Exploring Shot Difficulty on the PGA Tour Using Generalized Additive Modeling and Hierarchical Effects

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- Around 2010, researchers started getting interested in using shot difficulty to infer player strength.
- The most famous example of this is Broadie 2012 who developed the Strokes Gained metric.

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- Metrics that consider stroke level data use naive methods to evaluate shot probability (primarily one or two variable regressions without good solutions for non-linearity).
- Sparse features are a good candidate for Hierarchical Models and non-linear data is often best fit using Generalized Additive Modeling.

Data

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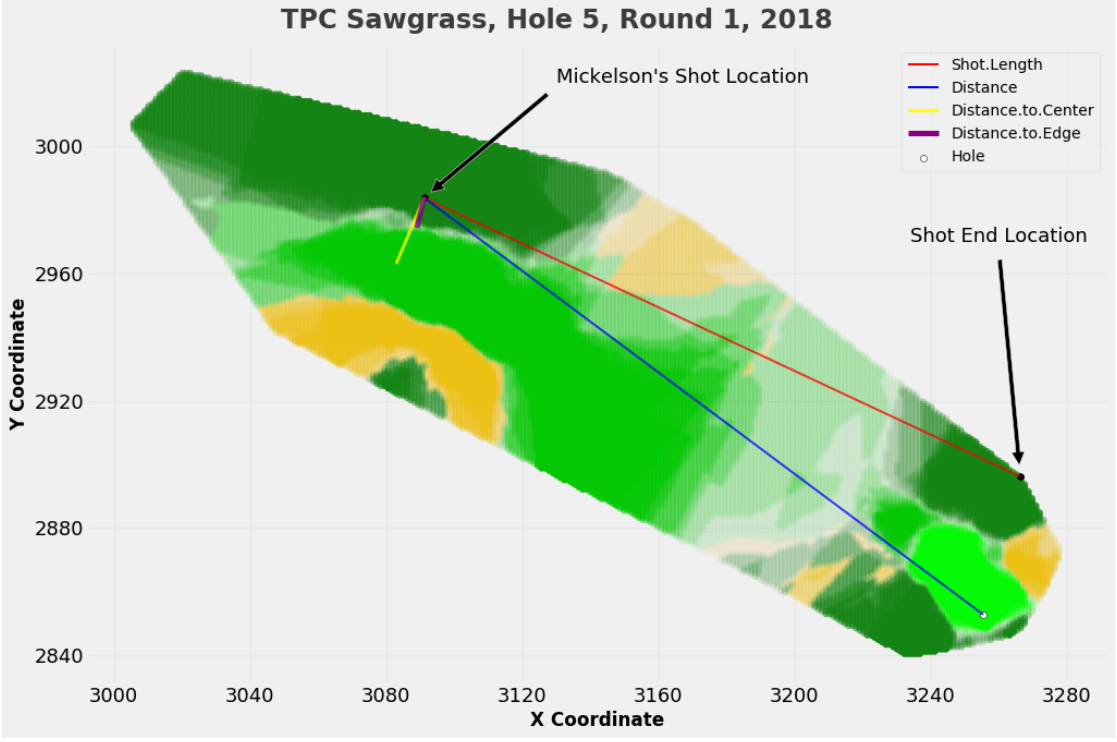
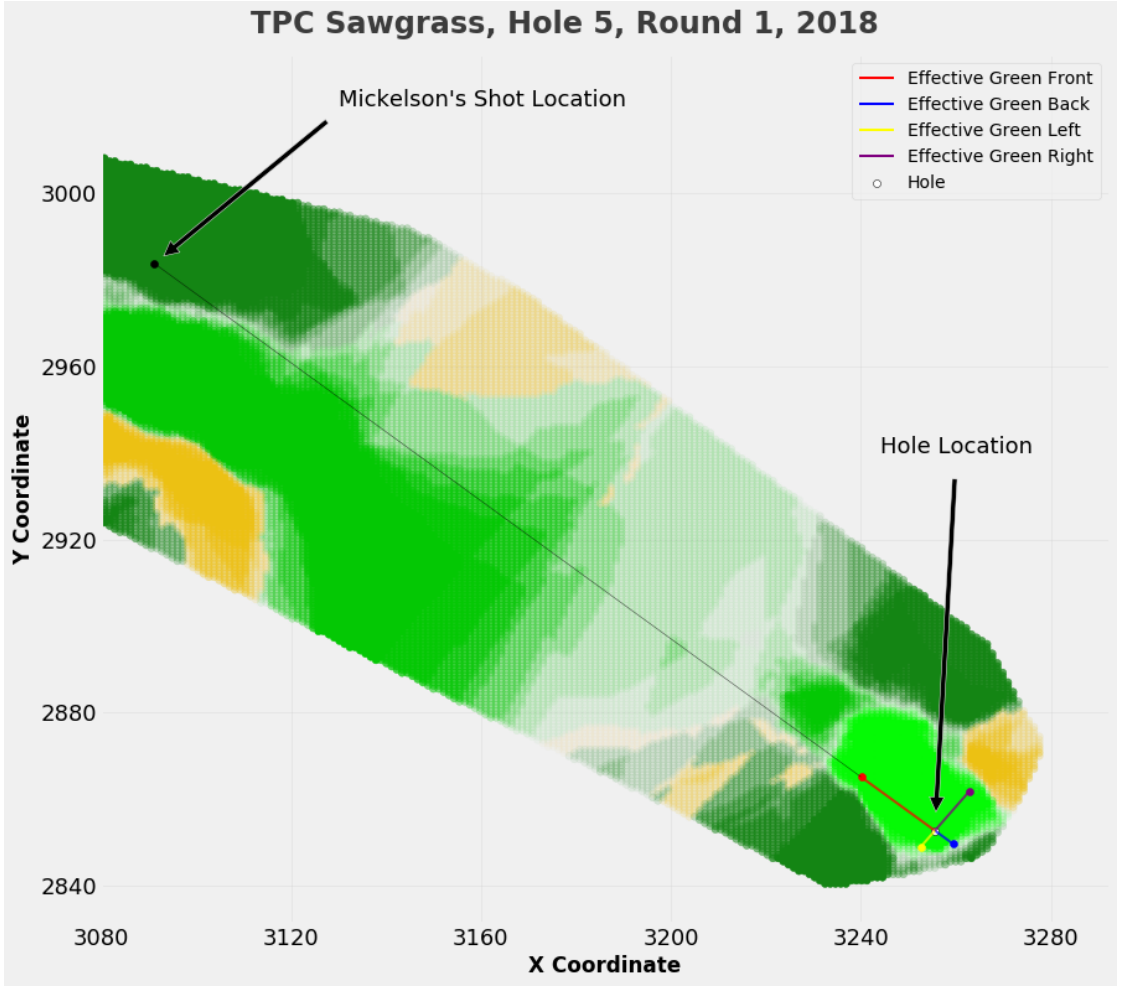


Effective Green

Effective green is the measure of how much green the golfer has to work with on a given shot.



