Response to Referee #1

Referee comments are in plain text
Author comments are in BOLD
NHESSD Manuscript text is in *italics*
Added Text is in ***Bold Italics***
(Line numbers refer to the marked manuscript)

We thank the Referee for the comments and address each point below.

I have read the manuscript with pleasure and a lot of interest and I think it is an important contribution. The manuscript is also well written and the presentation of the results is good. Therefore I am very favorable to its publication in your journal I only have some minor comments/suggestions which I feel would improve the manuscript. The authors compiled a new wave run up dataset, by extending the already broad Stockdon et al dataset with other measurements. Following they apply machine learning to conclude that the latter performs better in predicting wave run up heights. Machine learning in general have been already shown to be very capable predictors of wave runup. One of the earliest examples can be found here (https://link.springer.com/article/10.1007/s10236-011-0440-5) and maybe the most recent before the present work is Abolfathi et al 2016, with all studies reporting very good results.

Thank you for pointing us toward the manuscript of Vousdoukas et al (2011). We now cite this work on Line 97-99:

"Previous Machine Learning work has focused on predicting runup and swash, but only for engineered structures, impermeable slopes, and/or for laboratory experiments (e.g., Kazeminezhad and Etemad-Shahidi, 2015; Bonakdar and Etemad-Shahidi, 2011; Bakhtyar et al., 2008; Abolfathi et al., 2016) and not on natural beaches ***apart from Vousdoukas et al., (2011) which used artificial neural network (ANNs) for shoreline contour elevation (which includes the wave runup), on a natural beach in Portugal****."*

Since empirical run up formulas are simplifications of the actual processes deriving site specific 'recalibrations' of existing wave run up formulas has been considered a recommended practice. That way at least the effect of some unknown parameters is reduced. I would recommend the authors to mention that somewhere when they discuss previous studies, since among the recent ones mostly Stockdon 2006 aimed to propose a universal parameterization.

This is a good point, and we now added it to the discussion section.

Line 404-406:

"*Generally the results from machine learning technique are strictly related to the range of the training and validation datasets (original dataset in Fig. 1). This work demonstrated that the applicability of the predictors can sometimes be used beyond the range of the testing dataset (new dataset in Fig. 1). However it is unknown how predictors will perform in settings beyond those in the present work — future tests on new field data are therefore recommended.* ***Furthermore, parameterizations always work better when free parameters are optimized to a given site by using existing data and it should be considered when proposing universal parameterizations."***

Wave setup is part of run up and is driven by wave breaking. The latter is controlled by the nearshore beach slope (and not of the beachface only) a parameter which most times remains unknown, among others.

We added a comment that nearshore slope, which is a controlling parameter, is excluded from this predictor

Line 393-397

"Looking at the limitation of the proposed models, the variables taken into account (H_0, T_p, L_0, β) are easily accessible but also oversimplify the processes that affect swash. For instance, we do not include the influence of the wave directional spread (Guza and Feddersen, 2012), the cross-shore wind component and the tidal range (Vousdoukas et al., 2012). However, in order to include these and other aspects (e.g., role of underwater vegetation, ***nearshore bathymetry****) it is necessary to perform more field experiments that record swash, runup and other relevant variables. An additional limitation is that the swash formulas obtained in this study approaches a nonzero value as wave height approaches zero."*

and we clarify the concept at:

Line 411-413

"This result is in line with studies such as Ruggiero et al., (2001 and 2004) and in contrast with Stockdon et al., (2006), Senechal et al. (2011) and Ruessink et al., (1998). ***Although difficult to quantify and extremely simplified (this parameter together with sediment diameter should integrate the effect of the entire cross-shore profile), our results suggests that some parameter involving the beach profile should be considered when predicting runup characteristics."***

Moreover, infragravity motions and wave setup are not the same thing but they could be confused in some field measurements. The authors could elaborate on these aspects when they discuss infragravity parameterizations.

We distinguishing wave setup from infragravity motions, we state at the beginning of the manuscript:

Line 2-5

"The height reached by waves can be defined from water level elevation time series at the shoreline $\eta(t)$ as the sum of two distinguished components: the wave set up (the temporal mean of the time series $\langle\eta\rangle$ relative to the still water level) and the swash $\eta'(t)$ (the vertical fluctuation of the water level around the wave set up)."

and we have added (on line 74-75):

*"****In addition the similarity in the temporal scales of wave setup and infragravity motions could also be a confounding factor in measurements.*** *Finally, a number of other studies have also proposed other predictors that introduce other parameters to account for the cross-shore wind component and the tidal range "*

The weak point of machine learning techniques is that their predictive skill is limited to the conditions covered by the parameter space of the training dataset. GP is superior in that aspect to ANNs, since the final product is a relationship that is based on parameterizations which were derived considering the physical processes. At the same time it is not meant that the coefficients estimated will result in reasonable results beyond the range of the training dataset. In this case the training dataset is quite extensive but given that most of the global coastline is not included, it is not for granted that the solution could fail in other parts of the world.

First, we would like to point out that this GP routine is not 'aware' of physical processes (some previous GP work by other researchers have been forced to conform to physical laws). Only parameters and coefficients to combine these variables were given to the GP (along with the data).

We have clarified some aspects of our work in the discussion, and how it relates to generalization and extrapolation beyond the range of input data.

Line 366-367: "*In this work we use data compiled by Stockdon et al., (2006) to build new predictors, by the use of GP, for both total and infragravity swash elevations. We then test the generalizability of these new predictors using new data (including some extreme conditions).* ***This is different from previous applications of ML in coastal settings in two ways: First, we are testing the ML-derived predictor on data that is collected from a different setting (compared to the training data)— three beaches not included in the training data. Second, the testing data includes events that are outside the data range of the training data — we are extrapolating the ML-derived predictor as a test of its generalizability.***

Line 400-406

"*... the data used in the analysis does not include the limit condition of 'no waves-no swash'. Consequently, even if the GP formulas obtained do not correctly predict the limit condition corresponding to a no wave scenario, the prediction for both datasets has smaller errors compared to commonly used formulas.* ***Generally the results from machine learning technique are strictly related to the range of the training and validation datasets (original dataset in Fig. 1). This work demonstrated that the applicability of the predictors can sometimes be used beyond the range of the testing dataset (new dataset in Fig. 1). However it is unknown how predictors will perform in settings beyond those in the present work — future tests on new field data are therefore recommended."***

All this is not criticism, I just think the authors should discuss the above points. In addition I believe that it will be helpful for the reader to provide information about the range of input parameters for which the formulas are valid (maybe in form of a table).

We have included the information regarding the range of parameters on which the formulas have been developed on Figure 1, where the blue circles represent the training and validation dataset and the red crosses the testing one. Figure 2 includes the entire range of input and target parameters for which these predictors have been evaluated and tested (and therefore for which their validity has been assessed in the present work).

Moreover details on parameters intervals divided for experiment are reported in Table 1. For highlighting the aspects you suggested we included the following sentences at line 401-407

Line 401-407

“*... the data used in the analysis does not include the limit condition of ‘no waves-no swash’. Consequently, even if the GP formulas obtained do not correctly predict the limit condition corresponding to a no wave scenario, the prediction for both datasets has smaller errors compared to commonly used formulas.* ***Generally the results from machine learning technique are strictly related to the range of the training and validation datasets (original dataset in Fig. 1). This work demonstrated that the applicability of the predictors can sometimes be used beyond the range of the testing dataset (new dataset in Fig. 1). However it is unknown how predictors will perform in settings beyond those in the present work — future tests on new field data are therefore recommended.”***

Thank you for considering the revised version of this manuscript for publication in NHESSD

Response to Referee #2

Referee comments are in plain text
Author comments are in BOLD

This is an interesting paper and an important contribution to the prediction of wave runup and swash excursion. Results are presented in a clear and focused way. The manuscript is well written with a suitable and comprehensible outline. The figures are well readable and have informative captions. The basic idea and the application of the genetic programming algorithm are presented and discussed in a clear manner also understandable for scientists not familiar with machine learning techniques. The discussion of the physical meaning of the generated predictors is very valuable. A comparison with the results of previous predictors on the same dataset gives is well done and illuminates the advantages of the Genetic Programming approach. The manuscript should be published in the journal in its present state.

We thank the Referee for reading the manuscript and providing these positive comments.

Response to Referee #3

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Author comments are in BOLD
Manuscript text is in *italics*
Added Text is in *Bold Italics*
Line numbers refer to the marked manuscript

We thank the Referee for the comments and address each point below.

