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Using dynamic modelling to enhance the assessment of the beef water footprint

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ABSTRACT

Current water footprint assessment methods make a meaningful assessment of livestock water consumption difficult as they are mainly static, thus poorly adaptable to understanding future water consumption and requirements. They lack the integration of fundamental ruminant nutrition and growth equations within a dynamic context that accounts for short- and long-term behaviour and time delays associated with economically significant beef-producing areas. The current study utilised the System Dynamics methodology to conceptualise a water footprint for beef cattle within a dynamic and mechanistic modelling framework. The problem of assessing the water footprint of beef cattle was articulated, and a dynamic hypothesis was formed to represent the Texas livestock water use system as the initial step in developing the Dynamic Beef Water Footprint model (**DWFB**). The dynamic hypothesis development resulted in three causal loop diagrams (**CLD**): cattle population, growth and nutrition, and the livestock water footprint, that captured the daily water footprint of beef (**WF_B**). Simulations and sensitivity analysis from the hypothesised CLD structures indicated that the framework was able to capture the dynamic behaviour of the WF_B system. These behaviours included key reinforcing and balancing feedback processes that drive the WF_B. It is extremely difficult to identify policy interventions (i.e., management strategies) for complex systems, like the U.S. beef cattle system, because there are many actors (i.e., cow-calf, stocker, feedlot) and interrelated variables that have delayed effects within and across the supply chain. Identification and understanding of feedback processes driving water use over time will help to overcome policy resistance for more sustainable beef production. Thus, the causal loops identified in the current study provide a system-level insight for the drivers of the WF_B within and across each major segment of the beef supply chain to address freshwater concerns more adequately. Further, the nutrient scenarios and sensitivity analysis revealed that the high versus low nutrient composition of pasture, hay, and concentrates resulted in a significant difference in the WF_B (2 669 L/kg boneless beef, $P < 0.05$). The WF_B was sensitive to changes in nutrient composition and specific water demand (m^3/t) for each production phase, not only phases with high levels of concentrate feed use. As models evolve, there is potential for the DWFB to integrate precision livestock data, further improving quantification of the WF_B, precision water-efficient strategies, and selection of water-efficient livestock.

Implications

Application of dynamic-mechanistic models helps to address current livestock water footprint assessment methods. Identification of dominant feedback mechanisms contributing to the beef water footprint helps to develop effective and high-leverage policy interventions towards more sustainable water use at each phase of beef production and across the supply chain. As livestock data quality and availability continue to grow, adaptable models like the dynamic beef water footprint model will help further optimise management interventions and have the potential to aid in the identification of water-efficient livestock.

Introduction

Global demand for water resources has put pressure on sectors with large water footprints, such as industry, households, and agriculture (Mekonnen and Hoekstra, 2012). Livestock production has received much scrutiny in the agriculture sector, creating the

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impetus for assessing and reducing the livestock water footprint. Most livestock water consumption quantification is based on the water footprint assessment (**WFA**) method developed by Hoekstra and Hung (2002). The WFA includes the quantification of three specific water types: green (rainfed), blue (ground or surface, human managed), and grey (waste treatment) that account for the total direct and indirect water (i.e., virtual water) used to generate a product (Falkenmark, 1995). Efforts to understand, quantify, and standardise livestock water consumption have been made by the Water Footprint Network, the International Organisation for Standardisation (ISO, 2006), the Food and Agriculture Organisation (FAO, 2019), and LEAP guidelines (Boulay et al., 2018) amongst many other methods.

Current livestock water footprint literature indicates that, globally, beef cattle have the highest water footprint among different livestock, making quantification the predominant area of interest (Mekonnen and Hoekstra, 2012). Methodological differences in the beef water footprint (**WF_B**) are caused by accounting differences between green, blue, and grey waters, if at all, and adopted functional units. For example, a livestock water footprint may be reported in litres of water per kg of live weight, hundredweight, carcass weight, or boneless beef. Final values can be further adjusted for a territorial index of water scarcity based on available and returned water consumption over a given period (e.g., a month) (Boulay et al., 2018). Available water is the water remaining per area after the demand of humans and aquatic systems has been satisfied and returned water consumption is the water that returns into a watershed after it has been used (Boulay et al., 2018).

Standardising the evaluation of the livestock water footprint is essential to determine the actual resource consumption and allocation per area (e.g., country or state). It also indicates the aim to provide water indices and benchmarks to improve upon (Tedeschi et al., 2017a; 2017b). Within the United States, national water footprint studies have focused on blue water consumption in their quantification methods instead of green, blue, and grey water types using the Integrated Farm System Model (Rotz et al., 2019) and static-empirical models (Klopatek and Oltjen, 2022). These methods have provided a consistent and repeatable method of evaluating the blue water footprint on a regional basis and between specific production time points. For example, Klopatek and Oltjen (2022) estimated a 1.34% per year decrease in beef water intensity between 1991 and 2022. Despite these efforts, the current methodologies are based on static-empirical estimations with limited assessment periods. This limitation exists because they do not incorporate a mechanistic-dynamic modelling structure, which is required to more adequately test and evaluate the effects of management and policy interventions on the WF_B over time. Therefore, empirical equations need to be incorporated into a dynamic-mechanistic structure.

A dynamic modelling framework for beef water assessment

Empirical equations are developed from observed data, and the term static indicates a steady state which does not explicitly incorporate time. Conversely, mechanistic-dynamic models account for the interaction of key mechanisms that change in a system over time (Table 1; Tedeschi and Fox, 2020). Tedeschi and Fox (2020) described computer-based simulation models' evolution to evaluate ruminant livestock feed and water requirements more adequately. The culmination of advances in modelling ruminant nutrition resulted in the Ruminant Nutrition System model (Tedeschi and Fox, 2020). This mechanistic model incorporates the critical processes within the rumen, driven by feed inputs, animal class and phase, environment, and mechanistic responses that alter physiological processes like rumen volatile fatty acid absorption and body growth. For example, calculating net energy for growth and maintenance based on specific feed values alters the potential rates of full BW gain through a series of mechanistic relationships. Current livestock water consumption methodologies are missing fundamental ruminant nutrition equations, failing to account for continuous diurnal physiological and environmental processes captured by the Ruminant Nutrition System model (Table 1). Another limitation is that the current models are unable to account for time delays and the feedback mechanisms that influence water consumption rates, nutrient absorption, and growth. Such an example of water feedback is the impact of lowering water content in the rumen on acidosis. As animals do not drink water for extended periods, acidosis arises and results in poor fermentability in the rumen. Such feedback is never considered using empirical equations. Accounting for these complex feedback processes requires a mechanistic-dynamic modelling structure.