Course Visualizations

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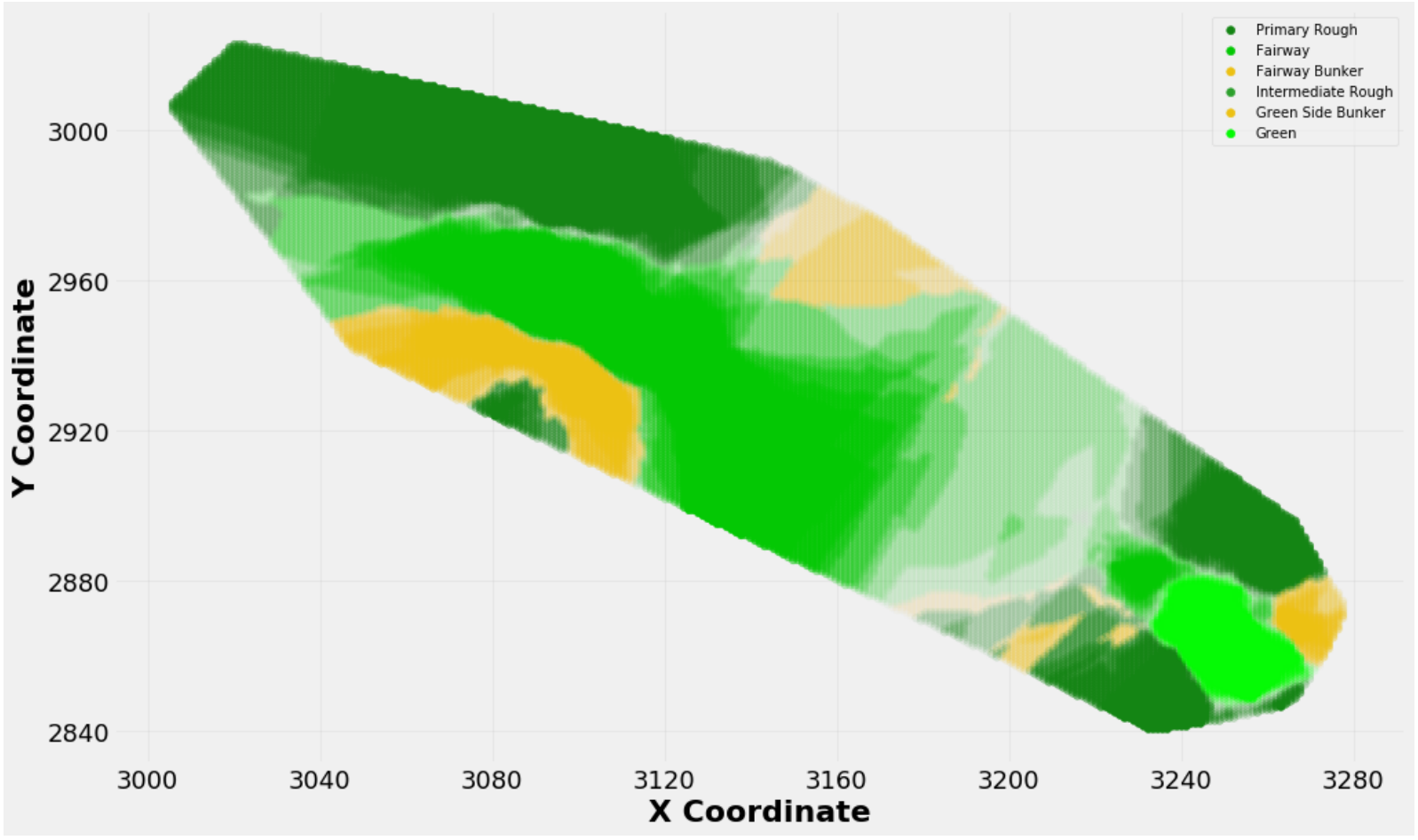
- The difficult feature to impute is location. To do this I fit a K Nearest Neighbors model and assigned opacity based on confidence.

