ESTIMATION OF SNOW LOSS FOR PHOTOVOLTAIC PLANTS IN NORWAY

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ABSTRACT: Large PV plants are increasingly common in locations with colder climates where snow can lead to significant PV power loss. For these locations, estimates of snow loss is necessary for accurate PV yield modeling. Robust estimation of snow loss is, however, challenging. Snow-induced loss is expected to vary with climate, weather, and PV plant design. In this work, we estimate snow loss from historical data for a set of PV plants in Norway. To extend the snow loss dataset, 12 years of weather data and a modified adaption of the Marion snow loss model are used to simulate snow loss for the analyzed PV plants over time. For the historical data, we observe variations in annual losses for the same system of more than 10 percentage points. For some of the systems, we find losses in a range from 0 to 100 % for the same month. As expected, systems with colder climates have higher loss than systems in warmer climates, and systems with higher tilt has lower loss than systems with lower tilt. With snow loss modeling we get improved understanding of typical and extreme values, and the potential inter-annual variation in monthly and annual snow loss.

Keywords: PV System, System Performance, Modeling, Soiling, Snow

1 INTRODUCTION

As cost reductions have made photovoltaics (PV) a favorable choice also in colder climates, deployment rates in regions with snow falls are rapidly increasing [1–3]. Snow on PV modules may lead to significant power loss. For certain locations snow fall can result in zero electricity production in the winter season and more than 30 % annual loss [4]. Consequently, it is an important loss mechanism to consider in PV system models to get accurate assessments of the expected energy generation from PV plants in snow-affected locations. Snow-induced PV power loss is expected to vary from year to year, between different system configurations and between different locations. To get accurate snow losses for a specific system, a model taking into account the different influential parameters is therefore necessary. Recent research has demonstrated that for snow-affected locations the uncertainty in yield estimations [5–8] and forecasting [9] can be reduced if snow loss models are included. Despite this, snow loss models are often not implemented in PV simulation software. The System Advisor Model (SAM) has implemented the model suggested by Marion et al. [5,6], but in other software, snow is either not considered [10] or estimated by constant soiling values [11] with little guidance on how these constant values should be obtained.

Accurate snow loss modeling is, however, challenging, because the parameters influencing the snow cover and resulting PV system loss are manifold. The influential parameters range from weather conditions (precipitation, temperature, irradiance, wind, etc.), to installation and technology specific configurations (tilt, module technology/orientation, objects obstructing snow sliding etc.) [1,12] and type of snow [4]. Multiple snow loss models have been suggested [4], but validation is typically lacking [6]. To include all the parameters influencing snow cover and resulting loss in a physical model is challenging, and most suggested models for PV snow loss are based on empirical correlations [4].

In our previous work [13], we show that the snow loss model suggested by Marion et al. [3], where empirical correlations are used to model natural snow clearing, performs better than models where snow loss is directly estimated based on empirical correlations between power loss and system and weather data. Ryberg et al. [6] and van Noord et al. [14] also find acceptable correlation between estimated and modeled snow loss using the Marion model.

To estimate the snow coverage on PV modules, the Marion model aims to predict: 1) presence of snow cover on PV modules, 2) when snow is cleared off the modules, and 3) the snow clearing rate. The separation of these three processes in the model, enables improvement of the model by developing the modeling of each process by either using additional physical modeling or collecting more empirical data. In the model, the snow clearing rate is estimated with an empirical snow clearing coefficient. Many different parameters related to system design and weather/snow conditions are assumed to impact how fast the snow is cleared [13]. Frameless modules [15], empty space below modules [12] will promote sliding, for instance. With more data from different system configurations in different climates, we would get improved understanding of which parameters that impact the snow clearing rate the most, and consequently also get better values for the snow clearing coefficient and its potential variation.

In our evaluation of the model [13], we estimate the snow clearing coefficient from the snow loss data for the analyzed system, and we observe that for thin snow covers, the natural snow clearing rate is faster than the clearing rate of thicker covers [13]. By introducing separate snow clearing coefficients for thin and thick snow covers, reduced error in modeled snow loss is achieved. This also seems to make the model more general: when using snow depth dependent snow clearing coefficients we get better results when we model losses for systems with similar technical configurations with the same coefficients compared to when we use one single coefficient [16]. For transferability, it is important that we can use the same empirical coefficients for systems with similar technical configurations.