Need for system dynamics models

Turner et al. (2016) described numerous examples of the need for a dynamic methodology to solve complex agriculture challenges more adequately. However, few researchers have published dynamic models relating to complex cattle challenges that provide meaningful insight for long-term solutions by identifying high-leverage policies (Molina et al., 2017; Tinsley et al., 2019). Further, these dynamic modelling studies have not been used to address the WF_B. Therefore, there is a need to more critically evaluate the WF_B using available ruminant nutrition and growth equations with a dynamic framework to advance available WFA methodologies and perform policy analyses. The first objective of our study was to develop a dynamic hypothesis that represents the overarching feedback processes within and across the beef cattle supply chain in Texas. The second objective was to identify feedback processes within the dynamic hypothesis and characterise their dynamic behaviour (i.e., reinforcing or balancing, see methods). The third objective was to evaluate changes to the WF_B by running model simulations and sensitivity analyses using key variables known to influence the feedback processes. Preliminary results have been published in abstract form at the 2022 Modeling of Nutrient Digestion and Utilization of Farm Animals conference (Menendez et al., 2022a).

Material and methods

Study area

Within the United States, Texas is one of the top-five cattle-producing states. This state features many large and diverse geographical and climatic regions where the three major phases of beef production exist: cow-calf, stocker, and feedlot. Additionally, cattle management in each region has its own respective ecological and resource limitations, such as soil characteristics, land productivity, water availability, and propensity for drought. Thus, this paper used Texas data and production systems at a state level of aggregation to guide the development of the dynamic framework of beef cattle water dynamics.

System dynamics methodology

The System Dynamics (**SD**) methodology is well suited to understanding complex systems (Sterman, 2000). Complexity is often due to an inability to account for many interacting variables over time and space. Many agricultural systems have long delays that further increase the complexity of interacting variables. For example, producing a calf requires 9 months from breeding to

Table 1
Overview of equation types in various models ranging from linear to dynamic for beef cattle. Equation sources include the Water Footprint Assessment (Hoekstra and Hung, 2002; Mekonnen and Hoekstra 2012), Ruminant Nutrition System (Tedeschi and Fox, 2020), National Academies of Science, Engineering and Medicine (NASEM, 2016), and Dynamic Beef Cattle Water Footprint (Menendez and Tedeschi, 2020) models and their equation types.

Method	Type	Example equations
WFA[1]	E	$WF = WF_{feed} + WF_{drink} + WF_{service}$
NASEM[2] and RNS[3,4]	E + M	$DMI = \frac{total\ \ NEm\ \ intake}{NEm\ \ concetration}$ $WI = \begin{cases} 7.3 + 0.0805 \times FBW - 0.00008 \times FWB^2 - 1.225 \times CETI + \\ 0.002327 \times FBW \times CETI + 0.041 \times CETI^2 \\ 6.3 + 0.106 \times FBW - 0.000096 \times FBW^2 - 1.6 \times CETI + \\ 0.00226 \times FBW \times CETI + 0.056 \times CETI^2 \end{cases}$ $S = Management\ \ Activities_{Phase}$
DWFB[5]	E + M + D	$\int WF = DMI + WI + S \times dt$

Abbreviations: WFA = Water Footprint Assessment; NASEM = National Academies of Science Engineering and Medicine; RNS = Ruminant Nutrition System; DWFB = Dynamic Beef Water Footprint; E = Empirical; M = Mechanistic; and D = Dynamic.
[1] Where WF is the water footprint of livestock (m^3/t), WF_{feed} is the water content of feed used for livestock (m^3), WF_{drink} is the drinking water consumed by livestock (m^3), and $WF_{service}$ is the service water used during production (m^3).
[2] Where, DMI is the DM intake (kg/d), total NEm intake is the total net energy maintenance intake (Mcal/d), and NEm concentration is the net energy maintenance concentration (Mcal/kg of DM).
[3] Where, WI is the water intake (L/d); FBW is the full (unshrunk) BW (kg); CETI is the current effective temperature index (°C).
[4] Where, S is the service water required for production activities in each phase. This equation is not published in the RNS or NASEM materials. Rather it is used to represent that this value changes mechanistically relative to management requirements and phase activities.
[5] Where, *dt* is the delta time integration timestep used for the differential equation.

calving and another 24 months from calving to slaughter of beef cattle, during which time many different management decisions and biological processes occur (animal and environmental). The SD approach uses a high level of aggregation to describe the overarching structure of a system to understand what is driving a particular challenge, like unsustainable WF_B levels. This approach includes capturing important non-linear dynamics, feedback, and time delays responsible for driving the system behaviour. The modelling process is based on five steps (Sterman, 2000). The current paper utilised steps one, two, and five of the SD method to articulate the problem and identify the causal loops [causal loop diagrams (**CLD**)] that control beef cattle water dynamics. Steps one and two were accomplished by conducting an extensive review of literature on water footprint papers, identifying key variables, using expert knowledge, and published SD models to best capture the structure of the WF_B system.

Step one included clearly articulating and defining the problem or subject to be modelled. This process included explicitly stating what the model aims to understand and defining the purpose of the model. In the current study, "the purpose" is to identify the dynamic feedback processes that contribute to the WF_B within and across the Texas beef supply chain; cow-calf, stocker/backgrounder, and feedlot. Step two included forming a dynamic hypothesis and model boundaries. The dynamic hypothesis aims to identify the primary feedback loops related to beef cattle water dynamics. Model boundaries were used to determine what endogenous variables should be included in the feedback loops and which variables are exogenous. Additionally, model boundaries determine what variables should be excluded from the model. Model boundaries may change until only the necessary variables to achieve the model's intended purpose have been selected.