This is a well written paper that proposes a new methodology to predict total and infragravity swash elevation. As such it is of interest to NHESS and coastal scientists/practitioners. The methodology followed is correct and well explained. In particular, there is a very clear explanation of Genetic Programming and how this technique has been used for this work. This is very well written in a way which is suitable for non-experts approaching the methodology for the first time. The data used are of very good quality and there is a good explanation of the range of parameters covered by the dataset. The results are discussed in concise and detailed way and the accuracy improvement over existing relationships is demonstrated.

My only minor suggestion is that the use of both MSE and RMSE is redundant and one of the two can be omitted. Therefore I recommend publication after minor revision.

We prefer to keep both MSE and RMSE in the manuscript to aid in the rapid comparisons with future prediction schemes — for instance, a future study may report only MSE or RMSE.

Minor corrections/suggestions.
Abstract Line 14: change the sentence: it contributes to the error, maybe it is contributes to the reduction of the error. However, beware of repetitions.

We addressed this.

Line 14: *"Using this newly compiled dataset we demonstrate that a ML approach can reduce the prediction errors compared to well-established parameterizations and therefore* ***it may improve*** *coastal hazards assessment (e.g. coastal inundation)."*

Also many repetitions of "wave runup" in the introduction, try to rephrase.

Line 33

We changed "*The first predictors of wave runup were…"* **into** *"The first predictors of* ***these phenomena*** *were…"*

Line 123, concomitant is possibly better replaceable by "associated".

Line 126: We replaced *"concomitant"* **with "*associated"***

Line 143-147: specify the countries of the beaches named as not all authors might be familiar with these.

We added the information about the countries where the experiments were performed.

Line146-150: "*The dissipative beaches of the original dataset (Fig. 2 d, h) are Terschelling* ***(Netherlands)*** *and Agate* ***(USA)****, and for the new dataset Ngarunui* ***in New Zealand*** *(although, during the experiment, the beach also experienced intermediate conditions). The purely intermediate beaches for the original and new dataset are Scripps* ***(USA)*** *and TrucVert (****France)****. Some beaches of the original dataset* ***(USA)*** *represent both intermediate and reflective conditions: Duck 94, Gleneden, Sandy Duck, Delilah and Duck 82. San Onofre for the original and Tairua* ***(New Zealand)*** *for new dataset are reflective.*"

Line 170. You might want to specify which is your stopping criterion, and when do you consider the solutions stable.

We moved and clarified the sentence from lines 203 – 204 to line 173-175

Line 173-175: ***"The search is stopped after the GP evaluated*** 10^{11} ***formulas because the solutions stabilized and no significant improvement in formula performance was found."***

Line 237: overfitting is mentioned, but it could be useful to explain what this is in the present context. Explanation in 240 occurs after the first use of the term and it is not clear.

We define overfitting before mentioning it (moved to line 242) and we add a definition of overfitting from a new reference: Dietterich T.: Overfitting and Undercomputing in Machine Learning, ACM Comput. Surv., 27 (3), doi:10.1145/ 212094.212114 1995.

Line 242-248: *"Generally, extremely complicated predictors fit the training and validation dataset better than simpler predictors but they may lose generalization power* ***when tested on a separate testing dataset*** *(overfitting).* ***In other words a predictor with overfitting could represent the noise in the training and validation subsets instead of defining a general predictive rule (e.g., Dietterich, 1995) and therefore it will result in smaller training errors but in higher testing errors.*** *Several viable techniques exist for selecting the best solution to avoid overfitting, all meant to balance the fact that simpler solutions (the minimum description length) might risk losing more accurate information contained in more complex models (e.g., O`Neill et al., 2010)."*

Some sentences are written in present tense (e.g. we use at the beginning of Section 3.3, and "...finally selected" at the start of 4.2). Please make the tense consistent.

We changed the past tense into present tense.

Line 127, 128

We changed ***"****were calculated****"*** **to "*****are calculated*****" and** ***"****were located****"*** **to "*****are located*****"**

Line 192

We changed *"We searched"* **to "*We searched*"**

Line 223, 225

We changed *"we used"* **to "*we use*", We changed** *"was tested"* **to "*is tested*",**

Line 256

We changed *"selected"* **to "*select*"**

Line 374-375

We changed *"did not"* **to "*do not*", and "***found***" to "*find*"**

Also, in Line 314 it is mentioned that experiments in Ngarunui beach are carried out under mild dissipative conditions. Is the difficulty in predicting these results due to the particular combination of H and T (hence L)? It would be useful to be more detailed in explaining this.

This sentence is connected to the previous one where we discussed that the Stockdon et al. formula for S_{Ig} has more scatter for Terschelling and Agate (which are dissipative). We did not highlighted the characteristic of these beaches in the paragraph, but we already defined them dissipative at line 277 (because the same happen for S_{tot}). Our intention on line 323 was to highlight the performance of the predictors on the dissipative beaches — settings where infragravity motion has the greatest importance. Ewe now clarify this on line 314-329.

Line 314-329: *"Generally the three formulas seem to perform similarly. Some differences are found in* ***dissipative settings (i.e.,*** *Agate and Terschelling)* ***—predictions by*** *Stockdon et al., (2006)* ***tend to overestimate S_{ig} compared to*** *the GP predictors* ***.*** *The same difficulty in predicting swash excursion on a dissipative beach is observed on Ngarunui (Fig. 7).* ***Even though*** *this experiment was performed under mild wave conditions (H_0 ~ 0.6-1.26 (m) and T_p ~8.1-12.4 (s), Table 1) compared to the experiments at Agate and Terschelling.* ***Note that dissipative beaches are the one were the infrragravity motion has greater importance****. Also Truc Vert presents dissipative conditions in the swash zone, while the surf zone is intermediate (ξ_0 up to 0.87 as reported by Senechal et al., 2011). For this experiment Eq. (13) and (7) (Fig. 7 a, c) overestimate S_Ig while Eq. (14)* ***has better performance for the dissipative beach Ngarunui,*** *suggesting that it could be the most appropriate for S_Ig predictions."*

In Line 356 it is claimed that the procedure followed is different from the use of a single data set. This needs clarification, as you always build one dataset that is divided in three for training validation and testing. The same was done in the development of ANN tools for overtopping in the CLASH project (van Gent et al. 2007), for example, when the dataset used was actually a composite one resulting from many datasets.

References

van Gent, M.R., van den Boogaard, H.F., Pozueta, B. and Medina, J.R., 2007. Neural network modelling of wave overtopping at coastal structures. Coastal Engineering, 54(8), pp.586-593.

We now clarify our study — discussing how our method is different than previous data splitting work.

Line 368-372: "*In this work we use data compiled by Stockdon et al., (2006) to build new predictors, by the use of GP, for both total and infragravity swash elevations. We then test the generalizability of these new predictors using new data (including some extreme conditions). This is different from* ***many previous applications of ML in coastal settings in two ways: First, we are testing the ML-derived predictor on data that is collected from a different setting (compared to the training data)— three beaches not included in the training data. Second, the testing data includes events that are outside the data range of the training data — we are extrapolating the ML-derived predictor as a test of its generalizability.***

Thank you for considering the revised version of this manuscript for publication in NHESSD

The use of genetic programming to develop a predictor of swash excursion on sandy beaches

Marinella Passarella[1], Evan B. Goldstein[2], Sandro De Muro[1], Giovanni Coco[3]

[1]Department of Chemical and Geological Sciences, Coastal and Marine Geomorphology Group (CMGG), Università degli Studi di Cagliari, 09124 Cagliari, Italy
[2]Department of Geological Sciences, University of North Carolina, 27599, U.S.A.
[3]School of Environment, Faculty of Science, University of Auckland, Auckland, 1142, New Zealand

Correspondence to: Marinella Passarella (marinella.passarella@unica.it)

Abstract

We use Genetic Programming (GP), a type of Machine Learning (ML) approach, to predict the total and infragravity swash excursion using previously published datasets that have been used extensively in swash prediction studies. Three previously published works with a range of new conditions are added to this dataset to extend the range of measured swash conditions. Using this newly compiled dataset we demonstrate that a ML approach can reduce the prediction errors compared to well-established parameterizations and therefore~~–~~ it may improve~~it contributes to the error in~~ coastal hazards assessment (e.g. coastal inundation). Predictors obtained using GP can also be physically sound and replicate the functionality and dependencies of previous published formulas. Overall, we show that ML techniques are capable of both improving predictability (compared to classical regression approaches) and providing physical insight into coastal processes.

