# UNIVERSIDAD AUTÓNOMA AGRARIA ANTONIO NARRO

## SUBDIRECCIÓN DE POSTGRADO



## EL ESTRÉS CALÓRICO EN EL GANADO LECHERO DE LA COMARCA LAGUNERA Y SU PRONÓSTICO MEDIANTE EL ÍNDICE TEMPERATURA HUMEDAD Y MODELOS MATEMÁTICOS

Tesis

Que presenta JOSÉ LUIS HERRERA GONZÁLEZ

como requisito parcial para obtener el Grado de
DOCTOR EN CIENCIAS EN PRODUCCIÓN AGROPECUARIA

Torreón, Coahuila                                    Octubre 2025

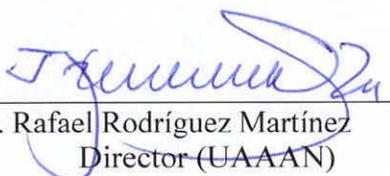# UNIVERSIDAD AUTÓNOMA AGRARIA ANTONIO NARRO

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Torreón, Coahuila

Octubre 2025

EL ESTRÉS CALÓRICO EN EL GANADO LECHERO DE LA COMARCA
LAGUNERA Y SU PRONÓSTICO MEDIANTE EL ÍNDICE TEMPERATURA
HUMEDAD Y MODELOS MATEMÁTICOS

Tesis

Elaborada por JOSÉ LUIS HERRERA GONZÁLEZ como requisito parcial para
obtener el grado de Doctor en Ciencias en Producción Agropecuaria con la
supervisión y aprobación del Comité de Asesoría
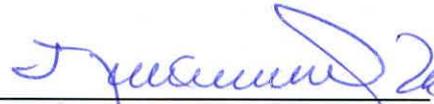
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# AGRADECIMIENTOS

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# DEDICATORIA

Esta tesis es dedicada a mi familia, que me apoyaron de manera incondicional a lo largo de esta etapa

**A mis padres:** Jesús Herrera Reyna y Dalila Venecia González Rosales por su amor, consejos, cuidado, guía y ejemplo.

**A mis hermanos:** Martha Alicia, Héctor Jesús y María Fernanda por compartir este momento tan importante de mi vida.

# CARTA DE ACEPTACIÓN

Aceptación del artículo número 1.

PeerJ

Dear Dr. Rodríguez-Martínez,

Thank you for your submission to PeerJ.

I am writing to inform you that your manuscript - **Time series (ARIMA) as a tool to predict the temperature-humidity index in the dairy region of the northern desert of Mexico** - has been **Accepted** for publication. Congratulations!

This is an editorial acceptance; publication is dependent on authors meeting all journal policies and guidelines.

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Congratulations again, and thank you for your submission.

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Aceptación del artículo número 2.

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Manuscript Number: **ATECH-D-25-01370R2**

Identifying the best indicator for forecasting the Temperature-Humidity Index for dairy cattle and its historical pattern (1940 -– 2024) in north-central Mexico

Dear Dr. Rodríguez-Martínez,

Thank you for submitting your manuscript to Smart Agricultural Technology.

I am pleased to inform you that your manuscript has been accepted for publication.

My comments, and any reviewer comments, are below.

Your accepted manuscript will now be transferred to our production department. We will create a proof which you will be asked to check, and you will also be asked to complete a number of online forms required for publication. If we need additional information from you during the production process, we will contact you directly.

We appreciate you submitting your manuscript to Smart Agricultural Technology and hope you will consider us again for future submissions.

Content: We encourage authors of original research papers to share the research objects – including raw data, methods, protocols, software, hardware and other outputs – associated with their paper. More information on how our open access Research Elements journals can help you do this is available at https://www.elsevier.com/authors/tools-and-resources/research-elements-journals?dgcid=ec_em_research_elements_email.

Kind regards,
Stephen Symons, PhD, CBiol., FRSB.
Editor-in-Chief
Smart Agricultural Technology

Editor and Reviewer comments:

# ÍNDICE GENERAL

# ÍNDICE DE FIGURAS

# HIPÓTESIS Y OBJETIVOS

## Hipótesis

Existiría un incremento en la exposición al estrés calórico del ganado lechero en la comarca lagunera

## Objetivo

El objetivo es encontrar modelos matemáticos que puedan predecir con exactitud el THI con un alto grado de probabilidad. Este conocimiento facilitaría la aplicación de estrategias para mitigar los efectos adversos sobre la salud y la productividad del ganado.

# RESUMEN

El estrés calórico en el ganado lechero de la comarca lagunera y su pronóstico mediante el índice temperatura humedad y modelos matemáticos.

José Luis Herrera González
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El entorno en el que se encuentra un animal puede tener un profundo impacto en su salud, bienestar y productividad. Este fenómeno es particularmente evidente en el caso del ganado lechero, por lo que, para cuantificar el impacto de la temperatura ambiente (∘ C) y la humedad relativa (%) en el ganado lechero, se emplea como métrica el índice temperatura humedad.

(ITH). Este indicador permite estimar en la práctica el estrés impuesto al ganado por la temperatura y la humedad ambientales. Se estimó un modelo autorregresivo estacional integrado de medias móviles (SARIMA) (4,1,0)(0,1,0)365utilizando datos diarios del ITH máximo diario de 4 años (2016-2019) de la Comarca Lagunera, una región árida del centro norte de México. El modelo resultante indicó que el ITH de cualquier día en la zona puede estimarse con base en los valores de ITH de los cuatro días anteriores. Además, los datos demuestran un aumento anual del número de días en que el ITH indica un riesgo de estrés térmico. Es esencial seguir construyendo modelos predictivos para desarrollar estrategias eficaces que mitiguen los efectos adversos del estrés térmico en el ganado lechero (y otras especies) de la región.

**Palabras clave:** ARIMA, Índice temperatura-humedad, Estrés por calor, Vacas lecheras, Zona árida, México, Modelos calibrados

# ABSTRACT

Heat stress in dairy cattle in the lagoon region and its forecast using the temperature-humidity index and mathematical models

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The environment in which an animal is situated can have a profound impact on its health, welfare, and productivity. This phenomenon is particularly evident in the case of dairy cattle, then, in order to quantify the impact of ambient temperature (C) and the relative humidity (%) on dairy cattle, the temperature-humidity index (ITH) is employed as a metric. This indicator enables the practical estimation of the stress imposed on cattle by ambient temperature and humidity. A seasonal autoregressive integrated moving average (SARIMA) (4,1,0) (0,1,0)365 model was estimated using daily data from the maximum daily ITH of 4 years (2016–2019) of the Comarca Lagunera, an arid region of central-northern Mexico. The resulting model indicated that the ITH of any given day in the area can be estimated based on the ITH values of the previous four days. Furthermore, the data demonstrate an annual increase in the number of days the ITH indicates a risk of heat stress. It is essential to continue building predictive models to develop effective strategies to mitigate the adverse effects of heat stress in dairy cattle (and other species) in the region.

**Keywords:** ARIMA, Temperature-humidity index, Heat stress, Dairy cows, Arid zone, Mexico.

# I. INTRODUCCIÓN

Es evidente que las aplicaciones de esta metodología para explicar y predecir la fenomenología en cuestiones agrícolas son numerosas y diversas. El presente estudio se centrará en series temporales que muestran un comportamiento consistente con las leyes de probabilidad, a diferencia de las series deterministas. En el campo de la producción lechera, el análisis de series temporales se ha aplicado en diversas áreas, incluyendo la modelización de enfermedades  (De Mol *et al.*, 1999), la cuantificación del efecto de la temperatura en la mortalidad de las vacas lecheras  (Morignant, 2015), el aumento de la producción debido a cambios en la dieta (Kerr *et al.*, 1991), la demanda de productos lácteos (Heien & Wessells, 1988) y la producción de metano y $CO_2$ (Lee *et al.*, 2017)**.**

Los modelos matemáticos son empleados por los científicos para predecir las consecuencias potenciales de los fenómenos naturales, con el objetivo de desarrollar estrategias para mitigar sus efectos adversos. Entre las herramientas mencionadas, se pueden identificar las siguientes: Una serie temporal puede definirse como una colección de observaciones realizadas secuencialmente a lo largo del tiempo, en un sentido amplio, y puede utilizarse para describir una variedad de conjuntos de datos. Una serie temporal puede definirse como un tipo específico de proceso estocástico. Las últimas décadas han mostrado grandes avances en la técnica y el alcance del uso de modelos en las ciencias biológicas, sin embargo, en el ámbito del bienestar de los animales de granja la variedad, tipo y complejidad de los modelos utilizados no han avanzado al mismo ritmo, a pesar de que podrían tener un gran alcance en este campo de investigación (Collins & Part,2013)

# II. REVISIÓN DE LITERATURA

## 2.1 Definición

La industria láctea depende de la lactancia exitosa de la vaca para su rentabilidad económica. El estrés térmico compromete la sostenibilidad económica al reducir la producción de leche y aumentar el riesgo de enfermedades metabólicas y patógenas. El estrés térmico altera las adaptaciones metabólicas, como la movilización y la distribución de nutrientes, que sustentan las demandas energéticas de la lactancia, las vacas con estrés térmico son incapaces de lograr los cambios homeoréticos necesarios que proporcionan los nutrientes y la energía necesarios para la síntesis de leche, lo que perjudica el rendimiento de la lactancia (Marquez-Acevedo *et al.*, 2023).

El término de estrés calórico (EC) en el ganado puede ser aplicado cuando la temperatura interna se eleva por encima de la zona de termoneutralidad, debido a su incapacidad para disipar eficientemente el calor generado internamente o que es absorbido del medio ambiente, es decir, es una respuesta no específica del animal a le temperatura del medio ambiente cuando el animal produce más calor del que puede disipar (Liu *et al.*, 2019). El EC también es definido como un evento que afecta la homeostasis, bienestar, confort y salud de las vacas debido a la carga calórica en las vacas (Boyu *et al.*, 2020) y que implica un problema muy fuerte del intercambio de calor en los animales y el medio (Wolfenson *et al.*, 1988)

Para Herbut *et al.* (2018) el EC es definido como la suma de fuerzas externas que actúan sobre los animales causando un incremento en la temperatura corporal que da origen a una respuesta fisiológica en los animales con la finalidad de desarrollar una respuesta termorreguladora en las vacas modernas (Kadzere *et al.*, 2002). Bajo cierta temperatura, humedad relativa (RH), radiación solar (RAD) y velocidad del viento (VV) que exceden la temperatura de zona de confort, las vacas productoras de leche sufren estrés por calor (Hammami *et al.*, 2013).

Bernabucci *et al.* (2014) el EC puede ser definido como la condición que ocurre cuando un animal no puede disipar una cantidad adecuada de calor, ya sea producido ya sea absorbido por su cuerpo para mantener el balance térmico corporal.

La exposición prolongada del ganado productor de leche a temperaturas altas, humedad relativa del medio ambiente y la radiación solar disminuyen su capacidad para la disipación de calor y se debe tener en cuenta que la misma vaca genera calor metabólico, por lo que, el calor acumulado, el calor producido aunado a la incapacidad del animal para enfriarse influenciada por las condiciones ambientales, generan el EC en las vacas (Gantner *et al.*, 2012)

El EC desarrolla cambios en la fisiología y metabolismo de los animales que traen como consecuencia el deterioro en la productividad de los animales afectando la rentabilidad de las empresas dedicadas a la producción pecuaria (St-Pierre *et al.*, 2003).

Existen factores del medio ambiente que tienen un impacto directo sobre la temperatura efectiva y estos son: 1) la temperatura del aire, 2) la humedad relativa, 3) movimiento del aire y 4) la radiación solar, Estos factores pueden interactuar, de tal manera que cuando la temperatura excede de los 27° C y aunque haya poca humedad, la temperatura efectiva está por encima de la zona de confort de las vacas con producciones de leche elevadas (Armstrong, 1994).

Los efectos acumulativos del estrés térmico comprometen el bienestar animal y reducen la rentabilidad de la industria lechera. Para mitigar estos efectos negativos, es fundamental que la transferencia de calor se realice correctamente fuera de la vaca (Drwencke *et al.*, 2020).

**2.2 Mecanismos de termorregulación**

El rango de temperatura óptimo para la mejor producción láctea en la vaca oscila entre los 10 a 20° C, este rango es conocido como la zona de termoneutralidad por encima o debajo de estos datos, se puede presentar estrés por frío o por calor (Linvill & Pardue, 1992)

En términos generales, a medida que la temperatura se eleva, el centro de termorregulación hipotalámico emite señales conducentes a tratar de regular la temperatura corporal, incluyendo un incremento periférico del flujo sanguíneo, sudoración y jadeo (Becker & Collier, 2020; West, 2003). Este fenómeno se agudiza más en las vacas lactantes *Bos Taurus* debido a que por su potencial del nivel de producción generan una mayor carga de calor corporal, este efecto se asocia negativamente con el incremento de la temperatura y de la humedad del medio que rodea al ganado (L. Polsky & von Keyserlingk, 2017).