In addition to the challenge of accurate snow loss modeling, there is a lack of established guidelines on how to take snow losses into account when used in e.g. PV yield modeling or PV system dimensioning. Input data for the snow loss estimation, temporal resolution of the loss parameter, inter-annual variations and the impact of climate change need to be discussed. As pointed out by Marion et al. [5], typical meteorological year (TMY) values are not sufficient to use as input in snow loss modeling for PV yield assessments. Because snow is not one of the parameters considered in the derivation of TMY, TMY data does not necessarily represent a typical snow year. Using a long time series of meteorological data, enabling quantification of typical values and the inter-annual variability is suggested instead [5]. It is, however, important to use recent data. Because of climate change, historical snow data might not be representative for future snow conditions. In Norway, it is estimated that climate change will lead to reductions in snow depth and length of snow season, and an increase in snowline elevation [17]. Temporal resolution of the snow loss parameter is to our knowledge not much discussed in the literature. In the simulation tool PVsyst, monthly constant snow losses are used for PV simulations [11]. While this can be sufficient in assessments of total yield, this will not sufficiently describe the potential inter- and intraday variation. This variation can be relevant in system dimensioning, in particular for hybrid/battery systems.

In this work, we estimate the snow loss for a set of PV plants in Norway. Two different system designs are evaluated: commercial systems with modules installed with low tilt angles on flat roofs, and residential systems on tilted roofs. The aim of this analysis is to describe the variations in both monthly and annual snow losses, with respect to both time, location and system configuration, and to discuss how this could be included in e.g. PV yield modeling. The losses are estimated using both historical data and simulations based on longer time series of weather data and a modified adaption of the Marion snow loss model.

2 METHODOLOGY

2.1 PV system data

Seven PV installations in Norway with a total installed capacity of 1.6 MWp are analyzed. The evaluated dataset is the same as the dataset used to validate the modified snow loss model in [16], but some of the data series are extended in time. Two different system types are evaluated: residential systems on tilted roofs, and commercial large-scale systems on flat roofed buildings. The commercial systems have modules installed with low tilt and east/west orientation. This configuration is not optimal for total annual production in Norway, but is commonly used on flat roofed buildings to increase the packing density and reduce the seasonality of the production profile. The modules are installed in portrait orientation at the residential systems, and landscape orientation at the commercial system. All the PV modules are crystalline silicon. Apart from some variations in exact orientation, and tilt for the residential systems, the installations of the same type are assumed technically identical. Tilt and length of analysis period for the systems are given in Table I.

Table I: Module tilt and length of analysis period for analyzed systems

System ID	Tilt	Analysis period
Residential systems		
R1	26	Jan 2019 – June 2021
R2	40	Jan 2018 – June 2021
R3	24	Jan 2019 – June 2021
Commercial systems		
C1	10	Jan 2015 – June 2021
C2	10	Jan 2017 – June 2021
C3	10	Jan 2018 – June 2021
C4	10	Jan 2018 – June 2021

The measured energy of the PV systems is collected from the inverters. For the commercial systems, the effective in plane irradiance and the module temperature is measured by reference cells. The residential systems have no on-site sensors. For all the locations, snow depth and snow fall data are collected from seNorge.no [18] and temperature and global horizontal irradiation (GHI) data are collected from nearby weather stations [19].

As illustrated in Figure 1, the analyzed systems are situated in three different geographic regions in Norway (East, West and Central), and in three different Köppen-Geiger (KG) [20] climate zones (Humid continental climate (Dfb), subarctic climate (Dfc) and oceanic climate (Cfb)). This gives variation in snow and weather conditions between the locations. Figure 2 shows 16 years of snow depth data for the four different combinations of geographic region and climate zone.

