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Hoolehua Plant Materials Center
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Site-Specific Observed Yield Data Collection for PIA-Prescribed Grazing Tool Forage Yield Model Testing: Kukuihaele, Waimea Plain, Kainaliu, Mana House, Kainalu, and Hoolehua

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Abstract

The Pacific Islands Area – Prescribed Grazing Tool (PIA-PGT) is used by conservation planners to help ranchers balance grazing-animal stocking rate with available forage production. A critical component of this tool is the forage model that predicts yield for specific species and locations. The objective of this study was to test the accuracy and precision of the forage model of the current PIA-PGT, four other forage models, and the average of the five models' yield predictions, referred to as the Ensemble model, against observed yield. Forage yield was observed for three grass species at five working pastures located on the islands of Hawaii and Molokai. Yield data was collected monthly over a two-year period and recorded as air-dry yield. The validation statistics percent bias, mean absolute error, and Nash-Sutcliffe Efficiency were calculated to assess model accuracy, precision and overall performance, respectively. The Ensemble model had the best overall performance at predicting forage yield and will be embedded into the PIA-PGT. The newly modified PIA-PGT, will provide better information for conservation planners to help ranchers balance grazing-animal stocking rate with available forage production, avoid overgrazing and soil degradation, and promote healthy grazing lands across the Pacific Islands Area.

Introduction

Stocking rate, the number of grazing-animals per acre, is one of the most important factors to consider when implementing the conservation practice Prescribed Grazing. Applying the appropriate stocking rate on a pasture greatly reduces the risk of overgrazing and the consequent degradation of pasture grass and soil (Briske et al., 2011). Selecting the appropriate stocking rate relies heavily on accurately estimating the available forage production of a pasture.

The current Pacific Islands Area-Prescribed Grazing Tool (PIA-PGT) provides conservation planners with estimated available forage production based on historical monthly air temperature and rainfall at a specific site (NRCS, 2024). However, the current tool uses one forage yield curve to calculate the available forage production for the 19 grass species that the Natural Resources Conservation Service (NRCS) recommends for the Pacific Islands Area. Consequently, the tool estimates available forage production of certain grass species better than others. The current model needs revision to improve forage yield predictions and available forage production estimates for all recommended species. Alternatively, there are four other forage yield models that are readily available that could also be incorporated into the tool: 1) The Pasture Groups from the NRCS soil survey; 2) the Range Type forage model; 3) the Hawaii Forage Production Estimator Tool, and 4) the EcoCrop model. Of these four models, three were created specifically for Hawaiian pastures.

The NRCS soil survey of the Hawaiian Islands has estimated forage yield values for land units known as Pasture Groups (SCS Staff, 1972; SCS Staff, 1973). Soil surveyors estimated forage yield based on consultation with local experts, published data, ranch records and clipping studies, then assigned the estimates to soil series (Fortiner et al., 2017). The soil series with similar forage yields were placed in groupings called Pasture Groups. In a similar manner, Joe May (2014) assigned forage yield estimates and monthly yield curves to Major Land Resource Areas, called range types. The range type was characterized by the environmental conditions and the plant species in the area. Both the Pasture Groups and Range Type yield estimates are based on the environmental conditions, soil and climatic conditions of areas where forage grows.

In contrast to the environment-based models, climate-based models were developed to predict forage yield solely from climatic conditions. Thorne (2011) estimated yield from monthly rainfall. The yield estimates were generated through linear regression of rainfall and forage yield data collected on three islands in Hawaii. Separate yield equations were developed for each island and an average equation for all other islands. This rainfall-based model was named the Hawaii Forage Production Estimator Tool (HFPET; Thorne and Hewlett, 2013). The EcoCrop model, developed by the United Nations' Food and Agriculture Organization, produced a crop suitability index value that ranges from 0 to 1 based on air temperature and rainfall described by a linear-segmented curve (FAO, 2022). The suitability index was shown to have a weak, but positive, relationship to sorghum grain yield due to complexities of reproductive development (Ramirez-Villegas et al., 2013). Forage grasses, unlike grain sorghum, may be harvested during vegetative growth when yield has a strong relation to simple environmental factors such as temperature (da Silva et al., 2012). Since forage yield is produced during the vegetative phase and has a strong relation to air temperature, the EcoCrop model has the potential to predict forage yield of grass species better than a crop species that produces grain. The advantage of climate-based models is they can be applied to any location where climate data is available.