El ganado sometido a una temperatura elevada adopta como medida de disipación de calor la pérdida de calor por diferentes métodos, destacando entre ellos, las pérdidas evaporativas y no evaporativas (conducción, convección y radiación.

Lees *et al.* (2018)  han desarrollado mecanismos que miden el jadeo, la respiración y la tasa respiratoria como herramientas para predecir el grado de estrés calórico que desarrollan las vacas productoras de leche. Con la inclusión de la tecnología de medición de alta precisión en los establos, se han propuesto sistemas de medición del grado de estrés calórico considerando el jadeo, el babeo, la salivación y la frecuencia respiratoria, en este sistema la calificación del estrés es de 0 a 4 puntos (Becker *et al.*, 2021)

El impacto del estrés calórico sobre el rendimiento del ganado es el resultado de respuestas termorreguladoras que provocan una reducción en el consumo de alimento y la absorción de nutrientes provocada por una redirección del flujo sanguíneo de los órganos internos hacia los tejidos periféricos en un intento de balancear la carga calórica corporal (Tao *et al.*, 2018).

La disminución del consumo de materia seca (CMS) es una respuesta generalizada del ganado, pero las vacas con producciones elevadas son las más susceptibles a la caída del alimento consumido (Yue *et al.*, 2020). Los efectos de la reducción del CMS, también se observa en los animales próximos al parto y tiene consecuencias en la cantidad de magnesio de las vacas de más de un parto, primerizas y sus respectivas crías (Kume *et al.*, 1998).

El estrés térmico provoca una disminución de la ingesta de materia seca y de la concentración de glucosa, y un aumento de la concentración de insulina, con una menor movilización de lípidos del tejido adiposo, sin embargo, las vacas sometidas a estrés térmico tienen concentraciones más bajas de NEFA y una mayor tasa de utilización periférica de glucosa, lo que sugiere que la captación de glucosa por otros tejidos reduce la cantidad de glucosa disponible para la síntesis de leche (Majkić *et al.*, 2019).

Chaiyabutr & Chanpongsang (2008) no encontraron diferencia en los niveles hormonales (triyodotiroxina T3, y el factor de crecimiento 1 análogo de insulina) entre vacas sometidas a enfriamiento y las que no lo recibieron, sin embargo, las vacas no enfriadas tuvieron una tendencia a tener menor cantidad de cortisol y tiroxina (T4).

Los principales objetivos del manejo nutricional de las vacas lecheras con estrés térmico son aumentar la densidad energética y nutricional para contrarrestar la reducción del consumo de materia seca (CMS) manteniendo al mismo tiempo la producción de leche (PM) y reducir el incremento térmico (IH) de la dieta para mejorar la termorregulación de los animales sometidos al EC (Gonzalez-Rivas *et al.*, 2018).

Otro mecanismo termorregulador en animales sometidos al EC es la disminución de la actividad diaria, cuyo objetivo es bajar la cantidad de calor generada por el metabolismo corporal (Cross *et al.*, 2020). El efecto del EC sobre la actividad, no sólo repercute en los animales gestantes, sino que el patrón de actividad también puede verse afectado negativamente en las crías de las madres expuestas al estrés calórico (Laporta *et al.*, 2017).

Osei-Amponsah *et al.* (2020) demostraron en su estudio que la mayoría de las vacas sometidas a estrés calórico medio o alto, tuvieron la tendencia de buscar sombras, pasaron más tiempos alrededor de los bebederos y mostraron signos de dolor.

Los efectos combinados de la elevada pérdida de potasio de la piel y la reducción de la ingesta de potasio y materia seca durante el estrés por calor sugirieron que las vacas lecheras en período de lactancia podrían beneficiarse aumentando el nivel de potasio en la dieta de las vacas, sobre todo si no cuentan en las instalaciones con sombreadores (Mallonée *et al.*, 1985).

**2.3 Medición de estrés calórico**

Existen una variedad amplia de índices bioclimáticos que suelen usarse para predecir el EC y que pueden asociarse al impacto en el ganado. El Índice temperatura-humedad (ITH) es una herramienta que tiene su origen en su medición en el humano (Steadman, 1979) y también es un indicador de uso internacional amplio para describir el estrés calórico en los animales (Hernández *et al.*, 2011) y se ha establecido como una herramienta global una relación útil entre el EC y la productividad de los animales McDowel *et al* (1976). Sin embargo, el ITH ha sido un indicador del confort de las vacas desde el año de 1960 (Vasseur *et al.*, 2012).

Sejian *et al.* (2013) consideran que el ITH es un buen marcador bioclimático y que podría calcularse usando una variedad de fórmulas desarrolladas a partir del estudio y medición del bulbo seco, bulbo húmedo, las temperaturas de punto de rocío y la humedad relativa del aire.

(Ravagnolo *et al.*, 2000) consideran que el ITH se calcula con la información disponible (temperatura y humedad) en la región donde se desee evaluar y puede ser usado para determinar el efecto del EC sobre la producción

y otros indicadores relacionados con la calidad de la leche, como la proteína y la grasa.

También se puede medir el estrés calórico con el Índice de Humedad del Globo Negro (IHGN), sin embargo, este método en comparación del ITH arrojó correlaciones menores con la temperatura rectal y la tasa respiratoria de los animales expuestos al EC en explotaciones comerciales de Brasil (Gomes da Silva *et al.*, 2007).

Bohmanova *et al.* (2007) mencionan que los índices de temperatura y humedad difieren en su capacidad para detectar el estrés térmico. Los índices con mayor ponderación de la humedad parecen ser más adecuados para climas húmedos. Por otro lado, en climas donde la humedad no alcanza niveles que puedan comprometer el enfriamiento por evaporación, son preferibles los índices con mayor énfasis en la temperatura ambiente.

La necesidad de predecir tanto el estrés térmico como las pérdidas de leche correspondientes condujo al desarrollo del índice de temperatura y humedad (ITH), que combina los efectos de la T y la HR asociados con el nivel de estrés térmico (Fodor *et al.*, 2018).

L. B. Polsky *et al.* (2017) dividieron el ITH como bajas (ITH ≤65) se asociaron con un IR mayor en comparación con las de ITH medio (>65 a <70) y alto (≥70) para estimar el efecto del estrés calórico sobre el tiempo en que la temperatura vaginal esta ≥ 39° C del día 9 al 11 antes de la inseminación artificial programada, la temperatura vaginal fue clasificada como alta con más del 22% o baja con menos del 22%. La media de temperatura vaginal fue de 38.9 ± 0.2° C y las medias máximas y mínimas de temperatura de la vagina fueron 39.7 ± 0.5° C y 38 ± 0.8° C.

Theusme *et al.* (2021) determinaron y escalaron los umbrales del índice de temperatura y humedad (ITH) para clasificar el estrés para cada especie de ganado: ITH bovinos productores de engorda y cerdo: 74 unidades; ITH bovinos productores de leche: 72 unidades; y ITH de ovejas: 23 unidades. Se detectaron

diferencias estadísticas entre los índices (P < 0,01) durante el verano para las zonas de valle y costa: (ITH de res = 72,9 y 51,8; ITH de leche = 80,6 y 67,4; ITH de cerdos = 83,9 y 65,2; ITH de ovejas = 29,5 y 20,1 unidades).

## 2.4 Impacto negativo del estrés calórico

Los efectos del EC sobre la producción láctea pueden ser separados en dos grandes categorías causales: aquellos que están mediados por la reducción del consumo voluntario asociado al incremento de la temperatura y los efectos fisiológicos y metabólicos del estrés térmico (Cowley *et al.*, 2015).

Como resultado de la incapacidad para la disipación corporal del calor en los animales sujetos al EC manifiestan elevación de la temperatura corporal, lo cual se ha demostrado mediante estudios que registran la temperatura rectal (Chen *et al.*, 1993).

El incremento de la temperatura rectal de 38.5 a 40° C en vacas en gestación tardía podría disminuir la producción de leche subsecuente al parto de 40 a 25 L por día, los efectos del EC en esas vacas podrían comprometer debido a la falta de crecimiento de la glándula mamaria durante la gestación tardía (Tao & Dahl, 2013).

Kaufman *et al.* (2018) estudiaron las relaciones entre el ITH con la temperatura rectal, vaginal y de la superficie de la ubre en vacas bajo estrés calórico, concluyendo que la temperatura rectal y vaginal están fuertemente relacionadas con el ITH y se pueden utilizar para determinar la carga calórica en el cuerpo. Además, la temperatura de la ubre mostró una relación de moderada a alta con la temperatura corporal y esta relación puede soportar el uso de los datos de la superficie corporal para manejar la carga calórica en vacas bajo EC.

El estrés térmico parece tener efectos desfavorables sobre los mecanismos del sistema inmunitario, en este contexto, los marcadores inmunitarios son indicadores muy valiosos para la detección del estrés térmico

en el ganado lechero, por lo que se requiere investigar más sobre posibles biomarcadores para el estrés térmico (Lemal *et al.*, 2023).

Si la magnitud del estrés térmico letal (EH) progresa, puede ser letal y la muerte puede ocurrir de forma aguda o días después, incluso si las condiciones ambientales se han vuelto libres de estrés; en consecuencia, el estrés térmico letal (EH) suele ser difícil de identificar y casi siempre se diagnostica erróneamente. Las causas multifactoriales de muerte probablemente involucran la disfunción y el desequilibrio de varios sistemas interdependientes, como se detalla a continuación: (1) dishomeostasis electrolítica, (2) pH sanguíneo inestable, (3) hiperpermeabilidad del tracto gastrointestinal, (4) sepsis, (5) inflamación grave inducida por activación inmunitaria, (6) hipercoagulación intravascular diseminada, (7) permeabilidad endotelial sistémica, (8) insuficiencia multiorgánica y (9) insuficiencia circulatoria (Burhans *et al.*, 2022).

Ellett *et al.* (2024) realizaron un estudio para comprobar la hipótesis de que el EC en vacas lecheras de alta producción disminuye la integridad intestinal, activa el sistema inmunológico y separa los nutrientes de la producción de leche, sin embargo, bajo las condiciones de la prueba que realizaron, la activación del sistema inmunológico a través de lipopolisacáridos (LPS) derivados del intestino no contribuyó a la disminución observada en la producción de leche durante la EC.

El EC tiene una influencia negativa en la producción, la reproducción, peso al nacimiento, ganancia de peso por día y por lo tanto en la rentabilidad de la empresa pecuaria (Armstrong, 1994). En la Comarca Lagunera, situada en la región árida del norte de México, las condiciones de EC están presentes durante todo el año (305 días), ejerciendo un impacto negativo en la producción de leche, la composición de la leche, el confort de las vacas y la proporción de vacas en producción de leche y vacas que no la producen (Rodriguez-Venegas *et al.*, 2022).

## 2.4.1 Producción de leche

El estrés térmico es un factor ambiental que afecta negativamente las propiedades morfológicas y fisiológicas del ganado lechero, Kibar *et al.* (2020) encontraron una correlación negativa (P<0,01) entre la producción de leche y la proporción de grasa de la leche y se detectó una correlación positiva (P<0,001) entre el estrés por calor y la temperatura corporal.

El ganado que está sometido al EC se encuentra en balance negativo de nitrógeno debido principalmente a la reducción del consumo de materia seca (CMS). Muroya *et al.* (2015) estudiaron la influencia del estrés calórico sobre la distribución del nitrógeno en la leche (NUL) y las vacas bajo estrés calórico manifestaron un valor del nitrógeno ureico en leche de 0.19 mg/ml de leche, cuando este valor debería estar entre 0.13 a 0.15 mg de NUL/ml de leche.

La exposición prolongada a ITH elevada disminuye significativamente la producción de leche, el rendimiento de grasa, proteína y lactosa de la leche en vacas de primer parto y vacas de tercera lactancia (Gantner *et al.*, 2012).

Nasr & El-Tarabany (2017) encontraron que con un nivel alto de ITH, se correlacionó negativamente con el rendimiento lácteo total (r = -0,12 P < 0,05), con el rendimiento de leche ajustado a 305 MY (r = -0,16 P < 0,05), el porcentaje de proteína (r = -0,15 P < 0,01), el porcentaje de grasa (r = -0,14 P < 0,01) y el porcentaje de lactosa (r = -0,26 P < 0,01). El presente estudio concluyó que el rendimiento de las vacas lecheras fue mejor en la mayoría de los parámetros investigados con un ITH bajo que con un ITH alto. Esto indica un efecto perjudicial del ITH tanto en el bienestar como en la rentabilidad económica

Ouellet *et al.* (2019) demostraron que las vacas expuestas a un mayor número de días consecutivos de estrés térmico produjeron menos grasa, proteína que las vacas no expuestas a estrés térmico, mientras que la producción de leche y la lactosa se mantuvieron sin cambios. Por lo tanto, sus resultados sugieren que los componentes de la leche son más sensibles que la producción de leche

al estrés térmico experimentado por las vacas Holstein en un clima continental húmedo.