Course Viz Example



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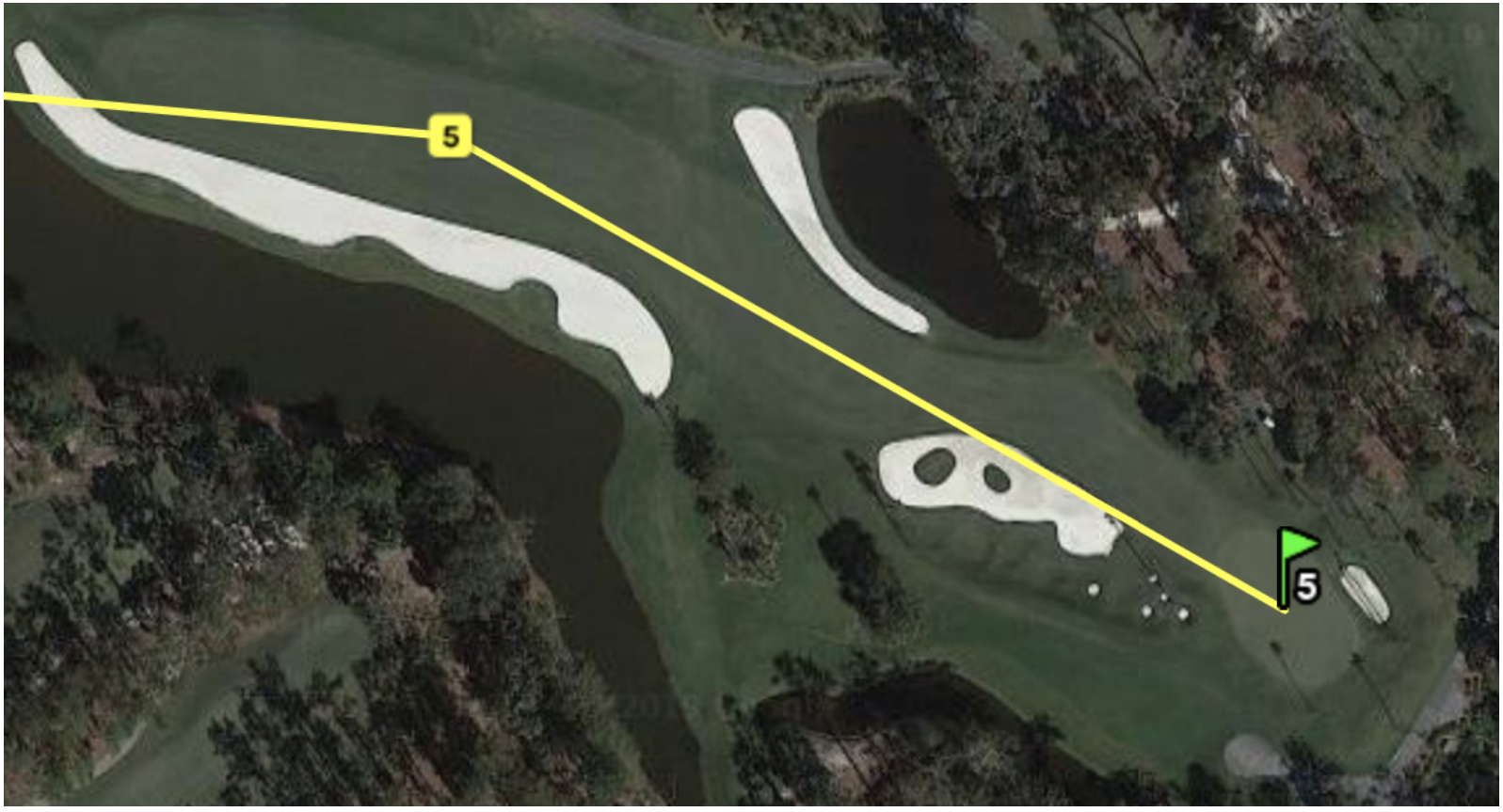

Exploratory Data Analysis

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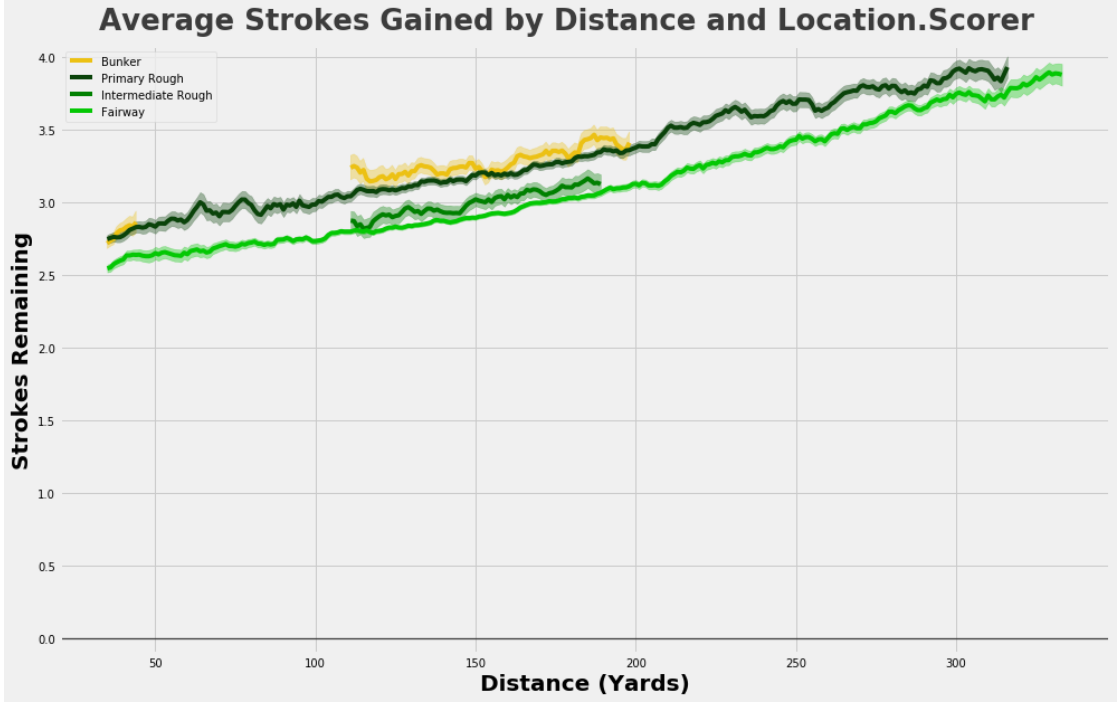

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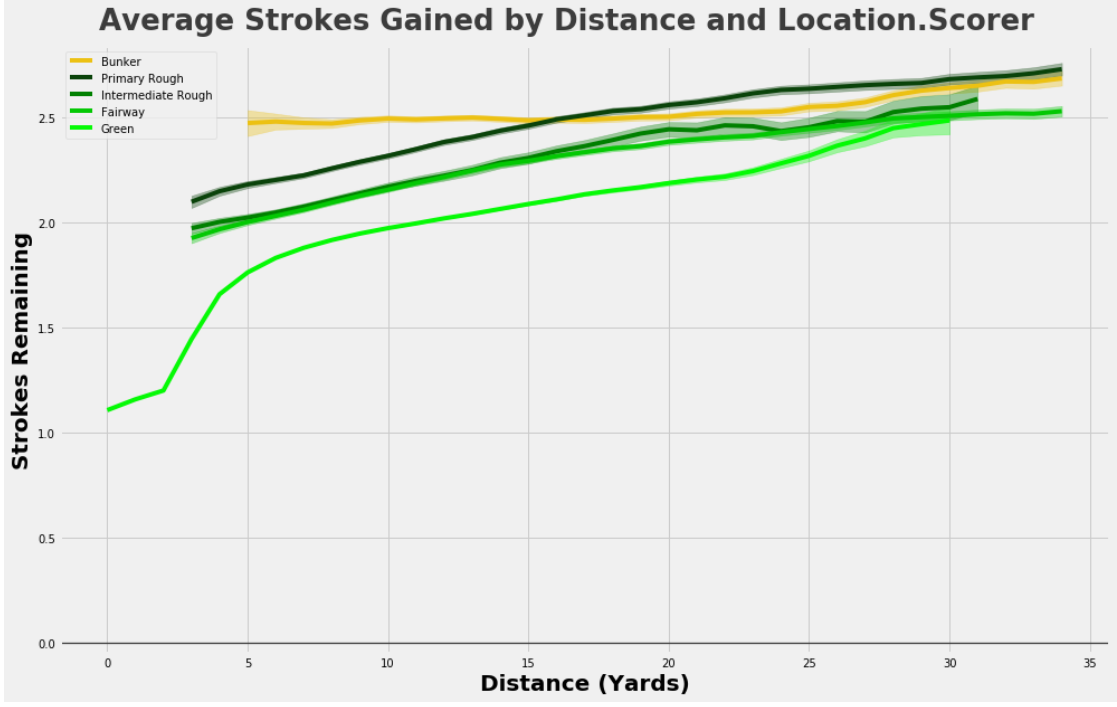