1. Introduction

Wave runup, is the final expression of waves travelling from deep to shallow water and is directly associated to coastal hazards like flooding or erosion. Wave runup height can be defined from water level elevation time series at the shoreline η(t) as the sum of two distinguished components: the wave set up (the temporal mean of the time series $\langle\eta\rangle$ relative to the still water level) and the swash η'(t) (the vertical fluctuation of the water level around the wave set up). Understanding and predicting swash characteristics is critical for researchers seeking to understand the dynamics of fluid motions and sediment transport in the swash zone (e.g., Elfrink and Baldock, 2002; Masselink and Puleo, 2006), and for managers and practitioners addressing hazard setbacks, risk and coastal vulnerability (e.g., Bosom and Jimenez, 2011; Vousdoukas et al., 2012). Wave runup, (and therefore swash excursion) is a key component to evaluate inundation hazards and vulnerability to storm impacts (e.g., Bosom and Jiménez, 2011; Stockdon et al, 2007; Serafin et al., 2017). Stockdon et al., (2007) found that the wave action counted for about 48 % of the maximum total water level during two hurricanes along USA coast. The problem of accurate predictions of wave runup and swash on sandy beaches has been a research topic for over 50 years but today we still struggle to provide reliable quantitative predictions.

The first predictors of ~~wave runup~~these phenomena were developed in the context of coastal structures (Miche, 1951; Hunt, 1959) and the formulas proposed, usually developed for steep slopes and under the assumption that runup motions reflect the standing component of the incident wave field. Overall these formulas suggested a dependence of the uprush elevation on wave steepness and structure slope. A variety of predictors have since then been developed for vertical runup (R) and swash (S) on sandy beaches (e.g. Guza and Thornton, 1982; Holman and Sallenger 1985; Holman 1986; Ruessink et al., 1998, Stockdon et al., 2006), with details of the parameterizations depending on different combinations of deep water significant wave height (H_{s0}), deep water wave length (L_0) and beach slope (β). Guza and Thorton (1982) proposed a linear relationship between the significant runup (R_s) and H_{s0} :

$$R_s = \mathrm{c}\, H_{s0}\ , \qquad (1)$$

where $c = 0.7$. Guza and Thornton (1982) also first distinguished between infragravity and incident swash components, indicating that the swash component related to low frequencies (infragravity, R_{Ig}) depends only on significant wave height (therefore excluding the beach slope) while the incident component can saturate as a result of the dissipative processes occurring in the surf zone. Their findings were later confirmed by several other studies although different dependencies on environmental parameters were suggested (e.g. Holman and Sallenger, 1985; Ruessink et al., 1998).

Holman and Sallenger (1985) studying an intermediate to reflective beach (Duck, North Carolina, USA) described R_s as:

$$R_s = c\ \xi_0\ H_{s0}, \qquad (2)$$

where c is a constant, H_{s0}/L_0 is the wave steepness and

$$\xi_0 = \frac{tan\beta}{\sqrt{{H_{s0}}/{L_0}}} \qquad (3)$$

where β is the foreshore beach slope and ξ_0 is the surf similarity index which is also often used for beach classification — beaches are classified as dissipative for values of ξ_0<0.23, reflective for ξ_0>1 and intermediate between the two (Short, 1999).

Stockdon et al., (2006) used 10 experiments from different locations to generate new parameterizations of wave runup on natural beaches. The 2% exceedance value of wave run up R_2 was defined as:

$$R_2 = 1.1\left(\langle\eta\rangle + \frac{S_{Tot}}{2}\right), \qquad (4)$$

where $\langle\eta\rangle$ is the maximum setup elevation and S_{Tot} is the total swash defined as:

$$S_{Tot} = \sqrt{(S_{in})^2 + \left(S_{Ig}\right)^2}\ , \tag{5}$$

where S_{in} ~~S_{in}~~ and S_{Ig} ~~S_{ig}~~ are the incident and infragravity components of swash. Stockdon et al. (2006) used regression techniques to obtain relationships for S_{in} ~~S_{in}~~ and S_{Ig} ~~S_{ig}~~:

$$S_{in} = 0.75\beta\sqrt{H_0 L_0}\ , \tag{6}$$

and

$$S_{Ig} = 0.06\sqrt{H_0 L_0}\ . \tag{7}$$

Stockdon et al., (2006) is the most commonly used empirical parameterization of runup but, as can be noted comparing eq. 6 and 7, the beach slope is missing from the predictor of the infragravity component of swash. The dependency (or not) of S_{Ig} ~~S_{ig}~~ on beach slope is a topic that has been debated but not solved and some authors (e.g., Ruessink et al., 1998) have indicated that infragravity swash is independent from the beach slope while a weak dependence on beach slope has instead been reported by others (e.g., Ruggiero et al., 2004). Cohn and Ruggiero, (2016) suggested a bathymetric control of the infragravity swash component through 1D and 2D numerical simulations performed using Xbeach (where incident swash contribution is excluded) and compared them with previous formulas (Ruggiero et al., 2001; Stockdon et al., 2006) and field data on dissipative beaches. They suggested that beach morphology (> -2 m MSL) influences the infragravity component of runup more than the nearshore morphology (< -2 m MSL) and indicated that including the foreshore beach slope in the formulation of S_{Ig} improves predictability. Overall, it remains unclear if and when S_{Ig} ~~S_Ig~~ depends on beach slope. In addition the similarity in the temporal scales of wave setup and infragravity motions could also be a confounding factor in measurements.~~Overall, it remains unclear if and when S_{Ig} S_{ig} depends on beach slope.~~ Finally, a number of other studies have also proposed other predictors that introduce other parameters to account for the cross-shore wind component and the tidal range (Vousdoukas et al., 2012), the presence of nearshore sandbars (Cox et al., 2013) or the sediment mean grain size for the case of gravel beaches (Poate et al., 2016). The above-mentioned empirical runup formulas have been developed primarily with classic regression approaches (e.g.; Ruessink et al., 1998; Ruggiero et al., 2001; Stockdon at. al., 2006; Vousdoukas et al., 2012).

Because of the importance of accurate predictions of swash excursion, the predictors provided by Stockdon et al., (2006) have been tested by various authors on beaches ranging from reflective to dissipative (e.g., Vousdoukas et al., 2012; Cohn and Ruggiero, 2016; Atkinson et al., 2017). Predictions using Stockdon et al. (2006) are certainly sound (especially considering the task of generating a universal formula for vertical swash excursion) even though differences between measurements and predictions, possibly associated to local conditions, are inevitably found. More importantly, the regression approach of multiple datasets first proposed by Stockdon et al. (2006) paves the way for our working hypothesis: can powerful data-driven techniques be used to provide robust, reliable and realistic predictions of swash excursion?

When enough data exists, Machine Learning (ML) is a viable approach to regression problems. ML is a sub-discipline of computer science focused on techniques that allow computers to find insightful relationships between variables involved in swash processes, learning at each iteration (algorithm training and validation) from the provided dataset. A key goal of ML is to develop predictors that are generalizable (able to describe the physical process beyond the training dataset itself). Many different data-driven techniques fall under the purview of Machine Learning (e.g., decision trees, artificial neural networks, Bayesian networks, and evolutionary computation), all of which have shown applicability in coastal settings (e.g., Pape et al., 2007; Knaapen and Hulscher, 2002; Dickson and Perry, 2015; Yates and Le Cozannet, 2012). Previous Machine Learning work has focused on predicting runup and swash, but only for engineered structures, impermeable slopes, and/or for laboratory experiments (e.g., Kazeminezhad and Etemad-Shahidi, 2015; Bonakdar and Etemad-Shahidi, 2011; Bakhtyar et al., 2008; Abolfathi et al., 2016) and not on natural beaches apart from Vousdoukas et al., (2011) which used artificial neural network (ANNs) for shoreline contour elevation (which includes the wave runup), on a natural beach in Portugal. In this study we focus on the use an evolutionary technique, Genetic Programming (GP), to solve the symbolic regression problem of developing new, optimized swash predictors.

In this contribution we first develop a swash excursion predictor using the original dataset of Stockdon et. al., (2006), one of the most comprehensive studies in this area of research. In addition, we use data from Guedes et al., (2013), Guedes et al., (2011, 2012), and Senechal, et al., (2011) to broaden the parameter space and to test the new swash equations. The data used in this work cover a broad range of swash excursion including extreme wave conditions (maximum H_0= 6.4 m in Senechal, et al., 2011). High swash excursions, generated by extreme storms, are of particular interest when studying coastal hazards because they relate to flooding, beach and dune erosion (Bosom and Jimenez, 2011; Stockdon et al., 2007). The new ML derived results are also compared to the most widely used predictors from Stockdon et al., (2006). Finally, we discuss the physical interpretation of the GP predictors and how we can use ML to gain knowledge of physical process related to the infragravity swash component.

2 Data

This work is based on two published video image-derived runup datasets — 13 field experiments in total. The first dataset (referred to here as the “original dataset”) is composed by 491 swash measurements from 10 experiments aggregated by Stockdon et al., (2006). The second dataset (referred to here as the “new dataset”) consists of 145 swash measurements compiled for this work from three experiments performed by Guedes et al., (2013), Guedes et al., (2011), and Senechal, et al., (2011).

