiology. It simulates the simplification of physiological plant processes such as photosynthesis and the cycles of nutrients and water. It requires fewer variables than other biogeochemical models. [104,105]. It has been mainly applied to study carbon balance in forests, but then it was adapted to grasslands [106,107].

It is the simpler of the biochemical models, but it is still capable of considering practices like grazing and irrigation [108,109].

3. Discussion

As it has been shown, there are many different types of meadow modeling; each of them has its weaknesses and its strengths.

Empirical models arise as the best tool to analyze a concrete situation, and current developments in AI and remote sensing make them more versatile. They are also very useful for making predictions within their data range, but if we need to make projections outside of their data range, their results will be highly speculative. Making them less reliable to predict outcomes from extreme weather conditions that have not been observed or management practices that have not been applied.

APSIM appears as a powerful tool to assess meadow production accounting, grazing, and mowing without the need for an extra model customization study. It performs equally well in warm climates as in cold climates [52,55]. Also, its user-friendly interface makes it usable. But most of the study is performed in *Lolium* sp. and *Trifolium* sp. pastures, not on seminatural meadows.

STICS is considered the agricultural model that better simulates nitrogen and water dynamics, but it is not parametrized for meadows [65].

LINGRA can be easily used with Python, R, or even Excel, and it has a robust defoliation and regrowth model, but all of its parametrizations are based on the grass monoculture of *Lolium* sp. or *Dactylis glomerata* [68,71,73].

CROPSYST is one of the most user-friendly models. It is capable of properly simulating most of the factors that affect plant growth and development. Although meadows are not parametrized, in some studies, they have been simplified as a monoculture of the dominant species [80,81].

WOFOST is a global model that can be used anywhere, and its graphical outputs are one of the easiest ways of visualizing results. But its design forces it to simplify meadows into a single crop, losing its accuracy [83,84,88].

PaSIM is developed specifically for meadows, and there are many papers where production has been accurately predicted. As a tradeoff, it needs to parametrize many parameters, making it more difficult to use [89,91,92,94].

Biome-BCG is the model that best represents meadow biodiversity and considers more ecological factors. Although it was not its main goal, it can predict production as well as agricultural models. But its high complexity makes it easy to make mistakes [99,101,106].

CenW is good at predicting carbon and nitrogen balance, especially useful to evaluate the implications of climate change in meadows, but is less accurate for predicting production than other models [105,106,109].

Some papers have compared various models. WOFOST and CROPSYST were used with similar results [29]. APIM was compared with GrassProg1, a simpler model for grasses, with no significant difference [110]. Biome-GCG and PaSIM were compared, and the only significant difference was that PaSIM estimated better evapotranspiration [97].

It is possible to aggregate model results into an ensemble model, which combines the characteristics of both empirical and dynamic models [13]. They are the combination of results from different models, which gives them higher robustness [31,90,111]. This combination can be performed in various ways, such as by building it using the median of all simulations or by weighting according to each error [111]. Ensemble models have shown higher accuracy than other models, but it requires calibrating and parametrizing all the models that want to be combined. It is a highly labor-intensive method [90,111].

Most models simplify meadow biodiversity into one virtual crop, acting as if the meadow is a monolithic living structure that does not change with time. But their compositions vary depending mainly on climate and management [49]. Obviating those changes could lead to errors, due to the changes in vegetation that will result in response changes. Taking vegetation changes into the model does not come for free; it increases its complexity and makes it more complex to use [13]. Some factors are not considered by any model. For instance, meadow floristic composition will affect nitrogen content in animal depositions, and all models consider it stable [112,113]. Also, its distribution would not be uniform;

animals tend to spend more time in some places than others, changing soil dynamics and biodiversity at a local level [114].

Any model considers soil erosion, which could be driven by overgrazing. Loss of soil would decrease meadow productivity in the long term [115]. Being a key component of livestock farming, the economic productivity of meadows must be considered, and only a few dynamic models, such as APSIM, take this into account [116]. Lastly, all models require precise climate data, usually temperature, rain, radiation, and wind. Given mountain orography, weather conditions can be abruptly different at low distances, adding to the need for more data acquisition [117]. As climate data are usually obtained from close locations, it can be inaccurate due to the orographic differences, which would lead to errors in the predictions.

New technologies open great opportunities to improve meadow modeling [118]. Using remote sensing makes it possible to get new objective variables at a relatively low work load cost, enhancing model robustness [119,120]. In addition, the use of animal monitoring sensors, can help obtain more data about animal behavior in the meadow, making animal grazing dynamics less speculative and more objective [121].

Climate change is one of the biggest challenges that meadows face. Due to its complexity, it is difficult to determine what practices are best suited to face it. Using models, we can anticipate its consequences and evaluate possible adaptation and mitigation practices. Although much has been studied, we still need to improve models and analyze them to find the best practices [116,122].

4. Conclusions

Mountain meadow production modeling is a difficult task. It is formed by many different species, and their management is complex, combining grazing and mowing. Empirical models can make good predictions inside their data range, but they can be very inaccurate outside. There are many dynamic models that can estimate production, but many of them are not parametrized for meadows or are data-intensive and complex to use.

Many models tend to focus on environmental parameters such as carbon or nitrogen fluxes or tend to simplify meadows into a virtual single crop. Despite the huge amount of information available for meadow modeling, there is little information about production modeling in meadows.

There is still study to do to tackle the challenge of vegetation changes and obtain better climate data for mountainous areas. Otherwise, we do not really know how mountain meadows will respond to the coming changes or which practices we should endorse to make them economic and environmentally sustainable.

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