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$$\begin{aligned} &\texttt{S.R} \sim \texttt{s(Dist)} + \texttt{Loc.S} + \texttt{s(Dist, by = Loc.S)} \\ &+ (1|\texttt{Course/Hole/Round}) + (1|\texttt{Player/Loc.S}) + \texttt{s(Time, k = k)} \\ &\quad + \texttt{s(Dist, by = Loc.S)} + \texttt{ti(Time, Dist)} \quad (\texttt{GAM.Time.Dist}) \end{aligned}$$

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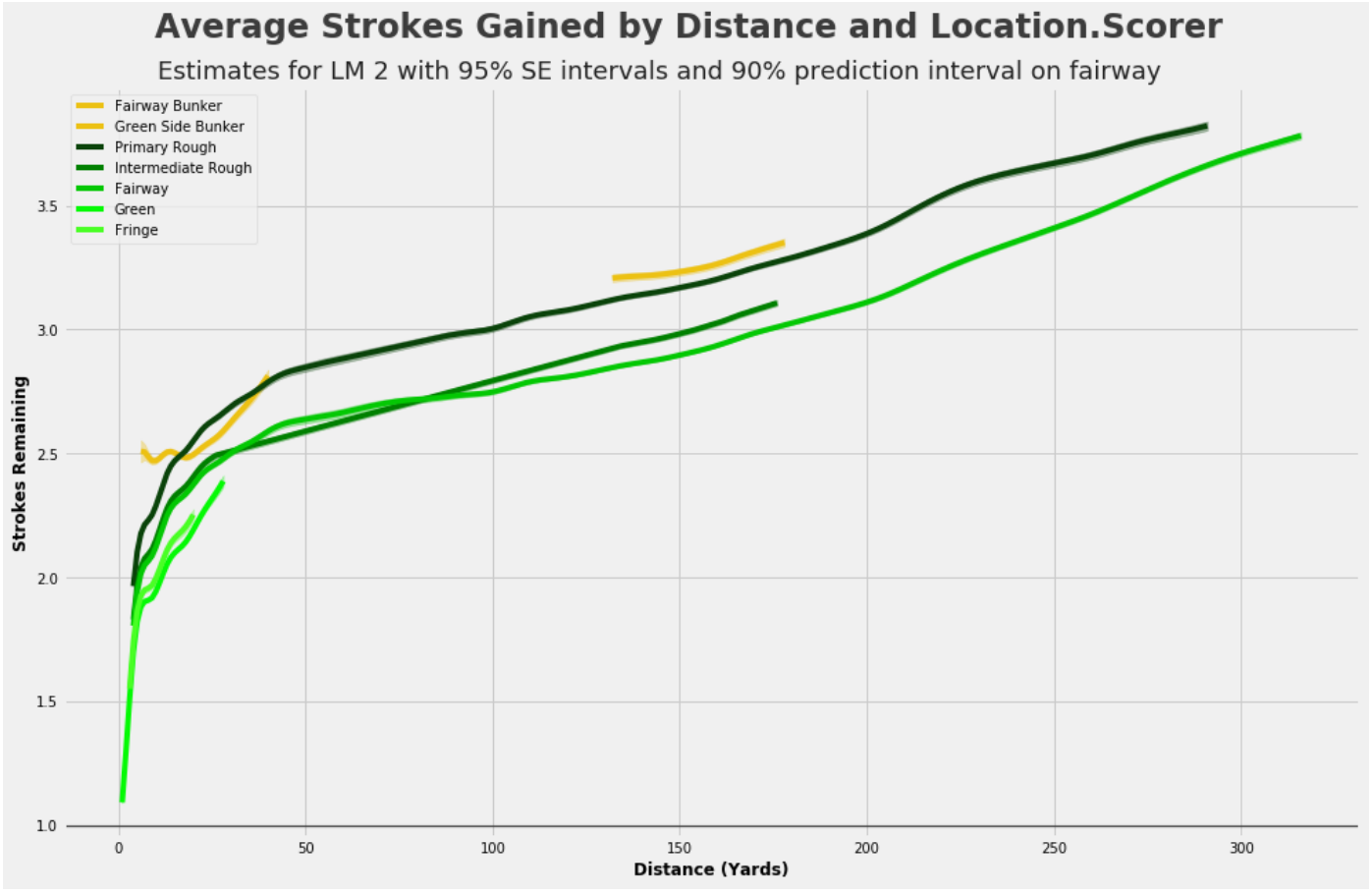
- Can also look at player, course and hole rankings for 2018.
- Finally, I can look at maps of shot difficulty using the course visualization techniques outlined above.