The environment- and climate-based models estimate forage yield differently and that difference can be useful. Yield estimates from models may differ because the components and processes that are simulated differ among the models. Taking the mean of yields from a group of models that differ in these ways typically result in better accuracy and precision than any single model (Liu et al., 2019; Watling et al., 2015). The group of models in this study is referred to as the Ensemble model.

The objective of this study was to improve the forage yield prediction capability of the PIA-PGT by evaluating the performance of the current PIA-PGT, Pasture Group, Range-Type, HFPET, EcoCrop, and Ensemble models against observed yield of three grass species at six locations in Hawaii. The three grass species were kikuyu (*Pennisetum clandestinum*), guineagrass (*Urochloa maxima*) and buffelgrass (*Pennisetum ciliare*). Kikuyu is found at elevations up to 6,000 feet while guineagrass occupies lower elevations (Fukumoto and Lee, 2003; Whitney et al., 1939). Buffelgrass was introduced to Hawaii in 1935 and grows in the dry lowlands (Hosaka and Carlson, 1957). The model that can better predict forage yield for these three species and environments across Hawaii will be embedded into the PIA-PGT.

Materials and Methods

Six sites across two islands within the State of Hawaii were selected for forage yield data collection under natural conditions to test the six forage yield models (Table 1). Four sites were located on the Island of Hawaii and two sites were on the Island of Molokai. All sites were working pastures except the site at the Hoolehua Plant Materials Center (HIPMC) on Molokai. The sites represent a broad range of temperatures, rainfall and soils (Table 1). Well-established stands of pure guineagrass, kikuyu or buffelgrass were found at these locations. Before yield data collection started, a composite soil sample from each site was collected to a depth of six inches and analyzed for pH and organic matter content. At each site, five plots were established randomly within the pasture. A 4ft x 4ft area at each plot location was fenced to prevent animal browsing. Forage samples were collected from each plot at the beginning of every month over a two-year period. A 2.4 feet^2 hoop was placed within the fenced plot and all forage within the hoop was cut to the recommended stubble height. The recommended stubble heights for guineagrass, kikuyu and buffelgrass are 8, 4, and 3 inches, respectively (NRCS, 2018). Forage samples were air-dried to constant weight and recorded. Daily air temperature and rainfall data were obtained from the Soil Climate Analysis Network (SCAN; Schaefer et al., 2007) or on-site weather stations (model 1000 series, Spectrum Technologies, Aurora, IL). The weather data were summarized into monthly values and used to run the climate-based forage yield models. In August 2021, a large brushfire swept through the Waimea Plain area preventing data collection. Data collection was extended two months to capture a two-year period of monthly yield data.

Table 1. Environmental description of six sites in Hawaii where forage yield data of three grass species were collected under natural conditions.

Site	Species	Annual Temp, F	Annual Rain, inches	Soil Great Group	Organic Matter, %
Kukuihaele	guinea	72	80	Haplustands	11
Kainaliu	guinea	68	55	Hydrudands	8 – 50
Kainalu	guinea	72	40	Palehumults	5
HIPMC	guinea, buffel	74	21	Eutrotorrox	3
Waimea Plain	kikuyu	63	40	Haplustands	10
Mana House	kikuyu	61	24	Haplustands	11

The current PIA-PGT required monthly rainfall, and annual forage yield and pasture area to estimate monthly forage production. Rainfall was retrieved from the SCAN database or automatic weather logger. Annual forage yield was set to the average range production in a normal year for the Pasture Group at the site (SCS Staff, 1972; SCS Staff, 1973). Additionally, the user is required to respond to two climate related questions: 1) Is water a limiting factor, and 2) Does temperature suppress growth? If yes, estimate% of temperature suppression. Question 1 was set to "YES" and Question 2 was set to "NO".

The Pasture Group was determined by identifying the soil series found at the forage yield data collection site through Web Soil Survey (Soil Survey Staff, 2019). The Pasture Group provided the annual forage yield during normal years and the distribution of the yield within a year (SCS Staff, 1972; SCS Staff, 1973).

Range Type was determined by soil series at the site (May, 2014). The Range Type was associated with an annual yield for below-normal, normal and above-normal years. For model testing, normal year yield was used. The Range Type also provided a yield curve that defined the percentage of yield for each month within a year.

