Summary Report

WP2 - Feasibility of developing existing grass growth models

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Introduction

Aim

Test the feasibility of developing existing grass growth models to use remotely sensed information to produce realistic grass growth curves.

Approach

- Review papers describing grass growth models
- Evaluate potential to incorporate different satellite sensing technologies into grass growth models.

Results

This stage of the project aims to identify a model (or, combination of models) that can provide daily or weekly estimates of:

- Yield (e.g. dry matter t/ha)
- Moisture content (%)
- Digestibility (e.g. ME content MJ/kg DM)
- Protein/N content (e.g. crude protein content, %)

These estimates should cover the period up to the first silage cut (with no grazing), or pre-grazing growth periods, but may not cover subsequent grass growth which is more complex as it is dependent on factors relating to the timing of the first cut.

The aim is to predict changes in grass yield and quality and so predict optimum dates for cutting silage, and potentially when to graze, and to use satellite data to improve the accuracy of these predictions.

Table 2-1 Review of Grass Growth Models

Model	Inputs	Outputs	Further notes	References
GrazeGro	Temperature, rainfall, radiation, soil type, N availability. Parameters controlling morphological development.	Biomass, organic matter digestibility, crude protein.	Process-based. Daily inputs and iteration Based on LINGRA model. LINGRA model code is downloadable.	Barrett P.D., Laidlaw A.S., Mayne C.S. (2004). GrazeGro: a European herbage growth model to predict pasture production in perennial ryegrass swards for decision support.
Brereton *et al*	Mean radiation, mean temperature. Mean nitrogen availability and mean soil moisture deficit over growing period. Grass ontogeny, length of regrowth period.	Yield	Static model with one growth rate over whole period dependent on mean environmental conditions.	Brereton, A.J., Danielov, S.A. & Scott, D., (1996). Agrometeorology of Grass and Grasslands for Middle Latitudes. *Technical Note No. 197. Geneva: World Meteorological Organisation.*
Jouven	Weather data (radiation, mean daily temperature, precipitation and PET) nitrogen index, soil water-holding capacity. Can describe different grassland communities.	Growth rate, pasture structure and digestibility.	Mechanistic – describes different plant growth stages that affect growth rate. Can be applied at field scale.	Jouven M., Carrère P., Baumont R. (2006). Model predicting dynamics of biomass, structure and digestibility of herbage in managed permanent pastures. 1. Model Description. *Grass and Forage Science* 61(2):112-124
Moorepark Grass Growth Model (i.e. linkage of Jouven model adapted for Ireland with soil N model 'Moorepark ANTS'.	N fertiliser application, weather data.	Biomass, N content.	Developed in C++	Paillette C.A., Delaby L., Shalloo L., O'Connor D., Hennessy D. (2015). Developing a predictive model for grass growth in grass-based milk production systems. *Grassland Science in Europe,* Vol 20 – Grassland and forages in high output dairy farming systems.
Groot & Lantinga	Temperature, radiation. Parameters controlling morphological development.	Organic matter yield, composition, digestibility, morphological development.	Assumes water availability are nutrient status are not limiting factors. Time-steps of 0.2h. Written in C++.	Groot J.C.J, Lantinga E.A. (2004). An object-oriented model of the morphological development and digestibility of perennial ryegrass. *Ecological Modelling* 177: 297-312
Thornley/Hurley Pasture Model	Latitude, radiation, maximum and minimum air temperature, relative	Dry matter yield, C content, N content, water content.	Based on Hurley Pasture Model, complex.	Thornley J.H.M. (2001). Modelling Grassland Ecosystems. *Proceedings*