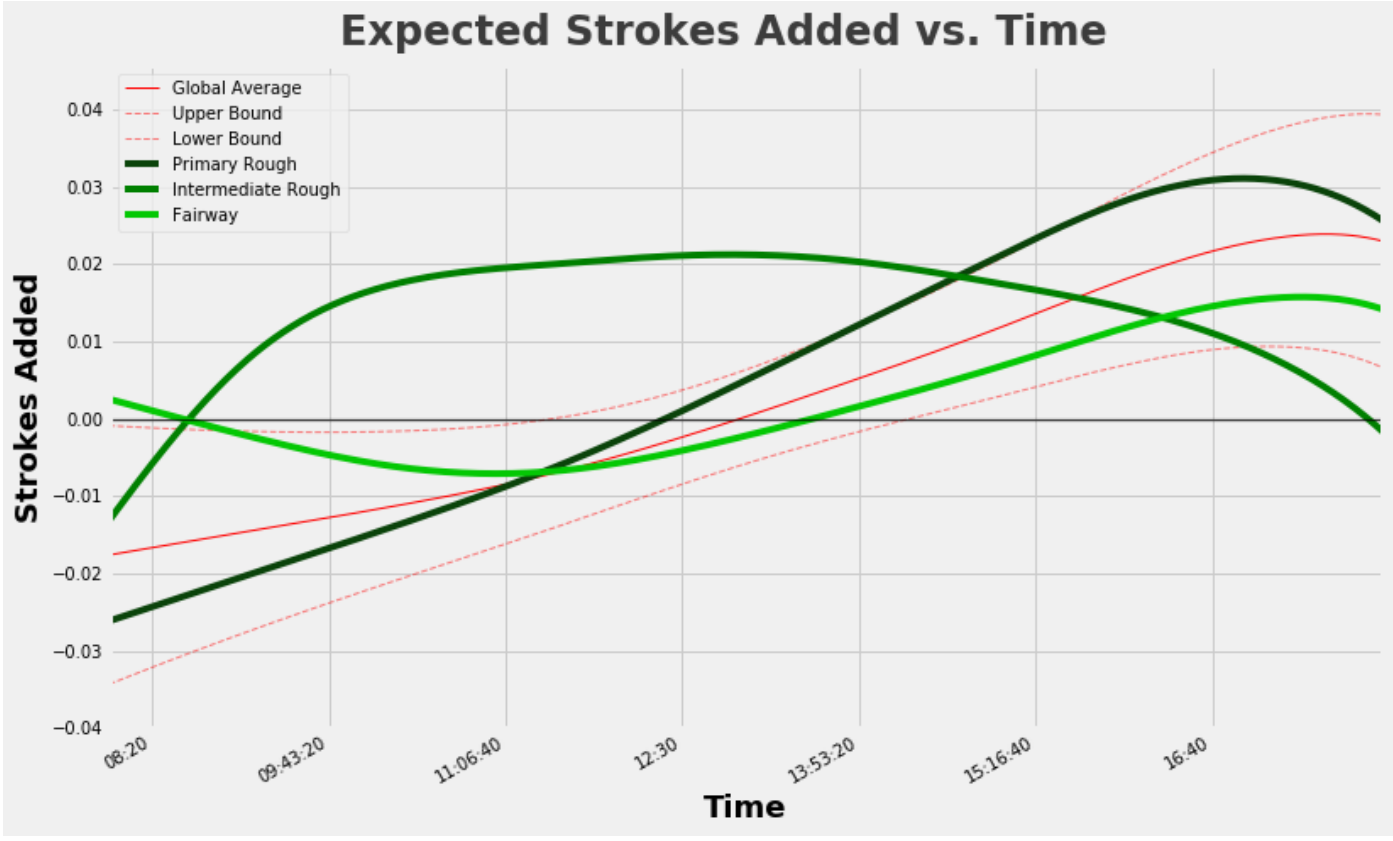
Location and Distance

The first thing to check is the strokes added by distance and location using the smoothing splines.



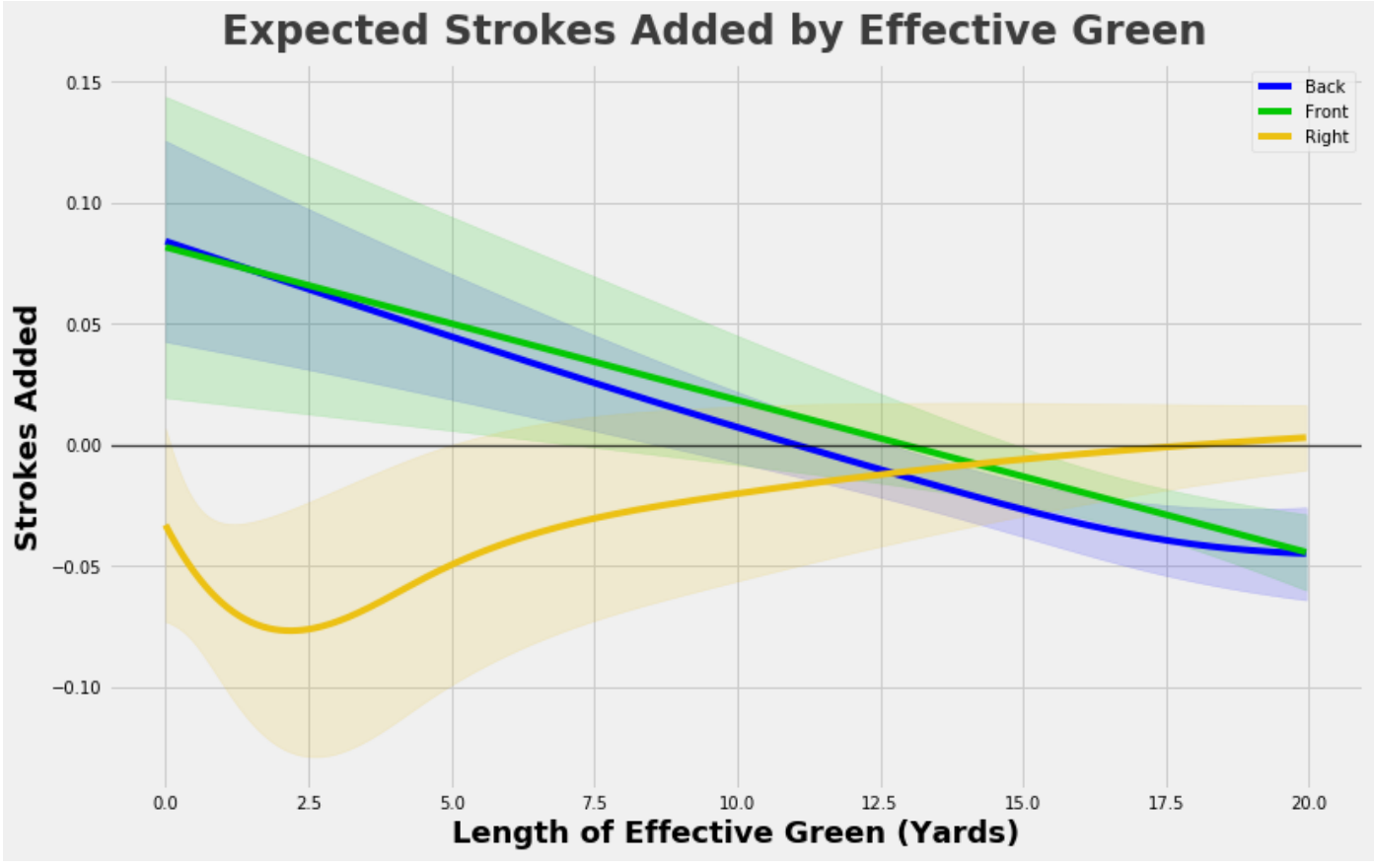
Time of Day

This shows convincing evidence that time of day matters, and that it is more pronounced on shots where it is harder to get spin on the ball.