The HFPET required monthly rainfall and the Hawaiian island where the site was located (Thorne and Hewlett, 2013). For the islands of Hawaii and Molokai, forage yield was set to 96 and 150 lbs. acre^{-1} for every inch of rain per month, respectively.

EcoCrop required the species-specific parameters that described suitability relative to temperature and rainfall, monthly rainfall and temperature, and potential annual forage yield to estimate monthly yield. Species-specific parameters were obtained from the EcoCrop database and defined the linear segmented curve (FAO, 2022). Potential annual forage yield for guineagrass, kikuyu and buffelgrass were obtained from the Feedipedia: Animal feed resources information system (INRAE CIRAD AFZ and FAO, 2022). The potential annual forage yield was evenly distributed to each month and multiplied by the suitability index derived from a site's monthly temperature and rainfall to obtain the monthly forage yield (Ramirez-Villegas et al., 2013).

Ensemble yield prediction was calculated as the mean average of yields from the PIA-PGT, Pasture Group, Range Type, HFPET, and EcoCrop (Liu et al., 2019; Watling et al., 2015). Model performance was evaluated by comparing predicted and observed forage yields.

Accuracy of the predicted yield was measured as Percent Bias (Moriasi et al., 2007). A positive percent bias indicated that the model generally under-predicted yields while a negative bias indicated over-predicting yields. A percent bias of 0.0 meant predicted yield perfectly matched observed.

$$Percent\ Bias = \frac{\sum_{i=1}^{n}(Yobserved_i - Ypredicted_i) \times 100}{\sum_{i=1}^{n} Yobserved_i}$$

$Yobserved_i$ = Observed yield for observation i
$Ypredicted_i$ = Predicted yield for prediction i
n = number of observations, i.e., sites, months and species

Precision of the predicted yield was measured as Mean Absolute Error (MAE; Moriasi et al., 2007). MAE ranges from 0 to ∞ where lower values indicated better precision.

$$MAE = \frac{\sum_{i=1}^{n}|Yobserved_i - Ypredicted_i|}{n}$$

$Yobserved_i$ = Observed yield for observation i
$Ypredicted_i$ = Predicted yield for prediction i
n = number of observations, i.e., sites, months and species

The Nash-Sutcliffe Efficiency (NSE) is an overall statistic that measured "noise" to "information" ratio. NSE ranges from -∞ to 1.0 where a value of 1.0 indicated predicted yield perfectly matched observed. Values between 0.0 and 1.0 generally indicated satisfactory model performance (Moriasi et al., 2007).

$$NSE = \frac{\sum_{i=1}^{n}(Yobserved_i - Ypredicted_i)^2}{\sum_{i=1}^{n}(Yobserved_i - Ymean)^2}$$

$Yobserved_i$ = Observed yield for observation i
$Ypredicted_i$ = Predicted yield for prediction i
n = number of observations, i.e., sites, months and species
Ymean = mean of observed yields

Results

The measured soil chemical properties and weather parameters showed large variation in environmental conditions that led to large variation in forage yield. Soil pH ranged from 5.5 to 7.2 while soil organic matter showed a particularly large range from 2.5 to 19.3% (Table 2). Annual air temperature ranged from 60 to 76 °F and annual rainfall was 11 to 66 inches (Table 3). Annual forage yield had a correspondingly large range from 1073 to 30317 air-dry lbs. acre^{-1}. Monthly forage yield and weather data may be found in the Appendix. This wide variation of environmental conditions and forage yields provided a robust test for the forage yield models.

Table 2. Soil chemical properties (0 – 6 inch depth) analyzed at six locations in Hawaii where monthly forage yield was measured over a two-year period. The chemical properties at Mana House were estimated from Web Soil Survey (WSS).

Location	pH	Organic matter, %
Kukuihaele	5.5	6.1
Kainaliu	6.0	16.5
Kainalu	6.1	3.9
HIPMC	6.6	2.5
Waimea Plain	6.7	19.3
Mana House	7.2 (WSS)	10.0 (WSS)

Table 3. Annual weather and forage yield data collected at six locations in Hawaii.

	Air Temperature, °F		Rainfall, inches		Forage Yield, air-dry lbs. acre^{-1}	
Location	Year 1	Year 2	Year 1	Year 2	Year 1	Year 2
Kukuihaele	71	70	54	59	6328	4502
Kainaliu	70	71	66	49	30317	26474
Kainalu	76	76	41	30	9467	6920
HIPMC	75	75	15	11	2142	1073
Waimea Plain†	63	62	18	16	8496	5936
Mana House	60	60	15	20	1304	2158

† Missing yield data in August 2021 due to large brushfire were replaced by extending yield data collection for two months that ended June 2022.