Endogenous variables are variables that have feedback (e.g., "A" affects "B," and "B" affects "A"). For example, as chickens ("A") lay eggs, the eggs ("B") hatch and create more chickens. Exogenous variables are variables that are only feed-forward (i.e., "A" affects "B," but "B" does not affect "A"). Expanding on our chicken example, a person may collect the eggs ("A"), but the eggs ("B") do not change the number of people, assuming the model is not accounting for human births. Consequently, this assumption of not accounting for human births is a model boundary. Model boundaries are necessary to keep the focus on understanding the relevant processes instead of attempting to model everything, a reason many models fail. A model boundary in the current study is using specific feed nutrient parameters that drive other model components (e.g., growth), but is not itself adjusted because the model does not include a crop growth or feed processing model. Crop growth and feed processing were excluded because the level of detail was not required to achieve our objectives since data exist for feedstuffs at regional levels. Further, the evaluation of field-level impacts on feedstuff nutrient composition is at an entirely different level of granularity compared to information needed for the supply chain level assessment in this study. Consequently, the current study model boundaries were determined by the largest phases of beef cattle production (cow-calf, stocker, and feedlot) at a regional level. We included endogenous and exogenous inputs sufficient to capture regional WF_B estimates but excluded levels of detail for sub-regional estimates or individual cattle. For example, sub-regional estimates would answer a more specific question about the WF_B and production efficiencies for counties or farms, which is not only a different modelling objective but also increases the computational intensity of the model by an order of magnitude.

The endogenous variable relationships were used to identify the specific feedback relationships or "loops" representing the WF_B system. To identify these relationships, the SD methodology employs polarity to determine if a causal loop is reinforcing or balancing. A positive (+) relationship between variables indicates that as the value increases or decreases, so does the variable it impacts (i.e., same direction). A negative (−) relationship between variables indicates that if a variable increases, the subsequent variable decreases (i.e., opposite direction). For example, as air temperature increases, animal drinking water increases (i.e., same direction, positive relationship), or as stocking rate increases, biomass resources decrease (i.e., opposite direction, negative relationship). The polarity of a completed feedback loop (i.e., variable "A" affects "B" and "B" affects "A") will result in either a reinforcing loop or a balancing loop.

Reinforcing loops are determined by an even number of "-" signs and indicate that the behaviour produced by this loop will result in exponential growth or decay. Balancing loops contain an odd number of "−" signs, indicating that this loop will cause the system's behaviour to move towards equilibrium. Causal relationships between variables may contain time delays between a change in one variable and its impact on another. Time delays are represented by double lines perpendicularly positioned on an arrow in the CLD (a notation specific to the Vensim™ modelling program). A professional visually based dynamic modelling software Vensim™ was used to develop and visualise the primary CLDs within the WF_B.

Step 3 model formulation consisted of programming mathematical ruminant nutrition equations for beef cattle into Vensim™. Step 4 included model testing (unit testing, parameter boundaries, and equation robustness), calibration, and statistical evaluation to ensure that the model replicated published livestock water footprint data (Sterman, 2000). Steps 3 and 4 for the DWFB model in the current study are described in detail by Menendez and Tedeschi (2020). The exclusion of steps 3 and 4 from the current study was necessary to focus on the feedback relationships (objective 1) and their results (objectives 2 and 3) rather than the detailed mathematical model components (i.e., model building and evaluation). Thus, to evaluate the feedback loops identified by step 2 of the dynamic modelling process (objective 1), we conducted a policy simulation analysis (step 5) of key exogenous variables (i.e., management or environmental parameters; objective 2). Specifically, we conducted a loop behavioural analysis, nutrition management scenario analysis, and Monte Carlo sensitivity analysis within the Vensim™ program.

Behavioural analysis

The behavioural analysis evaluated the simulation results of a variable of interest to identify its pattern of behaviour over time, which was categorised as reinforcing, balancing, or oscillating. Three variables of interest were selected for the behavioural analysis, the mature cow herd population (head of cattle), daily cattle growth (full BW, kg per day), and the daily WF_B (L/H_2O per kg boneless beef) from calving to slaughter, and the daily cattle water consumption ratio (dimensionless). This ratio is the regional cattle water use (Million Cubic Meters per day) divided by the regional water available for Texas livestock (Million Cubic Meters per day; Menendez and Tedeschi, 2020). The mature cow herd population and growth were evaluated with an 8-year simulation using the DWFB model (Menendez and Tedeschi, 2020). A 14-year (2004–2017) simulation was used to evaluate regional water availability and the proportion of daily cattle water consumption in a water-limited scenario.

Nutrition scenario analysis

It is estimated that 95% of the WF_B is from crop inputs (Mekonnen and Hoekstra, 2012). We simulated a typical forage for cow-calf and stocker phases [pasture and hay on a DM basis; total digestible nutrients (**TDN**) = 0.61–0.51, which varied by time of year; Menendez and Tedeschi, 2020] and a feedlot ration [hay = 15%, corn = 55%, soybean = 5%, dried distiller's grain = 25% level of inclusion on a DM basis, TDN was 0.61, 0.92, 0.94, and 0.72 respectively, NASEM, 2016] from cow-calf to feedlot phase (~22 months). Pasture and hay were represented by estimated green water use within the DWFB model (Menendez and Tedeschi, 2020), and concentrate blue water values were averages reported by Rotz et al. (2019) (corn = 280, soybean = 616, dried distiller's grain = 180 m^3/t). This simulation represented our base case. The TDN values were then adjusted by ± 10% resulting in two additional simulations (−10% and +10%), allowing for the assessment of changes to the daily WF_B. We assessed differences in simulation results using an ANOVA in Program R, where the WF_B and time to slaughter were the dependent variable(s) by treatment (i.e., TDN scenarios: Base, 90, 110%) differences between groups were assessed using Tukey Posthoc analysis for mean separation ($P < 0.05$).