The compiled dataset of total swash is plotted in Fig. 1. The compilation of a large dataset deriving from 13 different experiments requires merging data collected using different techniques and equipment. Details of each experiment can be found in the original references. Looking at the environmental forcing conditions, Figure 1 shows that the original and new dataset cover similar ranges of beach slope, while they differ in significant wave height (the new dataset includes wave heights over 6 m) and peak period (the original dataset includes more short period waves).

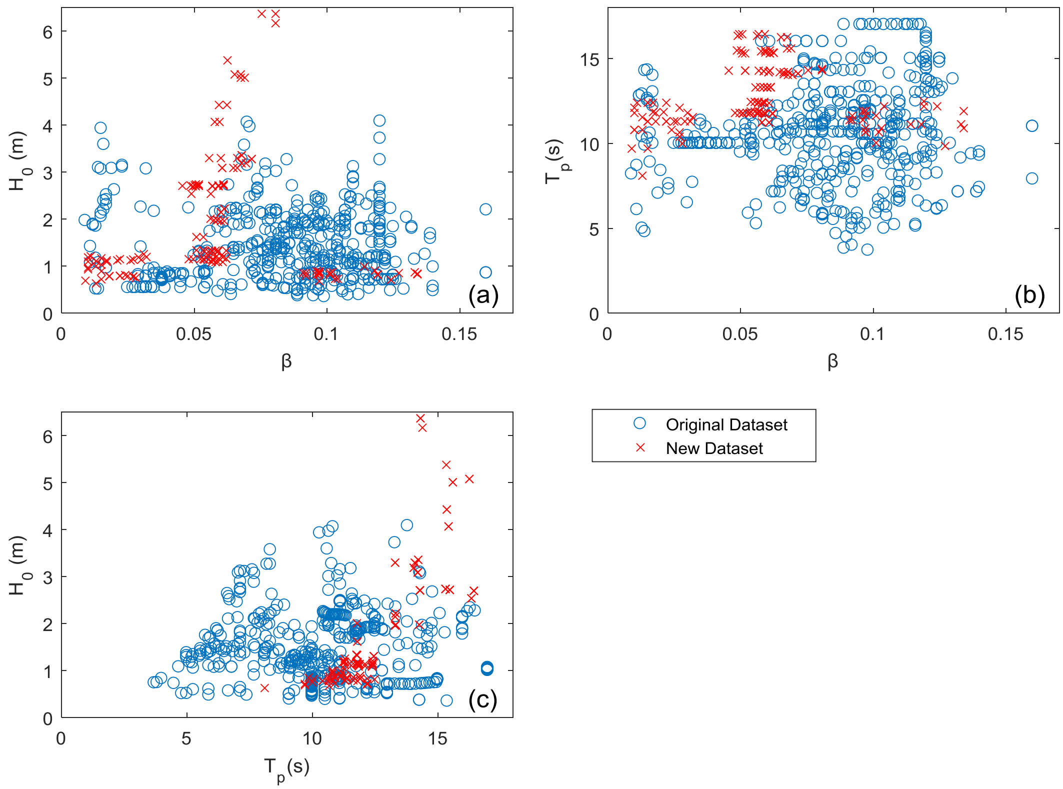

Figure 1: Environmental forcing conditions (blue circles: original dataset, red crosses: new dataset): (a) significant wave height versus beach slope; (b) wave peak period versus beach slope; (c) significant wave height versus wave peak period.

Both datasets include recordings of infragravity swash (S_{Ig}; m), total swash (S_{Tot}; m), beach slope (β) and associated~~concomitant~~ offshore wave characteristics: significant wave height (H_0; m) and peak period (T_p; s). From these measurements the offshore significant wave length (L_0; m), wave steepness (H_0/L_0), and Iribarren number (ξ_0) ~~were~~ are calculated. Experiments ~~were~~ are located in North America, Europe and Oceania and cover a large range of the environmental condition (see Table 1 and Fig. 1).

Table 1: Summary of wave and beach parameters for the original and the new datasets, beach name and type (following the classification of Short, (1999) based on Iribarren number (D stands for dissipative, I intermediate and R reflective); the last two rows indicates the range of parameters of the entire two datasets. Each experiment is associated to the citation where the measurements have been originally presented. If no reference is given, the citation to consider is Stockdon et al (2006).

Experiment	Dataset (data points)	Hs (m)	Tp (s)	β	ξ_0	Beach type	S_{Tot}(m)	S_{Ig}(m)
Duck 94 (Holland and Holman, 1996)	Original (52)	0.7-4.1	3.8-14.8	0.06-0.1	0.33-1.43	I, R	0.8-2.9	0.5-2.2
Gleneden	Original (42)	1.8-2.2	10.5-16	0.03-0.11	0.26-1.2	I, R	1.1-2.3	0.9-1.9
Sandy Duck	Original (95)	0.4-3.6	3.7-15.4	0.05-0.14	0.34-3.22	I,R	0.7-2.3	0.3-1.8
San Onofre	Original (59)	0.5-1.1	13-17	0.07-0.13	1.6-2.62	R	0.9-2.6	0.5-1.8
Terschelling (Ruessink et al., 1998)	Original (14)	0.5-3.9	4.8-10.6	0.01-0.03	0.07-0.22	D	0.2-1	0.2-0.9
Scripps Beach (Holland et al., 1995)	Original (41)	0.5-0.8	10-10	0.03-0.06	0.4-0.92	I	*0.3-0.7*	*0.3-0.7*
Delilah (Holland and Holman, 1993)	Original (138)	0.5-2.5	4.7-14.8	0.03-0.14	0.44-1.70	I,R	0.7-3.3	0.4-1.7
Duck 82 (Holman, 1986)	Original (36)	0.5-4.1	6.3-16.5	0.09-0.16	0.68-2.38	I,R	0.7-3	0.4-2.4
Agate (Ruggiero et al., 2001)	Original (14)	1.8-3.1	7.1-14.3	0.01-0.02	0.1-0.19	D	0.7-1.5	0.7-1.5
Ngarunui (Guedes et al., 2013)	New (32)	0.6-1.26	8.1-12.4	0.01-0.03	0.13-0.42	D	0.24-0.9	0.24-0.9
Tairua (Guedes et al., 2011)	New (25)	0.7-1	9.9-12.5	0.09-0.13	1.4-2.25	R	1.2-2.2	0.6-0.95
TrucVert (Senechal, et al., 2011).	New (88)	1.1-6.4	11.2-16.4	0.05-0.08	0.49-0.9	I	0.81-2.5	0.63-2.37
All beaches	~~Entire~~ Entire Original (491) (Stockdon et al., 2006)~~,~~ ~~(491)~~	0.4-4.1	3.7-17	0.01-0.16	0.07-3.22	D,I,R	0.2-3.3	0.2-2.4
All beaches	Entire New (145)	0.6-6.4	8.1-16.4	0.01-0.13	0.13-2.25	D,I,R	0.24-2.5	0.24-2.37

Both datasets include all beach types, from dissipative to reflective. The two datasets also have a similar range of S_{Tot} (although the original dataset records a larger swash, 0.2-3.3 m vs. 0.24-2.5 m of the new dataset), S_{Ig} (about 0.2-2.4 m for both), and β (about 0.01-0.1 for both). The two datasets differ in the range of offshore wave conditions — in the original dataset H_0 and T_p range over 0.4-4.1 (m) and 3.7-17 (s), respectively, while in the new dataset the ranges are 0.6-6.4 (m) and 8.1-16.4 (s).

The dissipative beaches of the original dataset (Fig. 2 d, h) are Terschelling (Netherlands) and Agate (USA), and for the new dataset Ngarunui in New Zealand (although, during the experiment, the beach also experienced intermediate conditions). The purely intermediate beaches for the original and new dataset are Scripps (USA) and TrucVert (France). Some beaches of the original dataset (USA) represent both intermediate and reflective conditions: Duck 94, Gleneden, Sandy Duck, Delilah and Duck 82. San Onofre for the original and Tairua (New Zealand) for new dataset are reflective.