The Ensemble model had better accuracy and precision to predict forage yield than the other models. All models had a positive percent bias that meant they generally under-predicted forage yield (Table 4). EcoCrop was the most accurate model with a percent bias of 10% (Table 4). Ensemble and Range Type were the second most accurate at 34%. Ensemble forage predictions had greater precision than the other models as measured by MAE at 426 lbs. acre^{-1} followed by PIA-PGT and HFPET (Table 4). The general performance statistic NSE was greatest for Ensemble at 0.23 with HFPET and PIA-PGT behind (Table 4). Overall, the Ensemble was the best model to predict forage yield with its superior precision and general performance over the other models, and better accuracy with the exception of EcoCrop.

The under-prediction of forage yield was most pronounced at sites with high soil organic matter content. All six models tended to under-predict forage yield as seen by their positive percent bias (Table 4). Visual inspection of the plot predicted v. observed forage yield showed the under-prediction is especially noticeable at sites Kainaliu and Waimea Plain (Figure 1). These two sites have high soil organic matter content at 16.5 and 19.3% (Table 2). None of the six models have a soil organic matter component that would make the forage yield responsive to this factor and may account for their lapse in prediction capability.

The HFPET and EcoCrop models displayed a specific type of under-prediction that may be due to the lack of a soil water component. In the charts that compare predicted and observed monthly forage yield, HFPET and EcoCrop showed instances where the model predicted yield to be 0, but a significant yield was observed (Figure 1). In many of these instances, rainfall during the month was either 0, for HFPET, or low, for EcoCrop, so the models predicted no yield. The observed yield was presumably supported by soil water which was not accounted for in either model and may have caused the under-predictions.

The wide-ranging environments and grass species in this study were able to discriminate between the better performing models from poorer performers. The Ensemble model had best overall performance. The test also showed the shortcomings of the poorer performing models such as lack of soil organic matter and soil water components and identified an approach to improve the climate-based models.

Table 4. Percent bias (% Bias), mean absolute error (MAE) and Nash-Sutcliffe efficiency (NSE) statistics of six forage model yield predictions for three grass species and six sites in Hawaii.

	PIA-PGT	HFPET	EcoCrop	Pasture Group	Range Type	Ensemble
% Bias	41	46	10	41	34	34
MAE	477	485	643	513	534	426
NSE	0.03	0.15	-0.370	-0.01	-0.06	0.23