Monte Carlo sensitivity analysis

Sensitivity analysis is a quantitative and qualitative model test that indicates the amount of variation of a variable of interest from the alteration of a constant variable. Therefore, we applied the same parameter value changes to all TDN values (±10%) and ran 10 000 simulations on the distribution of the daily WF_B. The Monte Carlo sensitivity analysis was conducted in Vensim™ using a Latin Hypercube sampling technique with a random uniform distribution. Next, we performed another Monte Carlo sensitivity analysis to evaluate the daily WF_B by altering the daily DM forage production rates 12.5, 50, 62.5 (kg DM per ha per day) in each cattle phase to adjust the specific water demand (SWD; m^3/t; Menendez and Tedeschi, 2020) of forages and varied the SWD of grain crops (see blue water concentrate values above).

Results

Dynamic hypothesis

The dynamic hypothesis CLD contained two reinforcing loops (cattle growth and regional water resources) and three balancing loops (population capacity, feed conversion efficiency, and need for efficient systems, Fig. 1). Cattle Growth (R1): A fundamental biological component of cattle production is cattle weight, as it determines the forage and feed intake of an animal to meet daily nutrient requirements. As nutrient requirements are met, the animal gains weight and consumes more feed until the animal obtains the desired slaughter weight (NASEM, 2016), ending the reinforcing loop. Regional Water Resources (R2): As the daily WF_B increases, so does the total regional water use, diminishing regional water availability. Reduced regional water availability for cattle indicates that the maximum cattle meat production capacity has been exceeded and that access to local forage and feed has become

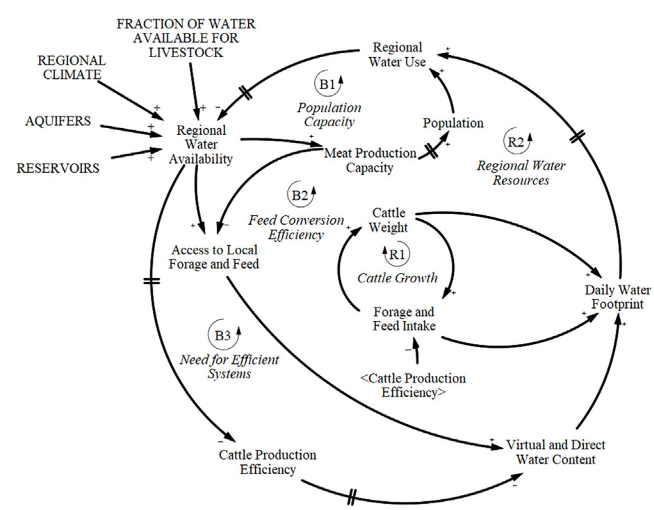

Fig. 1. Dynamic hypothesis of the beef cattle water footprint system at a state level for cow-calf through feedlot phases (i.e., causal loop diagram). Where, the variables in all capital letters are exogenous, the variables with only the first letter of each word capitalised are endogenous, and the italicised letters are loop names. Loops are either balancing (B) or reinforcing (R), determined by their polarity [loop numbers (e.g., R1) help identify specific loops, but numerical order does not indicate importance]. Polarity is denoted by a plus (+) same direction or a minus (−) opposite direction relative to the preceding variable. Double perpendicular lines are a notation specific to Vensim™ that denotes a significant time delay between variables.

limited (i.e., producers are utilising all available local resources). Restricted access to local forage and feed increases the sourcing of resources from outside the region (i.e., purchased hay or grain from another state). The purchase of non-local resources increases the virtual and direct water content of the inputs required to maintain cattle growth, thereby increasing the daily WF_B (Mekonnen and Hoekstra 2012). Population Capacity (B1): As cattle population numbers increase, so does the regional water use, and if the total water consumption exceeds the regional water availability, then the meat production capacity will be limited as the maximum number of animals that can be supported in a region has been exceeded, leading to reductions (e.g., selling, culling) of the cattle population until limits are no longer exceeded (Tinsley et al., 2019). However, reductions in the cattle population contain a delay as these changes do not happen instantaneously and vary among the cow-calf, stocker, and feedlot supply chain phases.

Feed Conversion Efficiency (B2): The cascading impacts of a larger daily WF_B on regional water use result in diminished regional water availability, which creates an impetus to increase cattle production efficiency to ensure that cattle operations are sustainable (Klopatek and Oltjen, 2022). A critical aspect of water use efficiency is related to cattle production efficiency, driven by reducing the amount of forage and feed consumed per kg of product (Tedeschi et al., 2017a; 2017b). These reductions are likely to come through sustainable intensification consisting of improved genetics (e.g., improved animal gain; low residual feed intake animals; Nkrumah et al., 2007), feed quality (e.g., improved storage or processing; Turgeon et al., 2010), and ruminant diet formulation (e.g., reduced digestible energy losses by methanogenesis; Min et al., 2022). Hence, the total forage and feed intake requirements on an animal basis will be reduced, leading to reductions in the daily WF_B while maintaining sustainable production levels. Need for Efficient Systems (B3): Another aspect of the increased daily WF_B values and regional water use and diminished regional water availability is increasing cattle production efficiency in terms of management (Rotz et al., 2019). For instance, cattle producers may be able to decrease direct water from wasted feedstuffs through precision feeding activities (e.g., individual animals receive and consume precisely what they require for optimal growth; Menendez et al., 2022b) and indirect virtual water content of feedstuffs (e.g., selecting water-efficient corn for total mixed rations).

Identified feedback processes and behaviour characterisation

The overarching WF_B CLD (Fig. 1) resulted in the identification of specific reinforcing and balancing loops for the (1) cattle population, (2) growth and nutrition, and (3) the livestock water footprint. First, the cow-calf phase (Fig. 2A: loop R1 Breeding Population) serves as the primary reinforcing structure that ensures beef cattle will be available each year through the development of replacement heifers and maintenance of a mature cow herd. After a two-year delay, replacement heifers will return to the mature cow herd and contribute to the next generation of progeny. This is a closed-loop system, meaning that the feedback exists between the number of calves born and the number of replacement animals available to sustain a commercially viable population. Five unique balancing loops were identified that caused the cattle population to decrease (Fig. 2A: loops B1-5). This includes calves and culls (cows and heifers). Calves not selected for rebreeding (heifers or steers) enter the portion of the beef cattle supply chain that terminates at slaughter when a desired mature weight is obtained. The desired number of stocker and feedlot cattle reduces the calves available for rebreeding (Fig. 2A: loops B1 Stocker Population; B2 Feedlot Cattle Population). The duration of resource allocation to cattle varies greatly throughout the beef supply chain. For example, weaned calves may remain at the same