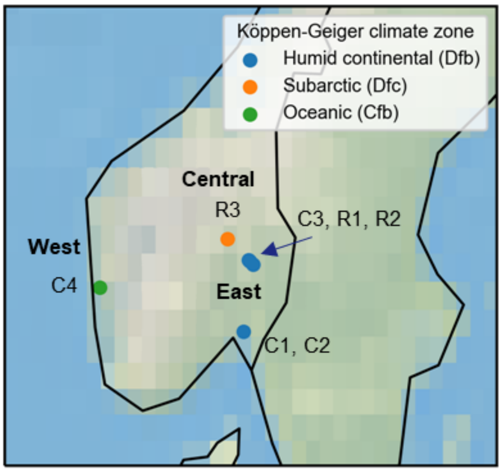

Figure 1: Location on the map for the analyzed systems. The locations are labeled with geographic region and climate zone is given by the marker color.

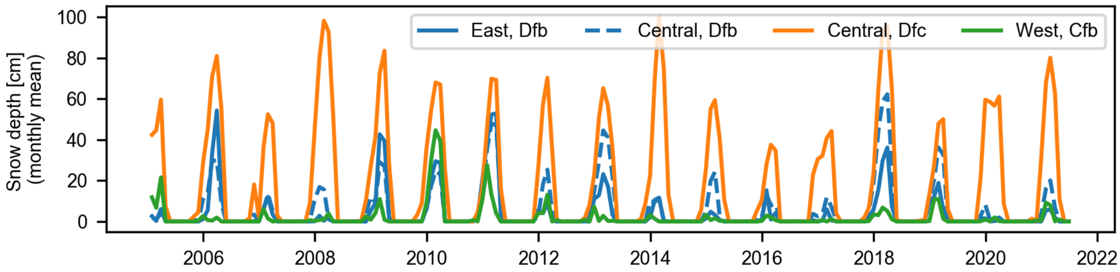

Figure 2: Sixteen years of snow depth data for the four combinations of geographic region and KG climate zone in the analyzed dataset.

2.2 Estimation of snow loss from historical PV data

To estimate historical snow losses from PV monitoring data, it is necessary to get an accurate estimate of what the energy production could have been if there was no snow. This requires an accurate model that considers all other losses of the PV system, and an efficient method to separate snow losses from other losses. To correctly estimate snow losses, it is especially important to take into account other wintertime losses such as losses caused by low irradiance, and high angles of incidence. These types of losses are typical for high latitude locations in the wintertime [21], and can introduce increased uncertainty in PV system modeling if not properly accounted for.

To estimate expected PV module power output for the commercial systems, the effective irradiance measured by the reference cells and the measured module temperature are used as input to a single diode model in pvlib python [22] to model PV module power output, using the procedure described in [13]. For the residential systems, detailed module data and onsite measurements are not available. Effective irradiance and module temperature are modeled in pvlib from measurements of GHI and ambient temperature from nearby weather stations. The GHI measurement is decomposed using the Erbs model [23] to estimate diffuse irradiance, and the Disc [24] model for direct irradiance. When modeling the in plane irradiance for the systems, the Hay and Davies' 1980 model [25] is used to determine the in plane diffuse irradiance from the sky. From the modeled in plane global irradiance, the effective irradiance is calculated by adding reflection losses using an incident angle modifier based on the physical model described in [26]. The module temperature is modeled using the PVsyst temperature model [27]. The expected power output from the modules is modeled using PVWatts [28].

The described PV module power output models do not take into account all the relevant losses (all other losses than snow-induced losses) of the systems. From the energy performance index (*EPI)* of the system, the ratio between measured and modeled energy, we observe that the calculated value is below 1. Additionally, the *EPI* has a systematic seasonal component suggesting higher losses in the winter months, also in periods without snow. We assume that the significant losses not accounted for in the model, can be estimated with a constant and a seasonal component. To accurately find the seasonal components for the analyzed systems, seasonal trend decomposition is performed on the daily *EPI*, after filtering out time periods with snow on the ground (which introduces a non-systematic seasonal component). Seasonal trend decomposition is suggested by [29] as a method to find and correct the seasonal component in PV performance metrics. The deviation between 1 and the median of the seasonally corrected *EPI* is used as an estimate of the constant system losses. These two components are then used to correct the modeled PV module output to find the expected system output. By this way aiming to take all other significant losses into account, the snow loss is then estimated to be the difference in expected system output and measured system output in periods where the snow data suggests snow on the ground.