Rodriguez-Venegas *et al*. (2023) reportaron que la grasa de la leche se vio afectada por el nivel de EC, mostrando el menor porcentaje de contenido graso (3,33 ± 0,02 a <68 ITH), mientras que los demás niveles de EC tuvieron un promedio de 3,42 % de grasa. En cuanto a la proteína de la leche, mientras que los niveles de ITH aumentaron, el porcentaje de proteína de la leche descendió (de 3,19 ± 0,01 a <68 ITH a 3,09 ± 0,003 a 77 ITH). La relación grasa/proteína de la leche fue mayor a 77 ITH, y el valor más bajo se encontró en 68-71 y 72-76 ITH (1,08 ± 0,003). El valor más alto de urea en la leche (11,0 ± 0,13) también se encontró en 77 ITH (11,0 ± 0,13), con el más bajo en 68-71 ITH.

West (2003) opina que parte de los efectos negativos del estrés térmico en la producción de leche podrían explicarse por la disminución de la ingesta y la absorción de nutrientes por las vísceras de la vaca, que se drenan a través del sistema portal. El flujo sanguíneo desviado hacia los tejidos periféricos para enfriar la leche puede alterar el metabolismo de los nutrientes y contribuir a una menor producción de leche durante el calor.

Smith *et al*. (2013) compararon el efecto del EC en dos razas de bovinos y sus resultados les permitieron concluir que el porcentaje de grasa en la leche Holstein fue menor durante el EC moderado y severo, en comparación con el porcentaje de grasa en la leche durante el EC leve. El porcentaje de grasa en la leche en vacas Jersey no varió según la categoría de EC. Las vacas Jersey parecieron ser más tolerantes al calor que las vacas Holstein, sin embargo, estas últimas produjeron mayores volúmenes de leche.

Burfeind *et al*. (2012) realizaron una comparación de la temperatura rectal de vacas recién paridas sometidas a un ITH moderado (59.8 ± 3.8) y otras con ITH elevado (74.1 ± 4.4) utilizando un termómetro vaginal digital (termocron) que registró la temperatura cada 10 minutos, estos investigadores demostraron que la prevalencia de fiebre (más de 39-5° C fue 7.4% y 28.1% para la temperatura rectal en los animales con estrés moderado y elevado, respectivamente.

Cuellar *et al.* (2023) concluyeron que las razas Pardo Suizo y sus cruces regularon la temperatura corporal durante el estrés por calor mejor que las Holstein, pero estas razas no fueron más resistentes al estrés por calor en términos de producción de leche. Por lo tanto, es probable que existan diferencias genéticas en la termo tolerancia que sean independientes de la regulación de la temperatura corporal.

## 2.4.2 Reproducción

El estrés asociado a las temperaturas elevadas con humedad alta disminuye la tasa de preñez en bovinos. Amundson *et al.* (2006) evaluaron el efecto de las condiciones ambientales en *Bos Taurus* cruzados sobre la tasa de preñez concluyendo que la velocidad del viento estuvo asociada positivamente con la tasa de preñez del ganado y una relación negativa de la elevación de temperatura con la tasa de preñez, sobre todo al inicio de la temporada reproductiva.

Algunos indicadores reproductivos como la duración e intensidad del estro, la fertilidad y la tasa de preñez se relacionan negativamente con el ITH superior a 75; El aumento del ITH de 70 a 82 disminuye linealmente la tasa de preñez de de 60 a 10% (Ryan *et al.*, 1992)

Ben Salem & Bouraoui (2009) determinaron que el estrés calórico en Túnez se presenta desde mayo hasta agosto y que la tasa de concepción y la tasa general de concepción fue menor durante la temporada de EC que en la época de invierno concluyendo que hay una fuerte relación entre la temporada de calor y la reproducción.

Los efectos adversos de EC comienzan en el desarrollo del ovocito y en las últimas etapas de su fertilidad; en el ciclo y su comportamiento estrales; en el desarrollo e implantación del embrión; en el entorno uterino; e incluso se extienden al feto (Sammad *et al.*, 2020).

Rensis & Scaramuzzi (2003) consideran que el EC reduce el grado de dominancia del folículo seleccionado, lo que se manifiesta como una menor capacidad esteroidogénica de sus células de la teca y la granulosa, así como una disminución de las concentraciones sanguíneas de estradiol. Los niveles plasmáticos de progesterona pueden aumentar o disminuir según si el estrés térmico es agudo o crónico y según el estado metabólico del animal. Estos cambios endocrinos reducen la actividad folicular y alteran el mecanismo ovulatorio, lo que conlleva una disminución de la calidad de los ovocitos y los embriones. El entorno uterino también se modifica, lo que reduce la probabilidad de implantación embrionaria (figura 1).
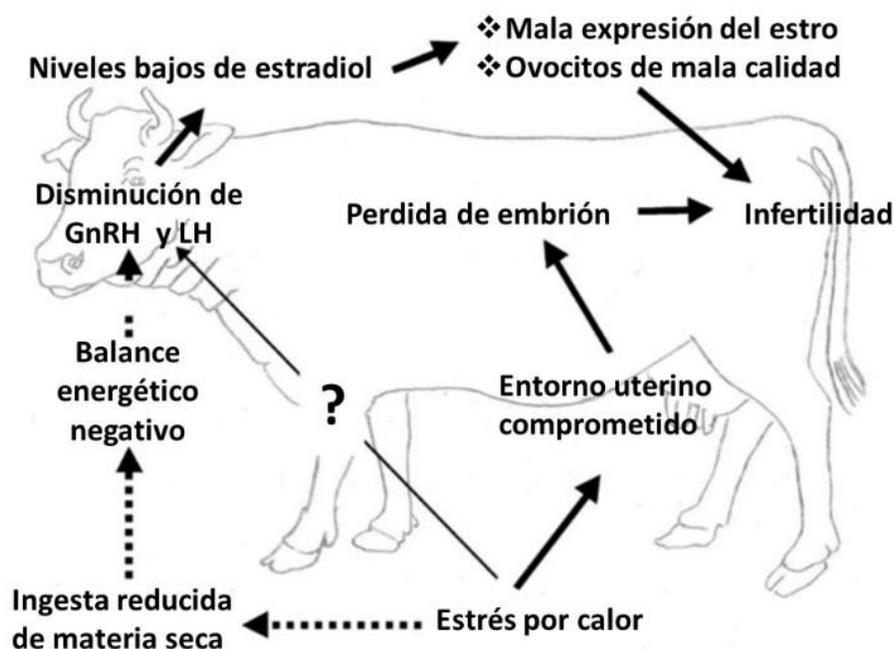


**Figura 1.** Adaptado Rensis y Scaramuzzi (2003)

Hagiya *et al.* (2017) demostraron que en las vacas, la tasa de concepción se vió afectada por la interacción entre el grupo con EC y el mes de inseminación;

con la inseminación de verano y principios de otoño, se observó una reducción de la tasa de concepción mucho mayor en los grupos con EC leve y moderado que en el grupo sin estrés.

Las crías nacidas de vacas expuestas al EC durante el perído seco y alimentadas del calostro de sus madres tienen una inmunidad pasiva menor a las crías nacidas de vacas que fueron enfriadas durante el estrés calórico, Monteiro *et al*. (2014) explican lo anterior, atribuyendo a que el EC durante las últimas 6 semanas de gestación afecta negativamente la habilidad de las becerras para adquirir inmunidad pasiva, sin importar el origen del calostro.

Tao *et al*. (2014) manifiestan que además del retraso en el crecimiento fetal, el estrés térmico materno durante el período seco mejora la respuesta insulínica de los terneros tras el destete, lo que sugiere la posibilidad de una lipogénesis y deposición de grasa aceleradas en las primeras etapas de la vida.

Los hatos grandes equipados con sistemas técnicos para el registro de datos meteorológicos y sanitarios a intervalos cortos, constituyen una base única para inferir asociaciones entre el ITH y las respuestas en las características de las vacas. Especialmente al inicio de la lactación, se identificaron efectos sistemáticamente perjudiciales del EC sobre la producción en el día de prueba y la fertilidad de las hembras. El efecto del aumento del ITH sobre la incidencia de enfermedades fue principalmente desfavorable, dependiendo de la patogénesis de la enfermedad (Gernand *et al*., 2019).

## 2.5 Uso de series de tiempo en producción animal

Los modelos matemáticos son empleados por los científicos para predecir las consecuencias potenciales de los fenómenos naturales, con el objetivo de desarrollar estrategias para mitigar sus efectos adversos. Entre las herramientas mencionadas, se pueden identificar las siguientes: Una serie de tiempo que se define como una colección de observaciones realizadas secuencialmente a lo largo del tiempo, en sentido amplio y puede utilizarse para describir diversos

conjuntos de datos. Una serie temporal que se define como un tipo específico de proceso estocástico. En las últimas décadas se ha observado un gran progreso en la técnica y el alcance del uso de modelos en las ciencias biológicas; sin embargo, en el ámbito del bienestar animal de granja, la variedad, el tipo y la complejidad de los modelos utilizados no han avanzado al mismo ritmo, a pesar de que podrían tener un gran alcance en este campo de investigación (Collins, 2013).

En el contexto del cambio climático, se prevé que la frecuencia y la gravedad de los fenómenos meteorológicos extremos aumenten en las regiones templadas y que puedan tener graves repercusiones en el ganado de granja, provocando pérdidas de producción o muertes. En un estudio, realizado en 12 zonas de Francia en el 2014 se evalúo la relación entre índice temperatura humedad y la mortalidad del ganado, donde se utilizaron modelos no lineales distribuidos para describir y cuantificar la relación entre estos (Morignant, 2015).

**III. ARTICULO 1**

Time series (ARIMA) as a tool to predict the temperature-humidity index in the dairy region of the northern desert of México

**Fwd: Decision on your PeerJ submission: "Time series (ARIMA) as a tool to predict the temperature-humidity index in the dairy region of the northern desert of Mexico" (#2024:09:105714:1:2:REVIEW)**

**Rafael Rodriguez Martinez** <rafael.rdz.mtz@gmail.com>
Para: Martín Alfredo Legarreta-González <mlegarreta@uttarahumara.edu.mx>

2 de diciembre de 2024, 14:36

Dr. Rafael Rodríguez Martínez
Departamento de Ciencias Médico Veterinarias
Universidad Autónoma Agraria Antonio Narro

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Warm regards,

# Time series (ARIMA) as a tool to predict the temperature-humidity index in the dairy region of the northern desert of Mexico

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## ABSTRACT

The environment in which an animal is situated can have a profound impact on its health, welfare, and productivity. This phenomenon is particularly evident in the case of dairy cattle, then, in order to quantify the impact of ambient temperature (°C) and the relative humidity (%) on dairy cattle, the temperature-humidity index (THI) is employed as a metric. This indicator enables the practical estimation of the stress imposed on cattle by ambient temperature and humidity. A seasonal autoregressive integrated moving average (SARIMA) $(4,1,0)(0,1,0)_{365}$ model was estimated using daily data from the maximum daily THI of 4 years (2016–2019) of the Comarca Lagunera, an arid region of central-northern Mexico. The resulting model indicated that the THI of any given day in the area can be estimated based on the THI values of the previous four days. Furthermore, the data demonstrate an annual increase in the number of days the THI indicates a risk of heat stress. It is essential to continue building predictive models to develop effective strategies to mitigate the adverse effects of heat stress in dairy cattle (and other species) in the region.

**Subjects** Agricultural Science, Environmental Sciences, Climate Change Biology, Environmental Impacts, Spatial and Geographic Information Science
**Keywords** ARIMA, Temperature-humidity index, Heat stress, Dairy cows, Arid zone, Mexico, Calibrated models

## INTRODUCTION

The negative impact of heat stress (HS) on livestock productivity has been well documented in the literature. Among others, the studies by *Armstrong (1994)*, *Kadzere et al. (2002)*, *Amundson et al. (2006)*, *Salem & Bouraoui (2009)*, *Gantner et al. (2011)* and *Hernández et al. (2011)* have all highlighted the detrimental effects of HS on animal

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thermoregulation and feed intake, fertility, and milk production. High-yielding animals are particularly susceptible to HS due to their elevated thermogenesis, which is a consequence of their heightened metabolic activity (*Bernabucci et al., 2014*; *St-Pierre, Cobanov & Schnitkey, 2003*). As dairy cows are primarily selected for their milk production, they are more susceptible to caloric stress, which has been demonstrated to significantly impair their fertility (*Sammad et al., 2020*). Furthermore, it has been demonstrated that in dairy cows increase their milk production from 35 to 45 kg/d, the temperature threshold for HS can be lowered by 5 °C. This indicates that higher milking cows are susceptible to HS at lower temperatures (*Armstrong, 1994*). Consequently, the dairy industry incurs economic losses due to heat stress. In the United States, the financial impact of heat stress is estimated to range from 897 to 1.5 billion dollars annually (*St-Pierre, Cobanov & Schnitkey, 2003*).