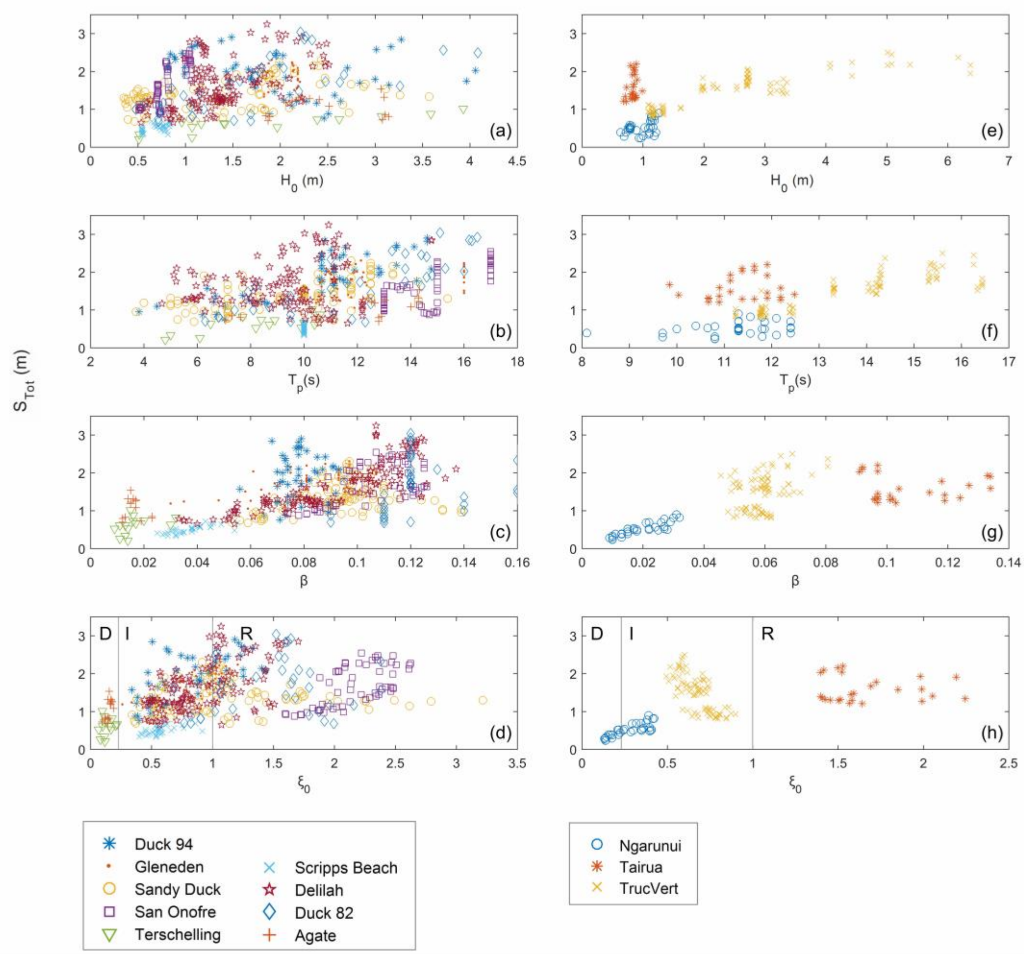

Figure 2 Total swash dependence on the environmental variables of the original (a,b,c,d) and new (e,f,g,h) datasets. The variables displayed are: significant wave height (a,e), wave peak period (b,f), beach slope (c,g) and Iribarren number (d,h). Beaches are considered dissipative (D) for values of $\xi_0<0.23$, reflective (R) for $\xi_0>1$ and intermediate (I) between the two (Short, 1999).

3. Methodology

The large amount of data available (636 field swash records), including multidimensional variables, supports the feasibility of a ML approach. The data covers a wide range of environmental conditions (including extreme storms) and beach type, ensuring the applicability of our results to sandy beaches spreading from dissipative to reflective. We now outline the methods of the study. In Sect. 3.1, we present the supervised ML approach. In Sect. 3.2 we present the data pre-processing technique used to decide what data is shown to the ML algorithm. In Sect. 3.3 we discuss the techniques used to test the results from the ML algorithm against the testing data.

3.1 Genetic Programming

GP is a population-based machine learning approach based on evolutionary computation (Koza, 1992). The process of genetic programming can generally be divided into four steps: 1) an initial population of solutions for the problem is produced. For regression tasks such as developing a predictor for swash, the initial population of candidate solutions is in the form of equations (encoded as a tree or graph with a predefined mix of variables, operators and coefficients; Fig. 3). For step 2 of the routine the solutions are all compared to the training data to determine 'fitness' using a predefined error metrics; 3) the best solutions that minimise the error are proposed and the worst solutions are discarded; 4) new solutions created through 'evolutionary' rules (crossover via reproduction and mutation) and are added to the population of retained solutions. Steps 2 through 4 are repeated until the algorithm is stopped. ~~-~~The search is stopped after the GP evaluated 10^{11} formulas because the solutions stabilized and ~~that 10^{11} formulas were created and evaluated by the GP process, because~~ no significant improvement in formula performance was found.

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At the end of a routine, when the solutions have stabilized, a final population of solutions exist. A range of final solutions is given by the algorithm — more mathematically complex solutions (with more variables, operators, and coefficients) that minimize error are given alongside more simple, parsimonious solutions with higher error. These solutions exist along a "Pareto Front" that balances decreases in error with increasing solution complexity. Given a range of solutions with different error and complexity, we do not know of a perfect method for a user to determine the single best solution from the suite of final solutions — a user must decide on the solution according to different criteria: minimization of the error, computational time, physical meaning. In our work we adopted the criteria of minimization of the error with an eye toward the ability to interpret physical meaning from the formulas. A compromise between error reduction (more complex predictors) and ability of the predictors to generalize (predictive power on new data) should be found during the selection of a predictor.

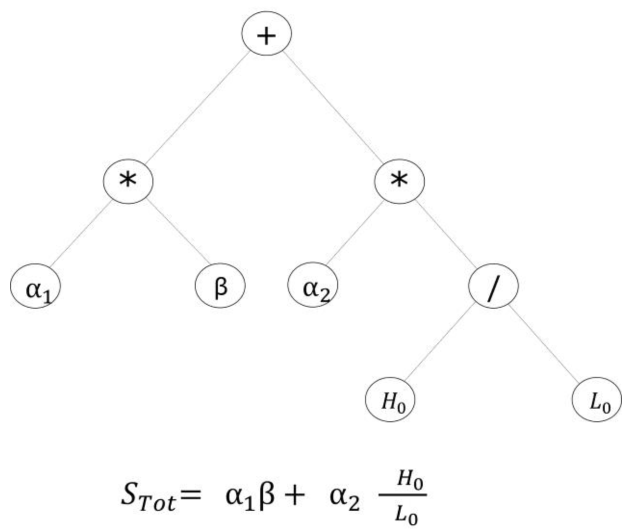

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Figure 3: Schematics of the GP structure and principle of operation for an example of simple total swash predictor. α_1 and α_2 are the coefficients, β, $H_0$and L_0 the variables and +, * and / the mathematical operators.

All genetic programming in this study is performed using the software "Eureqa" developed by Schmidt and Lipson, (2009; 2013) which has successfully been used for a range of coastal problems (e.g., Goldstein et al., 2013; Tinoco et al., 2015). We search~~ed~~ for predictors of total and infragravity swash elevation — ultimately searching for the best equation that satisfies $S_{Tot/Ig} = f(H_0, L_0, \beta, T_p)$. Note also that we perform some experiments searching for total and infragravity swash as a function of composite variables like wave steepness, wave power (P_w), and the Iribarren number. However, the predictors did not show improvement — also keep in mind that the GP can autonomously find these interrelationships between the basic parameters themselves, leading to the appearance of these composite variables in each optimization experiment. In addition to physical parameters, constants are included in the research and the mathematical operations allowed to the GP are: addition (+), subtraction (-), multiplication (*), division (/), exponential (^) and square root (√). Predictors developed on the training subset are assessed on the validation subset, using an error metric (also known as fitness function). From the available metrics we selected the mean squared error (MSE):

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - f(x)_i)^2 \, , \qquad (8)$$

where N is the number of samples, y_i is the measured value, and $f(x)_i$is the value predicted by GP as a function of x. ~~The search is stopped after that 10^{11} formulas were created and evaluated by the GP process, because no significant improvement in formula performance was found.~~

All selected formulas from the genetic programming routine are further optimized. First, the formulas are rearranged algebraically to ease interpretation by the user. Second, two coefficients of each selected formula are further optimized using a gradient descent algorithm in an iterative process.

3.2 Training, Validation and Testing

In order to obtain generalizable predictors, it is necessary to train, validate and test any ML routine on distinct and non-overlapping subsets of data (e.g., Domingos, 2012). There is no universal, optimal method to select enough data to explain variability of the dataset while still retaining the most data to use for testing — recent work by Galelli et al., (2014) highlights that, even with the numerous input variable selection methods that have been proposed, there is no single best method for all the typologies of environmental datasets, and for all environmental models.