An additional uncertainty in this methodology is that snow cover on the irradiance sensors can lead to underestimation of snow losses. To reduce this uncertainty, the reference cell measurements from the commercial systems were controlled and corrected by the external GHI data. Pyranometers is expected to have lower risk for full snow cover than reference cells, because of the shape and elevation of the sensor, and better ventilation and maintenance.

2.3 Modeling snow loss with the modified Marion model

In the Marion snow loss model [5] the presence of a new snow cover is assumed to happen after snow fall. The model further assumes that natural snow clearance will happen during melting. Melting is predicted to happen during the following conditions:

$$T_{amb} > G_{POA}/m. \qquad (1)$$

T_{amb} is the ambient temperature, G_{POA} is the in plane irradiance and m is an empirically defined value of -80 W/(m^2 °C). During melting, the snow will be cleared by sliding or direct melting on the modules [4]. To estimate the reduction in snow coverage in the melting period, measured in fractions of the system height, the tilt of the modules and an empirical snow clearing coefficient (*sc*) is used:

$$\textit{Snow slide amount} = sc * \sin(tilt). \qquad (2)$$

Based on these assumptions, the snow coverage on the modules is estimated, and the corresponding power loss calculated. If a module substring is partially covered by snow, the power output is assumed to be zero. This way, it is taken into account whether the modules are installed in portrait or landscape orientation. The pvlib python [22] implementation of the Marion model is used in this work to model the relative snow loss. To estimate the absolute energy loss, the modeled relative snow loss is multiplied with the modeled energy output of the system, modeled using the procedure described in Section 2.2.

In the development of the snow loss model, Marion et al. found *sc* to be 0.20 [5] for roof mounted systems. This value is the default *sc* in the implementation of the model in pvlib python [22] and the PV modeling software SAM [6]. The snow clearing coefficient is, as previously discussed, expected to depend on different system and module designs [13], because technical aspects can either promote or obstruct natural snow clearing [1]. In our evaluation of the model, we found that snow clearing is slower for the systems we have analyzed [13,16] compared to the validation systems the Marion model is based on. A possible explanation for the difference is higher roof interference for the systems that we have evaluated. In our evaluation of the model we also find that the rate of snow clearing is influenced by the thickness of the snow cover [13]. We therefore add a small modification to the Marion snow loss model by introducing a snow depth dependent *sc*. Because the dataset in this work is the same as in [16], we use the snow depth dependent snow clearing coefficients from [16] that gave the best modeling results. As also described in [16], we use snow depth data from the ground to separate between thin and thick snow covers for the commercial system where there is little sliding. For the residential systems where there is more sliding and where snow depth data from the ground are less representative, we use cumulative snow fall data as an indicator for snow cover thickness.

2.4. Simulation of snow losses for longer time series

To simulate losses for the analyzed systems over time, to get improved understanding of typical losses, we use long time series of weather and snow data to model snow losses, as proposed by [5]. GHI and ambient temperature data for all the locations from the time period 2005-2016 and the ERA5 database is collected from PVGIS [30]. The expected module power output for all the systems is modeled as described for the residential systems in section 2.2. System loss of 7 % is added using the PVWatts system loss function with default loss values for mismatch, wiring, LID, connections and name plate rating [28]. Snow losses are then modeled using the same procedure as described in 2.3.

3 RESULTS

3.1 Snow loss estimated from historical PV data

Figure 3 shows the annual historical snow loss for the analyzed systems (both system configurations) estimated from historical PV data. The loss is given relative to the mean expected annual yield. The mean value is chosen to avoid variations in the loss caused by variation in the total annual irradiation. We observe large variations in snow losses from year to year, and between different systems.