A variety of bioclimatic indices have been utilized as a means of predicting the HS and its impact on dairy cattle. Of these indices, the temperature-humidity index (THI) is the most utilized and practical. Its origins can be traced back to studies conducted in the 1940s. Moreover, it has been a valuable indicator of heat stress in dairy cattle since the 1960s (*Vasseur et al., 2012*). Since that time, the THI has been employed to assess the productive and reproductive response as a function of climate differences (*Hahn, Mader & Eigenberg, 2003*; *Ravagnolo, Misztal & Hoogenboom, 2000*; *Silva, Morais & Guilhermino, 2007*; *Tolkamp et al., 2010*). The THI is a practical bioclimatic marker that reflects the sum of external forces acting on animals (temperature and humidity) and their impact on body temperature homeostasis (*Silva, Morais & Guilhermino, 2007*). The THI is calculated using a variety of formulas developed from research that measure dry bulb, wet bulb, dew point temperatures, and relative humidity of the air (*Sejian et al., 2013*).

As previously proposed by *Houlahan et al. (2017)*, the objective of scientific inquiry is to gain an understanding of the natural world. The capacity to make predictions is the sole means of substantiating scientific comprehension, thereby establishing it as a foundational tenet of all scientific disciplines. In the modern era, prediction fulfills two vital functions. Firstly, prediction serves as a test of scientific understanding, thereby conferring authority and legitimacy upon it. Secondly, prediction may also function as a potential guide for decision-making (*Sarewitz & Pielke, 1999*).

In the Comarca Lagunera, situated in the northern arid region of Mexico, HS conditions are present throughout the year (305 d), exerting a detrimental impact on milk production, milk composition, cow comfort, and the ratio of milking cows to nonmilking cows. Furthermore, these conditions have the potential to impose an economic burden at the farm, regional, and societal levels (*Rodriguez-Venegas et al., 2023*). Mathematical models are employed by scientists to predict the potential consequences of natural phenomena, with the objective of developing strategies to mitigate their adverse effects. Among the aforementioned tools, the following may be identified: A time series can be defined as a collection of observations made sequentially over time, in a broad sense, and can be used to describe a variety of data sets. A time series can be defined as a specific type of stochastic process. The last decades have shown great progress in the technique and scope of the use of models in the biological sciences, however, in the area of farm animal welfare the variety,

type, and complexity of the models used have not advanced at the same pace, despite the fact that they could have a great scope in this field of research (*Collins & Part, 2013*). The present study will focus on time series exhibiting behavior consistent with the laws of probability, as opposed to deterministic series. In the field of dairy production by cows, time series analysis has been applied in several areas, including the modeling of diseases such as estrus (*de Mol et al., 1999*), the quantification of the effect of temperature on mortality in dairy cows (*Morignat et al., 2015*), the increase in production due to dietary changes (*Kerr, Cowan & Chaseling, 1991*), the demand for dairy products (*Heien & Wessells, 1988*), and methane and $CO_2$ production (*Lee et al., 2017*). It is evident that the applications of this methodology to explain and predict the phenomenology in agricultural issues are numerous and diverse. This enables the implementation of preventative measures in a timely manner, thereby preventing any adverse effects on the health, comfort, and productivity of cows. For this reason, this article examines the predictive capacity of the THI in relation to potential HS events in the Comarca Lagunera, employing the time series method.

## MATERIALS AND METHODS

The climate data from the Comarca Lagunera (102°22′, 104°47′ WL; 24°22′, 26°23′ NL, at 1,139 m) were the subject of this study. This arid region of northern Mexico accounts for 21% of the national dairy cow inventory and presents environmental conditions that present a significant challenge to Holstein cattle on dairy farms. These conditions include an average annual precipitation of 200 mm, extreme ambient temperatures that can range from −5 °C in winter to 41.5 °C in summer, and high solar radiation.

Ambient temperature (in degrees Celsius) and relative humidity (in percent) data were obtained to calculate daily THI using the DiGiTH™ application (DiGiTH Technologies, Mexico), from five representative geographical points (GPs), according to the process described in a previous study of *Rodriguez-Venegas et al. (2022)*. The THI was calculated as $(1.8T + 32) − [(0.55 − (0.0055 × RH)((1.8T) − 26)]$ (*Council, 1971*). GPs were as follows: GP1 is situated at 25.5° NL and 103.25° WL; GP2 is located at 25°61′ NL and 103°55′ WL; GP3 is situated at 25°90′ NL and 103°39′ WL; GP4 is situated at 25°51′ NL and 103°60′ WL; GP5 is located at 25°40′ NL and 103°31′ WL. The data set under consideration spanned the period from 2016 to 2019.

### ARIMA model forecast

In reference to a specific time series, the predicted observation is calculated using the equation designated as Eq. (1) (*Box et al., 2016*).

$$Y_t = Y_1 + Y_2 + Y_3 + \ldots + Y_t \tag{1}$$

where $Y$ is the observations in the time of $t$.

As mentioned by *Patle et al. (2015)*, Eq. (1) into Eq. (2)

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + e_t. \tag{2}$$

In a study conducted by *Gibrilla, Anornu & Adomako (2018)*, the two constants, $c$ and $phi_1$, were employed in an analogous manner to address random error in $t$. The aforementioned errors were accounted for through the utilization of the variable $e_t$.

$$Y_t = c + e_t - \phi_1 e_{t-1} - \phi_2 e_{t-2} - \ldots - \phi_q e_{t-q}. \tag{3}$$

## Sen's estimator

In general, the slope is employed for the assessment of linear patterns through the implementation of least squares estimation *via* linear regression. The slope estimation formula, as proposed by *Sen (1968)*, is presented in the following equation:

$$d_k = \frac{x_j - x_i}{j - i} \tag{4}$$

where,

$d_k$ is an estimated slope.

for $(1 \leq i < j \leq n)$, where $d$ is the slope, $x$ denotes the variable, $n$ is the number of data, and $i$, $j$ are indices.

Sen's slope is then calculated as the median from all slopes: $b_{Sen} = median(d_k)$.

## Mann-kendall trend test

The Mann-Kendall test is a non-parametric method used for the analysis of trends in time series data, initially proposed by *Kendall (1938)*. The alternative hypothesis postulates the existence of a monotonically increasing or decreasing trend.

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sign(x_j - x_i). \tag{5}$$

As presented by *Anand et al. (2020)*, the Mann–Kendall statistic ($S$) is calculated from Eq. (6).

$$sign(x_j - x_i) = \begin{cases} +1 \text{ if } (x_j - x_i) > 0, \\ 0 \text{ if } (x_j - x_i) = 0, \\ -1 \text{ if } (x_j - x_i) < 0 \end{cases} . \tag{6}$$

## Data analysis

We used R (Version 4.4.1) (*R Core Team, 2024*), and the R-packages fable (Version 0.3.4) (*O'Hara-Wild, Hyndman & Wang, 2024a*), fabletools (Version 0.4.2) (*O'Hara-Wild, Hyndman & Wang, 2024b*), forecast (Version 8.23.0) (*Hyndman & Khandakar, 2008*), ggplot2 (Version 1423.5.1;27), (*Hyndman & Khandakar, 2008*), lubridate (Version 1.9.3;29) (*Grolemund & Wickham, 2011*), and trend (Version 1.1.6) (*Pohlert, 2023*) for all our analyses.

A variant of the Hyndman-Khandakar algorithm (*Hyndman & Athanasopoulos, 2021*) was used for model selection. This algorithm integrates unit root tests, Akaike information criterion minimization (AICc) and maximum likelihood estimation (MLE) to derive an

ARIMA model. For the forecasting, a model calibration was used following the steps used by *Legarreta-González et al. (2024a, 2024b)* as follows:

### Train/test

1. Spliting of the time series into two sets.

   a. Training.
   b. Testing (12 months).

2. Visualization of the train/test split.
3. Modeling estimation, where the equation of the model was. $m^3 \sim date, training(splits)$.

### Modeltime workflow

The objective was to accelerate the evaluation and selection of models in a systematic and efficient manner in a systematic and efficient manner, with a view to facilitating the process of identifying the most appropriate models for a given context. In light of the vast array of time series models currently available, it is feasible to undertake an analysis of these models and to forecast future outcomes by employing the model-time approach.

### Workflow

**1. Creation of a Modeltime table.** The Modeltime table employs a system of identification numbers and the generation of generic descriptions to facilitate the organisation and monitoring of models.

**2. Model calibration.** The objective of model calibration is to quantify the extent of errors and to estimate confidence intervals. Model calibration was conducted on the test set.

**3. Forecast using the testing set.**

   1) Calibration of the data permits visualization of the test predictions, which may be regarded as a forecast.
   2) The subsequent step is to ascertain the accuracy of the testing process, thus facilitating comparison of the models.

**4. Analyses of the results.** The optimal model is selected based on an evaluation of the accuracy of the measures employed and the results of the forecasts, whereby the latter are assessed in terms of their predictive power.

**5. Refitting.** The final step was to perform a realignment in accordance with the established best practice prior to forecasting future outcomes.

## RESULTS

Two data sets were constructed using the most recent 12 months of data, thereby enabling the formation of a training and testing set utilizing the final 12 months of data as the testing set. The subsequent step was to estimate the models with the resulting estimates. Subsequently, the models were calibrated using the out-of-sample data, that is to say, the

testing set. The resulting fitted values and residuals for the testing set, which permit a comprehensive examination of the data, were calculated for the purpose of calibration. The aforementioned data permit the generation of a visual representation of the testing predictions, or forecast. This calibration is consistent with works of *Legarreta-González et al. (2024a, 2024b)* performed in time series analyses.

A seasonal autoregressive integrated moving average (SARIMA) $(4,1,0)(0,1,0)_{365}$ model was obtained with an $R^2$ of 0.63. The model comprises an autoregressive component of order four, indicating that the value of the THI on a given day exhibits an autocorrelation of four previous days. Additionally, a differencing of one was necessary to achieve stationarity. Furthermore, a seasonal component was incorporated, where m corresponds to the 365 days of the year, also with a differencing of one.

The estimators of the model are as follows Eq. (7):

$$\tau_t = (-0.3149\phi_{t-1} - 0.2765\phi_{t-2} - 0.3036\phi_{t-3} - 0.1904\phi_{t-4} + \varepsilon_t \tag{7}$$
$$\varepsilon_t \sim NID(0, 2.541)$$

The observed data (black line) and the model prediction (red line) in Fig. 1 exhibit a similar temporal behavior for THI, indicating that the model is performing well. This conclusion can be further substantiated in the subsequent section.

In consideration of the statistical data that quantify the trajectory of the forecast, a trend is discernible, indicating that the model anticipates an escalation in THI. The slope is 0.01334708, with a 95% confidence interval of [0.01026692, 0.01629877]. The Mann-Kendall trend test statistic is $S = 1.910000 \times 10^4$. The variance is $5.425116 \times 10^6$, and the $\tau = 2.875229 \times 10^{-1}$. The z-score is 8.1999, the sample size is 365, $p < 0.001$.

Figure 2 illustrates that the residuals of the model exhibit a "white noise" behavior, as although some peaks are evident, they are not statistically significant. This is further corroborated by Fig. 3 showing the Autocorrelation Function (ACF) and Partial Correlation Function (PACF), which indicate that the model has been estimated correctly.

## DISCUSSION

This article presents, for the first time, the behavior of the THI using an ARIMA model, for which neither AR nor MA values had been previously estimated for this animal welfare indicator. Due to their great influence on key elements for the success of livestock farming, such as production, health, and animal welfare, environmental control systems are used to maintain a series of variables, such as temperature, humidity, and contaminant concentrations, at optimal levels. These systems are the most efficient tools to guarantee better production in livestock buildings (*Besteiro et al., 2017*) and tools such as ARIMA models are used for this purpose. In our case, this tool was used to evaluate the use of THI data and predict its future behavior. This would contribute to the opportune use of the mechanisms that allow avoiding or reducing the effects of heat stress on farm animals, mainly dairy cattle.