Effective Green

More effective green is better in the front and the back, with some weird behavior on the right side.



Player Rankings

Can rank the strokes added for each player by location type in 2018.

Green		Fairway		Primary Rough		Bunker	
Player	S.A.	Player	S.A.	Player	S.A.	Player	S.A.
S. Burns	-0.036	T. Woods	-0.10	J. Thomas	-0.064	K. Na	-0.084
G. Chalmers	-0.034	W. Bryan	-0.078	W. Simpson	-0.063	R. Fowler	-0.075
J. Day	-0.030	W. Simpson	-0.076	J. Lovemark	-0.061	J. Day	-0.069
D. Summerhays	-0.029	K. Na	-0.075	P. Reed	-0.061	S. Power	-0.066
W. Simpson	-0.028	J. Day	-0.066	J. Dahmen	-0.060	O. Schniederjans	-0.066
K. Kisner	-0.027	J. Rose	-0.064	T. Hatton	-0.058	A. Baddeley	-0.062
B. Hossler	-0.027	T. Fleetwood	-0.061	B. Haas	-0.052	W. Kim	-0.061
P. Malnati	-0.025	J. Thomas	-0.061	P. Mickelson	-0.050	J. Spieth	-0.060
A. Noren	-0.024	D. Johnson	-0.060	D. Bozzelli	-0.050	D. Lee	-0.060
P. Rodgers	-0.022	P. Mickelson	-0.056	M. Kuchar	-0.048	W. Simpson	-0.057

Course Rankings

Can rank the strokes added for each course on the PGA Tour in 2018.

Course	Strokes Added
Pebble Beach GL	.039
Plantation Course at Kapalua	.031
Silverado Resort and Spa North	.028
Quail Hollow Club	.023
Torrey Pines GC (South)	.023
TPC San Antonio - AT&T Oaks	.022
TPC Summerlin	.022
Riviera CC	.018
Muirfield Village GC	.014
TPC Sawgrass	.012

Hole Rankings

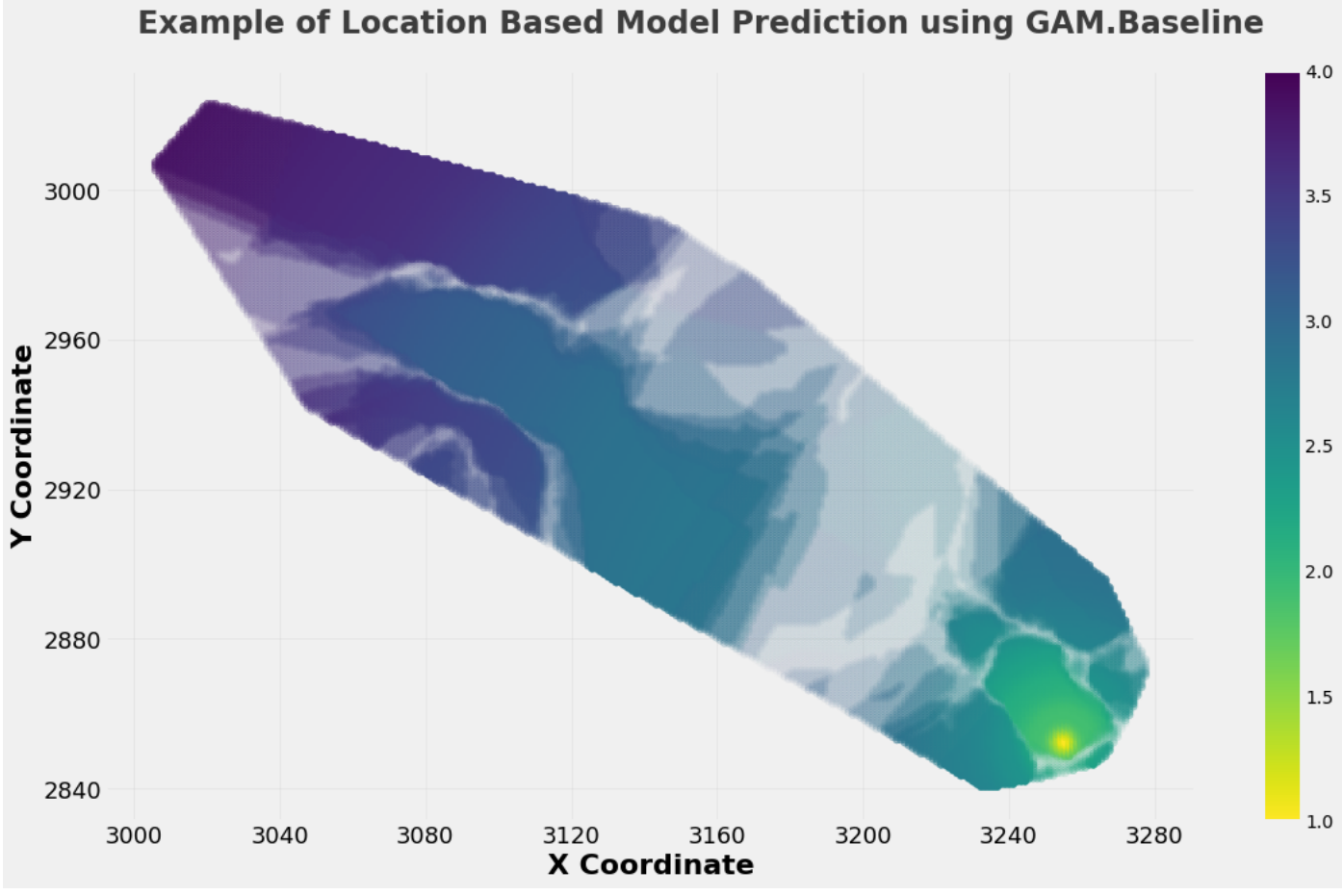
Can rank the strokes added for each course on the PGA Tour in 2018.