	humidity, rainfall (weather data can be monthly), N deposition rate. Can vary many aspects – e.g. fertiliser, grazing, cutting scenarios – but is complex.			*of the XIX International Grasslands Congress,* Saõ Pedro, Brazil*:* 1029-35
Gemini	Mean temperature, temperature range, photoperiod, precipitation, air moisture, PPFD, N input, disturbance regime, soil layers, plant population.	Dry matter yield, sward species composition	Focus is on competition between grassland species. Developed in C++. May be able to predict N content as this is considered in growth model, but does not explicitly state that the model predicts it. Complex with many parameters.	Soussana J.F., Maire V., Gross N., Bahelet B., Pagès L., Martin R., Hill D., Wirth C. (2012). Gemini: A grassland model simulating the role of plant traits for community dynamics and ecosystem functioning. Parameterization and evaluation. *Ecological Modelling* 231: 134-145
FOPROQ & FOSIM	Daily weather data – precipitation, PET, Temperature, Radiation. Latitude, parameters including initial stand character, quality – environmental factors. Has been parameterised for different N regimes.	DM yield, forage quality including crude protein content and ADF content (can output on daily basis).	With FOSIM, can simulate an entire growing season. Environmental factors affect growth rate and quality. Appears to strike a reasonable balance between a straightforward approach and having sufficient complexity to describe year to year variation in yield and quality. Parameterisations for different N regimes and seasons in north-west Germany provided in paper. Code not openly available.	Hermann A., Kelm M., Kornher A., Taube F. (2005). Performance of grassland under different cutting regimes as affected by sward composition, nitrogen input, soil conditions and weather – a simulation study. *European Journal of Agronomy* 22: 141-158
FONSCH developed from FOPROQ	Daily radiation, precipitation, Penman potential evapotranspiration, temperature (mean/minimum and maximum).	Water-soluble carbohydrate content.	Parameterisation for two different nitrogen levels and varieties given in paper. Based on field experiments on sandy loam site in northern Germany.	Wulfes R., Nyman P., Kornher A. (1999). Modelling non-structural carbohydrates in forage grasses with weather data. *Agricultural Systems* 61: 1-16
Eckersten et al (2007) partially based on SOIL-N model	Daily weather data (temperature, humidity, wind speed, precipitation, radiation). Site-specific parameterisation for initial soil mineral nitrogen and decomposition of humus (rest of parameters already	Biomass and N content – daily changes.	Coded in Matlab – code not openly available. Feedback between plant biomass and plant N and soil water and N models. N model is quite complex. Growth model simulates root and stem growth separately.	Eckersten H., Torssell B., Kornher A., Boström U. (2007). Modelling biomass, water and nitrogen in grass ley: Estimation of N uptake parameters. *European Journal of Agronomy* 27: 89-101

	set for clay, clay loam, sandy loam and loamy sand).		Parameterised based on Swedish data.	
C-Fix with MODIS temperature correction factor for grasses	Daily weather data: minimum and maximum temperature, precipitation, radiation, Fapar (fraction PAR absorbed by vegetation) as estimated from NDVI (can be derived from satellite data).	Above Ground dry matter (calculated from model prediction of gross primary productivity).	Forest model calibrated for grassland in Italy. Accounts for short term water stress. Accuracy of NDVI depends on size of grassland – smaller pockets surrounded by forest less accurate.	Maselli F., Argenti G., Chiesi M., Angeli L., Papale D. (2011). Simulation of grassland productivity by the combination of ground and satellite data. *Agriculture, Ecosystems and Environment* 165: 163-172
STICS-grassland	Daily weather data (rain, minimum and maximum temperature, windspeed, humidity, radiation), soil properties including initial N content. Must specify initial parameters of plant LAI, DM, N content and rooting depth. Can cope with cutting/grazing but then need to specify residual LAI. Can use LAI estimated from satellite data as an input which may be a good way of capturing varying field scale practices.	Biomass.	Model developed by INRA, based on French data. Plant and tiller densities are considered as stable – model an 'average' tiller as covering the whole field. Does not differentiate between reproductive and vegetative cycles of growth. STICS model is downloadable including grassland parameterisation – not for commercial use.	Ruget F., Satger S., Volaire F., Lelièvre F. (2009). Modelling tiller density, growth and yield of Mediterranean perennial grasslands with STICS. *Crop Science* 49(6): 2379-2385 Courault D., Hadria R., Ruget F., Olioso A., Duchemin B., Hagolle O., Dedieu G. (2010). Combined use of FORMOSAT-2 images with a crop model for biomass and water monitoring of permanent grassland in Mediterranean region. *Hydrology and Earth System Sciences* 14: 1731-1744
GRASIM	Daily weather data (rainfall, average radiation, minimum and maximum temperature), soil physical properties, grass growth parameters, soil nitrogen transformation coefficients, initial levels of soil water and soil nitrogen.	Biomass, protein, fibre content – daily output.	Developed for northeastern United States. Will simulate intensive rotational grazing as well as mechanical harvest.	Mohtar R.H., Buckmaster D.R., Fales S.L. (1997) A grazing simulation model: GRASIM A: Model Development. *Trans. ASAE* 40: 1483-1493.
PGSUS (based on modified McCall pasture model).	Initial herbage biomass. Daily weather data (solar radiation, mean, minimum and maximum temperature, precipitation, PET). Available soil water holding capacity (AWHC). Nitrogen application rate and date.	Biomass (kg DM/ha).	Simple model – daily growth rate and senescence rate modified by a few environmental factors. Resets every time a pasture herbage mass is provided then grows grass from there. If sufficient measurements are provided (at least 5) then some	Romera A.J., Beaukes P., Clark C., Clark D., Levy H., Tait A. (2010). Use of a pasture growth model to estimate herbage mass at a paddock scale and assist management on dairy farms. *Computers and Electronics in Agriculture* 74: 66-72