The design of THI prediction models consists of two stages: estimation and forecasting. *Hyndman & Khandakar (2008)* developed an algorithm for ARIMA model selection that
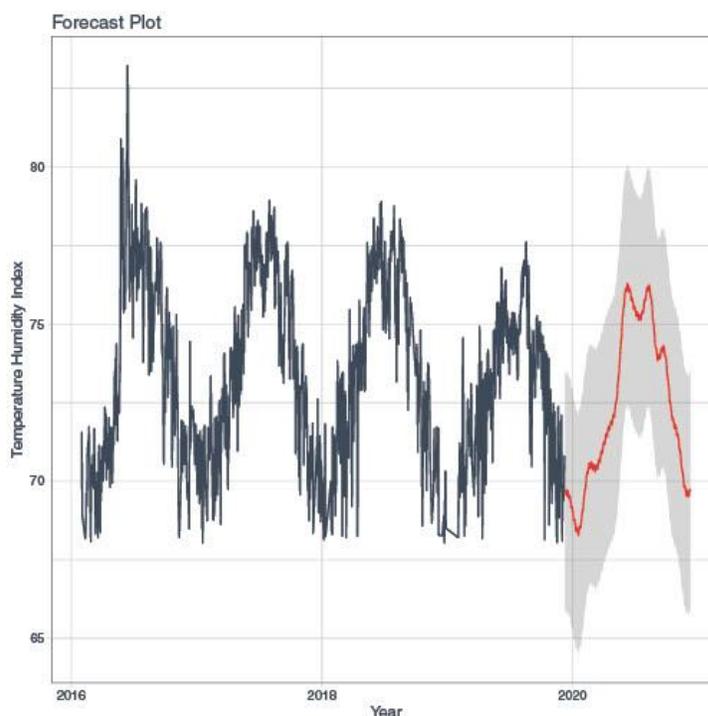
**Figure 1** Time series for temperature humidity index (THI), with observed values in black, and predicted by the model in red. Full-size ▣ DOI: 10.7717/peerj.18744/fig-1

uses the best AICc once the PAC/ACF requirements and stationarity are met. On the other hand, the geographic sites from which the data for the construction of the THI were obtained are representative of the region. Additionally, the climate data was as complete as possible, using a total of 1,404 THI data to design our ARIMA model.

The initial portion of the SARIMA model indicates that the THI of the present day is autocorrelated with the four preceding days. The coefficient for the previous day (t-1) to the THI to be estimated was −0.31, while the coefficients for t-2, t-3, and t-4 were −0.28, 0.30, and 0.19, respectively. A slope was observed, necessitating differentiation to achieve stationarity. No evidence of a moving average was observed, indicating that the THI of a given day can be predicted based on the model, with a confidence interval of 85%, by considering the THI values of four previous days. The second part of the model (0,1,0) allows for the detection of a seasonal pattern of 365 days, in which there is only a slope, but no AR or MA component.
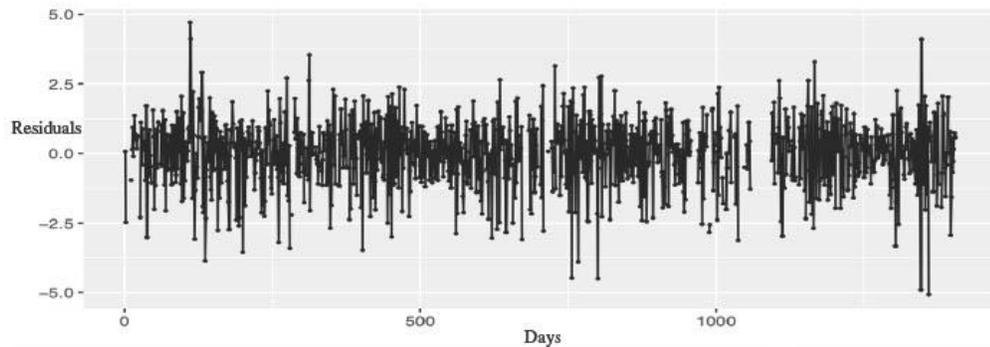
**Figure 2 Residuals analysis of the model.**

**Figure 3 Autocorrelation function (ACF), and the partial autocorrelation function (PACF) from the model.**

With regard of the Sen's slope was 0.01334708, Mann-Kendall trend test $S = 1.91 \times 10^4$ ($z = 8.2$, $n = 365$, $p\text{-value} = 2.407 \times 10^{-16}$) indicating a monotonic trend which signifies the presence of a slope in SARIMA prediction. There is a correlation with previous reports indicating an increase in the number of days with THI levels that induce heat stress in dairy cattle. In this context, *Reiczigel et al. (2009)* reported an increase in the number of days per year experiencing thermal stress (THI $\geq$ 68), from 5 to 17, over the past 30 years. Similarly, *Dunn et al. (2014)* proposed that by the year 2,100, the number of days exceeding the THI threshold may increase from an annual average of 1–2 to over 20. *Hempel et al. (2019)* proposed that the impact of prospective increases in thermal stress risk will vary across

locations. They posit that there will be a general trend towards an increase in the number and duration of thermal stress episodes. In their study of the Comarca Lagunera, *Rodriguez-Venegas et al. (2022)* observed an increase in the annual number of days with THI levels above the normal THI threshold (*i.e.*, $\geq$68) over time. The observed increase in temperature has the potential to compromise the reproductive and productive soundness of Holstein cows in northern arid Mexico.

The application of ARIMA models has been demonstrated in the forecasting of pen temperatures for animals of other species. *Besteiro et al. (2017)* developed a model for weaned piglets that employed a complete production cycle as the model estimation stage, resulting in a model that incorporated outdoor ambient temperature as the sole independent variable. In the present study, the THI is employed as a variable, which is not a single independent variable. Rather, it entails the integration of both ambient temperature and relative humidity.

The application of mathematical models for the prediction of factors influencing dairy cattle productivity is becoming increasingly prevalent in the scientific literature. For example, *Chavarría et al. (2024)* employed ARIMA models to estimate and robustly predict variables such as monthly herd milk production and discard rate. This illustrates the potential of time series modeling of retrospective data to forecast future trends and patterns of development in dairy herds in hot environments.

*Pereira et al. (2024)* focused on the impact of climate on dairy cattle, evaluating the performance of heat stress classifier models using confusion matrix metrics and contrasting them with the conventional approach based on temperature and humidity indices. The highest accuracy, 86.8%, was achieved, demonstrating the feasibility of developing precise and operational models for real-time monitoring of heat stress. In the context of dairy cattle, *Li et al. (2024)* employed machine learning techniques through a comprehensive evaluation of multiple feature sets to develop an effective core body temperature prediction model for dairy cows. This approach markedly enhanced the model's predictive capacity by integrating it with distinctive animal-related attributes and infrared temperature readings, thereby improving its accuracy. These findings may be further considered in other analyses in our region.

The findings suggest the possibility of further research in this region and in other locations experiencing elevated temperatures. The objective is to develop mathematical models that can accurately predict the THI with a high degree of probability. Such knowledge would facilitate the implementation of strategies to mitigate the adverse effects on livestock health and productivity such as scheduling baths at optimal times and switching to lower-calorie diets when elevated THI levels are predicted, may be employed to achieve the desired outcome.

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## ADDITIONAL INFORMATION AND DECLARATIONS

### Competing Interests

The authors declare that they have no competing interests.

### Author Contributions

- José Luis Herrera-González conceived and designed the experiments, performed the experiments, authored or reviewed drafts of the article, and approved the final draft.
- Rafael Rodríguez-Venegas conceived and designed the experiments, performed the experiments, authored or reviewed drafts of the article, and approved the final draft.
- Martín Alfredo Legarreta-González conceived and designed the experiments, performed the experiments, analyzed the data, prepared figures and/or tables, authored or reviewed drafts of the article, and approved the final draft.
- Pedro Antonio Robles-Trillo performed the experiments, prepared figures and/or tables, and approved the final draft.
- Ángeles De-Santiago-Miramontes performed the experiments, prepared figures and/or tables, and approved the final draft.
- Darithsa Loya-González analyzed the data, prepared figures and/or tables, and approved the final draft.
- Rafael Rodríguez-Martínez performed the experiments, authored or reviewed drafts of the article, and approved the final draft.

### Data Availability

The following information was supplied regarding data availability:
    The raw data is available in the Supplemental File.

### Supplemental Information

Supplemental information for this article can be found online at http://dx.doi.org/10.7717/peerj.18744#supplemental-information.

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**IV.ARTICULO 2**

Identifying the best indicator for forecasting the
Temperature-Humidity 1 Index for dairy cattle and its
historical pattern (1940 -– 2024) in 2 north-central Mexico.

Rafael Rodríguez Martínez <rafael.rdz.mtz@gmail.com>

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# Identifying the best indicator for forecasting the temperature-humidity index for dairy cattle and its historical pattern (1940 – 2024) in North-Central Mexico

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## ARTICLE INFO

## ABSTRACT

The most commonly used indicator to identify times of increased risk of heat stress for dairy cows is THI, which measures the heat load that cattle may suffer from air temperature (°C) and relative humidity (RH). The present study employed two working hypotheses: firstly, that measuring cumulative hours of exposure to THI results in a better prognosis for heat stress than using maximum THI values; and secondly, that under high THI conditions, THI has been increasing in the Comarca Lagunera. The present study employed a Big Data Predictive Analytics approach, utilising models estimated from 85 years of daily, hourly observations to estimate calibrated statistical models and forecast trends. The THI was organised in three categories: accumulated daily hours (HSacc), the daily average or mean of THI (THImean), and the daily maximum THI (THImax). The measurement of these variables was conducted at four levels of THI: more than 67, 69–71, 72–76 and 77 or more. For HSacc, the optimal model was identified as Prophet; for THImean and THImax, GLMNET was found to be the most suitable model, with positive slopes observed across almost all levels. The models predict and increment in the next 10 years of 0.14, 0.20 and 0.32 hours in the daily values of HSacc, THImean and THImax, respectively. It is evident that the findings of this study will play a pivotal role in the identification, implementation and assessment of strategies that have the potential to mitigate the adverse effects of heat stress in the region.

## 1. Introduction

In subtropical and tropical regions, heat stress (HS) is a prevalent phenomenon when climatic changes exceed the thermal conditions of dairy cows beyond their thermoneutral zone (TNZ). The TNZ is defined as the minimum metabolic rate at which a healthy animal can make physical adaptations to maintain a normal body temperature, with minimal change in metabolic activity. In response to HS, cattle undergo physiological adjustments to regulate their body temperature, resulting in decreased milk production and increased health and reproductive problems [8]. The prevailing environmental factors that exert a significant influence on livestock production are air temperature (AT) and relative humidity (RH) [13], with AT being the focus of the majority of research due to its deleterious effects on dairy cows. The upper critical temperature for dairy cattle is considered to be 25 °C [5].

On a global scale, there appears to be an accelerating trend in climate change in recent years. It is virtually certain that extreme warm temperatures will become more frequent over most land areas on daily and seasonal timescales as global average temperature increases, and heat waves will become more frequent and longer lasting [55]. The global average temperature has increased by approximately 0.7 °C since the beginning of the 20th century, and it is likely that this increase will reach between 1.8 and 4 °C by the year 2100 [7].

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The Temperature Humidity Index (THI) is the most widely utilised indicator for measuring the risk of HS in dairy cattle. As Reiczigel et al. [45] has previously observed, the THI has exceeded 68 (considered the threshold for HS), and there has been an escalation in the number of HS days per year, ranging from 5 to 17 days over the past three decades. Moreover, Dunn et al. [14] anticipates that by the year 2100, the number of days exceeding the threshold may rise from an annual average of 1 – 2 to more than 20. As asserted by Hempel et al. [18], the ramifications of heightened HS risk are poised to materialise in diverse manifestations, contingent on geographical location, with a prevailing tendency towards escalating frequency and duration of heat stress episodes. In accordance with the aforementioned theoretical framework, Rodriguez-Venegas et al. [48] hypothesised that in the Comarca Lagunera, located in the arid centre of northern Mexico, the number of days with a THI of 68 or more has increased. However, it should be noted that the findings of the present study, although constructed utilising a substantial database, correspond to a relatively brief period (2015 – 2020), thereby limiting their predictive capacity. In view of the aforementioned points, the objective of this study was to ascertain the most efficacious THI indicator to measure HS risk conditions. The indicators considered, on a daily basis, were maximum THI (THImax), average or mean THI (THImean), and cumulative hours of exposure to HS (HSacc). The categorisation of THI levels used in this study was based on the methodology proposed by Rodriguez-Venegas et al. [47].

## 2. Materials and methods

### 2.1. Climatic data collection and THI calculation

A substantial body of instrumental precipitation and temperature observations is available from a large number of weather stations in Mexico. In regions with comparable human populations, the density of these stations exceeds that maintained by the National Weather Service in the United States. Consequently, this aspect is of paramount importance in domains such as livestock, agriculture and non-traditional agriculture [49]. The values of the AT in centigrades and relative humidity for each hour, month and year of the period 1st January, 1940 to 31st December, 2025 for Torreón, Coahuila de Zaragoza State, Mexico (25.54°N 103.42°W, 1124 masl) were obtained from the database by Company [9]. The total number of observations recorded for the variables of date (comprising day, month and year), time, temperature and humidity was 745,128. The THI was calculated using the formula for temperature in centigrades proposed by Mader et al. [36] as follows:

$$THI = (0.8 \times Temp) + \left(\left(\frac{RH}{100}\right) \times (Temp - 14.4)\right) + 46.4. \qquad (1)$$

Following the acquisition of the THI data, the THI maximum (THImax) and THI average (THImean) values were ascertained, in addition to the HS accumulated hours (HSacc) at a daily level, for the three ranges of HS causative agents proposed by Rodriguez-Venegas et al. [47].