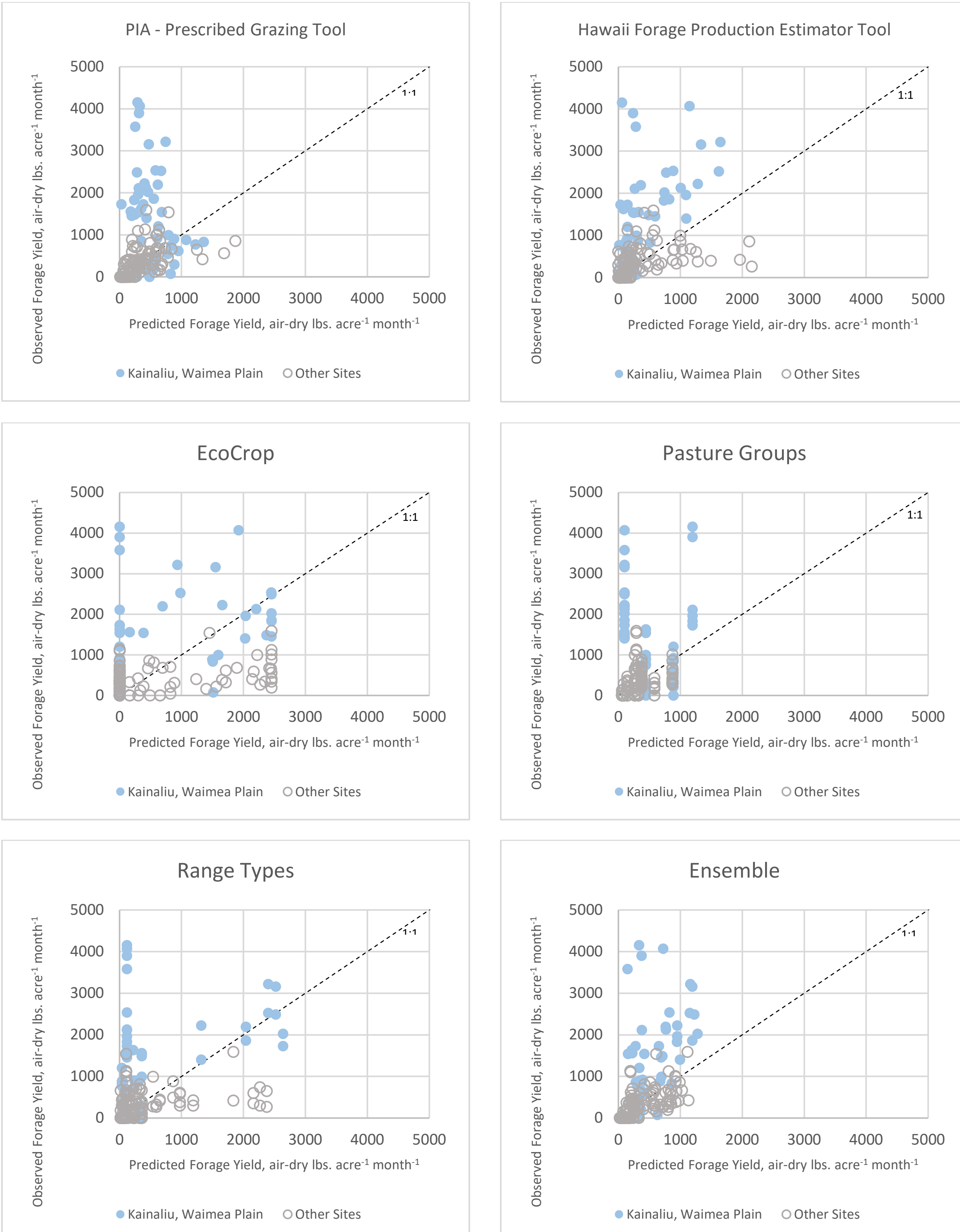

Figure 1. Comparison of predicted and observed monthly forage yield for six models. All models under-predicted monthly forage yield, primarily due to the sites Kainaliu and Waimea Plain.

Discussion

Multi-model ensembles are commonly used in weather and climate forecasting because they have better predictive capabilities than most or all individual models within the ensemble (Hagedorn, 2005). The better performance results from weather forecasting models simulating different processes, i.e., the models are independent and display improved prediction skill under certain circumstances. The error cancellation among the various model predictions improves the overall prediction of the ensemble (Hagedorn, 2005). In other words, the skillful model, under a certain circumstance, pulls the predictions of the less skilled model toward the observed value. Under a different circumstance, the previously less skilled model may become the better skilled model and pull predictions of the less skilled model toward the observed. The independence and skill of the forage models are apparent in the present study. The independence of the models can be seen in the pattern of the predicted vs. observed yield (Figure 1). The patterns result from the model error and show little commonality indicating independence. The skill of each model can be seen in the data points that fall on or near the 1:1 line under certain circumstances (Figure 1). Since all five forage models show independence and skill, it follows that the Ensemble would have better accuracy and precision in predicting forage yield than its constituent models.

While the Ensemble model performed better than any single model including the PIA-PGT, the Ensemble still under-predicted forage yield. One approach to better the Ensemble is to improve the constituent models. For example, the climate models, EcoCrop and HFPET, predicted no yield when there was significant yield observed; indicated by data points falling on the lower portion of the x-axis (Figure 1). Many of these mis-predictions happened when there was little or no rain during the month, but forage yield was observed. It is well known that stored soil water is able to support forage growth for several months (Budisantoso et al., 2008; Cullen and Johnson, 2012; Dahl, 1963). Presumably, the forage grass in this study was able to produce a yield from stored soil water without rain. Including a soil-water component to the climate-oriented model would account for yield produced from soil-water without rain and improve the overall prediction. Another approach to improve the climate models is to include a soil organic matter component. All forage models under-predicted yield at sites where soil organic matter was high, in particular Kainaliu and Waimea Plain (Figure 1). Other researchers have found a strong positive correlation between soil organic matter and forage yield (Miranda et al., 2021). So, adding a soil organic matter component that modulates forage yield would help capture the wide range of forage yield observed in pastures across Hawaii.