			model parameters are calibrated to the site using a genetic algorithm. Developed for pastures in New Zealand where frequent grazing keeps crop in vegetative growth stage.	
Ali et al (2015)	Satellite data – vegetation indices	Biomass	Machine learning approach – no mechanistic growth model involved. Machine learning approach (adaptive neuro-fuzzy inference system) is data-intensive – predictions not as good for sites with less data. Vegetation indices can become saturated and model overestimated in spring and autumn, and underestimated in summer.	Ali I., Cawkwell F., Dwyer E., Green S. (2015). Modeling managed grassland biomass estimation by using multitemporal remote sensing data – a machine learning approach. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 99: 1-16
STEP	Daily weather data, soil depth, soil texture (sand/clay %), C_3/C_4 ratio, root distribution per soil layer (%)	Biomass, LAI, canopy height	Parameterised for Sahelian grasslands so very different conditions to UK.	Lo Seen D., Rambal S., Hiernaux P. (1995). A Regional Sahelian Grassland Model To Be Coupled with Multispectral Satellite Data. I: Model Description and Validation. *Remote Sensing of Environment* 52: 181-193
SPUR	Many – weather data, soil hydrological properties and nutrients, grassland species.	Dry matter, leaching, soil moisture content	Complex model for US rangelands	Corson M.S., Skinner R.H., Rotz C.A. (2004). Modification of the SPUR rangeland model to simulate species composition and pasture productivity in humid temperate regions. *Agricultural Systems* 87: 169-191

Evaluation of the Potential to Incorporate Different Remote Sensing Technologies into Grass Growth Models

The majority of grass models require minimum inputs of temperature, radiation, rainfall and N availability. Most of the grass growth models do not use satellite data, or parameters that could be derived from satellite data (e.g. satellite-derived LAI), as a direct input. The C-Fix model (Maselli *et al.* 2011) is an exception as it uses NDVI measurements as a direct input. However, the simplicity of this model means that it only predicts biomass and does not predict quality. The STICS-grassland model can also use NDVI measurements to estimate daily LAI which is then used as an input to the model, but again the model as described by Courault *et al.* (2010) only predicts biomass and does not estimate quality indicators, such as N content and digestibility.

Another option is to update model outputs with actual measurements or satellite estimates of LAI or biomass and then run the model from there. However, a number of the models represent different pools of biomass (e.g. vegetative/reproductive growth) that contribute to predictions of future growth. Any attempt to reset these models part-way through a season by replacing a model estimate of biomass with a satellite measurement would involve the complexity of distributing the change amongst the different biomass pools. Some of the models also have parameters that change throughout the season dependent on growth, temperature conditions and other factors – for example the rate of leaf senescence. Changing biomass alone without also changing these parameters may mean that the model no longer provides a good representation of processes relevant to the stage of growth of the grass crop. It may, therefore, be preferable to choose a simple model, even if it does not provide estimates of protein content or digestibility, and use a simple statistical or process-based equation to estimate these outputs based on a model prediction of biomass.

Nitrogen availability is not included as a factor directly affecting growth in all of the models. A number of the models are parameterised for different nitrogen regimes and some models could be re-parameterised for specific sites given sufficient training data. This is probably not feasible in the timescale for the modelling work in this study, unless model code can be obtained for the PGSUS model which already implements code to re-parameterise the model for specific sites.

Alternatively, a model could be run under a range of possible conditions (e.g. different nitrogen regimes) and satellite estimates of biomass or LAI compared with model predictions to determine which set of conditions the growth at a particular site matches to most closely. Predictions could then be generated by running the model forward for that set of conditions. Model states such as the size of biomass pools would not be altered, so a more complex model that provides more outputs on forage quality could then be used.

If feasible, estimates of the following measurements from satellite data could prove useful for integration with models:

- Biomass
- LAI
- NDVI
- Grass N content
- Soil N content,
- Soil moisture.

The decision on what models would be most suitable to take forward for testing and which approach would be most appropriate will be influenced both by the availability of the model code and the outcomes of WP3 and WP4. To allow the modelling approach to be tested and to assess the predictive ability across the season, WP4 should provide measurements of the four characteristics that the modelling work aims to predict: biomass/yield (e.g. dry matter t/ha), moisture content (%), digestibility (e.g ME content MJ/kg DM) and protein/N content (e.g. crude protein content (%)), preferably at weekly intervals or else as frequently as is practical. Measurements of LAI could also be helpful to test whether satellite data can give good predictions of grass LAI in the UK, since an estimate of LAI derived from satellite data could potentially be used as a model input.

Grass growth models currently predict growth based on average growth responses to temperature, water availability and nitrogen availability, with varying degrees of complexity. Improving a model's predictions for a specific site often requires detailed data on soil nitrogen and other site conditions. Satellite data used in combination with grass growth models could potentially allow predictions for individual sites to be made with greater accuracy without the need for as many input variables. Satellite data estimates of biomass could also be combined with measurements provided by land managers, reducing the time demands for taking measurements in order to calibrate grass growth models such as PGSUS, but still making use of any data that farmers are able to collect.

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Additional articles:
Development of a tool for dynamic monitoring of grassland biomass and a livestock warning device in the Indian Ocean region by the combined use of modelling, remote sensing and GIS
Teagasc. 2013. Monitoring grass from space using satellite imaging to observe and predict grass growth rates