We adopt the maximum dissimilarity algorithm (MDA) as selection routine (e.g., Camus et al., 2011), already successfully tested in other works of predictors developed by GP for physical problems (e.g., Goldstein and Coco, 2014). The MDA is a routine for the selection of the most dissimilar points in a given dataset. Each data point is a vector composed by all the variables of our data set ($\eta, S_{Tot}, S_{Ig}, S_{in}, H_0, L_0, \beta, T_p, \xi_0, P_w, R$), where each variable is normalized between 0 and 1. At each iteration (i=1…n), the MDA finds the most different data point from the data selected in all previous iterations. Consequently the MDA selects a diverse set of data from the original 491 data points used by Stockdon et al., (2006). The operator must set the number of data points selected — we apply the MDA to 150 data points (~30% of the original dataset). We also run the analysis using a subset of variables (not including the variables representing swash elevations) but no significant loss in prediction power of the algorithms developed by the machine learning algorithm was observed~~)~~. The data selected by the MDA is used as the training subset and we use~~d~~ the remaining data (~70 % of the original dataset, not selected) as validation subset.

The predictors developed by the GP using this training data ~~was~~ is tested using the new dataset from Guedes et al., (2011), Guedes et al., (2013), and (Senechal, et al., 2011). This new dataset is completely independent from the training and unknown at the GP algorithm providing a test in the ability of the GP parameterization to generalise, even beyond the range of the testing and validation data (Fig. 1). The performance of our predictors using the testing data is compared to the Stockdon et al., (2006) predictors using the error metrics in Sect. 3.3.

3.3 Error Evaluation

We use three different error metrics for the testing phase and for comparing our predictor with known predictors in the literature. The mean square error as defined in Eq. (8), the root mean square error:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - f(x)_i)^2}\ , \qquad (9)$$

and the maximum absolute error:

$$MaxAE = max_{i=1\ldots N}(y_i - f(x)_i)\ , \qquad (10)$$

where N is the number of samples, y_i is the measured value, and $f(x)_i$ is the value predicted by the GP as a function of x.

4 Results

4.1 Results of GP experiments

After ~10^{11} formulas were evaluated, the solutions from the GP algorithm for both S_{Tot} and S_{Ig} follow a "Pareto front" where the error decreases (compared with the validation subset) as the size (or complexity) of the formula increases. Generally, extremely complicated predictors fit the training and validation dataset better than simpler predictors but they may lose generalization power when tested on a separate testing dataset (overfitting). In other words a predictor with overfitting could represent the noise in the training and validation subsets instead of defining a general predictive rule (Dietterich, 1995) and therefore it will result in smaller training errors but in higher testing errors.~~ (overfitting). ~~Several viable techniques exist for selecting the best solution to avoid overfitting, all meant to balance the fact that simpler solutions (the minimum description length) might risk losing more accurate information contained in more complex models (e.g., O`Neill et al., 2010). ~~Generally, extremely complicated predictors fit the training and validation dataset better than simpler predictors but they may lose generalization power (overfitting).~~ Picking a solution is a subjective task, and relies on specific domain knowledge on the part of the user — here we focus on predictors with clear physical plausibility (avoiding predictors with physical nonsense such as increase of S_{Tot} as H_0 decreases) and avoid predictors that are difficult to interpret, (e.g., extremely nonlinear relationships, possibly a result of overfitting the training dataset). We also focus on two predictors for both the S_{Tot} and S_{Ig}, evaluating a simpler and more complex predictor to determine if the more complex expression warrants use when generalized to the testing dataset.

4.2 Total Swash

Following the principle of error reduction and physical interpretability of the results, we finally select~~ed~~ from the pool of candidate solutions available from the GP experiments, two formulas for S_{Tot}, one simpler (Eq. 11) and one more elaborate~~d~~ (Eq. 12).

$$S_{Tot} = 12.314\,\beta + 0.087\,T_p - 0.047\,\frac{T_p}{H_0}\ , \qquad (11)$$

$$S_{Tot} = 146.737\,\beta^2 + \frac{T_p {H_0}^3}{5.800 + 10.595\,{H_0}^3} - 4397.838\,\beta^4\ . \qquad (12)$$

Note that the coefficients of both Eq. (11) and (12) are dimensional. Eq. (11) represents the best solution in terms of error reduction while maintaining a physical interpretability. It also stands out for its simplicity and only weak nonlinearity — it looks similar to a multiple linear regression. In Eq. 12 the first and the third term depend exclusively on β, while the second term includes the contribution of the incident waves. The total swash in both GP predictors is related to the wave peak period (instead of wave length) different from previous formulations (e.g. Stockdon et al., 2006; Holman and Sallenger 1985). Recently also Poate et al., (2016) used the wave peak period in their runup predictor for gravel beaches. The use of the peak period instead of the wave length has no influence on the physics of the predictor, but could allow the users a more direct utilization of the formula.

Figure 4 displays a comparison of performance of swash predictors obtained through the ML approach (Fig. 4a, 4b) and Stockdon et al. (2006) (Fig 4c), on the training and validation dataset. This does not constitute a test of the predictors, only a consistency check to see that the predictors are modelling the training and validation data appropriately. Overall Eq. (5) shows a higher scatter in the whole original dataset (details on the errors can be found in Table 2 and Sect. 4.4). It is not clear why all formulas do not successfully fit the data Duck 82 and Delilah (especially for $S_{Tot} > 2$ m). The Stockdon et al., (2006) predictor shows scatter at larger total swash, while the GP predictors shows slight under fitting of swash elevation during large events. Stockdon et al. (2006), Eq. (5), (6) and (7) in this contribution, mostly under predicts the data with exclusion of the Duck 82 dataset, which is largely over predicted for high values of the swash excursion. Both GP predictors more accurately fit data from dissipative beaches (Agate and Terschelling) compared with the Stockdon et al. (2006) formula.

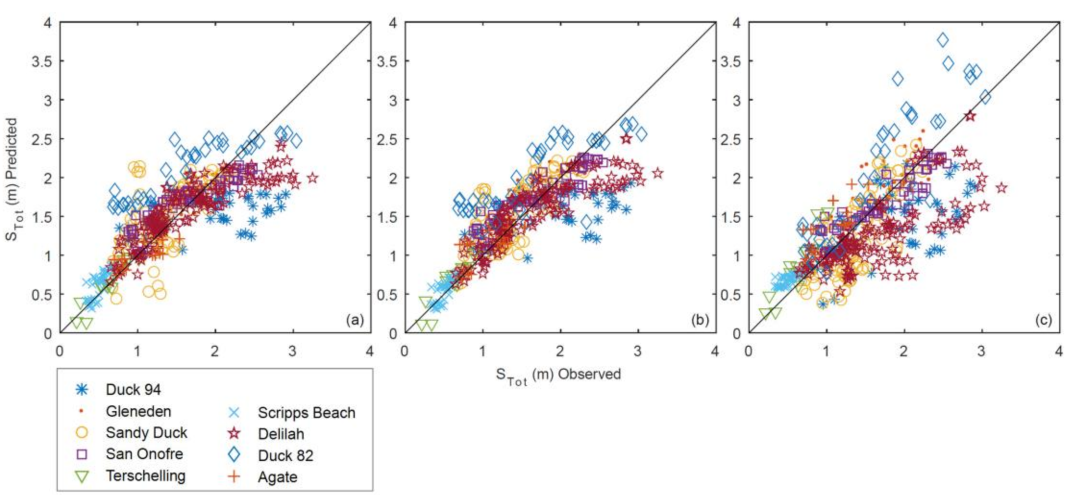

Figure 4: Observed versus predicted S_{Tot} using (a) GP Eq. (11), (b) GP Eq. (12) and(c) Stockdon et al., (2006) Eq. (5) for the original dataset (Stockdon et al., 2006). This is not a test of any predictor, only a consistency check — all data was shown to the GP algorithm and used to generate the linear regression in panel c.

Figure 5 shows the observed versus the predicted S_{Tot} — both GP models and Stockdon et al., (2006) — for the new, 'testing' dataset. Note that swash values (0- 2.5 m) are lower than the maxima observed in the original data set, but these values represent absolutely new, out of sample prediction for all equations. Overall the Stockdon et al., (2006) formula has higher scatter than both GP predictors (Fig. 5), and considerably overestimates swash measurement of Truc Vert (intermediate beach under extreme highly energetic wave storm) and Ngarunui (dissipative beach under mild wave conditions) while underestimates the observations at the reflective beach of Tairua. Equations (11) and (12), from the GP routine, perform similarly (Fig. 5 a, b).