Another way to improve the Ensemble model is to modify its structure rather than the constituent models. Wallach et al. (2016) proposed several changes to improve crop multi-model ensembles including:

1. Select models to be included in the multi-model ensemble based on pre-determined criteria such as model performance. Eliminating the poorer performing models could improve the ensemble.
2. Assign weights to single model outputs, where heavier weight is given to better performing models, so the overall result is a weighted average. Assignment of weights could be accomplished with methods such as Bayesian model averaging.
3. Create a multi-model ensemble by changing the parameters of a single model, known as perturbed physics ensemble. Each set of changed parameters is considered a separate model.

Any of these modifications separately or in combination could improve the accuracy and precision of the Ensemble model. A better Ensemble model would better help balance forage production and animal demand that would ultimately avoid overgrazing and soil degradation.

Conclusions

Out of six forage yield models tested, the Ensemble model performed the best overall. The Ensemble yield predictions had higher accuracy and precision than many of the other models in a test that compared model outputs against observed yield. This is consistent with weather and climate forecast models that are commonly ensembles, rather than single models, because of the ensemble’s superior performance.

Opportunities to improve the ensemble model were identified in this study. The inclusion of soil organic matter and soil water components into the climate models could reduce obvious mis-predictions of forage yield at sites where organic matter content is high or when little to no rain falls during a month. Modifying the constituent climate models would also improve the yield predictions and overall Ensemble performance.

As a result of this study, the Ensemble model will be embedded in the PIA-PGT. With the newly modified PIA-PGT, conservation planners and ranchers will be able to better assess forage production at a specific site to better advise on the stocking rate that may reduce overgrazing, prevent soil degradation and promote healthy ecosystems across the Pacific islands.

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Appendix. Forage yield and climate for six sites on the Islands of Hawaii and Molokai, Hawaii, 2020 to 2023.

1. Kukuihaele, Island of Hawaii, guineagrass, initial cut date 5/5/2020			
Harvest date	Air temp, °F	Rain, inches	Forage Yield, air-dry lbs. $acre^{-1}$
6/2/2020	70.2	4.17	568
6/30/2020	71.4	0.97	563
8/4/2020	72.0	3.16	1611
9/1/2020	72.6	1.93	722
10/6/2020	73.3	2.94	1434
11/4/2020	73.3	1.65	882
12/2/2020	71.2	9.97	604
1/5/2021	70.2	3.99	582
2/10/2021	67.8	6.95	440
3/3/2021	68.4	0.65	320
4/6/2021	67.4	7.77	352
5/4/2021	68.0	2.37	399
6/2/2021	70.6	1.77	413
7/2/2021	71.7	1.34	400
8/4/2021	72.2	8.57	448
9/1//2021	72.2	5.85	681
10/4/2021	72.2	3.21	808
11/1/2021	70.3	6.25	528
12/1/2021	70.0	1.56	440
1/3/2022	68.5	8.36	296
2/1/2022	67.9	2.29	184
3/1/2022	67.8	4.63	128
3/31/2022	69.0	4.15	408
5/5/2022	69.0	14.37	432
5/31/2022	70.4	1.56	400
6/29/2022	71.1	4.13	432
8/1/2022	72.4	4.69	408

9/1/2022	73.2	0.30	328
10/3/2022	73.6	6.50	152
11/1/2022	73.0	4.06	936
12/1/2022	70.6	7.26	416
1/4/2023	69.3	5.10	328
2/1/2023	68.2	7.42	312
3/6/2023	67.3	14.81	232
4/4/2023	70.8	0.47	464
5/3/2023	70.0	1.01	200
6/1/2023	70.6	2.76	270
6/30/2023	72.2	0.65	200
8/7/2023	72.8	6.92	656
9/1/2023	73.3	2.80	768
10/5/2023	73.4	1.53	520
11/1/2023	72.2	0.44	336
12/7/2023	71.3	6.64	400
1/4/2024	68.3	4.17	368
2/5/2024	68.9	9.02	360
3/5/2024	66.8	5.76	280