As expected, we observe that weather, system design and climate on snow losses seem to impact the snow losses. The inter-annual variation in snow losses for the systems, as well as the variation in losses between systems located in the same climate zone, but in different locations (C1 and C3), can be explained by typical variations in weather between different locations and different years. C3, R1 and R2 are located in the same area, but R2 has lower loss than R1 every year, and C3 typically has higher loss than both. This could be explained by the impact of tilt on the snow clearing, as snow clearing is inversely proportional with tilt. C1 and C2 have the same technical configuration and experiences the same weather as they are co-located, and their estimated losses are very similar. C4 located in oceanic climate typically has lower losses than the identical systems (C1-C3) located in humid continental climate. R3, located in a subarctic climate, typically has higher losses than R1, which has almost the same tilt but is located in a humid continental climate.

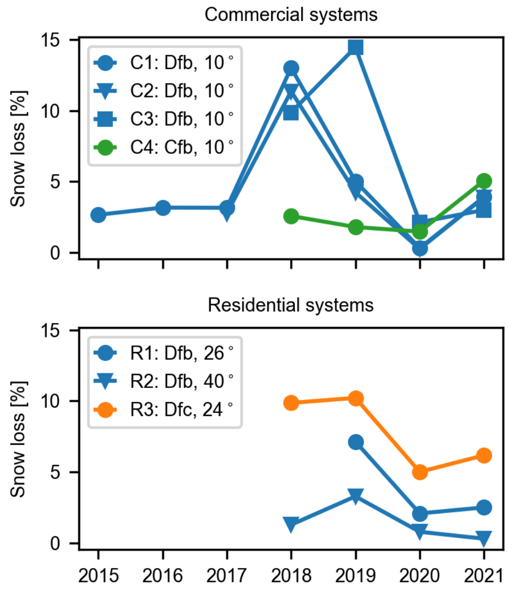

Figure 3: Annual snow loss for the analyzed systems, estimated from PV data. The losses are given relative to mean expected annual yield for the analysis period. The systems in humid continental climate is plotted in blue, green represents oceanic climate and orange represents subarctic climate.

Figure 4 shows the monthly losses for all the full years in the analysis period. Large variations in the monthly loss value are observed for several of the months. For most of the datasets the loss is typically increasing during late autumn, reaching its highest peak in midwinter, before it decreases in the spring. The snow data do, however, not follow the same trend. Typically, the locations have the most snow in the late winter months, but this also corresponds with higher temperatures.

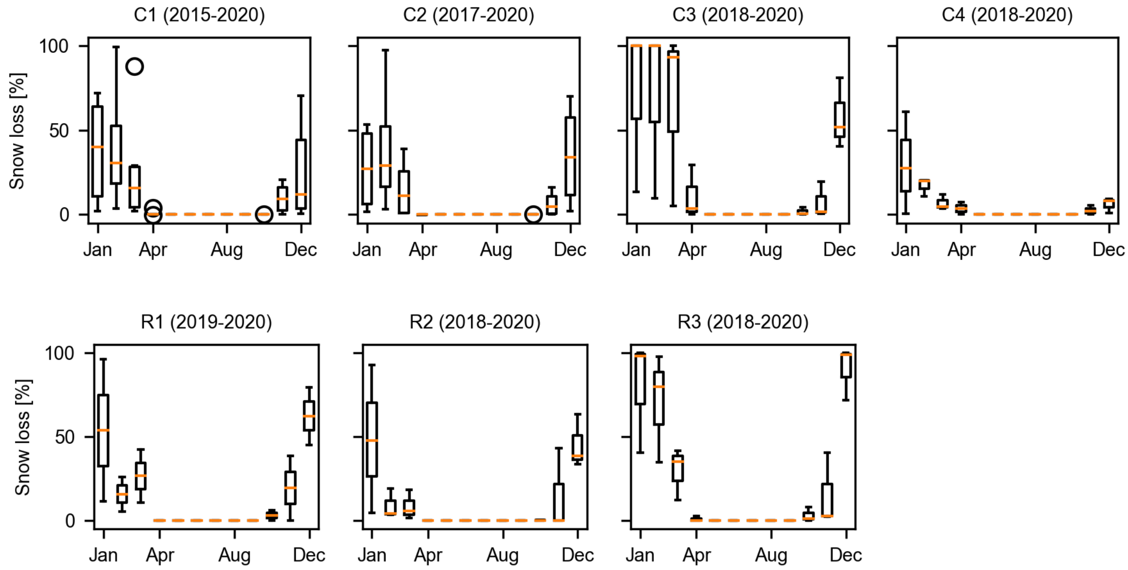

Figure 4: Monthly snow loss for the analyzed systems in the analysis period (given in the subfigure title), estimated from historical PV data. The estimated losses for each month is plotted using a boxplot to show the interannual variation. The box extends from the first to the third quartile values of the monthly loss data, with a line on the median. The whiskers extend to maximum 1.5 multiplied the interquartile range. Outliers are given as circles.