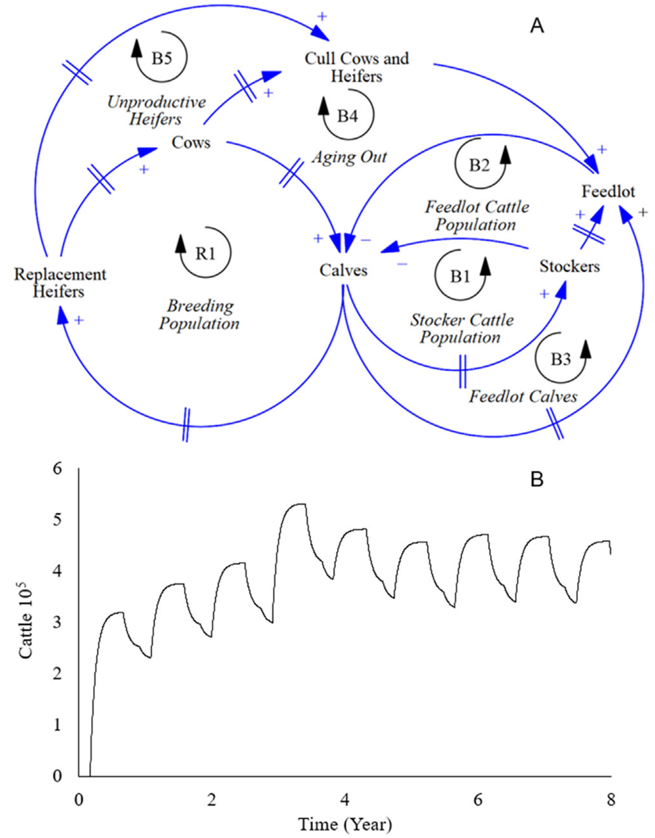

Fig. 2. The dynamic structure of the beef cattle population (panel A, i.e., causal loop diagram) and an example of oscillatory behaviour from the structure of the cattle population system (panel B). Where, the variables with only the first letter of each word capitalised are endogenous, and the italicised letters are loop names. Loops are either balancing (B) or reinforcing (R), determined by their polarity [loop numbers (e.g., R1) help identify specific loops, but numerical order does not indicate importance]. Polarity is denoted by a plus (+) same direction or a minus (−) opposite direction relative to the preceding variable. Double perpendicular lines are a notation specific to Vensim™ that denotes a significant time delay between variables.

ranch and region or be sold and shipped to an entirely different region when entering a new phase (e.g., stocker or feedlot phases). Calves may also be sold directly to a feedlot phase and circumvent the stocker phase (i.e., Fig. 2A; loop B3, Feedlot Calves). Some cattle fail to be productive within the cow-calf phase and do not or cannot produce calves (Fig. 2A: loops B4 Ageing Out; B5 Unproductive Heifers) and are culled for meat production, which decreases (balancing action) the total breeding population. Overall, Fig. 2A provides the fundamental structure of the primary reinforcing mechanism (R1: Breeding Population) and balancing mechanisms that sustain the beef cattle population and maintain a stable supply of beef for consumption. Simulation results of these six loops indicated that the Texas cattle population has an oscillatory behaviour (Fig. 2B).

Population dynamics (Fig. 2A) drive three reinforcing loops that encompass nutrition and growth dynamics within and across each major cattle production phase (Fig. 3); cow-calf, stocker, and feedlot (Fig. 3A). Each phase contains a reinforcing feedback mechanism that influences weight (kg). Weight drives the amount of DM intake, which influences the rate of daily weight gain (kg/day). Suckling calves (not weaned) consume milk primarily and then shift to forage-based diets as they mature (Fig. 2A: loop R1 Breeding Population, Fig. 3A: loop R2 Calf Development). Upon weaning, calves enter the stocker stage and consume forage primarily. The stocker phase's duration and the quality of forage used for animal