2. Kainaliu, Island of Hawaii, guineagrass, initial cut date 5/7/2020			
Harvest date	Air temp, °F	Rain, inches	Forage Yield, air-dry lbs. acre^{-1}
6/4/2020	70.3	5.73	3647
7/1/2020	71.4	0.97	5342
8/5/2020	72.0	3.17	6311
9/2/2020	72.4	1.90	3576
10/8/2020	72.7	7.68	4065
11/3/2020	72.8	1.60	3898
12/1/2020	71.6	7.30	1961
1/5/2021	69.9	1.77	2109
2/2/2021	68.2	3.96	1452
3/4/2021	67.8	3.26	1482
4/8/2021	68.0	8.55	2223
5/6/2021	68.0	4.98	2020
6/4/2021	70.1	8.92	3155
7/8/2021	70.8	10.82	2521
8/3/2021	72.1	5.48	1856
9/3/2021	72.1	6.73	2123
10/5/2021	71.9	5.92	2532
11/12/2021	71.3	0.41	4152
12/3/2021	71.1	0.25	1725
1/7/2022	69.5	4.91	1828
2/3/2022	68.4	1.71	1536
3/16/2022	69.2	2.18	1556
4/13/2022	69.5	7.32	1400
5/13/2022	69.3	1.01	1727
6/8/2022	70.5	5.16	2488
7/22/2022	71.7	10.98	3216
8/18/2022	72.3	2.44	2190
9/22/2022	72.7	9.01	3076
10/28/2022	72.8	9.74	3211

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-	-	-	-
-	-	-	-
1/27/2023	68.9	0.02	1472
4/12/2023	69.0	7.06	2256
5/4/2023	69.6	12.06	992
6/7/2023	70.0	13.80	2632
6/28/2023	71.0	4.00	1560
8/5/2023	71.9	6.56	3909
9/6/2023	72.2	3.87	3325
10/8/2023	72.5	3.01	2620
11/2/2023	72.1	3.26	2123
12/7/2023	71.2	9.48	3265

3. Kainalu, Island of Molokai, guineagrass, initial cut date 7/2/2020			
Harvest date	Air temp, °F	Rain, inches	Forage Yield, air-dry lbs. $acre^{-1}$
8/3/2020	78.1	3.79	1259
9/2/2020	79.1	0.99	1022
10/2/2020	79.5	1.50	236
11/2/2020	79.3	1.94	1014
12/2/2020	77.2	3.38	538
1/4/2021	76.2	3.70	958
2/2/2021	74.2	6.03	610
3/2/2021	73.6	2.44	636
4/2/2021	73.1	13.10	88
5/3/2021	73.4	1.38	609
6/2/2021	75.6	1.14	674
7/1/2021	76.9	1.20	555
8/3/2021	77.3	1.50	374
9/3/2021	77.7	3.90	955
10/4/2021	77.1	2.81	1447
11/2/2021	76.7	1.29	536
12/2/2021	76.6	1.72	268
1/4/2022	73.8	14.10	734
2/2/2022	72.5	0.20	487
3/2/2022	72.8	0.60	275
4/2/2022	75.8	0.00	199
5/2/2022	75.2	1.38	226
6/3/2022	76.3	0.93	259
7/1/2022	77.1	1.22	330

4. Hoolehua Plant Materials Center, Island of Molokai, guineagrass, initial cut date 9/8/2020			
Harvest date	Air temp, °F	Rain, inches	Forage Yield, air-dry lbs. $acre^{-1}$
10/2/2020	78.6	0.31	0
11/2/2020	77.9	0.78	0
12/2/2020	76.6	0.52	0
1/4/2021	74.7	1.31	16
2/2/2021	73.2	1.84	344
3/2/2021	72.2	1.59	392
4/2/2021	71.8	6.68	992
5/3/2021	72.2	0.80	280
6/3/2021	75.2	0.06	152
7/2/2021	76.6	0.05	0
8/3/2021	78.1	0.14	0
9/3/2021	77.6	0.90	0
10/4/2021	77.3	0.10	0
11/2/2021	76.1	0.07	0
12/2/2021	75.2	0.33	0
1/4/2022	72.4	5.93	656
2/2/2022	71.2	0.01	616
3/2/2022	71.6	0.72	96
4/2/2022	73.4	1.16	184
5/2/2022	74.4	0.02	0
6/3/2022	75.3	0.68	0
7/1/2022	76.8	0.03	0
8/2/2022	77.5	0.28	0
9/9/2022	78.7	1.35	0