3.2 Simulated snow loss

Based on the results presented in Figure 3 and Figure 4, it is not always clear what would be the best estimate for typical annual and monthly snow losses for the analyzed systems. Especially for the locations with large snow losses, there can be large variations for the same month between different years. With potentially large variations from year to year, estimating typical snow loss for short time series might give an output that is not necessarily representative for the system configurations and the location. Based on this, selecting a representative snow loss value for e.g. a PVSyst simulation seems challenging, as long time series for different system designs and locations would be needed.

Figure 5 and Figure 6 show the correlation between snow loss estimated from PV data and modeled snow loss using the modified Marion snow loss model for respectively annual and monthly losses. Both on the monthly and annual time scales we observe a linear relationship between modeled losses and losses estimated from historical PV data, indicating that the model can be used to predict the losses on both time scales. Some uncertainty in the prediction can, however, be expected. As seen in the figures, there are some deviations between modeled loss and loss estimated from PV data.

In Figure 7 and Figure 8 the simulated monthly and annual snow losses for the analyzed systems using 12 years of irradiation and temperature data from PVGIS is presented. With the longer time series, we get a better understanding of what is typical losses, and what the potential variation and the extreme values could be. With the longer time series, we now see for all of the systems that the losses are highest during mid-winter. Some of the systems get higher monthly median losses than what we observed in Figure 4. This suggests that the years in the analysis period used to estimate losses from historical data are not necessarily years that represent the long-term trend.

Using longer time series and modeling could also enable estimation of snow losses for locations where PV data is lacking. Additionally, future snow losses could be estimated using output data from climate models giving data for the future. To avoid the impact of extreme values, we propose to utilize the median value of the modeled losses as an estimate of the monthly/annual snow losses in yield simulations.

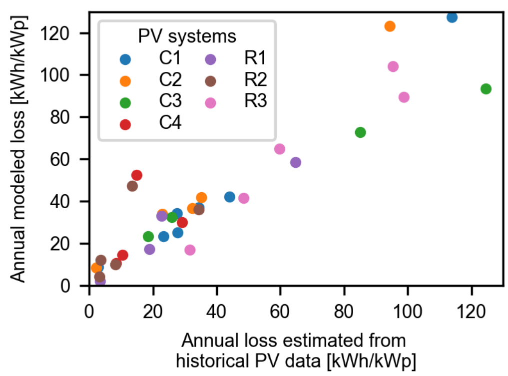

Figure 5: Annual modeled absolute loss compared to loss values estimated from historical PV data.

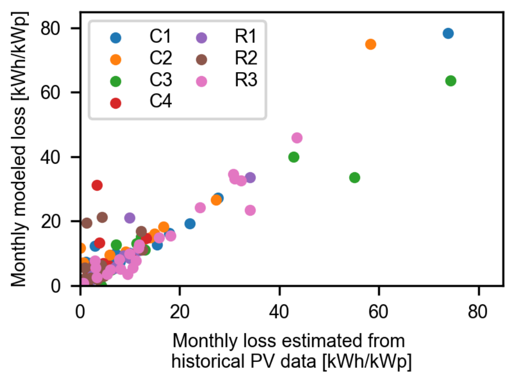

Figure 6: Monthly modeled absolute loss compared to loss values estimated from historical PV data.