Course	Hole	Strokes Added
Riviera CC	10	0.16
Pebble Beach GL	18	0.14
Pebble Beach GL	14	0.13
TPC San Antonio - AT&T Oaks	1	0.12
Torrey Pines GC (South)	13	0.11
Silverado Resort and Spa North	8	0.10
TPC River Highlands	15	0.10
Pebble Beach GL	11	0.09
TPC Summerlin	11	0.08
Silverado Resort and Spa North	3	0.08

Pebble Beach Hole 18

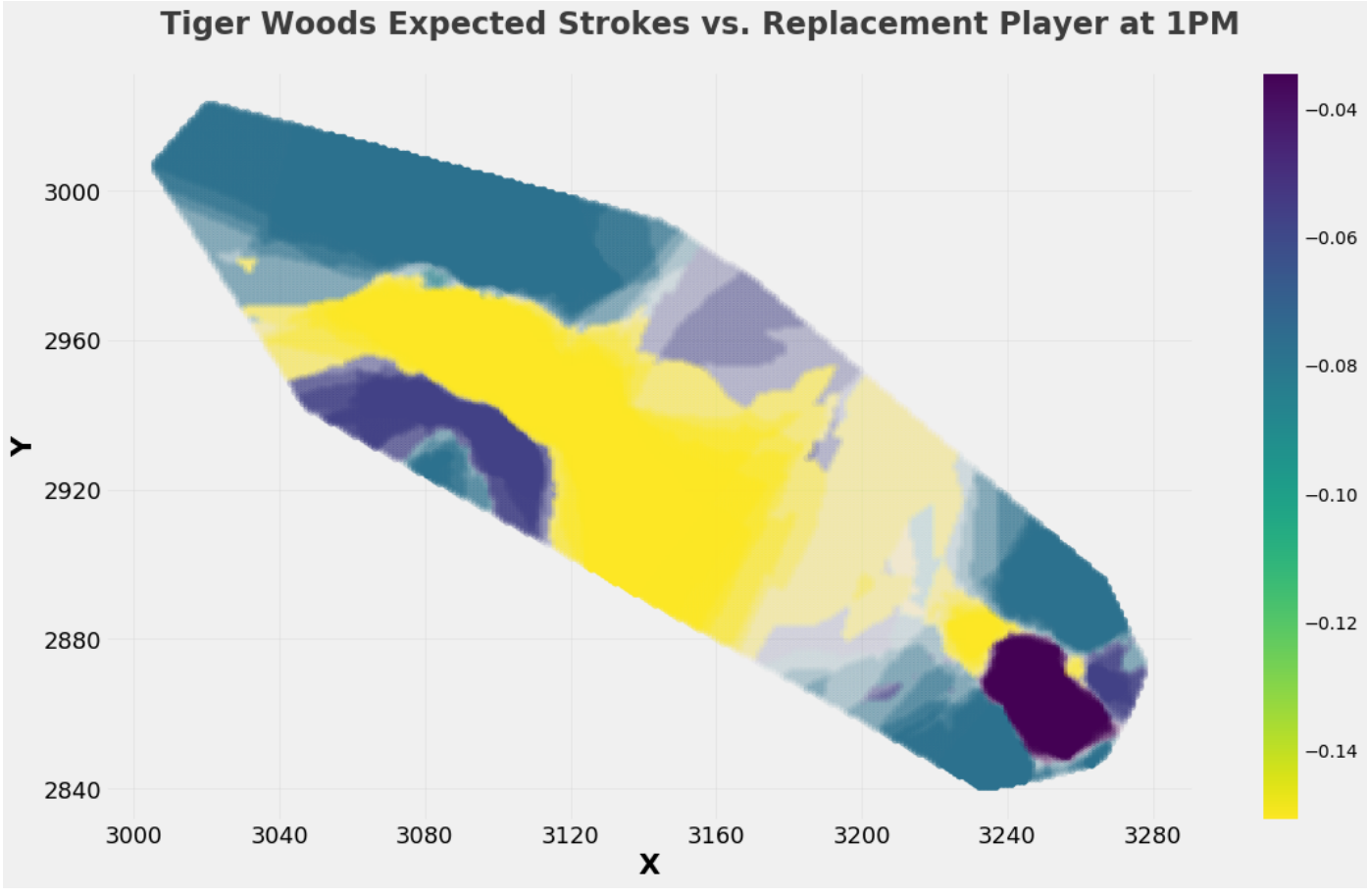
GAM Baseline Predictions

Using the out of sample imputation I mapped the difficulty of the course using the baseline GAM model.