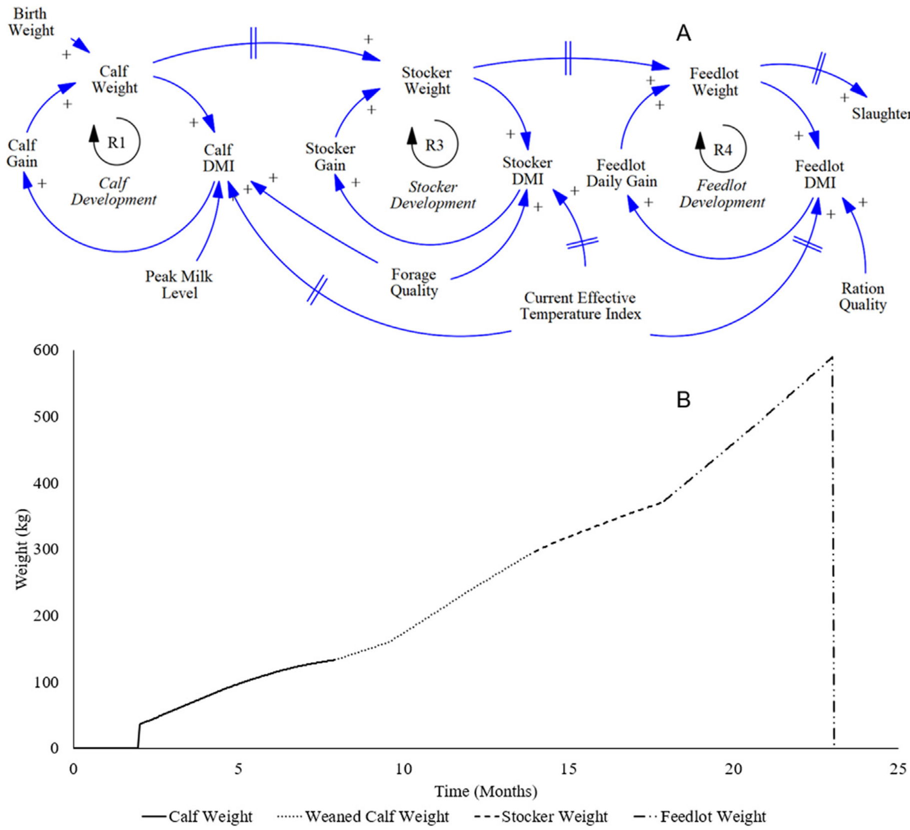

Fig. 3. The dynamic structure of cow-calf, stocker, and feedlot growth and nutrition and interlinkages across the supply chain (panel A; i.e., causal loop diagram) and a simulated example of the reinforcing cattle growth (kg per day) behaviour across the same production phases (panel B). Where DM intake, birth weight, peak milk level, forage quality, ration quality, and the current effective temperature index are key variables that impact nutrition during these phases of production (Tedeschi and Fox, 2020; Menendez and Tedeschi, 2020), the variables with only the first letter of each word capitalised are endogenous, and the italicised letters are loop names. Loops are either balancing (B) or reinforcing (R) determined by their polarity [loop numbers (e.g., R1) help identify specific loops, but numerical order does not indicate importance]. Polarity is denoted by a plus (+) same direction or a minus (−) opposite direction relative to the preceding variable. Double perpendicular lines are a notation specific to Vensim™ that denotes a significant time delay between variables.

feeding influence the rate of growth and weight that stocker cattle will obtain during this phase (Fig. 3A: loop R3 Stocker Development). The cow-calf, stocker, and feedlot phases (Fig. 3AB: loops R2, R3, R4) share the same nutrition and growth structure, indicating that if the adequate quality of nutrients is available and environmental conditions do not limit feed, then the cattle in each phase will continue to gain weight and increase DM intake; a reinforcing growth behaviour (Fig. 3B). Additionally, the three development loops (Fig. 3A: loops R2, R3, R4) are connected between each phase as the animal progresses across the beef cattle supply chain (Fig. 3A). Ultimately, feed and growth dynamics affect daily cattle water use and the daily WF_B at each phase (cow-calf, stocker, feedlot) and aggregated water use across the beef cattle supply chain (Fig. 3A).

A feed-forward relationship, not dynamic, was determined for the Daily WF_B from DM intake and cattle weight. The daily WF_B is an aggregation of drinking water and service water consumption (direct water use including grey water), and also of pasture, hay, supplementation, and concentrates (e.g., grains) water uses (virtual water) that represent the daily water use required to achieve cattle growth (Atzori et al., 2016). The daily WF_B inputs are quantitatively dependent on the amount of feed intake and are connected to the growth and nutrition feedback dynamics for each cattle phase (i.e., cow-calf, stocker, and feedlot, Fig. 3A). The daily water use (L per day) is then divided by the daily weight gain of boneless beef (kg per day) to obtain a daily WF_B (L/kg boneless beef). Drinking and service water were the two direct water uses identified in the WF_B CLD (Fig. 4A). The WF_B CLD linked daily cattle weight (i.e., boneless beef) and total daily cattle water use, representing the daily WF_B (Fig. 4A). A dynamic relationship was identified for the feed-forward estimation of the daily WF_B by linking it to regional water use and population (Fig. 4A). This feedback resulted in one balancing loop to account for cattle population carrying capacity (Fig. 4AB: loop B6 Water Scarcity). The water scarcity loop produced oscillatory behaviour in the cattle water consumption ratio over the 14-year simulation period.

Nutrition scenario and sensitivity analysis

The base case TDN scenario resulted in a water footprint of 8 208 (L/kg boneless beef). The increase in TDN (+10%) scenario reduced the WF_B (7 262 L kg boneless beef, $P < 0.05$) by 946 L/kg boneless beef (−11%) from the base case. Conversely, the reduction in TDN (−10%) scenario increased the WF_B (9 931 L/kg boneless beef, $P < 0.05$) by 1 723 L/kg boneless beef (+21%) compared to the base case ($P < 0.05$). The difference in the increased and decreased TDN scenarios was 2 669 L kg of boneless beef (27%, $P < 0.05$). The base case TDN scenario resulted in a 23.27-month time to slaughter. The 10% increase of TDN scenario resulted in a 2.77-month reduction (−11%) in time to slaughter (20.5 months, $P < 0.05$) compared to the base case. The 10% decrease in the TDN scenario resulted in a 4.92-month increase (+21%) in time to slaughter (28.19 months, $P < 0.05$) compared to the base case.

The sensitivity analysis of the daily WF_B from changes to the SWD base case resulted in maximum values of 16 800 and 13 440 L/kg boneless beef on days 545 and 700, respectively