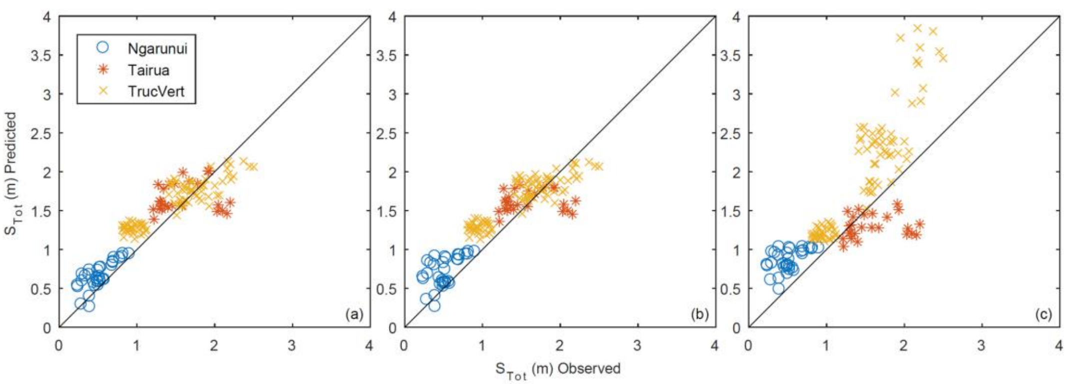

Figure 5: Observed versus predicted S_{Tot} with the new independent dataset. (a) GP Eq. (11) , (b) GP Eq. (12) and (c) Stockdon et al., (2006) — Eq. (5) in this manuscript.

4.3 Infragravity swash

The two formulas selected for describing S_{Ig} are Eq. (13) and the more complex Eq. (14):

$$S_{Ig} = 10\beta + \frac{\beta}{\beta - 0.306} + \frac{H_0 - 0.456}{0.447 + 136.411(\frac{H_0}{L_0})} \quad (13)$$

$$S_{Ig} = \frac{\beta}{0.028+\beta} + \frac{(-1)}{2412.255\,\beta - 5.521\,\beta L_0} + \frac{H_0 - 0.711}{0.465 + 173.470(\frac{H_0}{L_0})}, \quad (14)$$

As in the case of S_{Tot}, the coefficients of Eq. (13) and (14) for S_{Ig} are dimensional. The reader should also note that both formulas depend on the beach slope in contrast with Ruessink et al., (1998) and Stockdon et al., (2006), Eq. (7) in this manuscript, but in agreement with other slope inclusive predictors (Ruggiero et al., 2001; 2004). Eq. (14) represents the best solution in terms of error reduction while maintaining physical meaning and Eq. (13) is a simpler predictor where the contribution of beach slope and waves to infragravity swash remains separate. Both Eq. (13) and (14) have the same nonlinear term $\frac{H_0-0.456}{0.447+136.411(\frac{H_0}{L_0})}$, with slight difference in the coefficients, that describes the incoming waves. The threshold that flips this term from negative to positive is related to wave height and is probably an indication that for small waves the infragravity component is extremely limited (this terms needs to be negative to compensate for other terms that only depend on beach slope and provide a constant contribution). The ML predictor not only suggests that the beach slope is important when predicting infragravity swash, but also indicates a nonlinear interaction between waves and beach morphology through the wave length (second term of Eq. 14).

Figure 6 displays a consistency check, highlighting the performance of swash predictors obtained through a ML approach (Fig 6a, 6b) and Stockdon et al., (2006) (Fig 6c), on the training and validation dataset. It is not clear why all formulas provide less precise prediction with data from Duck 84 and Duck 82 but we note that these two experiments focused on intermediate to reflective conditions with relatively large wave conditions (Table 1). Generally the three formulas seem to perform similarly. Some differences are found in dissipative settings (i.e., ~~the overestimation of~~ Agate and Terschelling) ~~data~~ predictions by~~from~~ Stockdon et al., (2006)~~,~~ tend to overestimate S_{Ig} compared to ~~while~~ the GP predictors. ~~show less scatter.~~

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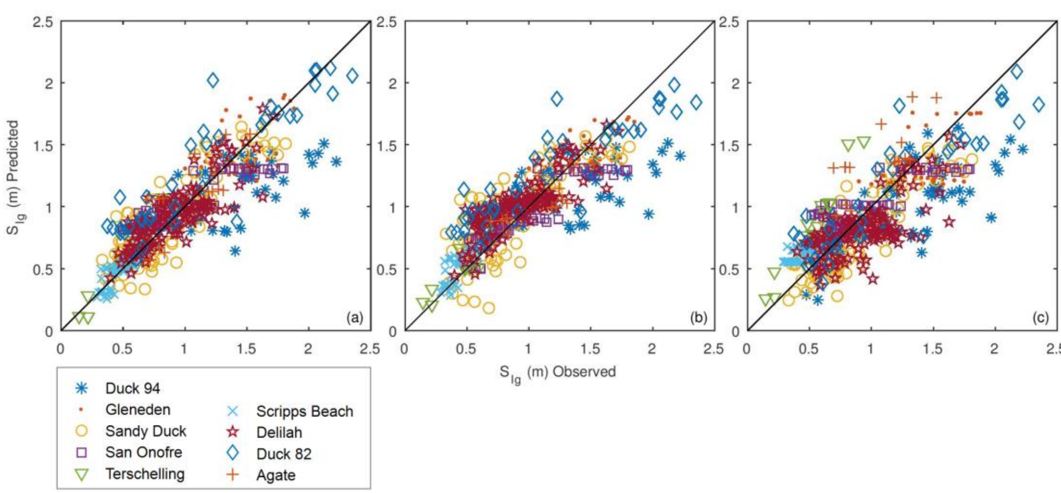

Figure 6: Observed versus predicted S_{Ig} by (a) GP Eq. (13), (b) GP Eq. (14) and (c) Stockdon et al., (2006) Eq. (7) on the original dataset (Stockdon et al., 2006). This is not a test of any predictor, only a consistency check — all data was shown to the GP algorithm and is the same data used to generate the linear regression in panel c.

The same difficulty in predicting swash excursion on a dissipative beach is observed on Ngarunui (Fig. 7). ~~Note that~~Even though this experiment was performed under mild wave conditions (H_0 ~ 0.6-1.26 (m) and T_p ~8.1-12.4 (s), Table 1) compared to the experiments at~~,~~ Agate and Terschelling. Note that dissipative beaches are the one were the infrragravity motion has greater importance. Also Truc Vert presents dissipative conditions in the swash zone, while the surf zone is intermediate (ξ_0 up to 0.87 as reported by Senechal et al., 2011). For this experiment Eq. (13) and (7) (Fig. 7 a, c) overestimate S_{Ig} while Eq. (14) has better performance for the dissipative beach Ngarunui~~performs clearly better~~, suggesting that it could be the most appropriate for S_{Ig} predictions.

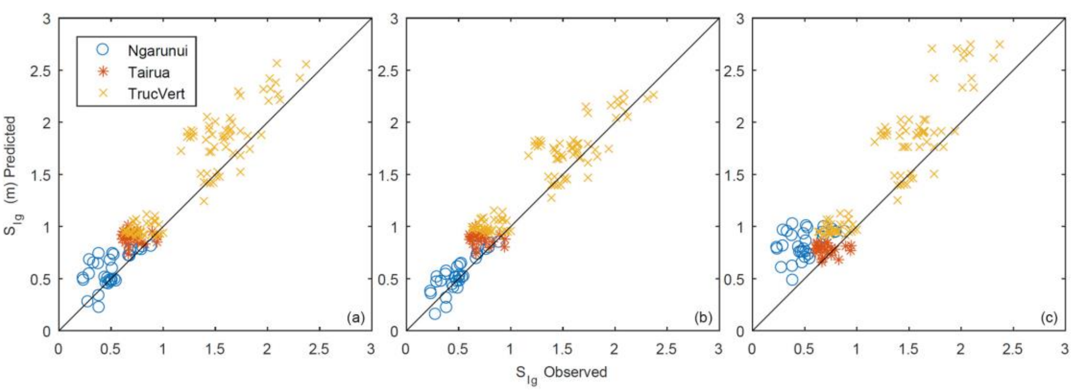

Figure 7: Observed versus predicted S_{Ig} using (a) GP Eq. (13), (b) GP Eq. (14) and (c) Stockdon et al., (2006) Eq. (7) on the new independent dataset.

Table 2 summarises the results of the errors calculated, through three error metrics (Sect. 3.3), of the two GP predictors and the Stockdon et al., (2006) formulas on both original and independent datasets.

Table 2: Results of error metrics for both total and infragravity swash, calculated for the GP predictors and Stockdon et al., (2006) on both original and new datasets. The results calculated with the original dataset (in Italics) do not represent a test of any predictor, only a consistency check — all original data was shown to the GP algorithm and used by Stockdon et al., (2006).