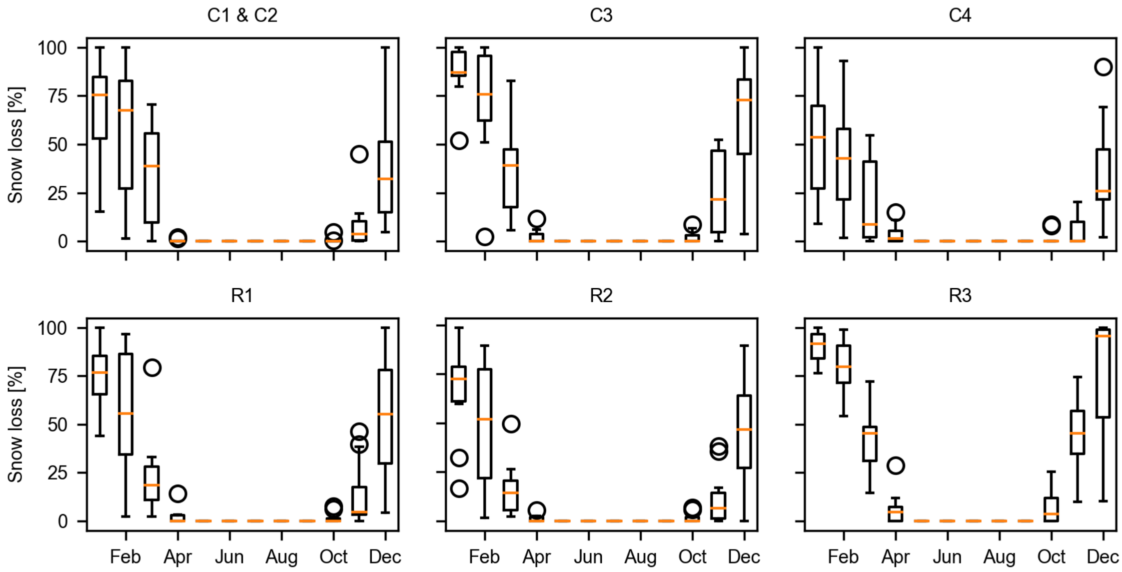

Figure 7: Monthly simulated losses for the analyzed systems, based on 12 years of PVGIS data and the modified Marion snow loss model. The simulated losses for each month is plotted using a boxplot to show the interannual variation. The box extends from the first to the third quartile values of the monthly loss data, with a line on the median. The whiskers extend to maximum 1.5 multiplied the interquartile range. Outliers are given as circles.

Using simulations to estimate PV systems snow loss could in addition to the loss value and estimation on interannual variability, also give realistic production profiles on daily and hourly timescale, which is useful in system size optimization and when building synthetic data series or adding synthetic performance loss for testing of e.g. fault detection algorithms [29]. The uncertainty in the modeling on high time resolutions is likely too high for e.g. monitoring purposes where the modeled PV output should match measured data, but to describe how snow losses vary within a day and from day to day, the modeling is useful.

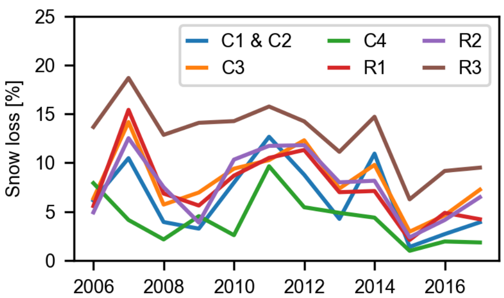

Figure 8: Simulated annual snow loss for the analyzed systems, based on 12 years of PVGIS data and the modified Marion snow loss model. The losses are given relative to mean expected annual yield for the analysis period.

4 CONCLUSIONS

In this work, we estimate annual and monthly snow loss for a set of PV plants in Norway. In both annual and monthly losses, we observe large interannual variations, and we see that systems in colder climates typically have higher losses than systems in warmer climates. We also observe that higher tilt gives reduced losses, confirming previous studies. A modified adaption of the Marion snow loss model where snow depth is considered in the snow clearing modeling is used with 12 years of weather data to simulate losses for a longer time series, to get improved understanding on the potential interannual variation in snow losses. We find that snow loss modeling is a useful tool for estimating monthly or annual snow losses for use in yield modeling when long time series of snow loss data for a given type of system in a given location is not available.

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