### 2.2. Statistical methods

#### 2.2.1. Time series

Four distinct methodologies were evaluated and tested in order to estimate time series models for historical THI values in the Mexican North-central region. The following methodologies were evaluated and tested:

1) Box et al. [6] ARIMA (Autoregressive Integrated Moving Average).
2) Facebook Prophet, which is an enhanced time series model that employs a three-component approach, incorporating a trend, seasonality, and a term accounting for the impact of vacation periods.
3) Lasso and Generalised Linear Regularized Models (GLMNET). This technique represents a method for fitting of generalized linear and analogous models by means of penalised maximum likelihood. The

regularization path is calculated for the penalty loop, also known as the elastic net, on a grid of values (on the logarithmic scale) for the regularization parameter, lambda. The values of the penalty and mixture employed in this model were set at 0.01 and 0.5.

4) A hybrid method that combined Prophet and XGBoost, which utilises a Classification and Regression Tree (CART) as a weak learner, with the objective of performing learning during each training iteration in order to fit the previous residuals. This process ultimately results in a strong learner.

For the last two models, the recipe specifications were:

a) Model: value ~ date, training (splits).
b) step timeseries signature: date.
c) step rm contains: am.pm, hour, minute, second and xts.
d) step fourier: date, period = 365, K = 5.
e) step dummy: all nominal.

#### 2.2.2. Modeltime workflow

The present study uses the workflow developed by *Modeltime.*, which was conceived with the purpose of optimising the evaluation and selection of models in a systematic and efficient way. The implementation of this methodology has been undertaken with the objective of facilitating the process of identifying the most appropriate models for a given context. The models were evaluated on an identical training and testing division. The following steps were presented by Herrera-González et al. [20] for the analyses, as mentioned below.

In order to circumvent the issue of overfitting, the 'hold-out (data)' method was employed in lieu of utilising the entirety of the data for training purposes. The dataset was then divided into two sets: a training set and a testing set. This finding suggests that the model exhibits effective generalisation capabilities, as evidenced by its ability to effectively predict unseen data that was not part of the training set. This approach is frequently employed when there is a sufficiently large dataset available for training, even subsequent to data splitting, as was the case with the dataset under consideration. In accordance with the established recipe, a cross-validation procedure was employed for both the GLMMNET and the hybrid models. The number of folds in the cross-validation was specified as K = 5 for both models.

#### 2.2.3. Train / test

1. Split time series into training and testing sets.
2. Make a train/test set (12 months).
3. Visualize the train/test split.
4. Modelling.

a. Model:

$$ppm \sim date, training(splits)$$

#### 2.2.4. Workflow

2.2.4.1. *Modeltime table* The Modeltime table implements a system of identification numbers and the generation of generic descriptions to facilitate the organisation and tracking of models.

2.2.4.2. *Calibration* The objective of model calibration is to quantify the magnitude of errors and estimate confidence intervals. The model calibration procedure was implemented on the out-of-sample data set (also termed the test set) in order to generate the true values, fitted values and residuals of the test set.

2.2.4.3. *Forecast (testing set)* Firstly, the calibration of the data allows for the visualisation of the test predictions, which can be considered a forecast. The subsequent stage of the process is to ascertain the precision of the testing procedure, thus enabling a comparison to be made between models.

*2.2.4.4. Analyze results* The selection of the most appropriate model is based on an evaluation of the precision of the measures used and the results of the forecasts. As previously stated, the latter are evaluated in terms of the smaller values of MAE and RMSE.

*2.2.4.5. Refitting* The final stage of the process entailed the execution of a realignment, in accordance with the best practices that had been previously established, prior to the forecasting of future results. Consequently, a rescaling procedure was implemented. The estimation period is extended to 10 years, with the objective of facilitating the forecasting of data.

### 2.2.5. Model selection

In order to select the most appropriate models, the smaller values of the Mean Absolute Error (MAE) were chosen. In instances where values are equal, the Root Square Mean of the Errors (RMSE) was employed as a secondary criterion, in conjunction with the maximum attainable value of Coefficiente of Determination (R-sq) as in the works of [23,67, 2,1,51,35].

### 2.2.6. Time series slope

The Sen's estimator and the Mann-Kendall Trend Test were used to estimate the slope of the best model. The Sen's slope is estimated using least squares estimation via linear regression. The equation used was that proposed by Sen [50]. This particular estimator possesses the capacity to predict changes in a given time series. In this study, the Sen's slope estimator was utilised to forecast over a ten-year period. This approach entailed the multiplication of the slope estimator by 3,650, representing the total number of days in a decade. The Mann-Kendall Trend Test was used to test monotonic trend in the time series.

### 2.3. Data analysis

We used the R programming language [44] and the R-packages broom [46], dials [30], dplyr [61], infer [10], lubridate [17], modeldata [27], modeltime [11], parsnip [31], purrr [62], readr [63], recipes [34], reshape2 [57], rsample [16], scales [64], stringr [59], tibble [39], tidymodels [33], tidyr [65], tidyverse [60], timetk [12], tinylabels [4], trend [42], tune [28], workflows [54], workflowsets [29], and yardstick [32] for our analyses and ggplot2 [58] for plots.

## 3. Results

### 3.1. Daily cumulative hours

#### 3.1.1. THI 68 or above

As illustrated in Table 1, the parameters for selecting the most suitable model are delineated. In this particular instance, the Facebook Prophet model was identified as the optimal selection, characterised by an MAE of 2.85, an RMSE of 3.96, and an $R^2$ of 0.81. Fig. 1 (a), shows the forecast plot exhibits a positive slope. The regression coefficient for the Sen's slope is $3.96 \times 10^{-5}$, with a p-value of less than 0.001. This indicates a significant increase in the accumulated HS daily hours over a 10-year period, with an estimated increment of approximately 0.14 hours. The Mann-Kendall test yielded a significance level of 0.001, with a test statistic of $S = 5.99 \times 10^7$, thereby indicating a monotonic trend in the time series.

#### 3.1.2. THI 68 − 71

The most suitable model for the calculation of daily low HS (see Table 1) is the GLMNET model (MAE = 2.14, RMSE = 2.63, $R^2$ = 0.06). As illustrated in Fig. 1 (b), the forecast plot with a 10-year prediction is presented. It is predicted that, given the value of the Sen's Slope of $-4.5 \times 10^{-5}$, a decrease of approximately (0.16) hours in a 10-year period can be expected. The Mann-Kendall test yielded a result of $S = -4.33 \times 10^{-7}$, with a p-value less than 0.001. This indicates the presence of a monotonic trend in the time series.

|  | MAE | RMSE | R-sq |
|---|---|---|---|
| **THI 68 or above** | | | |
| ARIMA | 13.37 | 15.66 | 0.00 |
| Prophet | 2.85 | 3.96 | 0.81 |
| GLMNET | 3.01 | 4.01 | 0.80 |
| Prophet w/ XGBoost errors | 2.92 | 4.08 | 0.80 |
| **THI 68 - 71** | | | |
| ARIMA | 2.42 | 2.87 | 0.00 |
| Prophet | 2.15 | 2.67 | 0.06 |
| GLMNET | 2.14 | 2.63 | 0.06 |
| Prophet w/ XGBoost errors | 2.18 | 2.71 | 0.09 |
| **THI 72 - 76** | | | |
| ARIMA | 3.49 | 4.03 | 0.02 |
| Prophet | 1.91 | 2.60 | 0.60 |
| GLMNET | 1.94 | 2.58 | 0.59 |
| Prophet w/ XGBoost errors | 1.89 | 2.62 | 0.59 |
| **THI 77 or above** | | | |
| ARIMA | 3.64 | 5.95 | 0.00 |
| Prophet | 2.22 | 2.93 | 0.70 |
| GLMNET | 2.22 | 2.83 | 0.68 |
| Prophet w/ XGBoost errors | 1.70 | 2.72 | 0.69 |

#### 3.1.3. THI 72 − 76

The Facebook Prophet with XGBoost errors model was identified as the most effective model in accordance with the findings presented in Table 1, with the model achieving values of 1.89, 2.62, and 0.59 for MAE, RMSE, and $R^2$, respectively. The forecast plot is displayed in Fig. 1 (c). It is predicted that an increment of 0.21 hours will occur in 10 years, since the value of Sen's Slope is $5.77 \times 10^{-5}$. The time series demonstrates a monotonic trend, as evidenced by the Mann-Kendall test result, which indicates a statistical significance level of p < 0.001, with a test statistic of $S = 4.63 \times 10^{-6}$.

#### 3.1.4. THI 77 or above

According to our results, an increment of 0.2 hours will occur in 10 years for HS with a THI of 77 or more (Sen's Slope = $5.5 \times 10^{-5}$). The model employed for the estimation is the Prophet model with XGBoost errors, with MAE = 1.70, RMSE = 2.72, R-squared = 0.69 (see Table 1). The time series demonstrates a monotonic trend, as evidenced by the results of the Mann-Kendall test, which yielded a statistical significance of $S = 4.03 \times 10^{-7}$, p < 0.001. The forecast plot is presented in Fig. 1 (d).

### 3.2. Daily THI mean

#### 3.2.1. THI of 68 or above

The parameters for selecting the most appropriate model are delineated 2. In this particular instance, the GLMNET model was identified as the optimal selection, characterised by an MAE of 1.10, an RMSE of 1.36, and an $R^2$ of 0.72. As demonstrated in Fig. 2, the forecast plot exhibits a positive slope. The slope of the regression line is $5.6 \times 10^{-5}$, p < 0.001. This predicts an increase in the THI mean of 10 years, calculated as 0.2. The Mann-Kendall test yielded a significance level of 0.001, with a test statistic of $S = 6.1 \times 10^7$, thereby indicating a monotonic trend in the time series.

#### 3.2.2. THI 68 − 71

The most appropriate model for the THI mean of low HS (see Table 2) is the GLMNET model (MAE = 0.42, RMSE = 0.53, $R^2$ = 0.22). Fig. 2 (b) shows the forecast plot with a 10-year prediction is presented. It is predicted that the Senate slope will be $7.15 \times 10^{-5}$. An increment of 0.27, will be observed. The Mann-Kendall test yielded a result of $S = 2.98 \times 10^{-7}$, p < 0.001, indicating a monotonic trend in the time series.
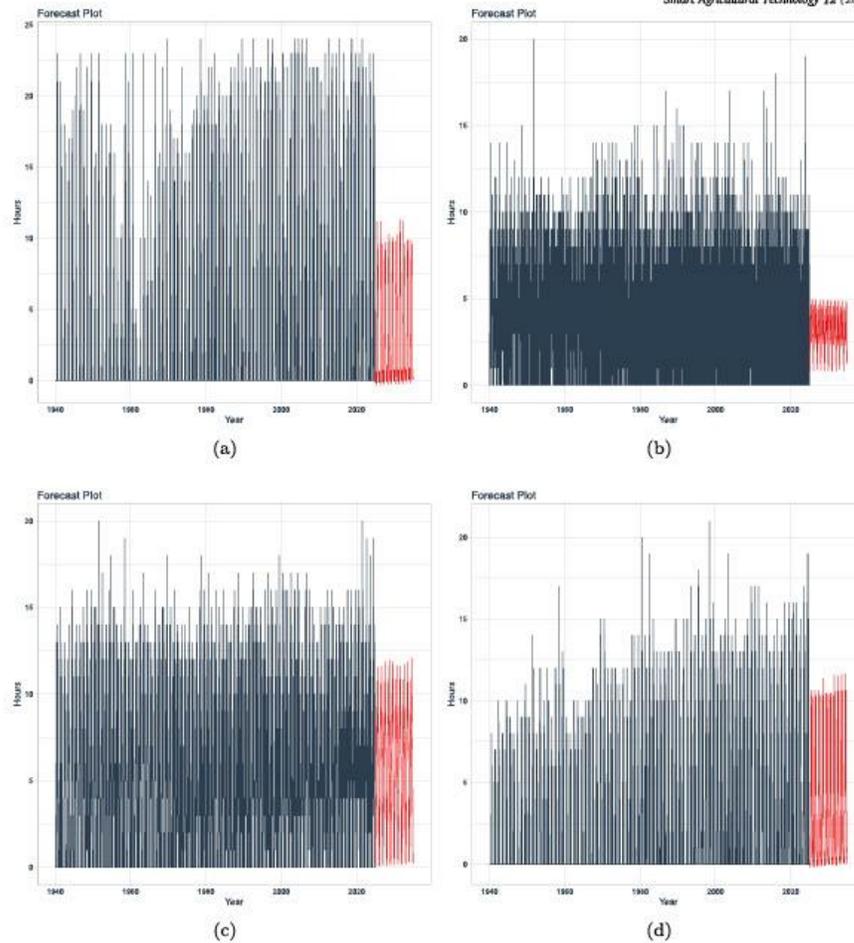
Fig. 1. Forecast plots for models of accumulated daily hours of Heat Stress in La Comarca Lagunera, Mexico. Black lines are the observed values, red lines best models 10-years forecast. (a) THI above 68 or above, (b) THI 68-71, (c) THI 72-76, (d) THI 77 or above.