Target	**Formula (Methodology)**	**Error Metrics**	**New Dataset (Independent)**	**Original Dataset Stockdon et al., (2006)**
Total Swash	Eq. (11) (GP)	MSE (m^2)	0.074	*0.144*
		RMSE (m)	0.272	*0.380*
		MaxAE (m)	0.695	*1.257*
	Eq. (12) (GP)	MSE (m^2)	0.083	*0.126*
		RMSE (m)	0.288	*0.355*
		MaxAE (m)	0.702	*1.258*
	Eq. (5) Stockdon et al., (2006)	MSE (m^2)	0.325	*0.214*
		RMSE (m)	0.570	*0.462*
		MaxAE (m)	1.771	*1.399*
Infragravity	Eq. (13) (GP)	MSE (m^2)	0.071	*0.047*
		RMSE (m)	0.267	*0.217*
		MaxAE (m)	0.679	*1.019*
	Eq. (14) (GP)	MSE (m^2)	0.047	*0.053*
		RMSE (m)	0.216	*0.231*
		MaxAE (m)	0.587	*1.025*
	Eq. (7)	MSE (m^2)	0.111	*0.068*

	Stockdon et al., (2006)	RMSE (m)	0.334	*0.261*
		MaxAE (m)	0.988	*1.056*

Overall the GP predictors perform better than the Stockdon et al., (2006) formulation for all the error metrics considered and for the new testing datasets (for both S_{Tot} and S_{Ig}). While for S_{Tot} the predictor of smaller size performs better than the more complex predictor, for S_{Ig} the errors decrease with increasing GP predictor size (Eq. (13) to (14)), when tested on the new dataset. Eq. (11) has the smallest RMSE (0.272 m), MSE (0.074 m^2) and MaxAE (0.695 m) of the S_{Tot} formulas, evaluated on the new dataset, while the predictor from Stockdon et al. (2006) — Eq. (5) of this manuscript — has the highest RMSE (0.570 m), MSE (0.325 m^2) and MaxAE (1.771 m). Eq. (14) performs slightly better than Eq. (13) in predicting S_{Ig} evaluated on the new dataset, while the difference is larger when compared to the predictor from Stockdon et al. (2006) — Eq. (7) of this manuscript.

5 Discussion

In this work we use data compiled by Stockdon et al., (2006) to build new predictors, by the use of GP, for both total and infragravity swash elevations. We then test the generalizability of these new predictors using new data (including some extreme conditions). This is different from many previous applications of ML in coastal settings in two ways: First, we are testing the ML-derived predictor on data that is collected from a different setting (compared to the training data) — three beaches not included in the training data. Second, the testing data includes events that are outside the data range of the training data — we are extrapolating the ML-derived predictor as a test of its generalizability~~the usual use of a single dataset, divided into three parts for training, validation and testing of ML derived predictors~~. We ~~did~~ do not assume a single criteria for the selection of the best predictors, but we fi~~ou~~nd a compromise between error reduction (on the testing dataset) and the physical interpretability of the results.

Results demonstrate that the GP predictors proposed in this work perform better than existing formulas and that ML can identify nonlinear relationships between the variables of this problem. Specifically, Eq. (14) introduces the dependence of S_{Ig} on the beach slope, but also its nonlinear relationship with the wave length. Furthermore, solutions for S_{Ig} found by the GP algorithm with the smaller size (not shown) show a simple linear dependence on H_0 with a constant (identical to early formulation of wave runup e.g. of Guza and Thornton, 1982). More complex predictors add a dependence on L_0, $\sqrt{H_0 L_0}$ (similar to Eq. 7 of this manuscript — from Stockdon et al., 2006) and $\frac{H_0}{L_0}$.

The GP algorithm found solutions for S_{Ig} that include the beach slope (β), a variable that is never excluded from predictors of further increasing size. Because the candidate solutions resulted from GP experiments follow a "Pareto front" distribution in which the increase in fitting (smaller MSE) grows as the size of the formula rises, the continuous inclusion of β for more complex predictors implies that including β in S_{Ig} formulation reduces prediction error. The improvement of classic empirical techniques, by innovation in data-driven methodologies, has already been discussed (e.g. the case of depth-averaged velocities over model vegetation by Tinoco et al., 2015). Experiments based on GP also highlighted a way to focus on and add dependencies in predictors describing coastal processes (e.g. grain size in the case of prediction of ripple wave length by Goldstein et al., 2013). The predictors proposed in this work perform well on a wide range on environmental conditions, including, as defined by Nicolae et al., (2016), the highest stormy condition dataset (Truc Vert beach) recorded in the field and available in the literature. Furthermore the work here demonstrates that ML derived results, when physically plausible, may be generalizable beyond the limits of the training data, extrapolating to a novel, out of sample data set.

Looking at the limitation of the proposed models, the variables taken into account (H_0, T_p, L_0, β) are easily accessible but also oversimplify the processes that affect swash. For instance, we do not include the influence of the wave directional spread (Guza and Feddersen, 2012), the cross-shore wind component and the tidal range (Vousdoukas et al., 2012). However, in order to include these and other aspects (e.g., role of underwater vegetation, nearshore bathymetry) it is necessary to perform more field experiments that record swash, runup and other relevant variables. An additional limitation is that the swash formulas obtained in this study approaches a nonzero value as wave height approaches zero. While this is physically incorrect, the data used in the analysis does not include the limit condition of ‘no waves-no swash’. Consequently, even if the GP formulas obtained do not correctly predict the limit condition corresponding to a no wave scenario, the prediction for both datasets has smaller errors compared to commonly used formulas. Generally the results from machine learning technique are strictly related to the range of the training and validation datasets (original dataset in Fig. 1). This work demonstrated that the applicability of the predictors can sometimes be used beyond the range of the testing dataset (new dataset in Fig. 1). However it is unknown how predictors will perform in settings beyond those in the present work — future tests on new field data are therefore recommended. Furthermore, parameterizations always work better when free parameters are optimized to a given site by using existing data and it should be considered when proposing universal parameterizations.

Our results contribute to the discussion on the role of beach slope on the prediction of the infragravity component of swash. The GP algorithm found an S_{Ig} dependence on beach slope and increasingly more complicated formulas (i.e., more precise predictions) found by the GP all include beach slope as one of the predictive variables. This result is in line with studies such as Ruggiero et al., (2001 and 2004) and in contrast with Stockdon et al., (2006), Senechal et al. (2011) and Ruessink et al., (1998). Although difficult to quantify and extremely simplified (this parameter together with sediment diameter should integrate the effect of the entire cross-shore profile), our results suggests that some parameter involving the beach profile should be considered when predicting runup characteristics.

Our results are relevant for a variety of applications where the errors related to empirical formulation obtained by classic regression techniques could be reduced. For instance in the case of coastal hazards, Stockdon et al., (2006) formulation for wave runup is used by Serafin and Ruggiero, (2014) for their extreme total water level estimation and by Bosom and Jimenez, (2011) in their framework for coastal hazards assessment. Accuracy in runup formulation has consequences for risk and vulnerability assessment as coastal management maps (De Muro et al. ~~in press~~2017; Perini et al., 2016), and other several studies regarding sediment transport (Puleo et al., 2000), swash zone hydrodynamics and morphodynamics (Puleo and Torres-Freyermut, 2016).

6 Conclusions

Starting ~~form~~ from a large dataset covering a wide range of swash, beach and wave field characteristics, we developed two new predictors for total and infragravity swash elevations, using the machine learning technique of Genetic Programming. We tested and compared our new formulas with previously developed and largely accepted parameterizations of swash (e.g., Stockdon at al., 2006) using independent published datasets. Results of the two GP predictors selected (one for total and one for infragravity swash) show better performance compared with the formulation of Stockdon et al., (2006), evaluated using an independent (unknown to the algorithm) dataset (which included extreme highly energetic wave storm, particularly relevant for coastal hazards). This work contributes to reducing the uncertainty in predicting the swash excursion and consequently in assessing the coastal vulnerability and hazards (e.g. inundation) which depend in part upon wave swash (Bosom and Jimenez, 2011). A better prediction of swash excursion could also influence retreat or accommodation strategies and integrated planning for the mitigation of coastal hazards. Furthermore, GP results indicate that the beach slope influences the infragravity component of the swash — GP predictors improve in performance when the beach slope was included. We therefore conclude that beach slope is a relevant parameter when predicting the infragravity component of the swash elevation, even though this is contrary to several previous studies (e.g., Stockdon et al., 2006; Ruessink 1998; Senechal et al., 2011). ML and specifically GP can be a useful tool for data-rich problems providing robust predictors and possibly also physical insight. The role and importance of the scientist is not reduced or substituted by the machine but instead improved thanks to a powerful data analysis tool.

Competing interests

The authors declare that they have no conflict of interest.

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