5. Waimea Plain, Island of Hawaii, kikuyu, initial cut date 5/6/2020			
Harvest date	Air temp, °F	Rain, inches	Forage Yield, air-dry lbs. acre^{-1}
6/3/2020	62.9	1.52	920
6/30/2020	63.5	0.51	296
8/4/2020	64.6	3.07	992
9/1/2020	65.1	0.70	744
10/6/2020	64.9	0.88	1627
11/4/2020	65.4	0.30	0
12/2/2020	63.1	1.29	856
1/5/2021	61.8	1.54	1200
2/12/2021	59.6	3.34	880
3/2/2021	60.2	0.67	293
4/6/2021	59.8	3.06	72
5/4/2021	59.6	1.25	616
6/2/2021	62.8	0.65	200
7/2/2021	63.0	0.63	0
8/4/2021	64.2	2.47	-
9/1/2021	64.1	1.53	2440
10/4/2021	63.8	0.68	0
11/1/2021	62.4	1.85	472
12/1/2021	61.9	0.79	344
1/3/2022	60.5	5.40	832
2/2/2022	59.7	0.18	768
3/2/2022	59.4	0.48	0
4/6/2022	60.9	1.63	192
5/4/2022	61.0	1.91	544
6/2/2022	61.9	1.16	160
6/30/2022	62.4	1.27	456
8/3/2022	63.9	2.31	832
8/30/2022	62.3	0.72	448
10/4/2022	65.0	0.30	32

11/3/2022	65.4	1.29	304
12/2/2022	62.3	2.12	320
1/5/2023	61.1	5.03	832
2/1/2023	60.2	0.68	608
3/3/2023	59.9	7.07	296
4/7/2023	62.5	1.61	832
5/1/2023	61.7	1.03	424
6/2/2023	61.8	1.20	984
6/29/2023	63.0	0.25	104
8/3/2023	64.3	2.74	616
8/31/2023	64.1	0.52	672
10/3/2023	64.8	0.96	320
11/2/2023	64.0	0.59	-
12/8/2023	62.9	3.02	792
1/12/2024	60.1	2.93	1181
2/5/2024	60.6	2.73	632
3/16/2024	58.3	2.90	776

6. Mana House, Island of Hawaii, kikuyu, initial cut date 1/3/2022			
Harvest date	Air temp, °F	Rain, inches	Forage Yield, air-dry lbs. $acre^{-1}$
2/2/2022	56.4	0.85	432
3/2/2022	56.0	0.64	0
4/1/2022	58.3	0.47	0
5/4/2022	58.6	1.04	0
6/1/2022	59.4	1.14	0
6/30/2022	59.9	0.90	0
8/2/2022	61.5	0.61	104
8/30/2022	62.5	1.26	0
10/4/2022	62.3	0.59	88
11/3/2022	62.6	2.37	328
12/2/2022	59.7	1.28	192
1/5/2023	58.4	4.10	160
2/1/2023	57.3	1.12	0
3/3/2023	57.5	6.73	304
4/7/2023	59.0	2.12	464
5/1/2023	58.6	1.46	96
6/2/2023	59.1	1.07	176
6/29/2023	60.1	0.50	0
8/3/2023	61.2	1.16	224
8/31/2023	62.2	0.31	368
10/3/2023	62.3	0.38	0
11/3/2023	61.9	0.35	0
12/8/2023	60.4	3.01	216
1/5/2024	57.4	1.64	310
2/5/2024	58.1	1.70	240
3/16/2024	55.5	1.73	440

7. Hoolehua Plant Materials Center, Island of Molokai, buffelgrass, initial cut date 8/3/2020			
Harvest date	Air temp, °F	Rain, inches	Forage Yield, air-dry lbs. $acre^{-1}$
9/3/2020	79.0	0.67	0
10/2/2020	78.9	0.02	0
11/2/2020	77.4	0.50	0
12/2/2020	76.7	0.26	0
1/4/2021	74.4	1.36	40
2/2/2021	73.1	1.96	704
3/2/2021	72.3	1.61	208
4/2/2021	71.9	6.88	664
5/3/2021	72.4	0.71	120
6/3/2021	75.3	0.14	56
7/2/2021	76.6	0.05	0
8/3/2021	78.1	0.14	0
9/3/2021	77.6	0.90	0
10/4/2021	77.4	0.15	0
11/2/2021	76	0.11	0
12/2/2021	74.8	0.20	0
1/4/2022	72.5	6.70	856
2/2/2022	70.5	0.20	160
3/2/2022	71.4	0.50	0
4/2/2022	73.5	1.10	0
5/2/2022	74.6	0.00	0
6/2/2022	75.4	1.10	0
7/2/2022	76.8	0.10	0
8/2/2022	77.5	0.28	0