### 3.2.3. THI 72 – 76

As shown in Table 2, the GLMNET model emerged as the most effective model, with values of 0.43, 0.56, and 0.23 for MAE, RMSE, and $R^2$, respectively. The forecast plot is displayed in Fig. 2 (c). It is predicted that in 10 years' time, an increment of 0.01 will occur, since the value of Sen's slope is $1.81 \times 10^{-6}$. The time series demonstrates a monotonic trend, as evidenced by the Mann-Kendall test result, which indicates a statistical significance level of $p < 0.001$, with a test statistic of $S = 2.83 \times 10^{-6}$.

### 3.2.4. THI 77 or above

It is predicted that there will be an increment of 0.21 in 10 years for THImean of 77 or above (Sen's Slope = $5.65 \times 10^{-5}$). The model employed for the estimation is the GLMNET, with MAE = 0.73, RMSE = 0.89, R-Sq = 0.29 (see Table 2). The time series demonstrates a mono-

tonic trend, as evidenced by the results of the Mann-Kendall test, which yielded a statistical significance of $S = 2.47 \times 10^{-6}$ $p < 0.001$. The forecast plot is presented in Fig. 2 (d).

### 3.3. Daily maximum THI

#### 3.3.1. THI 68 or above

The parameters for selecting the most suitable model are delineated (Table 3), in this particular instance, the Prophet w/ XGBoost errors model was identified as the optimal selection, characterised by an MAE of 1.64, an RMSE of 2.07, and an $R^2$ of 0.73. As demonstrated in Fig. 3 (a), the forecast plot exhibits a positive slope. The slope of the regression line is found to be $8.85 \times 10^{-5}$, $p < 0.001$ and the p-value is less than 0.001. This indicates that there is a high probability of an increase in THImax of approximately 0.32 over a 10-year period. The Mann-Kendall

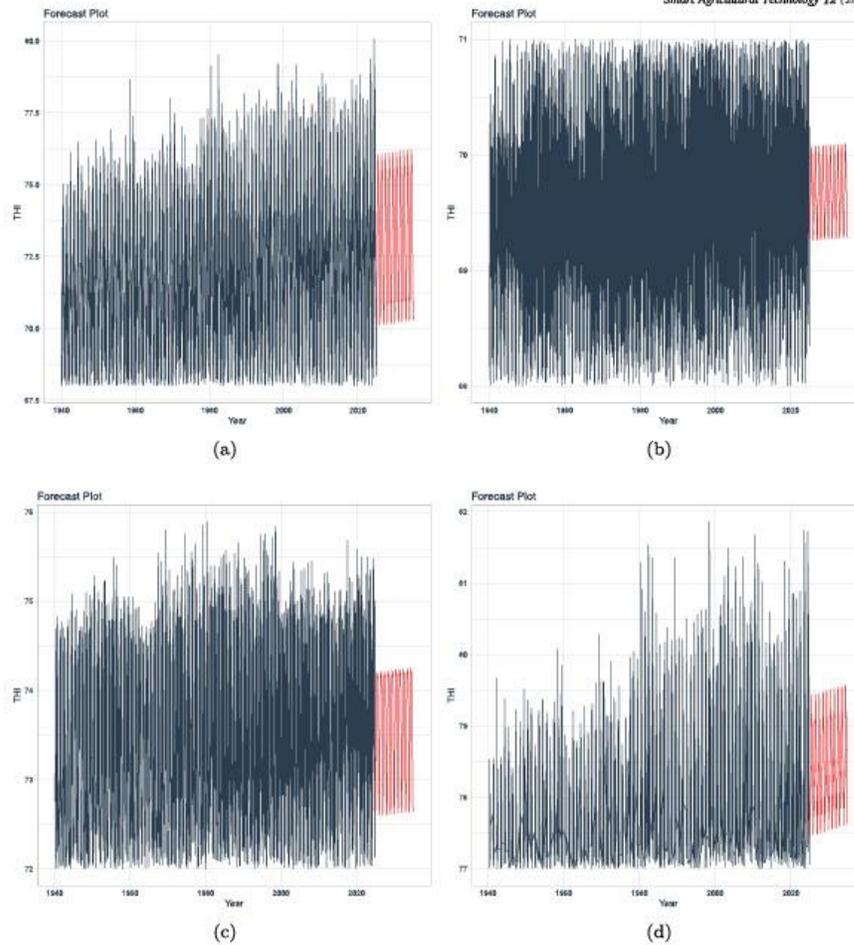J.L. Herrera-González, M.A. Legarreta-González, F.G. Vélis-Deras et al.

Fig. 2. Forecast plots for models of daily THI mean in La Comarca Lagunera, Mexico. Black lines are the observed values, red lines best models 10-years forecast. (a) THI above 68 or above, (b) THI 68-71, (c) THI 72-76, (d) THI 77 or above.

test yielded a significance level of 0.001, with a test statistic of $S = 6.13 \times 10^7$, thereby indicating a monotonic trend in the time series.

### 3.3.2. THI Max 68 – 71

The optimum model for the THImax of low HS (Table 3) is the Facebook Prophet model (MAE = 0.44, RMSE = 0.58, $R^2$ = 0.14). As illustrated in Fig. 3 (b), the forecast plot with a 10-year prediction is presented. Given the value of the Sen's Slope of $2.18 \times 10^{-5}$, there will be an increment of 0.08 in 10 years. The Mann-Kendall test yielded a statistical significance of $S = 2.88 \times 10^{-6}$ p = 0.045, indicating a monotonic trend in the time series.

### 3.3.3. THI Max 72 – 76

The Facebook Prophet model emerged as the optimal model for THI Max 72 - 76, with values of 0.59, 0.80 and 0.41 for MAE, RMSE and R2,

respectively (Table 3). $R^2$, respectively. The forecast plot is displayed in Fig. 3 (c). It is predicted that in 10 years' time, an increment of 0.01 will be observed, since the value of Sen's slope is $2.04 \times 10^{-6}$. The time series presents a monotonic trend, as evidenced by the Mann-Kendall test result, which indicates a statistical significance level of p < 0.001, with a test statistic of $S = 5.61 \times 10^{-6}$.

### 3.3.4. Maximum value of THI 77 or above

According to the selected model, an increase of 0.34 is expected over 10 years for a THImax of 77 or higher (Sen slope = $9.36 \times 10^{-5}$)). The model employed for the estimation is the GLMNET, with MAE = 1.19, RMSE = 1.45, R-Sq = 0.32 (see Table 3). The time series demonstrates a monotonic trend, as evidenced by the results of the Mann-Kendall test, which yielded a statistical significance of $S = 2.13 \times 10^{-1}$ and a p-value of less than 0.001. The forecast plot is presented in Fig. 3 (d).
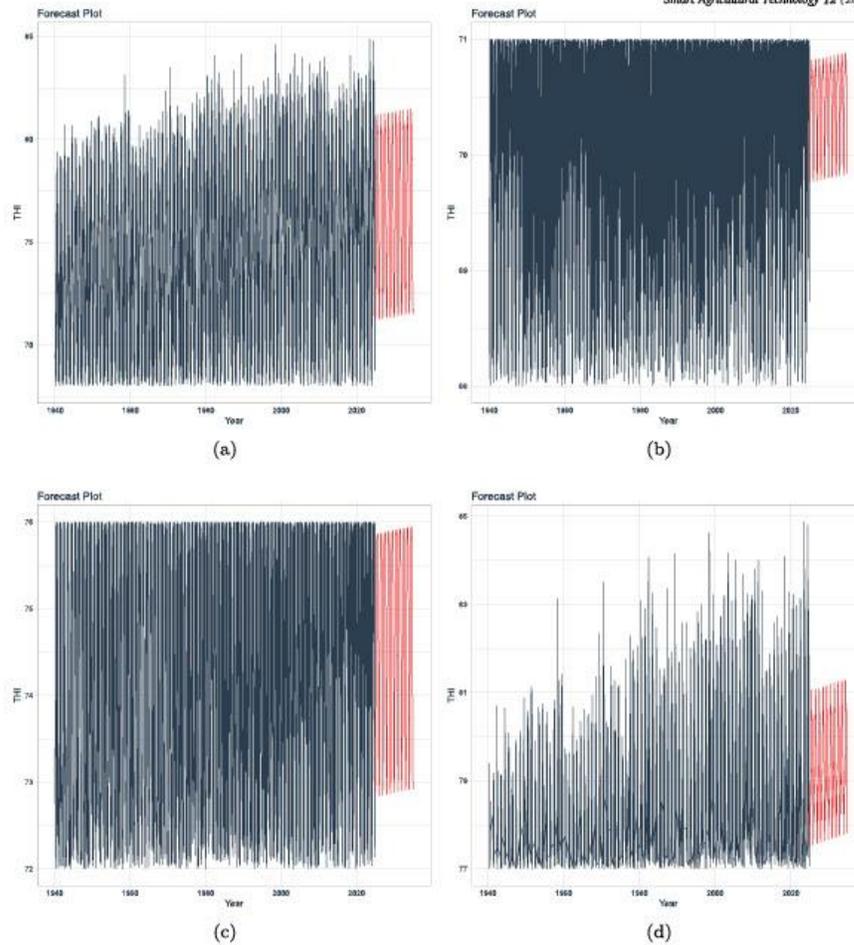
Fig. 3. Forecast plots for models of daily Maximum THI in La Comarca Lagunera, Mexico. Black lines are the observed values, red lines best models 10-years forecast. (a) THI above 68 or above, (b) THI 68-71, (c) THI 72-76, (d) THI 77 or above.

### 3.4. 1940 – 1999 vs 2000 – 2024 comparative

In the present study, the slopes of the daily THImean greater than 68 were estimated for the period from 1 January 1940 to 31 December 1999, with a magnitude of $4.9 \times 10^{-5}$ (p < 0.001). In a similar vein, for the period spanning from 1 January 2000 to 31 December 2024, a slope of $1.4 \times 10^{-5}$ (p = 0.03) was obtained. Fig. 4 shows the time series plot with the trend line for each period.

### 4. Discussion

The present study evaluated three indicators of HS: cumulative hours of exposure (HSacc), average or mean THI (THImean), and maximum THI (THImax). The findings confirmed that hours of heat stress in the region have increased from 1940 to 2024, which may mean an increase

between cumulative heat exposure and milk yield or health outcomes [40,53,3,15].

### 4.1. Best model

The most effective predictor of THI in climatic terms was THImean, as the MAE and RMSE values obtained for the THI's models $\geq 68$, $69 - 71$, $72 - 76$ and $\geq 77$ were the lowest compared to the other models. However, it is probable that when utilising biological indicators, such as respiration rate, body temperature, quantity and quality of milk produced, and reproductive rate, HSacc will be a superior indicator because it incorporates the effect of cumulative hours of HS on dairy cows. The inclusion of HSacc was based on the consideration that prolonged exposure (eight or more hours per day) to elevated levels of THI is more damaging than a shorter exposure, for example one or two hours. In this
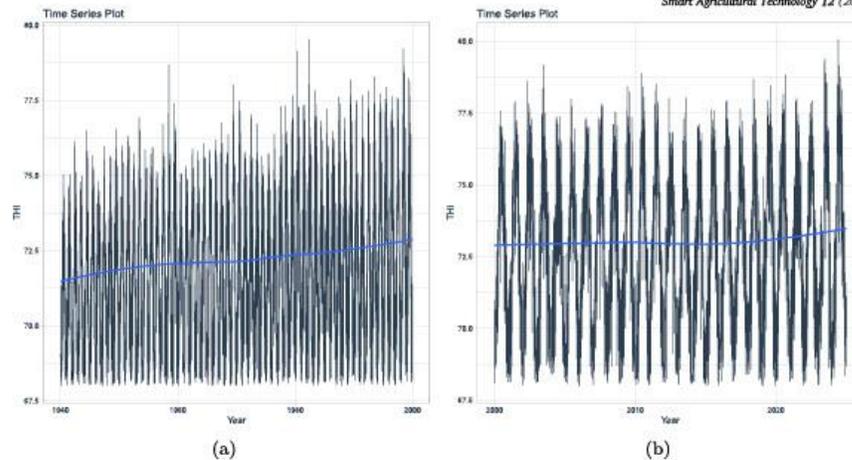
(a)                (b)

Fig. 4. Time series plots of the daily mean of THI with trend line. (a) 1940 - 1999, (b) 2000 - 2024.