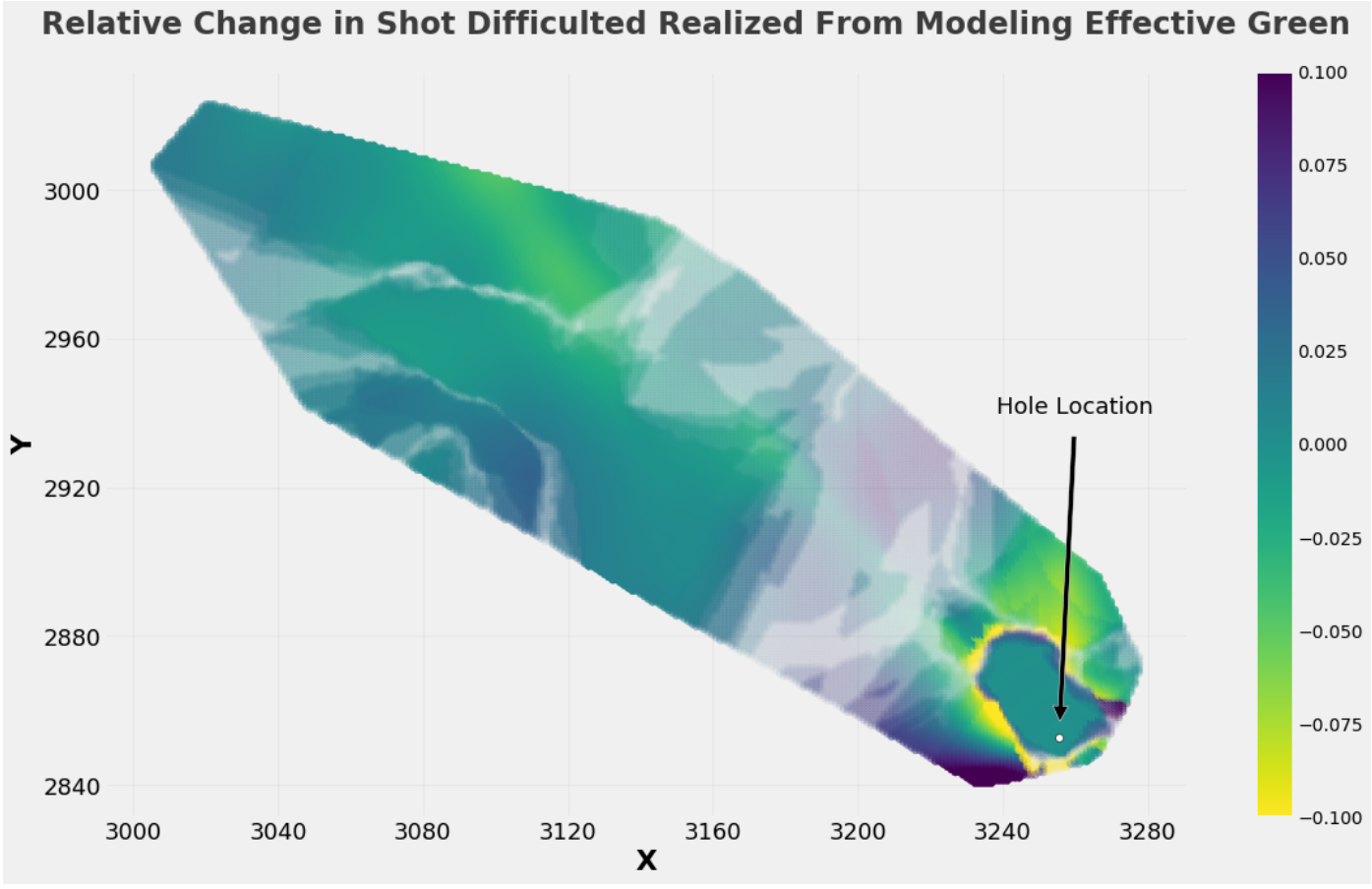
Tiger Woods Strokes Above Baseline

This model makes it simple to compare Tiger Woods to a replacement player on any given hole.



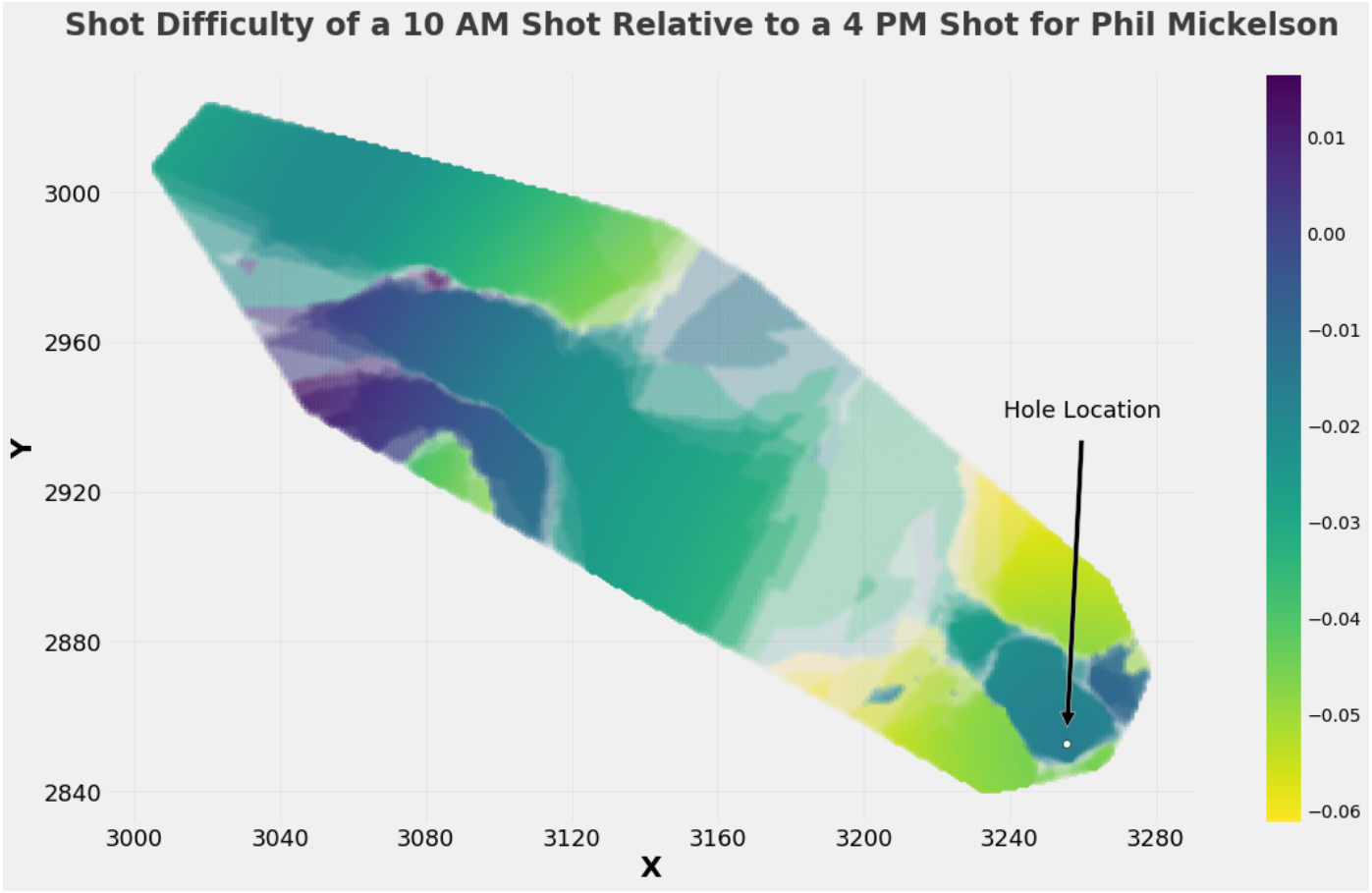
Stroke Difference With Effective Green

This graphic shows the difference in shot difficulty when considering effective green.



Difficulty at 10AM vs. 4PM

Can compare the increase in shot difficulty for Phil Mickelson between 4PM and 10AM.



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- Thanks for listening.