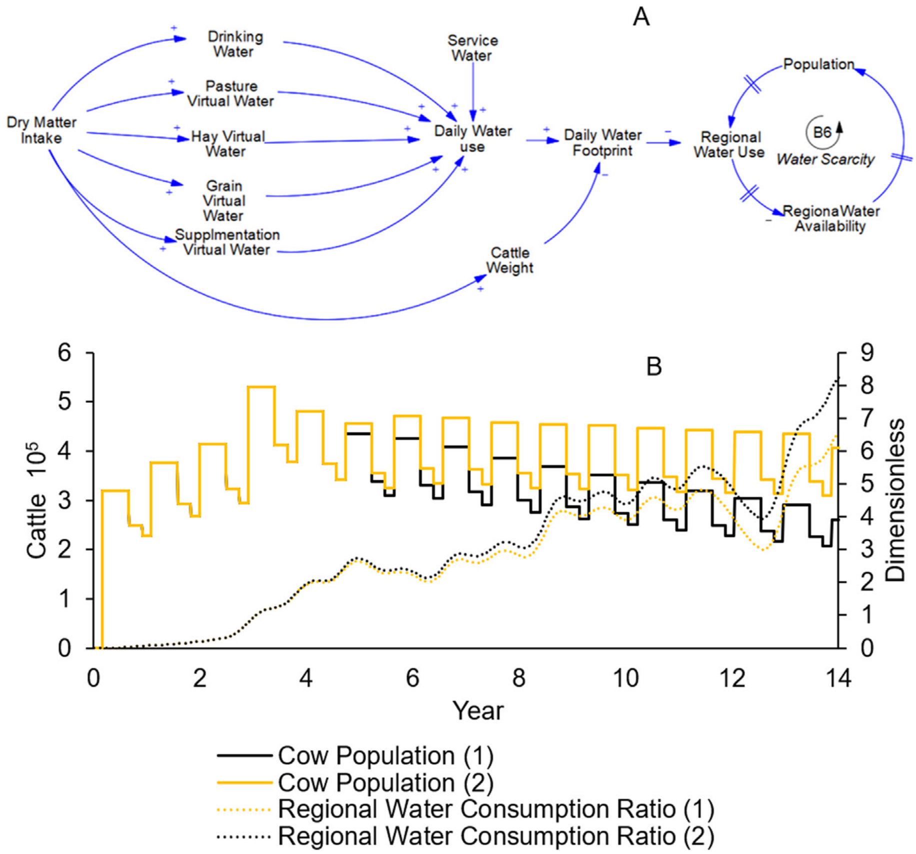

Fig. 4. Daily water footprint and regional water scarcity causal loop diagram (panel A) and two simulations of cow population and their respective regional water consumption ratios (panel B). Where, the variables with only the first letter of each word capitalised are endogenous, and the italicised letters are loop names. Loops are either balancing (B) or reinforcing (R), determined by their polarity [loop numbers (e.g., R1) help identify specific loops, but numerical order does not indicate importance]. Polarity is denoted by a plus (+) same direction or a minus (−) opposite direction relative to the preceding variable. Double perpendicular lines are a notation specific to Vensim™ that denotes a significant time delay between variables. This ratio is the regional cattle water use (Million Cubic Meters per day) divided by the regional water available for Texas livestock (Million Cubic Meters per day; Menendez and Tedeschi, 2020).

(Fig. 5A), which is a 3 360 L/kg boneless beef reduction. The sensitivity analysis of the daily WF_B from changes to the TDN (±10%) base case resulted in a 31% difference between minimum and maximum values of 6 940 and 10 030 L/kg boneless beef, respectively (Fig. 5B). Relative to the base case, the WF_B was less sensitive to changes in TDN within and across production phases than changes to SWD values (Fig. 5AB). Further, there are peaks and dips in the daily WF_B across the time horizon (i.e., simulation time duration) and not only an additive-linear relationship demonstrating that variation exists within and across production phases (Fig. 5AB).

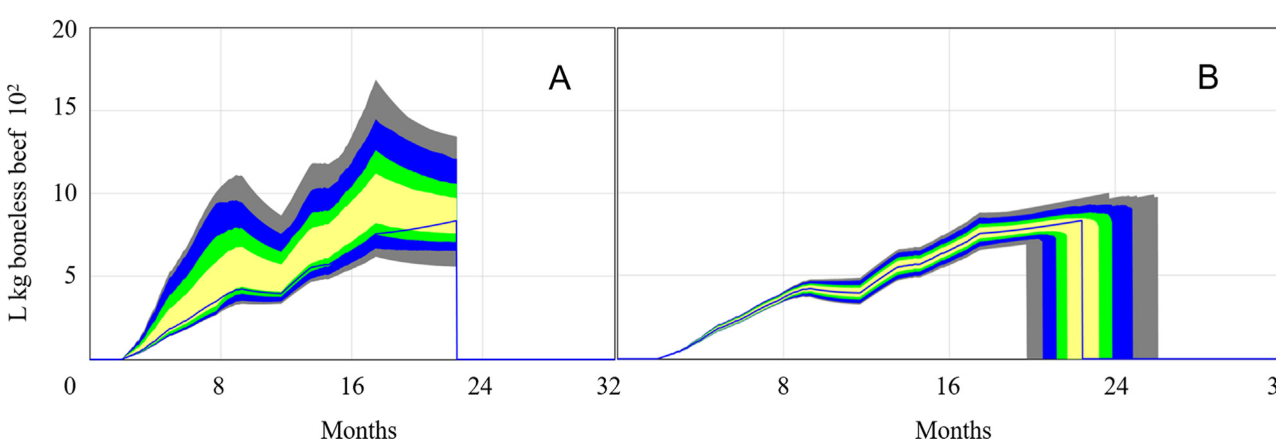

Fig. 5. Sensitivity analysis (±10%) of the specific water demand (m^3/t) for forages (panel A) and total digestible nutrients (panel B, dimensionless) of forage and concentrate feedstuffs on the average daily water footprint (L kg boneless beef) across all beef cattle phases (i.e., cow-calf, stocker, feedlot). Yellow, green, blue, and grey colours represent the percentiles of simulated water footprint values, from the base case scenario, within given ranges where yellow = 50%, green = 75%, blue = 95%, and grey = 100%.

Discussion

The SD methodology was successfully employed and contextualised by incorporating existing WFA methods and ruminant nutrition equations (empirical and mechanistic) into a dynamic hypothesis. The behavioural analysis of key feedback processes was successfully evaluated using the full DWFB model (Menendez and Tedeschi, 2020). Firstly, the population model produced the oscillatory behaviour seen in other animal population models (Fig. 2B; Ford, 2010). Capturing this behaviour is essential because it indicates that cattle populations within the DWFB model respond appropriately to environmental and human management stressors, specifically breeding (i.e., births) and deaths (i.e., slaughter or culling). Consequently, a critical opportunity exists to evaluate reproductive efficiency, weaning rates, and heifer retention into a regional WF_B using the DWFB model (Menendez and Tedeschi, 2020).

The behaviour of the growth and nutrition models also showed reinforcing growth feedback relationships. These reinforcing loops were either slowed or accelerated by nutrient quality, environment, and management factors for each phase of beef cattle production (Fig. 3A). These factors affect growth rates and have been the focus of many research and production efforts (NASEM, 2016). Consequently, the model structure provides a systems approach to evaluate the sensitivity of the WF_B at specific production phases. A critical next step will be to perform more detailed analyses using producer or supply chain-specific coefficients. Similarly, behavioural tests of the daily WF_B produced the expected increase of WF_B levels as the time required to reach slaughter was prolonged, especially in the feedlot stage (Fig. 2AB, Fig. 5AB), and these behaviours are supported by value ranges reported by Mekonnen and Hoekstra (2012).