Table 2
Model selection parameters for daily THI mean.

| | MAE | RMSE | R-sq |
|---|---|---|---|
| **THI 68 or above** | | | |
| ARIMA | 2.14 | 2.57 | 0.00 |
| Prophet | 1.12 | 1.39 | 0.73 |
| GLMNET | 1.10 | 1.36 | 0.72 |
| Prophet w/ XGBoost errors | 1.15 | 1.44 | 0.71 |
| **THI 68 - 71** | | | |
| ARIMA | 0.66 | 0.78 | 0.00 |
| Prophet | 0.43 | 0.53 | 0.23 |
| GLMNET | 0.42 | 0.53 | 0.22 |
| Prophet w/ XGBoost errors | 0.45 | 0.56 | 0.20 |
| **THI 72 - 76** | | | |
| ARIMA | 0.48 | 0.63 | 0.00 |
| Prophet | 0.43 | 0.56 | 0.25 |
| GLMNET | 0.43 | 0.56 | 0.23 |
| Prophet w/ XGBoost errors | 0.55 | 0.68 | 0.22 |
| **THI 77 or above** | | | |
| ARIMA | 1.10 | 1.35 | 0.00 |
| Prophet | 0.79 | 0.97 | 0.29 |
| GLMNET | 0.73 | 0.89 | 0.29 |
| Prophet w/ XGBoost errors | 0.74 | 0.92 | 0.24 |

Table 3
Model selection parameters for daily maximum THI.

| | MAE | RMSE | R-sq |
|---|---|---|---|
| **THI 68 or above** | | | |
| ARIMA | 3.31 | 4.10 | 0.00 |
| Prophet | 1.65 | 2.04 | 0.75 |
| GLMNET | 1.56 | 1.99 | 0.74 |
| Prophet w/ XGBoost errors | 1.64 | 2.07 | 0.73 |
| **THI 68 - 71** | | | |
| ARIMA | 0.48 | 0.62 | 0.00 |
| Prophet | 0.44 | 0.58 | 0.14 |
| GLMNET | 0.45 | 0.59 | 0.14 |
| Prophet w/ XGBoost errors | 0.44 | 0.60 | 0.10 |
| **THI 72 - 76** | | | |
| ARIMA | 0.80 | 1.01 | 0.00 |
| Prophet | 0.59 | 0.80 | 0.41 |
| GLMNET | 0.59 | 0.80 | 0.39 |
| Prophet w/ XGBoost errors | 0.59 | 0.83 | 0.39 |
| **THI 77 or above** | | | |
| ARIMA | 1.98 | 2.42 | 0.00 |
| Prophet | 1.31 | 1.63 | 0.31 |
| GLMNET | 1.19 | 1.45 | 0.32 |
| Prophet w/ XGBoost errors | 1.26 | 1.57 | 0.24 |

regard, Hempel et al. [18] proposes to estimate the number of days of heat stress from hourly THI values.

### 4.2. Cumulative HS

For this indicator, the best model was Facebook Prophet, except for the THI range of 72 – 76. The findings of this study indicate a potential correlation between elevated cumulative hours of HS and a probable impact on the health, productivity and welfare of dairy cattle in the region. This finding is consistent with the expectation of further increases in summer temperatures due to ongoing climate change [22]. Solymosi et al. [52] have observed an increase in the number of days per year with HS between 1973 and 2008, and that variability over the last two decades shows an increasing trend. This finding suggests that extreme weather events are occurring more frequently today than in previous decades. In a recent study, Woodward et al. [66] further corroborated this position, noting that regions already experiencing a high number of heat stress risk days and heat stress load in the 2020s will experience the greatest increases in heat stress risk in the 2050s. This observation supports the hypothesis that the prominent factor is not the number of days experiencing heat stress, but the total number of hours of exposure to such conditions.

The negative value of cumulative daily hours observed in the THI interval of 68-71 ($-4.5 \times 10^{-5}$) suggests a potential decline in HS intensity in the region over time, predicting a decrease in the next 10 years for this THI range. However, this level of THI exerts the least influence on the health, welfare and productivity of dairy cows. Indeed, elevated levels are recognised to pose the greatest risks to the health and productivity of dairy cattle [26,43,56]. In contrast, moderate (72 – 76) and intense ($\geq$ 77) THI exhibited an upward trend which is a predicted increment of hours per day, in the 10 years, which may signify an elevated risk of heat stress with considerable adverse consequences for cattle, particularly those with high productivity [25], a characteristic of farms in the region.

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### 4.3. Mean THI

For all measured THImean levels ($\geq 68$, $69 - 71$, $72 - 76$, and $\geq 77$), the most appropriate model is GLMNET, with positive slope values which translate to predicted increments of 0.32, 0.27, 0.01 and 0.21 in 10 years, respectively. The findings suggest a correlation between an increase in hours and daily THImean values. This may pose a future challenge for dairy cow adaptation and farm managers, particularly given the rise in high stress levels ($\geq 77$) THI, which are considered the most detrimental for cattle. [56] posits that, the THI values of 87 and 77 are to be regarded as the upper maximum and critical minimum, respectively, above which the risk of death for dairy cows in intensive systems is increased.

### 4.4. Maximum THI

For the THImax indicator, all levels except THImax $68 - 71$ exhibited a positive slope that predicts increments of Maximum THI in the 10 years. However, the value obtained for $68 - 71$ THI was not statistically significant. In this particular case, as in the case of the average THI, the optimal model was GLMNET. Consequently, the findings suggest that the daily hours of exposure to THI values that are detrimental to dairy cattle are likely to increase in the future. The maximum THI values have been utilised to quantify the intensity of heat stress, measuring THI a during the afternoon to indicate the maximum HS experienced by dairy cows. However, with the exception of cases of extreme heat stress, it has been observed that short period THI values have a minor impact on the prediction of animal responses to heat stress [24].

### 4.5. Heat stress comparatives

A comparison of the THImean from 1940 to 2000 and from 2000 to 2024 was conducted, revealing that the trend was more pronounced during the initial 60-year period of observation than during the final 24 years. This finding is supported by the Sen's slope, which exhibited a value of $4.9 \times 10^{-5}$ for the first period and $1.4 \times 10^{-5}$ for the latter, indicating that the trend almost flatten. On the other hand, comparing the number of hours that cows were exposed to THI that exceeded 77 points during the years 1984 and 2024, the results indicated 656 hours and 1,578 hours of exposure, respectively, which is approximately 2.4 times more in the latter year. This finding suggests that cows have been subjected to increasingly severe environmental challenges in recent years, particularly with regard to the most harmful HS level.

### 4.6. Limitations of the study

It should be noted that the present study did not include physiological and productive variables that are affected by HS, as these were not part of the study's objective. As previously stated, it is probable that the most effective indicator will be Cumulative HS, should these variables be incorporated into subsequent studies.

### 4.7. Study implication

The issue of diminished milk yield in dairy cattle as a consequence of exposure to elevated ambient temperatures represents a significant challenge for those engaged in the dairy farming industry. This problem may be exacerbated by the possibility of increased heat stress due to climate change, which would reduce the availability of nutrients provided by dairy products even more than previously suggested by studies conducted by Hutchins et al. [21]. It is possible to achieve this objective by implementing strategies to reduce HS in dairy cattle. There are a number of strategies that can be employed in this regard, including nutritional, infrastructural and genetic strategies [37,38,41]. In view of the geographical distribution of major milk producers worldwide and the escalating heat stress conditions experienced by cattle, HS forecasting has become a key strategy to ensure sustained maintenance of production levels [19]. As posited by Solymosi et al. [52], it is important to monitor potential HS conditions in order to develop a forecasting system to assist in the mitigation of anticipated production losses. In terms of future research, estimation of dynamic models in which not only the THI and its temporal pattern are modelled, but also its effect on productive and reproductive variables would facilitate, from a practical point of view, the taking of better decisions.

In the Comarca Lagunera, dairy herds are predominantly large (3,000 or more cows) and highly technified. In this regard, Hutchins et al. [21] emphasise that smaller herds are more susceptible to HS-related mortalities, as large dairy farms possess adaptive capacity associated with investments in infrastructure, such as sprinkler systems and fans, and management practices, including calving planning and feeding strategies during periods of heat stress. However, even on large farms, there is a risk of substantial losses due to extreme stress conditions. Globally, there is an observed trend of increasing dairy farm size; therefore, it is recommended that this analysis be replicated in arid and semi-arid regions, as well as in regions where there is already evidence of increasing HS episodes.

### 5. Conclusions

It is reasonable to predict that the number of hours of heat stress experienced by dairy cows in the Comarca Lagunera will increase in the coming years and decades. This prediction is based on GLMENT, which shows an increase in hours and daily THImean (the best indicator) of 0.2 hours over a 10-year period, especially at levels of $72-76$ THI and $\geq 77$. It has been demonstrated that these levels have a considerable detrimental effect on health, welfare and productivity, particularly in cattle at high production levels.

The most appropriate model for THI at the cumulative hours level is Prophet, while at the climatic indicator level it is the average THI. However, it is important to assess cumulative hours of heat stress related to biological and productive parameters.

### CRediT authorship contribution statement

José Luis Herrera-González: Writing – review & editing, Writing – original draft, Investigation, Conceptualization. Martín Alfredo Legarreta-González: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. Francisco Gerardo Véliz-Deras: Writing – review & editing, Supervision, Funding acquisition, Formal analysis. Rafael Rodríguez-Venegas: Writing – original draft, Supervision, Investigation. Guadalupe Calderón-Leyva: Writing – original draft, Methodology. Pedro Antonio Robles-Trillo: Writing – original draft, Investigation, Data curation. Rafael Rodríguez-Martínez: Writing – review & editing, Writing – original draft, Supervision, Funding acquisition, Formal analysis, Conceptualization.

### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

### Data availability

The authors do not have permission to share data.

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# V. CONCLUSIONES

## Conclusión primer estudio

La utilización de modelos matemáticos para anticipar factores que afectan la producción de vacas lecheras es cada vez más común en la investigación científica. Esto demuestra la capacidad de la modelización de series de datos pasados para prever tendencias futuras y patrones de evolución en ganaderías de leche en climas cálidos. Otras investigaciones se han enfocado en cómo el clima influye en el ganado lechero, analizando la efectividad de modelos que clasifican el estrés por calor a través de métricas de matrices de confusión y comparándolos con métodos tradicionales fundamentados en índices de temperatura y humedad. Se obtuvo la mayor tasa de precisión, alcanzando un 86,8%, lo que evidencia la posibilidad de crear modelos precisos y prácticos para el monitoreo en tiempo real del estrés térmico. En el sector del ganado lechero se utilizaron técnicas de aprendizaje automático mediante un análisis detallado de diversos conjuntos de características para construir un modelo eficiente que permita predecir la temperatura corporal central de las vacas lecheras. Esta metodología mejoró considerablemente la capacidad de predicción al combinarla con características específicas del animal y lecturas térmicas infrarrojas, aumentando así su precisión. Estos resultados podrían ser aplicables en otras investigaciones dentro de nuestra área. Los resultados indican que existe la posibilidad de continuar la investigación en esta zona y en otros lugares con altas temperaturas. El objetivo es crear modelos matemáticos que puedan estimar el índice de temperatura y humedad con un alto nivel de certeza. Este conocimiento facilitaría la implementación de técnicas para reducir los efectos perjudiciales sobre la salud y la producción de los animales, como la programación de baños en momentos adecuados y el ajuste de alimentos a dietas con menor contenido calórico ante pronósticos de niveles altos de temperatura y humedad.

**Conclusión segundo estudio**

Es lógico suponer que, en el futuro próximo y a lo largo de los años, las horas de estrés térmico que experimenten las vacas lecheras en la región de Comarca Lagunera irán en aumento. Esta suposición se fundamenta en el GLMENT, que indica una elevación de 0. 2 horas en el promedio diario de ITH (el indicador más relevante) durante un lapso de diez años, especialmente en los rangos de 72 a 76 ITH y superiores a 77. Se ha evidenciado que estos parámetros tienen un impacto negativo significativo en la salud, el bienestar y la producción, en particular en el ganado que presenta altos niveles de producción.

El modelo más adecuado para calcular el ITH en términos de horas acumulativas es Prophet, mientras que, para los índices climatológicos, el ITH promedio es el más efectivo. Sin embargo, resulta crucial analizar las horas de estrés térmico acumuladas en relación con diversos parámetros biológicos y de producción.

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