Linking the feed-forward daily WF_B estimate to regional water use and population dynamics illustrated how the dynamic framework captures the water footprint system. Further, the population dynamics simulations relative to cow populations show that the model is sensitive to delayed water limitations, including drought (Fig. 4). Often, population models can simulate “overshoot and collapse” behaviour (Sterman, 2000). The overshoot and collapse behaviour is a harsh system response that reflects unsustainable population growth and large fluctuations in beef production and price (i.e., supply and demand). These principles can be used in understanding and avoiding the overshoot and collapse of beef cattle supply chains in water-limited areas, which is critical for beef cattle stakeholders as livestock water use limitations and pressure for more sustainable beef production grow. Behavioural results increased the confidence that the WF_B framework was adequate for livestock WFA and identified the long-term behaviour types (e.g., oscillation, exponential growth/decay) of cattle population, growth and nutrition, and WF_B within this system.

As expected, increasing TDN reduced the time to slaughter and the WF_B because fewer resources were used. This was contrasted by the increase in time and WF_B when TDN was decreased. As more precise coefficients are identified for feeding efficiencies, they can be incorporated into the DWFB model framework because it accounts for fundamental nutrient and growth relationships. Further, an opportunity exists to evaluate financial and economic trade-offs between TDN values and time to slaughter relative to specific production systems, phases, or across supply chains. Interestingly, the sensitivity analysis of TDN resulted in varying levels of efficiency across the supply chain, indicating that each phase of production has room for improvement, not only the feedlot sector (i.e., indicative of the most feed use). Identification of this behaviour is important because it highlights the contribution of each preceding phase, such as cow-calf to stocker on the WF_B. The next step is to vary nutrient quality and animal efficiencies within each phase relative to known production environments and resources. The daily WF_B was most sensitive to SWD; however, ambiguity exists for SWD values as pasture and hay (forage) growth, even within a region, depends on the climate, management of stocking rates, and soil fertility of the land. Thus, improving forage water use efficiencies is likely a high-leverage solution to improve the WF_B, which should be investigated. Water efficiencies and productivity of irrigated forages and crops have increased over the past 30 years (Klopatek and Oltjen, 2022) and tremendous potential exists for extensive rangeland and dryland systems that rely primarily upon green water. The advent of climate-smart commodities and their monitoring, measuring, recording, and verification will likely provide additional resolution for rangeland and dryland agriculture efficiency and future potential.

The benefit of modelling is that it provides a framework for testing and verifying livestock water use, which can inform policy and identify which actions or solutions provide the greatest benefit. As demonstrated by the DWFB model, factors such as TDN, DM intake, and animal weight can greatly affect the water footprint of animals. One of the challenges with static models is that they rely on established equations that predict these factors (e.g., animal growth models); however, large differences in individual animal variability can be difficult to account for within the model. For example, individual animal DM intake can be difficult to estimate for grazing animals, where changes in forage quality, physiological state, and environmental factors can result in values ranging from 10 to 30% of the mean (Coleman, 2005). Empirical equations for predicting intake typically only account for 50–70% of the variation in intake, often with relatively high standard errors (Galyean and Gunter, 2016). Likewise, climatic factors within forage production systems can influence seasonal differences in forage quality and TDN (Hendrickson et al. 1997; Smart et al. 2007). Though this model seeks to quantify the WF_B of cattle within Texas at the regional scale, a benefit to developing this dynamic model is that it can incorporate data across different systems. This is important as the advent of precision livestock farming can greatly increase the granularity of the data being fed into models and our ability to estimate the WF_B across regional, local, and individual animal scales.

Integrating dynamic models informed by real-time data is the next step for coupling precision livestock farming with precision system modelling (Menendez et al. 2022b). For example, satellite and unmanned aerial vehicles derived vegetation indices can estimate forage production and quality through the season, adding greater detail of digestible energy at the individual pasture or ranch scale (Jansen et al., 2021; Wijesingha et al., 2020). Technological advances have sought alternative methods for estimating the live weight of cattle, including walk-over weigh scales for in-pasture measurements and biometric measurements derived from cameras (Dickinson et al., 2013; González et al., 2014). Real-time weights can be incorporated into the DWFB model to better estimate growth for differing classes of cattle under different production systems. Precision system models can use these data to estimate water intake for individual animals and create phenotypic selections based on water efficiency metrics (Ahlberg et al., 2019). Precision data in this application can help producers select more water-efficient animals and define water intake variability between individual animals and refine empirical equations for estimating water intake. By developing dynamic models that can account for precision data, we can begin to quantify differences in the WF_B between individual animals or across operations within the same region. Estimates from the DWFB model can be linked to individual animals using radio frequency identification tag technology to quantify and track the WF_B of the animal through the supply chain, potentially creating markets for water-efficient cattle.

Conclusion

In conclusion, the advancement of WF_B assessment is essential to achieve long-term improvements in livestock water use within and across the beef cattle supply chain. The current research developed a dynamic framework to advance current WFA methods. The behavioural and sensitivity evaluations indicated that the framework could formulate the DWFB model for Texas with critical ruminant nutrition and growth equations using dynamic modelling software. A dynamic daily WF_B is likely to begin to resolve issues amongst existing WFA methodologies as it more accurately represents the dynamic nature of daily and total livestock water use and can supply multiple functional units. The CLDs and their descriptions are essential to understanding the complexity of the underlying structure and dominant loops that drive the long-term behaviour of this system. A systems understanding enables model users and policymakers to identify systemic solutions to decrease the WF_B rather than only generating reports. Overall, freshwater challenges in agriculture livestock systems may be resolved using this modelling framework to enhance the current livestock WF_B and supply chain assessment methods and quantify regional beef sustainability. Moreover, the adaptability of this model to become a precision system model that incorporates precision livestock data provides an exciting next step as the adoption of precision livestock farming increases within the beef cattle sector.

Ethics approval

Not required – No live animals.

Data and model availability statement

The model and data are not deposited in an official repository. The model and data that support the study findings are available from the authors upon request.

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Modelling, writing/editing, citations, and analysis – All.

Declaration of interest

The authors declare there are no conflicts of interest.

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Transparency declaration

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